

In the Matter of:

**Economic Conference on Marketing and Consumer
Protection**

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Final Version*

Condensed Transcript with Word Index



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1		3	
1	FEDERAL TRADE COMMISSION	1	FEDERAL TRADE COMMISSION
2		2	I N D E X (Continued)
3		3	
4		4	PAGE:
5	ECONOMIC CONFERENCE ON	5	Lunch Panel:
6		6	"Can Marketing go too Far?" 170
7	MARKETING AND CONSUMER PROTECTION	7	Moderator: Andrew Stivers
8		8	
9		9	Session Three:
10		10	"Algorithmic Bias? A Study of the data- 224
11		11	based discrimination in the serving of
12		12	ads in social media," Catherine Tucker
13	Friday, September 16, 2016	13	Discussant: Kanishka Misra
14	8:30 a.m.	14	
15		15	"The Value of Information in Mobile Ad 258
16		16	Targeting," Hema Yoganarasimhan
17		17	Discussant: Sridhar Narayanan
18	Federal Trade Commission	18	
19	Conference Rooms	19	"Direct-to-Consumer Advertising and 298
20	400 Seventh Street, S.W.	20	Online Search," Matthew Chesnes
21	Washington, D.C.	21	Discussant: Jura Liaukonyte
22		22	
23		23	
24		24	
25		25	
2		4	
1	FEDERAL TRADE COMMISSION	1	FEDERAL TRADE COMMISSION
2	I N D E X	2	I N D E X (Continued)
3		3	
4	PAGE:	4	PAGE:
5	Welcome and Introduction	5	SESSION FOUR:
6	By Ginger Jin 5	6	"Might I Interest You in an Extended 324
7		7	Warranty," Sriram Venkataraman
8	Session One:	8	Discussant: Matthew Jones
9	"The Impact of Privacy Policy on the 22	9	
10	Auction Market for Online Display	10	"What Determines Consumer Complaining 358
11	Advertising," Garrett Johnson	11	Behavior," Devesh Raval
12	Discussant: Douglas Smith	12	Discussant: Anne Coughlan
13		13	
14	"Sponsorship Disclosure and Consumer 53	14	CONCLUSION:
15	Deception: Assessing Native Advertising	15	Closing Remarks, K. Sudhir 390
16	in Mobile Search," Navdeep Sahni	16	
17	Discussant: Yesim Orhun	17	
18		18	
19	Session Two:	19	
20	"The Benefit of Collective Reputation," 100	20	
21	Zvika Neeman	21	
22	Discussant: Anthony Dukes	22	
23		23	
24	"Tailored Cheap Talk," Pedro Gardete 130	24	
25	Discussant: Upender Subramanian	25	

5	<p>1 WELCOME AND INTRODUCTION</p> <p>2 (8:37 a.m.)</p> <p>3 DR. JIN: Hi, good morning. Thank you so</p> <p>4 much for coming here. I know some of you have been at</p> <p>5 FTC before and some of you probably this is your first</p> <p>6 time to be here. Welcome you all.</p> <p>7 I'm Ginger Jin. I'm the Director of FTC</p> <p>8 Bureau of Economics. When I took the director's role</p> <p>9 in this January, I had a strong feeling that FTC</p> <p>10 activity is very much related to marketing. Our</p> <p>11 bureau has over 80 Ph.D. economists, and we could</p> <p>12 benefit greatly from the marketing research community,</p> <p>13 the literature, the ongoing research in this</p> <p>14 community.</p> <p>15 So I reached out to K. Sudhir and Avi</p> <p>16 Goldfarb just tentatively. To my pleasant surprise,</p> <p>17 both of them responded immediately and positively with</p> <p>18 many potential good ideas for getting together the</p> <p>19 FTC and the marketing research community. So I'm</p> <p>20 really glad that you can make today's conference. I</p> <p>21 hope will enjoy the conference and will find it</p> <p>22 interesting and be able to engage with us more in the</p> <p>23 future.</p> <p>24 I would also like to thank all of you for</p> <p>25 responding enthusiastically to our call for papers.</p>	7	<p>1 to all of them.</p> <p>2 (Applause.)</p> <p>3 DR. JIN: And also thanks to the FTC admin</p> <p>4 team, event team, media team, for getting all the</p> <p>5 video and audio available for today.</p> <p>6 So FTC has a history of over 100 years. It</p> <p>7 has a lot of interesting institutional features. To</p> <p>8 be honest, I didn't know all of that before I come to</p> <p>9 FTC. So I want to take this moment to just give you a</p> <p>10 brief review of exactly what we do at FTC, especially</p> <p>11 about marketing, about consumer protection.</p> <p>12 So just to give you some sense, we know that</p> <p>13 FTC is in markets. Many markets would have one or</p> <p>14 more firms competing for consumers. So you probably</p> <p>15 have heard about competition and antitrust, which is</p> <p>16 one mission of FTC. I would argue that another even</p> <p>17 more important mission in the FTC is consumer</p> <p>18 protection. And that's because firms interact</p> <p>19 directly with consumers, and also the ultimate goal of</p> <p>20 preserving competition is to protect consumers.</p> <p>21 Okay. And, moreover, if we think that firms</p> <p>22 -- if they feel like they are under unfair</p> <p>23 competition, they would have resources to go for</p> <p>24 private litigation and sort of seek some judgment from</p> <p>25 the court. It's really hard for individual consumers</p>
6	<p>1 We actually received over 50 submissions, which was</p> <p>2 really, really a good surprise to us. It also makes</p> <p>3 our scientific screening committee work really hard.</p> <p>4 Sudhir, Avi, Ganesh Iyer, and Andrew Stivers from FTC,</p> <p>5 they did a fantastic job putting together an agenda.</p> <p>6 But they wouldn't have be able to do so without your</p> <p>7 willingness to participate, to discuss, and to present</p> <p>8 the papers. So thank you all for doing that and being</p> <p>9 here.</p> <p>10 I also want to thank INFORMS for cohosting</p> <p>11 today's conference, as well as Marketing Science</p> <p>12 Journal. I want to thank Laura Kmitch and Constance</p> <p>13 Herasingh. They probably are out of the room making</p> <p>14 sure that everything is running smoothly, as well as</p> <p>15 Stacy Awe. I think she is not here today, but she's</p> <p>16 from Yale and has been an assistant to Sudhir and</p> <p>17 very helpful throughout the planning of the</p> <p>18 conference.</p> <p>19 A lot of my staff are on the ground here as</p> <p>20 early as 7:30. So I want to thank all of them. Ben</p> <p>21 Chartock, Jason Chen, Aaron Keller, Jennifer Snyder,</p> <p>22 Stephanie Aaron, Marilyn McNaughton, Maria Villofler,</p> <p>23 and Crystal Meadows. And they are -- we wouldn't be able</p> <p>24 to have the conference running so smoothly without</p> <p>25 them on the ground. So let's give a round of applause</p>	8	<p>1 to do so. Even if they can file class act litigation,</p> <p>2 it's going to be -- whatever the redress they can get</p> <p>3 will be shared with lawyers and some of them can be</p> <p>4 very aggressive.</p> <p>5 So it's really important for federal</p> <p>6 agencies like the Federal Trade Commission to act on</p> <p>7 behalf of individual consumers to protect them from</p> <p>8 deceptive and unfairness, deceptive and unfair</p> <p>9 practice.</p> <p>10 So FTC over 100 years actually has a lot of</p> <p>11 functions. The foremost is law enforcement. So I</p> <p>12 want to take this role. My daughter, who is 10 years</p> <p>13 old, asked me, Mom, what's your new job? I said, I'm</p> <p>14 going to be a policewoman. And she was saying how</p> <p>15 come you don't wear the police uniform?</p> <p>16 So we're a law enforcement agency without</p> <p>17 uniform. We enforce over 70 laws against business</p> <p>18 practices that are anticompetitive, deceptive, or</p> <p>19 unfair. We can bring lawsuits in federal courts. We</p> <p>20 can also bring lawsuits in front of administrative law</p> <p>21 judge inside our commission. And if the decision of</p> <p>22 the judge was -- is contested, we can even hold</p> <p>23 commission hearings.</p> <p>24 And after decisions from the court, we can</p> <p>25 enforce the final commission orders. It would also</p>

9	<p>1 redress harm to consumers. So that's probably the 2 majority of our work inside FTC. In addition, we also 3 have rulemaking authorities. We can make rules for 4 industry-wide practice. We also function as 5 information collector. We watch out for new and 6 problematic practices. We oftentimes, especially in 7 the Bureau of Economics, engage in investigative 8 research. We do a lot of research as well as policy 9 advocacy.</p> <p>10 So given that we are enforcing over 70 laws, 11 it's probably very hard for me to give you a full list 12 of all the laws we enforce. So I'll just give you a 13 sub-sample so that you will have an idea of what we're 14 enforcing.</p> <p>15 We start from the 1914, the Federal Trade 16 Commission Act, which gives us very broad jurisdiction 17 over almost every industry, deceptive and unfairness 18 and anticompetitive practice. And we enforce the Fair 19 Packaging and Labeling Act together with FDA; and the 20 Truth in Lending Act in 1968; the Motor Vehicle 21 Information and Cost-Saving Act in 1972; and this is 22 interesting, this Petroleum Marketing Practices is 23 actually about franchisor and franchisee relationships 24 in gas stations. So that was enacted in 1978. 25 And more recently we engaged in</p>	11	<p>1 avoidable by consumers, and not outweighed by 2 countervailing benefits to consumers or competition.</p> <p>3 So let me give you a few examples of exactly 4 what we do so that you will have a sense of the 5 activities here. So I will first go over some 6 examples and conclude with some challenges we face 7 today. And I hope you can help us addressing those 8 challenges.</p> <p>9 So the first example is fraud. The Bureau of 10 Economics actually worked with the Bureau of Consumer 11 Protection to conduct nationwide fraud surveys for 12 three rounds. And actually the fourth round is 13 ongoing right now. So I'm -- here I list a few 14 reports from those surveys.</p> <p>15 In the latest one that we have data on, 16 which is 2011, we actually observed about 10.8 percent 17 of U.S. adults or 25.6 million people were fraud 18 victims. This is -- I don't know whether you think 19 this is a big number or small number. It was kind of 20 shocking and a surprise to me when I read the number, 21 and in total we estimate there are about 37.8 million 22 incidences of fraud during the year of 2011.</p> <p>23 So our fraud survey also gives us some sense 24 about what type of fraud are most popular on the 25 ground. Okay? So this graph is sort of showing you</p>
10	<p>1 Telemarketing and Consumer Fraud and Abuse Prevention 2 Act; Children's Online Privacy Protection Act; 3 Identity Theft Assumption and Deterrence Act; College 4 Scholarship Fraud Prevention; Crime Against Charitable 5 Americans; Do-Not-Call Registry legislation; unlawful 6 internet gambling enforcement; U.S. Safe Web Act; 7 Credit Card Accountability Responsibility and 8 Disclosure Act; Patient Protection Affordable Care 9 Act; and Restore Online Shoppers Confidence Act.</p> <p>10 So of this history, it's just a subset of 11 the laws that we enforce. You probably would get a 12 sense that we actually enforce the laws in many, many 13 industries, and recently more about online businesses 14 in all kinds of actions.</p> <p>15 So in terms of consumer protection, we sort 16 of use two common legal standards here. In 1983, FTC 17 actually published a clarification on Deception Policy 18 Statement, which means we can go after the deceptions 19 that are likely to mislead consumers acting reasonably 20 in the circumstances to the consumer's detriment.</p> <p>21 I will give you a few examples of what we 22 mean by this legal language or unfairness. In 1980, we 23 clarified that it's going to be a three-prong 24 exercise. It has to generate substantial injury or 25 likely to generate substantial injury, not reasonably</p>	12	<p>1 the top, I guess, 15 to 20 types of fraud by number of 2 victims. The number one actually is also number one 3 in the last round of fraud survey. It's weight loss 4 products. Okay? And it follows by a lot of creative 5 scams such as a prize, promotions, bidding buyers 6 club, internet services, work-at-home programs, credit 7 repair, and on and on.</p> <p>8 So you can see that the frauds we are 9 supposed to police are really widespread and can take 10 many forms. So the challenge we face is how can we 11 attack those frauds given there are so many going on in 12 the market and how can we educate consumers to avoid 13 those scams, and eventually how to penalize and deter 14 those scammers, especially when they are fly by night. 15 Okay? They sort of gather all the money and already 16 spend it by the time that we catch them. How can we 17 really penalize them and deter them is a quite 18 important legal as well as economic question.</p> <p>19 So that's the first example. The second 20 example is actually a lot of cases that we have 21 brought before were about deceptive advertising. Some 22 of you may have heard about this or even own a car 23 from Volkswagen. Okay? So this is a typical ad that 24 Volkswagen put up for their really clean diesel. 25 Okay? It turns out that it's only really clean when</p>

13	<p>1 it's tested because they have a defeat device which is 2 a software hidden in the car, and that software would 3 understand that the car is under a test mode and sort 4 of trigger cleaning process inside the car. But when 5 it's not in the testing environment, it actually can 6 generate NOx as much as 40 times above the federal 7 standard, which would have a significant consequence 8 for the environment as well as for people's health.</p> <p>9 So in March of this year, FTC sued 10 Volkswagen over deceptive diesel claims. And thanks 11 to our collaboration with a lot of other federal 12 agencies such as DOJ and EPA, were able to reach a 13 historical settlement which is as much as \$10 billion, 14 which means they -- Volkswagen is willing to pay up to 15 \$10 billion to consumers who have been deceived by 16 these ads, and they all have options to sell the car 17 back to Volkswagen with substantial monetary 18 compensation, or they can have the car repaired and 19 still own the car. And even with that option, they 20 will receive significant monetary compensation.</p> <p>21 So this is quite a victory for FTC and 22 eventually to all the consumers in the market. So 23 that's the example of deceptive advertising.</p> <p>24 Another example is privacy protection. If 25 you had been here yesterday for the Disclosure</p>	15	<p>1 their Playstation Vita console has game-changing 2 technology features. Okay? It turns out to be false.</p> <p>3 In addition, their ad agency -- I think in Los 4 Angeles, Deutsch LA, misled consumers by urging its 5 employees to create awareness and excitement about 6 this console on Twitter without disclosure of their 7 connection.</p> <p>8 Okay. So we think this is not acceptable. 9 So we reached a settlement with them. For both 10 companies, we have cease-and-desist orders, and Sony 11 also agreed to pay either \$25 in cash or \$50 in 12 merchant credit to buyers that have bought this 13 console before June of 2012.</p> <p>14 The last example I want to give is about 15 multi-level marketing. Okay? I don't know how much 16 you know about multi-level marketing. It's turned out 17 to be a very big industry. So this year we brought a 18 case against Herbalife, which is the third largest 19 multi-level marketing company in the world. We allege 20 that they deceived consumers into believing 21 substantial income from the multi-level marketing 22 business opportunity, which is a deception count.</p> <p>23 We also allege that they incentivized 24 distributors to buy products and to recruit others to 25 join and buy products so that they can advance in the</p>
14	<p>1 Workshop, there has been a lot of attention on 2 privacy, consumer privacy and how to protect it. So a 3 recent case we brought is for Practice Fusion, which 4 is a cloud-based electronic record management company. 5 So we allege this company started to collect patient 6 evaluation of doctors since April 2012. For over a 7 year, the website has collected a lot of consumer 8 reviews. In April 2013, they decided to go live with 9 over 613,000 consumer reviews.</p> <p>10 However, some of them include highly 11 sensitive personal and health information. And at the 12 time that they entered those reviews, the privacy 13 notice they received did not indicate there will be a 14 public display of consumer reviews. So we think this 15 has violated consumers' privacy, and we are able to 16 reach a settlement in June of this year with a 20-year 17 order to constrain this company.</p> <p>18 The fourth example is online endorsement. I 19 know many of you have done very interesting research 20 about online activities, online advertising, online 21 endorsements. This is an area that we are very active 22 in watching and policing.</p> <p>23 So one example is a case we brought in 2014. 24 We alleged that Sony Computer Entertainment America, 25 which is a branch of Sony Company, falsely claimed</p>	16	<p>1 company's marketing program rather than in response to 2 the actual consumer demand. And this is an unfairness 3 count.</p> <p>4 So we're able to reach a settlement in this 5 July. After a two-year investigation, that settlement 6 included a \$200 million payment from Herbalife for 7 consumer redress as well as restructure its business 8 from top to bottom. We hope this is a historical case 9 that will help to shape the whole industry of multi- 10 level marketing.</p> <p>11 So with all these examples, you can see that 12 we cover a lot of areas. We try to keep up with the 13 business practices going on in the market. We also 14 face a lot of ongoing challenges. The first one is 15 how to detect potential violators. We sort of have 16 some sense -- we have a lot of experience in dealing 17 with offline violators, but our knowledge is that many 18 of them have moved to online with probably more 19 decentralized networks, with more creative actions in 20 desktop, in mobile environments. And so really we want 21 to engage you in understanding the marketplace and try 22 to think more about how can we do a better job 23 detecting potential violators for both online and 24 offline markets.</p> <p>25 Another question is how can we link consumer</p>

17	<p>1 misperception to firm behavior. In many cases, we 2 observe outcome. Those outcomes could be driven by 3 many factors, including the firm's wrongdoing, but as 4 well as other noises in the market. How can we 5 distinguish all those things and use the information 6 we have to go after real violators? How can we define 7 the measure of consumer harm and countervailing 8 benefits? And that is already hard in the offline 9 markets, but it's become even more challenging in a 10 world of big data and connected things. So we really 11 want to hear your research in this area.</p> <p>12 There also is a sort of policy question if 13 we are sure that there's something wrong going on in 14 the field, we want to change the market. Should we 15 discipline the firm? Should we educate consumers? 16 Should we do both of them, given our limited 17 resources? So that's probably a more policy-oriented 18 question, but it's also very related to our 19 understanding of the market and about the potential 20 effect of our policies in this area. And how to 21 regulate a market when consumer knowledge and business 22 practices are both evolving.</p> <p>23 And we know that consumers care about 24 privacy from many consumer surveys, but they also 25 behave in a way that seems sometimes inconsistent with</p>	19	<p>1 technician, Jennifer. So we would require everyone to 2 speak into the microphone, the presenter will speak 3 into the microphone. We also will have walking mics 4 around the room. So when you want to ask a question 5 or want to make a comment, we hope that you can speak 6 to -- can wait for the microphone to come to you and 7 speak to the microphone so that we can record the 8 whole conference.</p> <p>9 And there are actually restrooms on this 10 floor. If you go out of this conference room and past 11 the glass doors you just used to come into this floor, 12 there will be a restroom on your right-hand side.</p> <p>13 In case of emergency, if emergency occurs 14 and requires you to leave the conference center but 15 remain the building, please follow the instructions 16 provided over the building's PA system. If an 17 emergency occurs that requires the evacuation from 18 this building, alarm will sound and everyone will have 19 to leave immediately upon the alarm. And we are 20 supposed to leave in an orderly manner, not rushing to 21 the door in a congested way.</p> <p>22 And so in that case -- and hopefully it's 23 not going to happen, but in that case, we'll need to 24 leave the building through the main 7th Street exit. 25 After leaving the building, we'll turn left and</p>
18	<p>1 what they say in those surveys. So consumer knowledge 2 definitely is evolving and businesses probably are 3 adjusting their practices to this kind of consumer 4 demand. With others evolving and probably both of 5 them will change given our position in policymaking. 6 So this is a very dynamic and ongoing environment. 7 It's really challenging for us to think about the 8 interactions between the different players here. So, 9 again, that's -- we really want to engage your 10 thoughts and your creative thinking on exactly how to 11 address that question.</p> <p>12 And, finally, if you have any ideas or any 13 comments or suggestions as to how we can better engage 14 with your community, how can we learn from your 15 research community, it's really, really important for 16 us to keep up with that literature.</p> <p>17 So with that, I will mention a few sort of 18 logistical things that we have to say, and then we'll 19 move on to the real content of papers.</p> <p>20 You probably already have the pamphlet about 21 wi-fi and information. Okay? And this is a federal 22 building, so if you are going to leave the building 23 unfortunately you probably have to go through the 24 security again. Okay?</p> <p>25 And this conference will be recorded by our</p>	20	<p>1 proceed south past E Street and there will be a FTC 2 emergency assembly place. Okay? And so we'll be -- 3 we'll remain there until further instruction. If you 4 notice any suspicious activity, please alert the 5 building security.</p> <p>6 So, finally, please be advised that this 7 event will be recorded and we'll have a transcript 8 later on available on the website. What you provided 9 to us might be -- the event might be photographed, 10 webcast or recorded, and what you say here, your 11 image, and what you submitted here will all be subject 12 to potential posting on FTC.gov or at any social media 13 website related to FTC.</p> <p>14 So with that disclosure, the privacy notice, 15 I want to thank you all for coming here. So we'll 16 kick off with our first paper. Our plan is to have 40 17 minutes per paper. So we'll have 25 minutes for 18 presentation and 10 minutes for discussant, and 19 hopefully we'll have five minutes for floor 20 discussion.</p> <p>21 So our first paper will be presented by 22 Garrett Johnson from the University of Rochester about 23 the impact of Privacy Policy on the Auction Market for 24 Online Display Advertising. So that title basically 25 captures a lot of key words I just said about the FTC's</p>

21	<p>1 business. So that's a great start. 2 Garrett? 3 (Applause.) 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>	23	<p>1 And after a few seconds, you'd have about 100 2 companies that know that you visited The Chicago 3 Tribune. 4 Now, this helps make salient, you know, we 5 talk about tracking, but it really helps make salient 6 just the amount of tracking that happens online. And 7 as you spend more time on the internet, you become 8 intertwined in this web of companies that are in some 9 cases just kind of benignly tracking for the purposes 10 of ad measurement, and in some cases benignly tracking 11 for the purposes of measuring traffic online. But in 12 other cases they're really trying to create a rich 13 profile of who you are as a consumer, what your 14 interests are, so that that information can be used to 15 enrich ad targeting. 16 All right. So start with an overview. So 17 as you know and probably as the reason I'm here, U.S. 18 regulators are interested in possibly regulating this 19 industry. And that is at all levels of Government 20 from the White House to the FTC to -- there's a bill 21 in the Senate, there's a bill in the House of 22 Representatives. So all levels are interested in this 23 topic. 24 And it's a really challenging topic because 25 on the one hand you have the privacy concerns.</p>
22	<p>1 SESSION ONE: 2 THE IMPACT OF PRIVACY POLICY ON THE AUCTION MARKET 3 FOR ONLINE DISPLAY ADVERTISING 4 DR. JOHNSON: All right. Well, good 5 morning. Very excited to have this conference. I 6 really want to thank the organizers for doing this. 7 This just makes me so happy to see the logos of 8 Marketing Science and the FTC close together. 9 This is an area -- the area of online 10 display advertising that I think is really ripe for 11 research, but also has a lot of challenges from a 12 regulatory sense and from a researcher's sense. Firms 13 in this industry have essentially rewritten the social 14 contract as it pertains to online privacy with a lot 15 of kind of benefits and maybe some harms that have 16 accrued from that. 17 To get things started, usually I would start 18 with my own laptop and I would go to The Chicago 19 Tribune and I would open this add-on to Chrome called 20 Disconnect that shows you all the different firms that 21 know that I visited The Chicago Tribune. And you'd 22 see that there'd be about eight companies or 10 23 companies that would know that. And then I would 24 press the unblock tracks button and the amount of 25 companies would spread like amoebas in a Petrie dish.</p>	24	<p>1 Certainly some users are very concerned about privacy 2 practices that are prevailing in the industry. And on 3 the other hand you have an industry that is very 4 dynamic, that has grown from \$1.7 billion in 2002 to 5 \$7.9 billion in 2013, which is kind of when this paper 6 was written. Nowadays it would be about \$11 billion. 7 So for FTC people, that's about the same order of 8 magnitude as the Volkswagen settlement. 9 So the goal today is to measure the effect 10 that privacy policy would have on advertiser and 11 publisher profits. So you'll notice that there's one 12 thing absent from a welfare calculation there, and 13 that is the welfare of consumers. That's a really 14 challenging question to also tackle. I have some 15 followup work that I intend to spend a couple minutes 16 at the end of the presentation talking about that 17 looks at the consumer side. But really the focus of 18 this paper is to quantify the effect on the firm side. 19 So the way I'm going to do this is I'm going 20 to use an empirical auction setting and I've got to 21 gather a lot of data from realtime bidding and this 22 advertising auction marketplaces, and then I'm going 23 to use a structural toolkit to construct a world with 24 privacy legislation. 25 So I think one thing that I'm excited about</p>

25	<p>1 for this paper is that there's been a lot of growth in 2 the economics and privacy literature, but this paper, 3 to my knowledge, is the first paper to take a 4 structural approach to answering this question. And I 5 think it's actually a really natural set of tools to 6 use for privacy legislation because usually these sort 7 of regulations are irreversible.</p> <p>8 And we would like to try to be able to 9 construct a world ahead of time that would inform what 10 we think would be the consequences in such a privacy 11 environment, or such a policy environment, and so I 12 think the structural toolkit is going to be very 13 helpful in this regard.</p> <p>14 Now, the challenge, of course -- and there's 15 a myriad of challenges in this project -- the main 16 challenge is that I don't get to observe the 17 information that firms have about users. And so I'm 18 going to model that as unobserved heterogeneity in the 19 marketplace and I'm going to extend models of 20 unobserved heterogeneity in auctions to be able to 21 answer the question.</p> <p>22 Now, the high-level results is that I -- my 23 model shows that the surplus in the industry would 24 fall by something on the order of 40 percent. Now, 25 I'm someone that's very motivated by these policy</p>	27	<p>1 what's exciting here is that the industry has really 2 changed a lot from the old days of buying and selling 3 advertising. So on the one hand you have users who 4 are people like you and I that are creating the 5 opportunity for ads to be sold.</p> <p>6 And in this marketplace, the unit of 7 advertising is an ad impression, which is really fine- 8 grained. It's a single ad on a single computer for a 9 single user on one position for one page load. So any 10 time you're loading the page you're creating more ads, 11 and the ads that I see are a different marketplace 12 than the ads that you see.</p> <p>13 Now, on the sale side of the marketplace you 14 have publishers like The Chicago Tribune and The New 15 York Times; and the buy side, of course, you have the 16 advertisers. And they're going to meet in some 17 marketplace in the middle. Now, that marketplace 18 predominantly takes two forms. One is the guaranteed 19 contract marketplace, and the other are ad exchanges. 20 On the guaranteed side, the sort of contracts you'd 21 see are basically bulk buys of advertising ahead of 22 time. So a contract that you would see would be Coca- 23 Cola contracting with Yahoo! to purchase every user 24 that visits the Yahoo! front page in the United States 25 on a certain day. And that would come with a price</p>
26	<p>1 questions. It's really important for me to get these 2 numbers right. I think that, you know, to be very 3 transparent I've got more to do to show -- to advance 4 those numbers to really -- to really nail them, and to 5 more importantly show how those numbers can vary under 6 different scenarios. So I think there's more work to 7 be done there, but it gets the conversation started.</p> <p>8 All right. So just -- because I don't have 9 a lot of time, I'm going to move fairly quickly 10 through things. So there's a number of papers that 11 have looked at privacy policy, that have looked at the 12 online display marketplace. The intersection, there's 13 fewer papers.</p> <p>14 One notable paper is by Avi and Catherine 15 that looked at a switch in the European marketplace 16 where advertisers were suggested that they shouldn't 17 be tracking. And Avi and Catherine found that that 18 decreased ad effectiveness on the order of 60 percent 19 according to causal effect marketing surveys. So that 20 was a really helpful way of starting the discussion 21 off. But my paper is going to take a structural 22 approach to try and quantify this effect in dollars 23 and cents.</p> <p>24 All right. So I want to begin by giving you 25 a taste of what the industry looks like. Part of</p>	28	<p>1 tag, of course.</p> <p>2 Now, the thing with contracts is that they 3 have contracting costs, and the contracting costs can 4 be really high in this marketplace. So a second 5 approach is to use a realtime auction hosted by a set 6 of firms called ad exchanges. And that is where 7 things have really changed in this marketplace from 8 the sort of handshake deals to basically computer- 9 mediated commerce that determines how ads are bought 10 and sold.</p> <p>11 Now, my data set comes from an ad exchange, 12 and really that's where the tracking happens. Right? 13 If you're trying to find people that visited Madden 14 Football in the past, you're not going to buy like a 15 bulk buy on Yahoo! What you're going to want to do is 16 try to find these people across all webpages on the 17 internet and you're going to buy them on the ad 18 exchanges.</p> <p>19 All right. So to participate in the ad 20 exchanges, there's two main ways of doing it. There's 21 the one way which is realtime bidding. The second is 22 what I call offline bidding.</p> <p>23 Now, what the realtime bidders do is they're 24 going to evaluate and bid on the individual ad 25 impressions that are coming down the pipes. And to do</p>

<p style="text-align: right;">29</p> <p>1 so, they're going to employ computer algorithms. And 2 they need to do so because this marketplace clears in 3 less than .01 seconds. And so we can't hire, you 4 know, undergrads or MBAs with fast fingers. We really 5 need computers to be cranking through this data. 6 So this is the prominent way that people buy 7 and sell ads now in these marketplaces. My data set 8 is about five or six years old, and so much more of 9 the data is from offline bidders. Now, what they do 10 is to solve the speed problem, they basically operate 11 as proxy bidders that specify their bids ahead of 12 time. So they're going to specify rules like the 13 target audience that they're going after, the fixed 14 bid that they're going to submit again and again, and 15 then they're going to submit a budget. And the way 16 that was operationalized at the time is they would 17 just randomly submit their bid over time to spread 18 their budget across time. 19 Now, the important thing to realize is that 20 both these bidders are going to employ user tracking 21 information, and the bid data is going to look very 22 different. On the realtime bids, you're going to see 23 basically continuously distributed bids whereas an 24 offline bidder you're going to see the same bid again 25 and again. And so the challenge is to model how these</p>	<p style="text-align: right;">31</p> <p>1 perspective of modeling it's kind of like tying both 2 hands behind my back. 3 Now, what helps me is that I get to see the 4 same users being bid upon again and again and again, 5 and using that panel structure it's going to allow me 6 to try to disentangle what could be coming from the 7 panel -- sorry, from the tracking reports. 8 All right. So let's start with the offline 9 bidders. Just to remind you what they're doing is 10 they're specifying a target audience that you can 11 visualize. There's a space of users and the red 12 circle is the space of users that the advertiser cares 13 about. And they're going to be submitting this fixed 14 bid with a certain probability. 15 Now, the way I conceptualize this exercise 16 is that it's really important to know the size of this 17 target audience. And the reason for that is that you 18 can imagine that right now the advertisers have a lot 19 of information, including gender. And so you can 20 think that, let's say, Gillette is bidding on men, 21 they're bidding \$1 for men and men occur with a half 22 probability in the population, I'm reliably informed. 23 And so what I'm going to do in the counterfactual is 24 I'm going to say that the bid is going to scale down 25 by the size of that audience. And so in the</p>
<p style="text-align: right;">30</p> <p>1 two different kinds of agents are using information. 2 All right. So let me talk to you a bit 3 about this identification. So, big picture, 4 unobserved auction heterogeneity refers to the case 5 where bidders know more about the object for sale than 6 we do as the modeler or as the econometrician, and in 7 this case we'd have some observed heterogeneity. So I 8 get to observe that ads are being sold on certain 9 publisher sites and certain ad slots, and I get to 10 observe a little bit of information about users like 11 the country of origin. But the unobserved auction 12 heterogeneity in this case is the tracking reports 13 that advertisers have about users. 14 Now, the problem is that the existing models 15 of unobserved heterogeneity, you can just sort of 16 think conceptually it's going to be pretty hard to 17 kind of find what's invisible in this marketplace. 18 And so the existing models require that there is no 19 binding reserved priced and that you observe all the 20 bids. 21 My data is really unpleasant in that regard 22 because 80 percent of the time the reserve price bid 23 binds part of me. One percent of the time I only 24 observe a single bid, and 10 percent of the time I 25 observe at most two bids. So really from a</p>	<p style="text-align: right;">32</p> <p>1 counterfactual the advertiser will be bidding 50 2 cents. 3 So the crucial thing is that this bid is 4 going to be scaling up or down based on the size of 5 this target audience, and so I want to quantify that. 6 There's going to be some challenges, though. The 7 first challenge is that if these people are randomly 8 submitting bids, then I'm only going to observe a 9 subset of users that are hit with these bids. 10 The second challenge is that this is a 11 competitive marketplace where I observe at most one or 12 two bids. So there will be cases where there's 13 competition that sensors the highest bid, and so I 14 don't get to observe users for which I am interested. 15 So the way that I solve this problem is I 16 basically say, well, this can be -- this world can be 17 understood to contain four types of users, people that 18 nobody wants, people that only Advertiser I wants, 19 people that have some overlap between I and I's 20 competition, and those for which I am uniquely -- 21 sorry, the competition is uniquely interested. 22 And so I'm going to treat this as a mixture 23 model, and I'm going to identify this using repeated 24 observations. The basic intuition is that if I see 25 the same user again and again and they only get</p>

33	<p>1 reached by Advertiser I, then it becomes increasingly 2 likely that they're only in I's set. And so these 3 repeated observations are going to allow me to pin 4 down the size of these different elements in this 5 figure. 6 There's a question from -- yeah? 7 AUDIENCE: So the history is attached to the 8 eyeball? Everybody gets, like, their trackings? 9 MR. JOHNSON: So, in this case -- in this 10 case I'm going to be able to -- the nice thing about 11 this is that this model allows for a fully general 12 overlap between I and I's competition. And so this 13 model can accommodate cases where advertisers are 14 potentially getting different information, number one, 15 and, number two, if they're interested in different 16 characteristics of the users. 17 AUDIENCE: And in reality -- no, I'm just 18 wondering, like, is it sort of, like, okay, here's an 19 eyeball and the -- does the -- how do I know what that 20 eyeball -- I'm sorry. So the reality if there's an 21 eyeball, do they have information? Is it different 22 information? Is it the same information? Does the 23 auctioneer offer the same information? 24 MR. JOHNSON: Yes. So, in reality these ad 25 exchanges get some information -- they typically have</p>	35	<p>1 that's, you know, obviously a challenge for 2 researchers and certainly a challenge for regulators 3 as well. Heck, it's even a challenge for industry. 4 All right. So I've talked about one type of 5 bidders, which are these offline bidders, and I've 6 told you that one nice feature of the model is I'm 7 able to have a lot of richness to advertisers 8 targeting different users. 9 In the realtime side, I have very rich 10 bidding space, but I'm going to have to pin down some 11 of the common, unobserved heterogeneity a bit more. 12 So what I'm going to say is that in the realtime space 13 the valuations of the advertisers of the product of 14 two terms. The X term is an idiosyncratic term, which 15 varies continuously, and then there's going to be the 16 second term which is an unobserved heterogeneity term. 17 Now, the assumption that I need to make in 18 this case is that that unobserved heterogeneity term 19 is fixed for a given user. And so you can think of 20 this as capturing to some extent a user's 21 responsiveness to advertising and their income that 22 they have to spend on various things. But because I'm 23 making this assumption, it's going to not fit very 24 well with the world where BMW is going after rich 25 people and Kraft Mac & Cheese is going after poor</p>
34	<p>1 some information that they can make available to 2 everyone, but oftentimes advertisers bring their own 3 information to the marketplace. So a specific example 4 of this would be retargeting. So you look at a pair 5 of socks on Macy's and Macy's hunts you down for the 6 rest of your real life to convince you to buy a pair 7 of socks on the internet. Other advertisers don't 8 have that informations but Macy's has that 9 information. 10 So that's -- you know, that's actually 11 another challenge in this setting, is -- you need to 12 make some simplifying assumptions about who's got what 13 information. 14 AUDIENCE: Just to clarify, it's not Macy's 15 that has -- sorry. It's not Macy's that has 16 information about the ad network, right? 17 MR. JOHNSON: We're sort of splitting hairs 18 here, but Macy's or Macy's ad agency or somebody 19 somewhere who's representing Macy's has got that 20 information. 21 All right. So very good questions. And, 22 you know, one thing you're probably realizing if 23 you're new to this area, there's a lot of nuanced 24 stuff going on in the institutions that have really 25 changed a lot in the last five or six years. So</p>	36	<p>1 people. But, again, given the data that I have I 2 think this is as rich as I can make the model. 3 So under some assumptions I can pin down 4 these two things, and the counterfactual I'm going to 5 run is I'm going to shut down the variance in the 6 unobserved heterogeneity component, which models the 7 tracking reports, and I'm just going to allow the 8 idiosyncratic term to vary. 9 All right. So let me explain how I go about 10 identifying this model. You know, really what I need 11 to do is kind of identify this by a certain amount of 12 brut force, because it is so challenging to 13 disentangle this. So what I'm going to do is -- you 14 ever run a thought experiment where if you observe the 15 same user again and again and again, like hundreds of 16 times or thousands of times, then for that same user 17 you're holding fixed the Y component. You're holding 18 fixed their unobserved tracking component. 19 But so that's going to tell you -- the 20 variance in the bids is going to inform you as the X 21 component. However, if I hold -- if I look across 22 people and I look at some quantile like the maximum, I 23 can sort of sort everyone in the audience by the 24 maximum bid that they achieve after observing 1,000 25 bids, let's say, and that's going to tell me something</p>

37	<p>1 about the unobserved heterogeneity component. So</p> <p>2 that's how I go about identifying the model.</p> <p>3 Now, there's a question over there?</p> <p>4 AUDIENCE: Yeah. Is your counterfactual --</p> <p>5 how does that correspond to an ad blocker? Are you</p> <p>6 basically implementing ad blocking into this</p> <p>7 counterfactual?</p> <p>8 MR. JOHNSON: No. Because ad blocking -- so</p> <p>9 this -- you know, our whole story of, you know, an</p> <p>10 auction runs in .01 seconds, the story is really</p> <p>11 boring with ad blocking. It basically stops when you</p> <p>12 install the ad blocker. There's no auction, there's</p> <p>13 nothing that happens. And so -- unless ad blocker</p> <p>14 starts selling ads, which apparently they want to do.</p> <p>15 Yeah, they're a delightful company.</p> <p>16 So, yes, the ad blocking basically, the</p> <p>17 answer is -- we know the answer is zero until maybe</p> <p>18 yesterday. The answer becomes something for ad</p> <p>19 blocker, Ad Block Plus.</p> <p>20 All right. So I'm not sure how I'm doing on</p> <p>21 time, but someone will yell at me eventually. So let</p> <p>22 me tell you a little bit about the theory. It just</p> <p>23 kind of shows you what's going on in the background.</p> <p>24 So in a structural auction paradigm, what we</p> <p>25 do is we observe a bunch of bids and we want to</p>	39	<p>1 you should bid \$1.01 and the chance that you win</p> <p>2 improves discontinuously. This means that there's</p> <p>3 some bids that theory tells us that we should never</p> <p>4 observe.</p> <p>5 To just kind of visualize that in the simple</p> <p>6 world where you've got two uniformly distributed first</p> <p>7 price bidders, the optimal strategy is to bid half</p> <p>8 your evaluation. Now, if you then put in some person</p> <p>9 that's bidding 25 cents half the time, then at a</p> <p>10 certain point you cross an indifference threshold and</p> <p>11 the optimal bids kick up and you observe this gap</p> <p>12 where your theory tells you you should never see bids.</p> <p>13 Now, the challenge is when you work with</p> <p>14 real-life data is that these are pretty small stakes</p> <p>15 auctions, it's pretty costly for advertisers to learn,</p> <p>16 so of course these people go and they bid in these</p> <p>17 gaps. And so a big part of the headache that's kind</p> <p>18 of held up this project is to think of an intelligent</p> <p>19 way to model this to gain as much information as</p> <p>20 possible and to be able to do so reliably.</p> <p>21 All right. So the results then, as I said</p> <p>22 at the beginning of the presentation, it's something</p> <p>23 on the order of 40 percent. It decreased if you were</p> <p>24 to ban tracking outright. It's felt a little bit more</p> <p>25 by the advertisers and the publishers, though pretty</p>
38	<p>1 transform those bids into the valuation of advertisers</p> <p>2 or of the bidders in the auction. And then in the</p> <p>3 counterfactual we're going to -- we're going to make</p> <p>4 some change to the environment holding the valuations</p> <p>5 fixed and then simulate our toy model of the world.</p> <p>6 So what this assumes is that we have some</p> <p>7 model that connects valuations and bids. And here the</p> <p>8 auctioneer uses a really unusual mechanism in that it</p> <p>9 makes offline bidders play by second price bids, which</p> <p>10 means that they're paying the second highest bid or</p> <p>11 the binding reserve price, and it makes the realtime</p> <p>12 bidders play by first price rules.</p> <p>13 Now, why are they doing this? I don't know.</p> <p>14 It's a little crazy. Most of the industry now uses</p> <p>15 second price rules. By the time -- I'm just</p> <p>16 speculating that maybe they're trying to penalize</p> <p>17 these more agile first price bidders a bit.</p> <p>18 So kind of the simple version of the theory</p> <p>19 is that it's a dominant strategy to bid your own</p> <p>20 valuation for the second price bidders. The first</p> <p>21 price bidders want to shade their evaluation so they</p> <p>22 maintain some surplus. The challenge in this setting</p> <p>23 is that if you are a first price bidder and you're</p> <p>24 facing someone that's bidding a dollar again and again</p> <p>25 and again, you never want to bid .99 centers because</p>	40	<p>1 evenly.</p> <p>2 The scope of the results is that I'm</p> <p>3 focusing on the top three websites in the data, which</p> <p>4 is about half the revenue. So to kind of a do a back-</p> <p>5 of-the-envelope calculation, at least in 2013 you</p> <p>6 would take \$6.8 billion, multiply it by the 20 percent</p> <p>7 share that does this realtime auction stuff, multiply</p> <p>8 it by the impact on the industry, and it's something</p> <p>9 like a half a billion dollars.</p> <p>10 Now, today the revenues are closer to \$11</p> <p>11 billion. The auction share is closer to 40 percent.</p> <p>12 And so you're looking at \$1.5 or \$2 billion impact on</p> <p>13 the industry.</p> <p>14 All right. So since I have a little bit of</p> <p>15 time, I wanted to tell you about some followup work</p> <p>16 that I'm working on that that I think will be</p> <p>17 interesting to this audience and that I hope to talk a</p> <p>18 bit more offline.</p> <p>19 So in this industry, the industry tried to</p> <p>20 do -- well, it did do a self-regulation mechanism.</p> <p>21 You may recognize this little triangle with the I in</p> <p>22 the middle from the top corners of the banner ads that</p> <p>23 you see on the internet, those of you that aren't</p> <p>24 blocking ads. If you click on one of those things,</p> <p>25 it's going to take you to a website that's going to</p>

41	<p>1 tell you about the benefits of personalized 2 advertising, but then will allow you to opt out of 3 this form of advertising. 4 And I was able to obtain a proprietary data 5 set from an ad exchange to take a look at this 6 question that's quite recent. This is a year ago. 7 And I think this is important to look at because as 8 Ginger remarked, when people -- we asked people about 9 how much they care about privacy; everybody says that 10 they care a lot about it. 11 And when you look at if they take any sort 12 of action that is consistent with those beliefs, you 13 realize that a very small minority does that. And I 14 think that, you know, both research perspectives have 15 something to teach us, but certainly from a regulatory 16 perspective what you care about is what's actually 17 going to happen in real-life. And so I think that 18 discussion should be informed by this revealed 19 preference study. 20 So the big questions I answer here that 21 maybe -- or that I'm trying to ask here but maybe I'm 22 not going to tell you with the stenographer writing, 23 is, first of all, how many opt out. It's actually a 24 very, very few. I've tried to get a sense of who are 25 these people that opt out. I looked at how the</p>	43	<p>1 shared by regulators and us as academics, but also 2 shared by people in industry. 3 So, again, I thank you for putting together 4 this conference which I think speaks to very important 5 issues and it's really exciting as someone that thinks 6 of these issues as my bread and butter to see the 7 leaders of the field pushing the same research 8 questions. So thank you. I look forward to the 9 discussion and some questions afterwards. 10 (Applause.) 11 DR. JIN: Thank you, Garrett. That's an 12 exciting research agenda. It's extremely relevant for 13 FTC. So our discussant is Doug Smith from the Bureau 14 of Economics at FTC. 15 DR. SMITH: All right. So I'm just going to 16 take a minute here. 17 DR. JIN: While Doug is pulling up his 18 slides, I want to remind everyone that we want to 19 record everybody's conversation here. So please wait 20 for the mic to come to you. If you have a question, 21 please raise your hand, we'll try to come to you 22 immediately. We also have flash cards at the 23 back for presenters and discussant so that you will be 24 tracked by time. Thank you. 25 DR. SMITH: So, hi. So I'm discussing this</p>
42	<p>1 marketplace outcome is different for those that opt 2 out, and it's about -- pretty comparable actually to 3 what I'm seeing in this project. And then I look for 4 heterogenous impacts, which I think is really 5 important from a regulatory perspective. And it turns 6 out that certain types of publishers have a lot more 7 of these users than others. So, again, I hope to talk 8 more about this project offline. 9 But getting back to the main study here, the 10 goal was to try to enrich a policy discussion that I 11 think is very interesting and very important with some 12 numbers that try to estimate the impact of this policy 13 on the industry. 14 Now, again, this paper is the first paper to 15 take the structural tools to a privacy policy 16 question. I think it's a set of tools that can be 17 very helpful to answering these questions. The 18 takeaway from marketers is that there's just such an 19 exciting change in the industry from measurement to 20 the way that ads are bought and sold, to the privacy 21 questions. Advertising has really pushed the frontier 22 of what is possible in the last decade. But to use a 23 Star Trek analogy, the frontier is starting to push 24 back with people blocking ads, among other things. 25 And so that creates challenges that are not just</p>	44	<p>1 paper that Garrett just presented very well. And I 2 don't have a lot of time. So I just, you know, first 3 wanted to say that, you know, this is a very clever 4 approach to dealing with this problem. Garrett has 5 drawn from a lot of different auction literature to 6 kind of deal with the very specific market he's 7 looking at, and the way that the pieces fit together 8 to identify these values is very impressive. 9 You know, basically all this machinery is 10 really for the purpose of just when an advertiser is 11 bidding, what is the actual value that they assign to 12 this potential ad? And so one thing I wanted 13 to highlight about the nature of the exercise that he 14 does is that when he's looking at the counterfactual, 15 one thing that there just isn't data on is what the 16 advertisers would value -- how much the advertiser 17 would value a user who they aren't targeting. 18 So they observe all this bidding on certain 19 people, but the counterfactual has to deal with the 20 fact that, you know, without knowing who's who, you're 21 going to be buying sort of an ad with an expected 22 value that covers just sort of the average cross 23 population. And so knowing what the person -- what an 24 advertiser would value somebody that they're not 25 generally targeting is sort of crucial to figuring out</p>

45	<p>1 these values.</p> <p>2 And the paper -- you know, the paper --</p> <p>3 Garrett talks about this in the paper and he knows</p> <p>4 that the value could really be anything from zero to</p> <p>5 the reservation price. And I think kind of as a sort</p> <p>6 of, you know, very clean way to do it, he does the</p> <p>7 counterfactuals estimating that the value for sending</p> <p>8 an ad to a user who you're not targeting is just zero.</p> <p>9 I think, though, that this really is an area</p> <p>10 of uncertainty. This data isn't really telling us</p> <p>11 anything about this. And so in that sense, you know,</p> <p>12 a useful exercise would probably be to provide</p> <p>13 estimates using a reservation price or something sort</p> <p>14 of analogous to that as an alternative and just sort</p> <p>15 of seeing how much matters.</p> <p>16 So you can imagine they could get very</p> <p>17 similar results, in which case we know this</p> <p>18 uncertainty doesn't affect much, or potentially get</p> <p>19 something slightly different and then know that</p> <p>20 there's sort of a dimension that we don't understand.</p> <p>21 So besides just that comment about the</p> <p>22 paper, I want to sort of step back a little and think</p> <p>23 about what this tells us about the policy question</p> <p>24 here. And, you know, as Garrett mentioned, you know,</p> <p>25 obviously advertising publishes just part of the</p>	47	<p>1 So another aspect to sort of think about the</p> <p>2 bigger picture is this question of how are consumers</p> <p>3 actually going to react to these privacy policies. So</p> <p>4 one thing I think that maybe is worth explaining a</p> <p>5 little bit is sort of what the policies are that all</p> <p>6 under consideration.</p> <p>7 So Garrett actually considers three sort of</p> <p>8 alternative policies to the status quo. One of them</p> <p>9 is just to allow consumers to opt out from targeting.</p> <p>10 And he draws from various sources to sort of get a</p> <p>11 ballpark of about 10 percent of consumers he predicts</p> <p>12 would opt out. Another possible policy is just an</p> <p>13 opt-in policy where, you know, unless you say you're</p> <p>14 willing to be tracked, you won't be tracked. And,</p> <p>15 again, using various studies, he sort of estimates</p> <p>16 maybe around 90 percent might decide not to opt in.</p> <p>17 And then the third policy consideration is just a</p> <p>18 blanket prohibition, which would be, you know, a</p> <p>19 default by automatically 100 percent not in.</p> <p>20 So -- but a thing that -- you know, and this</p> <p>21 is, again, something that Garrett raises in the paper,</p> <p>22 you know, companies may adjust the incentives they</p> <p>23 offer for people if they, in fact, face a significant</p> <p>24 number of untracked customers. And so, you know, you</p> <p>25 can imagine companies sort of trying to get you to opt</p>
46	<p>1 picture. We need to also understand the effect on</p> <p>2 consumers. And generally, you know, people talk about</p> <p>3 these things as sort of two components to --</p> <p>4 particularly as an economic question. You know, is</p> <p>5 the tracking here, is it making the pie bigger, you</p> <p>6 know, so that everyone can benefit? And this would be</p> <p>7 basically through better matching, you know, more or</p> <p>8 better matches.</p> <p>9 Alternatively, or perhaps as well, is</p> <p>10 targeting and allowing companies to take a bigger</p> <p>11 portion of the surplus generated through -- generally</p> <p>12 through price discrimination. And then, you know, you</p> <p>13 also need calculations maybe account for consumers</p> <p>14 privacy, just specific preferences.</p> <p>15 But, you know, so this is sort of what</p> <p>16 Garrett has done is an input into this process, but</p> <p>17 there's these other components to consider as well.</p> <p>18 Oh, I'm sorry, I want to say one other thing about</p> <p>19 this. But I think that, you know, looking at data,</p> <p>20 particularly how firms end up making transactions and</p> <p>21 what prices and such we can probably actually get some</p> <p>22 interesting insights into these questions but more on</p> <p>23 the firm level data. But I think this is something</p> <p>24 that I'd encourage people to sort of start thinking</p> <p>25 about how to explore.</p>	48	<p>1 in. And I think that that's an area where it really</p> <p>2 needs to be explored further and provides some</p> <p>3 interesting potential for future research</p> <p>4 opportunities.</p> <p>5 Okay. That's actually basically all I had</p> <p>6 to say. You know, I think, again, this is a really</p> <p>7 interesting contribution both methodologically and</p> <p>8 sort of helping us start thinking about this policy</p> <p>9 area. And something that I didn't realize Garrett was</p> <p>10 going to mention repeatedly, but he has a really good</p> <p>11 point, is just that these things are evolving so much.</p> <p>12 And so it will be very interesting to see how in</p> <p>13 similar exercises what kind of answers they get in the</p> <p>14 future. Thank you.</p> <p>15 (Applause.)</p> <p>16 DR. JIN: Thank you. We still have time to</p> <p>17 pick up questions. If possible, I will ask you to</p> <p>18 state your name and affiliation first and then ask</p> <p>19 questions. Thank you.</p> <p>20 DR. LIAUKONYTE: My name is Jura Liaukonyte,</p> <p>21 I'm from Cornell. So one of the things that I've</p> <p>22 learned that was amazingly surprising about realtime</p> <p>23 bidding is how much ad fraud there is. There's a</p> <p>24 ridiculous amount, like 50, 40 percent, which is</p> <p>25 essentially publishers stating they are putting ads</p>

49	<p>1 but they are not putting ads. How does that affect 2 the welfare calculations, if at all? 3 My thinking from sort of equilibrium 4 perspective is that if there was no ad fraud, the 5 prices would be higher. Right? So the advertisers 6 are already incorporating that information in their 7 bids. 8 DR. JOHNSON: Yeah, I think you're right 9 that there's -- if you expect -- if you expect the 10 value of an ad to be a dollar as an advertiser and 11 then you expect the ad to be kind of true half the 12 time, then you're going to deflate your bids 13 accordingly. So hopefully they're accounting for that 14 in the marketplace. But the lack of transparency 15 makes that really difficult. I've heard that the 16 numbers aren't quite so high. 17 You know, one more thing that's changed is 18 that now the marketplace allows for cost per viewable 19 impression payment models rather than cost per 20 impression payment models. So that mitigates those 21 concerns a little bit. Yeah, it is kind of the wild 22 west even for industry people in this marketplace, 23 especially if you're getting away from kind of the big 24 three, the Facebooks and Googles and whatever, Yahoos 25 of the world.</p>	51	<p>1 advertising-based publishing to consumer micro- 2 payments. 3 So I think that's part of how to think of 4 it. Now, in terms of, you know, you brought up these, 5 you know, what happens under an opt-out versus opt-in, 6 and I kind of ballparked a guess of what would 7 be the proportion of consumers. The problem with that 8 exercise is that it's really hard to know. That 9 equilibrium could change very quickly. Like, right 10 now there's a very tiny amount of people that opt out 11 using the industry mechanism. 12 Now, if there were to be some huge scandal 13 where everybody's information became available on some 14 website, then that could change pretty quickly. So, 15 you know, inherently it's hard to talk about those 16 things, but I think it's important to keep those big- 17 picture numbers like \$3 or \$4 per person in mind when 18 we do this discussion. 19 By the way, in Europe they're considering in 20 May 2018, as I understand it, and I'm always trying to 21 wrestle with just what they have in mind. So I 22 appreciate if people could clarify this for me. My 23 impression is they want to move to an opt-in based 24 system. And you would expect that if you ask a bunch 25 of consumers would you like to opt in to being</p>
50	<p>1 You had a question? 2 AUDIENCE: Okay. So this gives us a sense 3 of how much a certain kind of policy might affect 4 industry. And you're leaving consumers aside. Given 5 this, you know, is there anything you think you can 6 say about consumers in terms of the model or in terms 7 of at least how bad things would have to be for 8 consumers in order to make the policy worthwhile? 9 DR. JOHNSON: Wow. So the consumer side -- 10 so one way you can think about this is, you know, this 11 industry is about \$11 billion. There's -- I'm 12 Canadian -- there's 350 million-ish people in 13 the United States. So we're looking at like \$30 or so 14 per person, right? So that kind of brings up the 15 point that you made, which is, you know, the -- you 16 might think that the firms could find some way of 17 rewarding consumers. 18 It's pretty hard to in our current kind of 19 financial infrastructure to do micro-awards 20 commensurate with, like, \$30. You know, if that 21 infrastructure changes in the future with digital 22 currency, you know, we're into uncharted territory 23 where perhaps advertisers could try to compensate you 24 a little bit for the value of your private information 25 or perhaps consumers will switch from a model of</p>	52	<p>1 followed around by 100 different advertisers, the 2 answer is going to be go away. So that could, you 3 know, pretty radically shift things in Europe and that 4 would inform what's going on here for sure. 5 All right. Well, we'll yield the time to 6 the next people then. Thank you. 7 (Applause.) 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>

<p style="text-align: right;">53</p> <p>1 SPONSORSHIP DISCLOSURE AND CONSUMER DECEPTION: 2 ASSESSING NATIVE ADVERTISING IN MOBILE SEARCH 3 DR. JIN: Thank you. We'll move on to the 4 next paper by Harikesh Nair from Stanford University 5 about Sponsorship Disclosure and Consumer Deception: 6 Assessing Native Advertising in Mobile Search. And to 7 make sure that our presenter would have full 25 8 minutes, I would request you to hold back your 9 question unless it's just for clarification. Thank 10 you. 11 DR. NAIR: Thanks, Ginger. Good morning, 12 everyone. Thank you again to both Marketing Science 13 and to the FTC for organizing this conference. It's 14 really fantastic to bring these two institutions and 15 fields together. 16 So this is a paper co-authored with my 17 colleague, Navdeep Sahni, at Stanford, and this is 18 based on a bunch of field experiments that we did with 19 a mobile restaurant search platform. And we have two 20 papers that came out of these experiments. One is on 21 assessing the role of advertising as a signal, and 22 this particular paper on native advertising gives us a 23 sense of how deceptive native advertising is. And 24 there's been a lot of interest in this topic. So I'll 25 try my best to give you a sense for what we've been</p>	<p style="text-align: right;">55</p> <p>1 right now because of the advent of native advertising. 2 And there are many definitions of native advertising, 3 but one thing that we can all broadly get behind is 4 that it's advertising that kind of matches the form, 5 the style and the layout of the media content into 6 which it's integrated. 7 So it's really content -- it's really 8 advertising that kind of looks like content. So the 9 line between what's content and what's advertising, 10 it's blurring and that kind of advertising is kind of 11 proliferating. We have a large number of estimates in 12 the industry. So there are various kinds of very 13 large numbers going out there. But that kind of 14 advertising is actually the one that is gaining a lot 15 of prominence, especially on mobile where a lot of 16 attention is going towards within apps, in-app 17 advertising or whatnot. 18 While industry adopts that format, there is 19 a significant policy concern. And from the regulator 20 side, the main concern is of deception, which is that 21 consumers are harmed when the commercial nature of 22 content is not properly disclosed. 23 As Ginger mentioned, the FTC has a very 24 precise term for what is a deceptive practice. A 25 practice is considered deceptive if it's likely to</p>
<p style="text-align: right;">54</p> <p>1 doing. 2 Native advertising also has a long view 3 throughout the century. So let me start by giving you 4 a sense for how this issue has played out in media 5 historically. In the 19th century, at least in the 6 United States, most of the news media in the U.S. were 7 owned by particular parties, and that changed very 8 rapidly at the turn of the century as news and media 9 oriented to a more professionally oriented journalism 10 and journalists started emphasizing the core norms of 11 objectivity and autonomy. 12 And in that business model, rather than get 13 money from political parties, the ad supported 14 business model was born. And in that kind of 15 situation, in order to make sure that news was 16 autonomous and media was autonomous, publishers 17 instituted a separation of the church and the state 18 that separated the business side from the news side of 19 the media side of the business. 20 And the so-called separation between content 21 that is produced by a media platform and advertising 22 is a steadfast principle of media, okay, and has been 23 very clearly pointed out in the previous conference 24 that the FTC did on native advertising. That line is 25 very fast blurring in the -- in the digital ecosystem</p>	<p style="text-align: right;">56</p> <p>1 mislead consumers who are acting reasonably and it 2 would be material to the decision to buy or use the 3 product or consume the advertisements. Okay? 4 So we're going to try to assess to what 5 extent native advertising on the particular 6 platform -- it's a case study -- is going to be 7 materially deceptive and to give a sense for what 8 people mean when they say something is material. It 9 essentially means it affects their actual actions, 10 okay, in some fashion with respect to the 11 advertisements or to the product, which actually if 12 you think about it imposes a high data bar because you 13 actually need to observe actions in order to make a 14 real statement about it. 15 As we all know in this room, paid search is 16 a very large component of digital advertising and 17 therefore assessment of deception in that marketplace 18 is likely to be of interest and of impact to the 19 digital advertising industry. Okay? 20 New regulations have come in in 2015, in the 21 last month of 2015, where the FTC now stipulates that 22 any disclosure in online advertising must be 23 sufficiently prominent and unambiguous in order to 24 change the apparent meaning of the claims and to leave 25 an accurate impression to the exposed user as to the</p>

57	<p>1 commercial nature of the sponsorship of the content. 2 Okay? 3 If you've been following the press on this, 4 these regulations have been controversial. The 5 digital advertising industry has expressed some 6 skepticism about it and a debate has been going on. 7 Unfortunately I could not make it to the disclosure 8 conference yesterday, but I'm sure that there are 9 various opinions on this. 10 Generally industry bemoans government 11 intervention in the creative process and believes that 12 self-regulation and current levels of disclosure may 13 be sufficient. In particular, the official IAB 14 statement in response to the FTC's guidelines said 15 that it may be overly prescriptive, especially absent 16 any compelling evidence to justify some terms or the 17 other. So there is really a large paucity of studies 18 in this area. So hopefully this paper has something 19 to say about this in one case study, and that will 20 spur more broader studies in this area. That's the 21 idea here. 22 Okay. So the goals of this particular paper 23 are to look at does native advertising work, which is 24 important 25 to establish before we proceed to see whether it's</p>	59	<p>1 using a gray label with the word "sponsor" as opposed 2 to the word "ad." Okay? 3 So then my question, you know, is this 4 deceptive or not? Okay. Is this is a deceptive ad? 5 How do you assess that? Okay? 6 So here's a stylus picture that gets a sense 7 for how to address that. Here is a screen shot from 8 an app. And let's say you search for a restaurant and 9 then three restaurants show up above the fold, and one 10 has an ad on it. The real question is how -- how do 11 we as researchers decide whether this is deceptive or 12 not. Okay? 13 The existing way of doing this in our view 14 has significant drawbacks. Most of the existing 15 approaches involve exposed survey with recall. So you 16 might be called in a random phone survey and you might 17 be asked when you put a search last week on Google or 18 on Yelp or whatnot, did you realize that there were 19 paid ads shown? And if the consumer says yes, you 20 might be asked did you realize that it was deceptive? 21 Were you deceived? And you might say, yeah, I was 22 deceived and we -- we have -- and the researcher may 23 report the percentage of consumers who said they were 24 deceived or confused or whatnot. 25 Now, a couple of criticisms of this approach</p>
58	<p>1 actually very important from a deception perspective. 2 And I guess one of the aspects of the paper is also to 3 present a new way to assess deception without asking 4 people whether they were deceived; instead to focus on 5 real preference arguments alone. Okay? 6 Then we're going to assess that for paid 7 search ads using a field experiment implemented on a 8 restaurant platform. So let me do my best to get 9 that out there and I look forward to comments and 10 reactions. 11 So just to level set the audience, here are 12 two kinds of in-app advertising from two platforms. 13 One is Yelp, which is similar to the one that I'm 14 going to talk about. The other one is Facebook. I 15 will search for restaurant in the Bay area near Palo 16 Alto, and out comes an ad for a restaurant called 17 Bliss Pops on position one. And that's in Redwood 18 City. That is closer to my geography of search. 19 And you see that Yelp reveals that it's an 20 ad with a yellow label, which is similar to what 21 Google used to do a few months back, and that's a 22 nature of sponsorship disclosure, that this is a 23 sponsored ad. On the right side is an in-stream ad 24 within the Facebook screen for Progressive, and they 25 reveal that this is actually sponsored by Progressive</p>	60	<p>1 which are well known would be that first you're not 2 really assessing deception in a context where the -- 3 where the fact that they were deceived is not 4 consequential. For example, if I'm really looking for 5 a nice dinner with my wife and we have a babysitter at 6 home, do I really care about the fact that this is not 7 the right restaurant that I was recommended to? 8 The other one would be the exposed recall 9 may be imperfect, and the way you ask the question may 10 prime deception, and that's a well-known aspect. 11 And the final thing is that the marginal 12 consumer to whom disclosure may change the behavior, 13 for whom disclosure may actually be materially 14 deceived. He or she is -- that individual is the one 15 that we care about. There's no sense that the survey 16 is identifying the opinion of the marginal consumer. 17 It might be the average consumer. Okay? 18 So we're going to try to find a way to 19 assess deception using a real preference argument. So 20 we are going to construct an experimental design that 21 is going to get at that. And that experimental design 22 may be useful in other situations we think in which we 23 would like to assess issues related to disclosure, 24 more broadly defined not just in advertising. Okay? 25 So here's our idea. We're going to</p>

61	<p>1 randomize people into a new condition. So in the 2 middle is the current disclosure condition, which is 3 what we want to assess whether it's deceptive or not. 4 Okay? We're going to randomize consumers into a 5 condition which we call a prominent disclosure 6 condition in which the fact that this is an ad, okay, 7 is highlighted in a much more prominent and 8 conspicuous way. Okay?</p> <p>9 Now, we can think about what will be a 10 prominent and conspicuous way, but we are going to 11 implement a particular way of doing it, which is to 12 highlight the ad with a border. And I'll show you 13 exactly what we did. And we think of it as two 14 different worlds. One is the current world, that's 15 the middle one; and the one on the right side is a 16 full information world, a world in which consumers 17 fully understand at least that this is an ad.</p> <p>18 We are also going to randomize consumers 19 into another extreme world in which the same listing 20 is provided of the same position here for a restaurant 21 one, but without any disclosure that this is paid 22 advertising. Okay? So think of this as two extreme 23 worlds, one in which there's full information on the 24 right and one on the left is absolutely no information 25 on the left. So it's full deception on the left.</p>	63	<p>1 don't disclosure behavior changes dramatically, that 2 also tells us that, you know, this is something that 3 we really need to care about as a regulator because if 4 I don't disclose behavior would be quite different. 5 Okay?</p> <p>6 So that's the basic idea of the design. The 7 main advantages, it's based on real preference on 8 actions alone. We don't need to ask consumers 9 anything. Okay?</p> <p>10 Question over there? Yeah?</p> <p>11 AUDIENCE: Okay. Just a quick question. So 12 I was curious as to do you see the behaviors changing 13 with time? So initially I might just think I've been 14 (indiscernible) for a long time and I know that the 15 top one is an ad.</p> <p>16 DR. NAIR: Correct.</p> <p>17 AUDIENCE: So -- but, you know, over time in 18 these two different populations, do you see the 19 behavior change?</p> <p>20 DR. NAIR: Yes. That's a very good 21 question. Definitely there will be some dynamics in 22 those and potentially some learning about the platform 23 as a whole. We are not able to assess that, those 24 dynamics, because for an econometric reason I'm going 25 to assess my outcomes at a single point for the first</p>
62	<p>1 Okay?</p> <p>2 And then we're going to track behavior under 3 each of these conditions. Okay? Then we're going to 4 ask whether the behavior under the full information 5 world looks similar to the behavior under the current 6 disclosure regime. Okay?</p> <p>7 Now, if your choices look very different 8 when you are fully informed versus currently, well, 9 that means that there was deception because actions 10 are very different. So that's very simple. And if -- 11 so just by comparison of the current disclosure 12 condition to a prominent disclosure condition will 13 give us a sense for whether there's deception or not.</p> <p>14 Okay. Now, if they are similar, stickily 15 similar, we say that we cannot detect any evidence of 16 deception. Okay?</p> <p>17 Now, comparing the current disclosure 18 condition to a no-disclosure condition, if I find that 19 behavior is roughly the same in a world where you are 20 not told that this is sponsored versus the current 21 world, well, how do I -- what do I conclude from that? 22 Well, we kind of conclude that, you know, issues of 23 disclosure and whether or not this is an advertisement 24 or not is not that relevant for consumers in terms of 25 how they make actions. But if we find that -- if I</p>	64	<p>1 search of consumers on this platform and their 2 response to the first search, just because of an 3 endogeneity problem that comes up.</p> <p>4 In the paper, we actually report what 5 happens at the end of our experiment, which is roughly 6 a month into the experiment, and the results that we 7 report persist and there is some attenuation of that. 8 But I cannot speak more than that. My basal guess is, 9 yeah, of course there will be dynamics as people learn 10 and understand the platform. So -- but we can't speak 11 much to that in this paper.</p> <p>12 So you have to decide --</p> <p>13 DR. SMITH: Yeah, I'm sorry. So I'm curious 14 why you're -- for the low scope for disclosure 15 to see why you're comparing the no-disclosure to 16 current disclosure versus no-disclosure to prominent 17 disclosure.</p> <p>18 DR. NAIR: You know, the way we were 19 thinking about it is that the current disclosure to 20 more prominent disclosure is easy for a firm to 21 implement. And if -- in a world with full 22 information, choices look very different. That is 23 evidence of deception.</p> <p>24 The one on the left might be actually more 25 difficult for a firm to implement. Actually, I talk</p>

65	<p>1 about how we were able to implement it because the 2 same advertisement has been shown without any 3 disclosure to consumers that this is actually an 4 advertisement. So it might be hard to implement that 5 in practice. And I was trying to tell you why such a 6 design may be actually useful because you could get a 7 sense for if I rate a disclosure from all the way from 8 nothing to very high, if there are very dramatic 9 changes, that will help us to understand to what 10 extent do consumers care about disclosure. 11 Okay. So let me just skip this in the 12 interest of time and tell you a little bit about the 13 platform. So the experiments were implemented on a 14 platform called Zomato, and it was implemented in 15 2014. Zomato turns out to be a very large restaurant 16 search platform in many countries that were 17 underserved by traditional search and digital 18 platforms, in particular in India, Jakarta, Manila, 19 Dubai, which were the cities where our experiment was 20 implemented. 21 In 2015, they acquired another platform 22 called Urban Spoon in the United States. Some of you 23 may know about it. And so they were getting pretty 24 big in the United States and Australia as well. But 25 the U.S. data and the Australia data are not in our</p>	67	<p>1 the experiment and the experiment ends. So almost all 2 the data is from in August of 2014. 3 Here's an example search session. This is 4 from the Android app on which the experiment is 5 implemented. As you open the app, you can start 6 putting a search for a restaurant. You can use any of 7 the pre-filled categories. For example, most of the 8 searches -- many of the searches at least in this -- 9 the countries that we implemented the experiment are 10 for home delivery. 11 And once you bring a search, a bunch of 12 listings show up and the figure that is in the green 13 is the average rating of users on Zomato. And let's 14 say Café 6 is one of the restaurants, and if you click 15 on that listing you'll get to a restaurant page where 16 additional information is available. So let me zoom 17 in on that. And this additional information would 18 involve a map of where it's located, additional 19 reviews, you can see the menu. And, in addition, you 20 can call the restaurant and make an order or do 21 something else. Okay? 22 So it's quite information rich. And then we 23 are going to take -- use measures of consumer 24 activity, two measures. One is click -- whether or 25 not you click on the restaurant, and the second</p>
66	<p>1 experiment. Okay? 2 To give you a sense for it, Yelp is the 3 largest local business search engine in the United 4 States. They had roughly about 100 million to 120 5 million visitors in 2015. Zomato has about 80 million 6 visitors. But Yelp is not just for your restaurants 7 alone. They're for all local businesses. Okay? 8 So to understand the context of our 9 experiment, in 2014 August when we implemented the 10 experiment, the Zomato platform had a robust 11 advertising market for searches on the desktop on 12 Zomato.com. But there was no advertising on mobile. 13 Okay? 14 Many thousands of advertisers would be 15 advertising on the platform. You would put -- if a 16 consumer puts in a search, a search ad would be shown, 17 but there was no mobile advertising. So this 18 experiment was implemented as part of pre-mobile test 19 and learn methodologies for the firm. And then in 20 August 2014 we go in and implement the mobile 21 advertising experiments. 22 In the end of September, a new update was 23 launched on Android on the Google Play store in which 24 mobile advertising was actually included. If a 25 consumer downloads that update, he or she is out of</p>	68	<p>1 whether or not you call the restaurant. Okay? 2 We do not have actual orders placed to the 3 restaurant as of this point. I don't know any phone 4 that actually correlates in-app or online ad behavior 5 all the way to restaurant sales. So we just don't 6 have that. 7 Recently, Navdeep and I, we have audio- 8 analyzed a large number of MP3 files where we actually 9 listened in to about 3,000 calls that were made 10 because we recorded a bunch of them. And we report 11 that roughly 75 percent of these are about home 12 delivery, making an order, because there's no real 13 Open Table in these markets and most of it is for 14 delivery. So we think calls is a much more important 15 and more credible metric of actual orders compared to 16 clicks on advertising. Okay. 17 The experiment was imported as an update 18 into the app. It was launched from the Google Play 19 app store. Any user who downloads it in one of these 20 cities is in the experiment, okay, and then stays in 21 it. So it's persistent user randomization over time. 22 There's no re-randomization at the session level. 23 Okay. So these are the conditions into 24 which users are randomized. The typical disclosure 25 condition is the one in the middle where the fact that</p>

69	<p>1 it's an ad is revealed through a yellow label. Okay?</p> <p>2 The prominent disclosure condition is the one on the</p> <p>3 right where we add a yellow label to -- sorry, a</p> <p>4 yellow border to it. And then the no-disclosure</p> <p>5 condition is on the left. For instance, the</p> <p>6 advertiser Mia Bella occurs in the same position in</p> <p>7 the same location, everything remains the same, but</p> <p>8 there is no disclosure to consumers that this is</p> <p>9 actually paid advertising. Okay?</p> <p>10 So just to clarify, there are no ads on the</p> <p>11 restaurant pages. There are only ads on these</p> <p>12 listings. So these are paid search ads. And then</p> <p>13 everything else about the listings, including the</p> <p>14 position, the nature of the content, color, everything</p> <p>15 else remains the same across these conditions.</p> <p>16 Okay?</p> <p>17 So my full information world, what I'm</p> <p>18 calling is on the right side. The no-information</p> <p>19 world about the sponsorship status is on the left</p> <p>20 side. We also randomized consumers into a condition</p> <p>21 where there are no ads. Okay? So in this particular</p> <p>22 example, Mia Bella, the restaurant, is not advertised,</p> <p>23 but it may show up if it's relevant somewhere down in</p> <p>24 the organic listings. Okay?</p> <p>25 There are some more details about the</p>	71	<p>1 there is advertisements with and without highlight.</p> <p>2 Yes?</p> <p>3 AUDIENCE: I think I am seeing this right,</p> <p>4 but you didn't highlight the word "sponsored" like you</p> <p>5 did he word "ad."</p> <p>6 DR. NAIR: Correct.</p> <p>7 AUDIENCE: Is there a reason why you made</p> <p>8 that decision?</p> <p>9 DR. NAIR: We did a little bit of pre-</p> <p>10 experimentation testing, and this seems to be the one</p> <p>11 that we feel that the survey said users fully</p> <p>12 understand that this was an ad. Yes. And I think</p> <p>13 there is psychologists and others who think about</p> <p>14 vision and others who have done more studies in that.</p> <p>15 And so, yeah, those are additional ways to consider</p> <p>16 it. But this is what we have done, yeah.</p> <p>17 Okay. So there are 321 locations. A</p> <p>18 location is a five mile by five mile zone within a</p> <p>19 city. That is the unit of geography at which ads are</p> <p>20 sold on Zomato.com at the desktop. So there's -- all</p> <p>21 the randomization is at that level. And there are</p> <p>22 roughly 622 advertisers spread across these 321</p> <p>23 locations. So it's a larger scale to the extent that</p> <p>24 we have more than one advertiser. Okay.</p> <p>25 Okay. So, this was related to your</p>
70	<p>1 experiment, in particular how we picked advertisers.</p> <p>2 For instance, we did not randomly pick an advertiser.</p> <p>3 We did not randomize our advertisers. We picked</p> <p>4 advertisers who actually wanted to advertise, which</p> <p>5 was important for making sure that this is data from a</p> <p>6 signaling equilibrium, which we wanted to test.</p> <p>7 We did not want to disturb an equilibrium,</p> <p>8 okay, by picking a random advertiser who will not</p> <p>9 have advertised and showing an ad of that advertiser.</p> <p>10 But in the interest of time, I'll proceed a little bit</p> <p>11 more. And if you wanted to get more details on the</p> <p>12 experimental design, please approach me and we will be</p> <p>13 happy to talk offline.</p> <p>14 In addition to the ad label, we also changed</p> <p>15 the way in which disclosure is included by using the</p> <p>16 word "sponsored" instead of the word "ad," okay,</p> <p>17 because there's been some questions about not just</p> <p>18 noticeability but also interpretation of the label.</p> <p>19 So we tried sponsored. But then we have a</p> <p>20 randomization into just sponsored condition, which is</p> <p>21 on the extreme left, and the condition in which the</p> <p>22 sponsor with a highlight on the second one from the</p> <p>23 left. Okay.</p> <p>24 So there's one condition in which there's no</p> <p>25 advertisements. There are other conditions in which</p>	72	<p>1 question. It so turns out that the consumers who were</p> <p>2 randomizing your condition and saw the first ad -- the ad</p> <p>3 exposure are randomized, but the</p> <p>4 set of people who came back may be different from the</p> <p>5 set of people who saw the first ad. And therefore we</p> <p>6 are going to base all our results on the</p> <p>7 responsiveness to the first ad. Okay? And there's</p> <p>8 more results in the paper.</p> <p>9 Okay. Let me take up three of the main</p> <p>10 results. The first one is that consumers do not</p> <p>11 notice enough the sponsorship disclosures of native</p> <p>12 ads, and thus are tricked into clicking on them. And</p> <p>13 here what I'm showing you is the probability of</p> <p>14 calling, okay, relative to the typical disclosure</p> <p>15 condition. Okay? So the baseline is the typical</p> <p>16 disclosure condition, and the box represents the</p> <p>17 difference from the typical disclosure condition -- of</p> <p>18 the highlighted condition and the no-disclosure</p> <p>19 condition.</p> <p>20 So basic punchline of the paper is that when</p> <p>21 the ad is highlighted, there is no difference. Okay?</p> <p>22 So we don't find any evidence of deception. Okay?</p> <p>23 A second punchline of the paper is that when</p> <p>24 ads are not disclosed calls fall. Okay? We explore</p> <p>25 this a little bit more in our separate paper on</p>

73	<p>1 signaling. We show that standard signaling models can 2 explain that phenomenon, in particular calls to a 3 restaurant increase in the presence of disclosure. 4 Okay? So that's an important finding from the paper. 5 And there's a bunch of results in the other 6 paper, in particular documenting that it so turns out 7 that the better rated advertisers, restaurants, are 8 advertising. There is -- consumers who have more 9 uncertainty are the ones who respond more to the 10 disclosure. And restaurants about which consumers 11 have more uncertainty are the ones who get more bang 12 for their buck from the disclosure that seems to be 13 consistent with signaling. 14 How much time do I have? Zero, Garrett, but 15 go for it. 16 DR. JOHNSON: All right. So just going 17 back, like, how large do you think the difference 18 would be from the highlighted exposure and, given that 19 expectation, what was your power to detect a 20 difference? 21 DR. NAIR: Yes. So there's a bunch of 22 questions about power, okay? The -- I can tell you 23 just off the top of my head, the power is not a big 24 issue in this paper because the difference from the 25 typical disclosure condition to a no-disclosure</p>	75	<p>1 search cause or inertia or whatnot. So native 2 advertising works by tricking consumers into clicking, 3 and that's the way the mechanism works. I'm just 4 telling you that we don't find evidence for that at 5 least in our data. 6 Firstly, there's about an 85 percent chance 7 of continued search after clicking on an ad. So 8 there's lots of search happening. So it does not seem 9 to be that you click and suddenly you buy exactly what 10 you clicked on. There is substantive continued search 11 after click visiting an advertiser's page. 12 On average, people visit about 50 to 60 13 listings before calling an advertiser if they call. 14 So that seems to be an outcome of fairly thoughtful 15 search and deliberation. 16 In addition, I will just read out the 17 result. We find that much of the improved conversion 18 for people who have been -- to whom it has been 19 disclosed that this is an ad comes from people who 20 actually don't click on the ad. Okay? But they get 21 exposed to the ad, they continue searching, all within 22 the same session, they put another search and then 23 click on the organic listing of that ad. Okay? 24 So it does not seem to be that much of a 25 lift is coming from people who click on ad, but from</p>
74	<p>1 condition -- for instance, that P value is to the 2 order of .002. Yes? So you've got to find, like, 3 some serious occurrences by chance in order to move 4 that -- move that P value all the way to .05. So -- 5 and then we have exact P values reported in the paper 6 as well that take the power into consideration. So 7 that's just a very quick answer off the top of my 8 head. 9 I've been asked a question before, so 10 recently we've been doing more and more on assessing 11 power and making sure that this is not something that 12 occurred by chance. And now P value is just too small 13 to succumb to that. Okay. 14 All right. So the basic punchline here, 15 therefore, is that we find no evidence of deception, 16 but we find that there is a strong case to regulate 17 because in the absence of disclosure consumer behavior 18 looks very different. So if a typical disclosure is 19 not provided, behavior could be very different. 20 We found no difference between sponsor and ad 21 label 22 conditions. So the consumers do not seem to be 23 confused by the label. And, finally, quickly in one 24 minute, assessing the idea that if consumers click, 25 then they continue to buy because maybe they have some</p>	76	<p>1 exposure. So the mechanism by which advertising works 2 in this market seems to be exposure, not clicking. 3 Okay? And therefore we think that clicks are actually 4 a very bad way to assess advertising. 5 Okay. So the punchline here is that there 6 is very little evidence of consumer naiveté, a locking 7 or inertia condition while clicking. And so the 8 notion that consumers are tricked into clicking and 9 they stick with that click does not seem to have much 10 support in this data. 11 No detectable evidence of material 12 deception, at least in this market. Choices look 13 pretty similar to a world with full information, and 14 ads seem to work on the basis of exposure. Some other 15 data from Brett Gordon and Florian Zettelmeyer are 16 doing with Facebook also seems to suggest this. 17 Okay. So I'll skip this. The punchline 18 here is that in a world without disclosure we find 19 that consumers would have gone to restaurants that 20 were more poorly rated and had fewer ratings. So it 21 seems that disclosure actually helps consumers. 22 Okay. So I just want to emphasize that we 23 can't really speak directly to consumer welfare 24 because we actually don't observe actual choices. But 25 it just seems to suggest that consumer choices do not</p>

77	<p>1 change materially and the ads are more prominent. So</p> <p>2 listening to the concern for welfare losses from</p> <p>3 current disclosure standards at least in this market</p> <p>4 may be minimal. So -- and advertising seems to help</p> <p>5 consumers, okay, because of signaling.</p> <p>6 Thank you. And I'll just put up my</p> <p>7 conclusions out there and look forward to comments.</p> <p>8 (Applause.)</p> <p>9 DR. JIN: Thank you, Harikesh. Our</p> <p>10 discussant is Yesim Orhun from the University of</p> <p>11 Michigan.</p> <p>12 DR. ORHUN: All right. Thank you. Could</p> <p>13 somebody help me make this full? I'm not a Windows</p> <p>14 person. Control what? L?</p> <p>15 Thank you. Thank you for inviting me here</p> <p>16 to discuss this paper. Let me jump in in the interest</p> <p>17 of time and really, first of all, emphasize why the</p> <p>18 design of this paper is so neat and so useful to</p> <p>19 understand material deception.</p> <p>20 So if you look at the FTC policy statement</p> <p>21 on deception, there are three things you've got to</p> <p>22 care about. First that there was some reasonable</p> <p>23 potential for being misled. Second, consumers were</p> <p>24 kind of acting reasonably, and that at least some</p> <p>25 material changed. What does that mean? They consume</p>	79	<p>1 So basically once you ask the question this</p> <p>2 way, much more precise, and honestly much more</p> <p>3 relevant for this topic, then their experimental</p> <p>4 design is really right on the money. It answers this</p> <p>5 really relevant question by putting two bookends to</p> <p>6 it. Native as a middle, the two bookends are full</p> <p>7 deception where literally you put the ad and don't</p> <p>8 tell people that it's an ad. Right? Which you don't</p> <p>9 do in experimental economics, but you can do with</p> <p>10 field experiments here. Full deception. And the</p> <p>11 other bookend is full information.</p> <p>12 Well, for the sake of argument let's say</p> <p>13 it's full information. You may have quibbles about</p> <p>14 whether highlighting it makes it full information, but</p> <p>15 this is actionably the best the authors can do. And I</p> <p>16 actually buy it. Okay?</p> <p>17 So those are the two theoretical bookends</p> <p>18 that they are able to implement very well in the</p> <p>19 field. In other situations, like think of Airborne's</p> <p>20 claims of -- you know, that were false of, you know,</p> <p>21 preventing you from getting the flu, you may have</p> <p>22 difficulty thinking about these two bookends. What</p> <p>23 would be a very fully deceptive advertising and what</p> <p>24 would be full information advertising isn't as clear.</p> <p>25 But in this case it's perfectly clear and</p>
78	<p>1 or choose differently because of the deception. So</p> <p>2 that is actually a choice argument. So that lends</p> <p>3 itself very well, as Harikesh explained, to a field</p> <p>4 experiment to revealed preference to ask, you know,</p> <p>5 would people have chosen differently except for</p> <p>6 deception.</p> <p>7 Now, that may seem very straightforward to</p> <p>8 do in the field. It actually isn't because it's</p> <p>9 different than what is the first question you've got</p> <p>10 to ask. Right? So what is the counterfactual? That</p> <p>11 counterfactual, you know, you may use structural</p> <p>12 methods, but in this case actually it's not that easy</p> <p>13 even with a field experiment. The comparison should</p> <p>14 not be no ads. That doesn't make a lot of sense,</p> <p>15 right? If native ads are different than a no ad world</p> <p>16 or a different ad world, that could be because native</p> <p>17 ads are differentially effective. That doesn't</p> <p>18 necessarily mean they are deceptive.</p> <p>19 So the question is how do we link the change</p> <p>20 of behavior? Not only demonstrate that the behavior</p> <p>21 is different, but link it to deception. And the paper</p> <p>22 does a very neat job by focusing on a very specific</p> <p>23 question. I'm going to rephrase the research question</p> <p>24 in my own words, which is do native ads mislead</p> <p>25 consumers to think that they are not ads. Okay?</p>	80	<p>1 actionable, executable in the field. So this is</p> <p>2 great. So they have six conditions. For the interest</p> <p>3 of time, I'm not going to go through them all.</p> <p>4 Harikesh did go through them.</p> <p>5 The relevant one isn't the no ad condition</p> <p>6 for the reasons we talked about. If it is in effect,</p> <p>7 it's not very clear if it's because of deception.</p> <p>8 First, I also want to simplify the design by</p> <p>9 pointing out that sponsored versus ad doesn't matter.</p> <p>10 So let's just look at this design as no ad condition,</p> <p>11 deception condition, native ad regardless if it's an</p> <p>12 ad or sponsored, and then full information condition.</p> <p>13 Okay? So basically four conditions.</p> <p>14 And what Harikesh argued is that comparison</p> <p>15 of native ad to the full information is the way to</p> <p>16 figure out whether this ad was deceptive. I would</p> <p>17 actually also add that comparison of the native ad to</p> <p>18 the full deception condition is another way to figure</p> <p>19 out whether this was deceiving. If they're very</p> <p>20 similar, then I would say that's deceiving.</p> <p>21 One other way of, you know, interpreting is</p> <p>22 that consumers don't care about the disclosure. But I</p> <p>23 don't think that you can pull the two apart, whether</p> <p>24 they don't care or whether they don't notice.</p> <p>25 But in any case, these are the three main</p>

81	<p>1 things we're going to compare. For the first sign of 2 regressions, Harikesh didn't have the time to go into 3 detail, so let me do that. They actually don't 4 compare these exact three. They pool the full 5 information, the two together, to get power. Since 6 sponsored versus ad doesn't matter, they might have as 7 well pooled all the native ones, which I think is a 8 good robustness check.</p> <p>9 What they find is actually no effect on 10 visiting the restaurant's page. So if you just have 11 this result, you might have thought, well, maybe they 12 are deceptive or maybe this is not effective, but 13 thankfully they actually have much more to say. They 14 look at calls and they find a huge difference between 15 the deception condition and the other two conditions.</p> <p>16 And the other two conditions are actually 17 insignificant from one another, not different from one 18 another. And so they conclude that the native ad is 19 much closer to the full information case than the 20 deception case. That's why the bookends are so 21 useful.</p> <p>22 They do another thing that I think is very 23 valuable that Harikesh didn't have time to talk about. 24 They actually look at how the type of restaurants' 25 consumers call changes as a function of disclosure.</p>	83	<p>1 affecting all the rest of the restaurants which we 2 think we are keeping fixed? It might be useful to 3 discuss.</p> <p>4 But in essence, what's important to take 5 away is that the native ads is much closer to full 6 information than deception case, even here.</p> <p>7 Another set of results that they have which 8 I found very interesting is to answer the question are 9 consumers tricked into conversion. Here they're 10 comparing deception versus disclosure. They're now 11 lumping all four conditions of disclosure into one, 12 which makes sense, and they're crossing it with 13 whether the restaurant clicked on was reached 14 organically through search and below, or by clicking 15 on the ad.</p> <p>16 So the paper can give more detail as to why 17 this two-by-two answers this question. But here 18 the findings they have on consumers are not stuck if 19 they click on native ads. First, they show that 20 disclosure does not impact whether somebody continues 21 to search or not after a page visit. In general, 22 organic arrivals search less afterwards than ad links.</p> <p>23 This makes sense because if you went to a 24 restaurant by an ad, you're probably -- your match 25 value was probably not so high so you're continuing to</p>
82	<p>1 So they see -- they run an interesting regression so 2 I'm going to talk about this in detail. They look at 3 the number of calls a restaurant gets across different 4 conditions using restaurant fixed effect. So this is 5 a within-restaurant -- it controls for all the 6 heterogeneity -- the data is really rich. They can 7 control for all kinds of heterogeneity, including 8 search characteristics which I urge them to do, and 9 restaurant characteristics.</p> <p>10 So if you just look at the main effects, you 11 might interpret this as kind of an effect of 12 experimentation on all of the conditions on all 13 restaurants. But, by the way, these are not 14 advertised restaurants, these are all the restaurants.</p> <p>15 They don't find a main effect there. It's 16 kind of comforting because you don't actually want 17 your experimental conditions to kind of change the 18 calling behavior to all the restaurants, but just, you 19 know, implemented or shopped restaurants.</p> <p>20 But interestingly they do find that the type 21 of restaurants the people call changes. People are 22 much less likely to call high-rating restaurants. 23 They're much less sensitive to rating. This was 24 actually a little confusing to me. It's an 25 interesting result. But why are the conditions</p>	84	<p>1 search. Also, ads appear at the very top and organic 2 links appear at the bottom and the search behavior may 3 change. It may be more likely to converge at the 4 bottom. So there are some things going on maybe we 5 want to control for rank.</p> <p>6 But importantly disclosure doesn't impact. 7 What does that mean? I actually wanted to think about 8 these bookends again. This means that native 9 advertising is close to deception. What do I want to 10 make out of that? Does that mean native advertising 11 is deceiving in this case? I don't have the other 12 bookend. They lump the native ads and the highlighted 13 conditions together. So one thing to potentially 14 explore is bring that bookend back and see if it's 15 kind of closer to full information. I was confused by 16 this.</p> <p>17 Another result that's really interesting is 18 calling only increases with disclosure if the page 19 visit was organic, not through an ad click. So their 20 other paper is also very, very neat. They actually 21 show that increasing in calls due to disclosure may be 22 a signaling story, right -- is a signaling story. So 23 my question is why doesn't the signaling story work 24 when you click on the ads, but works in the organic 25 links which are much lower and much less frequently</p>

85	<p>1 visited.</p> <p>2 So those were my kind of, you know, overview</p> <p>3 of the results. I think it's very cool. I personally</p> <p>4 took a lot away from this paper. Three things</p> <p>5 importantly that I want to re-highlight. First, the</p> <p>6 role of experimentation for identification of material</p> <p>7 deception. This idea that you can think at least</p> <p>8 theoretically of those two bookends, deception and</p> <p>9 full information, is extremely useful. Whenever it's</p> <p>10 employable, let's do it, right? This is very useful.</p> <p>11 The elements of design in this paper are</p> <p>12 extremely clear and very well thought out. And the</p> <p>13 punchline is that the consumer response to the same ad</p> <p>14 when it's native looks similar to the full information</p> <p>15 case, but quite different from the deception case.</p> <p>16 And I want to highlight this difference between the</p> <p>17 deception condition and the native ad condition</p> <p>18 because I think that also directly speaks to</p> <p>19 deception. Thank you very much.</p> <p>20 (Applause.)</p> <p>21 DR. JIN: Thank you, Yesim. We still have a</p> <p>22 few minutes for questions.</p> <p>23 AUDIENCE: This is a fascinating experiment</p> <p>24 and I think it's great. I had one question about the</p> <p>25 specific setting in which this is happening. Is this</p>	87	<p>1 of ratings, yeah. So in a world where ratings provide</p> <p>2 a lot of information, the incremental value of</p> <p>3 advertising as a signal is more rated. So what we are</p> <p>4 measuring is over and above the effective ratings.</p> <p>5 We can't say anything particular about the</p> <p>6 value of ratings in this paper because we don't</p> <p>7 randomize ratings. So where we have a conditioning on</p> <p>8 the ratings and the organic algorithm and then what</p> <p>9 we're measuring is over and above. So we randomize</p> <p>10 disclosure, but not the position on the ratings. So</p> <p>11 the paper has little to say about that.</p> <p>12 Now, attention, absolutely I think</p> <p>13 advertising plays an important role in increasing</p> <p>14 attention. But that attention seems to be translating</p> <p>15 into clicks and exploration of the restaurants, but</p> <p>16 not necessarily into conversion. Yes.</p> <p>17 So, for example, in the -- in the no ad</p> <p>18 condition, the listing is very much at the bottom, but</p> <p>19 in the -- what Yesim called a typical disclosure</p> <p>20 condition or the deception condition, it looks like an</p> <p>21 organic link but it's on the top. Okay?</p> <p>22 Going from A to B is a very dramatic</p> <p>23 increase in attention because it went from somewhere</p> <p>24 down there to the top, where we find very little</p> <p>25 increase in the call rate. We do find an increase in</p>
86	<p>1 in a setting in which ratings are easily arrivable?</p> <p>2 So we will actually have an ability to assess what the</p> <p>3 quality is because the ratings are very high. And</p> <p>4 perhaps some of the restaurants are more rated by the</p> <p>5 particular nature of the setting compared to a setting</p> <p>6 where I just don't have any information rating. So I</p> <p>7 just wanted to get your thoughts on that.</p> <p>8 And, second, I was curious whether this is</p> <p>9 really so much more of an attention story, that when</p> <p>10 you start highlighting something you get more</p> <p>11 attention. And in a particular place where actually</p> <p>12 quality can be easily assessed, there is much less</p> <p>13 chance for deception than in other settings.</p> <p>14 DR. NAIR: Those are two great questions.</p> <p>15 No, absolutely on the ratings, the effect</p> <p>16 that we are measuring is over and above any</p> <p>17 information content of ratings. In particular, to the</p> <p>18 extent that you believe that the advertisement serves</p> <p>19 as a signal here, in a world without ratings, the</p> <p>20 signaling value of advertising would be much higher.</p> <p>21 And in a world with no ratings -- sorry, in a world in</p> <p>22 which rates convey all information, advertising does</p> <p>23 not have any role to play as a signal.</p> <p>24 AUDIENCE: (Off microphone).</p> <p>25 DR. NAIR: Yes. So in terms of the effect</p>	88	<p>1 the click rates.</p> <p>2 So that's -- and when moving from an ad</p> <p>3 which is provided as typical to an ad which is</p> <p>4 highlighted, also we don't increase -- we don't see a</p> <p>5 dramatic increase in call rates. So we think that</p> <p>6 attention does matter on clicks, but it's not</p> <p>7 necessarily -- just because I'm getting you into the</p> <p>8 consideration set, that does not necessarily translate</p> <p>9 into actual conversion. That seems to be the story</p> <p>10 that we see.</p> <p>11 The closest panels I know to the literature</p> <p>12 on searches, a paper by Raluca Ursu, where she looks</p> <p>13 at Expedia but it's not for paid ads, but it's for</p> <p>14 organic ads, she sees that if you're in a higher</p> <p>15 position on Expedia, that does translate into higher</p> <p>16 clicks. But it does not translate into -- necessarily</p> <p>17 into conversion for the hotels at least in a monotonic</p> <p>18 way.</p> <p>19 So that's why we think that clicks perhaps</p> <p>20 are not the right metric, but open to more</p> <p>21 interpretations. Thank you.</p> <p>22 AUDIENCE: So my question was kind of</p> <p>23 related to Sridhar's question. It wasn't quite clear</p> <p>24 to me how this -- Sridhar called it attention and I</p> <p>25 call it salience. So I throw the other visual cues</p>

89	<p>1 like the box with the yellow thing would be 2 disentangled from signaling. And my thought perhaps 3 was it might be useful to have a setting -- and I know 4 these field experiments are not easy to repeat, but 5 where you have similar visual cues without the 6 advertising message so that it would help to have the 7 signaling story separate from a salient attention 8 story.</p> <p>9 DR. NAIR: Yeah. So thanks for asking that. 10 And absolutely we do have the condition. We have a 11 condition where the same restaurant is shown to 12 consumers without any advertising message. And then 13 we have a condition in which the same restaurant is 14 shown to a consumer with an advertising message. The 15 difference between that is what picks up signaling. 16 And then we have another condition in which an ad is 17 shown with and without a highlight, the difference in 18 between that is not picking up signaling, but speaks 19 to attention or prominence. Okay?</p> <p>20 What we find is that if the same listing is 21 shown without an ad, calls are lower. If the same 22 listing is shown with an ad disclosure, calls are 23 higher. That's why we say that seems consistent with 24 signaling.</p> <p>25 If the same listing is shown as an ad with a</p>	91	<p>1 ad, if additional salience or additional highlighting 2 changes behavior in a full information world to a 3 small information world, and also to understand what 4 will happen if we provide the same information but 5 code it as an ad versus not coded as an ad.</p> <p>6 His paper does not have a control group and 7 talks about the difference between if an ad is coded 8 as sponsored versus coded as advertisement, and that 9 does change in behavior. This was not really the 10 focus of our paper, but we are happy to report 11 heterogeneity in that to see whether it's consistent 12 with these results or whatnot. Yeah. And, also, his 13 paper's results bear on clicks. We do find results on 14 clicks. Our results on calls seem to be pretty 15 different.</p> <p>16 Yes, Anne?</p> <p>17 DR. COUGHLAN: I'm kind of interested in your 18 thoughts about the distinction between misleading and 19 deceiving. And I'm thinking back to what Ginger said 20 in the introduction. There's been a lot of use of the 21 word deception that I'm not sure has been actually 22 demonstrated here. Whether or not it changes a 23 consumer's call behavior or indeed their purchase 24 behavior doesn't mean that they've been harmed.</p> <p>25 And so I don't know if anybody would like to</p>
90	<p>1 highlight, calls are not necessarily higher. So 2 that's why I responded to Sridhar's question that the 3 additional highlighting or additional attention does 4 not seem to be translating to calls. It does 5 translate to clicks.</p> <p>6 Yes, Catherine, go ahead.</p> <p>7 DR. TUCKER: Hello, yes. So I think it's more 8 suggestion than question.</p> <p>9 DR. NAIR: Yes.</p> <p>10 DR. TUCKER: But hopefully it's a doable 11 suggestion. So as you know, Ben Edelman's got this 12 old paper where he shows that old people, inexperienced 13 internet people, react differently to the word 14 sponsored and ad. And I was just thinking with your 15 wonderful geographic data, you can actually look to 16 see whether that's an artifact of his setting or yours 17 and look and divide up the world into the experienced 18 and inexperienced and see if you see any heterogeneity 19 effects.</p> <p>20 DR. NAIR: Sure, yes. Absolutely. So I'm 21 aware of Ben's paper. And we will definitely look at 22 that. But just to respond to that, the main interest 23 of this paper is not as much the difference between 24 the word ad versus sponsored, which is the point of 25 his paper, but to understand conditional on the word</p>	92	<p>1 chat about that. But it would seem to be important to 2 be precise about those words and the implications for 3 policy and action.</p> <p>4 DR. NAIR: Yes. I'm so glad you asked that 5 because we grappled with this quite a bit as we were 6 thinking through the paper. I do not think that these 7 results translate into a statement that consumers were 8 harmed or not harmed at all. Yes? Because harm, in 9 my mind at least, will require measuring actual 10 consumer welfare. And so we don't have a stance on 11 consumer utility and we don't have a way of assessing 12 welfare. So we don't know whether consumers were 13 harmed or not unharmed.</p> <p>14 But the sense in which I'm saying deception 15 is the sense in which the FTC provides precise 16 definition of it, deception is said to have occurred 17 if a reasonable consumer's behavior with respect to 18 the advertisements or with respect to the product 19 changes. And I'm just documenting very little change 20 in subsequent behavior when ads are highlighted and 21 presumably people understand that they are actually 22 ads.</p> <p>23 Now, does that -- that does not translate 24 into a statement about harm. I don't know because I'm 25 not in a position to measure welfare. We tried to</p>

93	<p>1 show that it does not seem to change in harm because 2 with disclosure compared to a world with no 3 disclosure, people seem to be going to better 4 restaurants which have higher ratings, and to 5 restaurants with fewer ratings. So it seems 6 consistent with signaling. It may not translate to 7 harm, but without taking a stance on utility or 8 measuring welfare, per se, I do not know. I would ask 9 the FTC folks to tell us how we -- I should think 10 about it.</p> <p>11 DR. PAPPALARDO: I have a related question, which 12 is if you don't test the effect of disclosure on 13 consumer comprehension as part of the experiment, then 14 how do you know that the consumer was misled to their 15 detriment?</p> <p>16 DR. NAIR: Correct. So we don't really have 17 a way of getting inside consumers' minds to the extent 18 that we would like to. And we think that ways of 19 asking people subject to the usual Heisenberg 20 critique, the asking changes when they complement and 21 how they report to that.</p> <p>22 So I -- all I can offer you is what patterns 23 of consumer actions. And the action seems to be of 24 deliberate search, not of knee-jerk reaction, of 25 substantial consumption of listings prior to calling,</p>	95	<p>1 and still want to engage with the ad. 2 DR. NAIR: Right. 3 AUDIENCE: But it may change, you know, how 4 they perceive what's being said. So it's not that if 5 consumer doesn't click that means they weren't -- that 6 they were deceived or were not deceived. 7 DR. NAIR: Correct. 8 AUDIENCE: It's the weight of credibility of 9 the message, not just pure engagement. 10 DR. NAIR: I am in agreement with you. And 11 I think the -- what our paper is trying to document is 12 that the translation of that change in credibility in 13 response to disclosure is in a positive way to the 14 restaurant. In a world with disclosure, consumers are 15 actually going to the restaurant at a higher rate. 16 They're calling the restaurant at a higher rate. 17 Okay? And that's all we're trying to say, that when 18 consumers see the same listing framed as an ad, the 19 credibility of the restaurant increases. 20 Yes? And that seems to be suggested with 21 signaling, and this is real data that just documented 22 that. 23 AUDIENCE: I just want to take on your 24 Heisenberg example. We don't stop physics from doing 25 measurements, nor should it stop social sciences. I</p>
94	<p>1 and of a responsiveness of reactions to ads that seem 2 consistent with the theory. And most of these actions 3 don't look like knee-jerk reactions, and they seem 4 consistent with people really understanding that what 5 they are seeing is an ad.</p> <p>6 And in a setting where ads are made more 7 salient, they don't seem to be behaving very 8 differently as well. But in a setting where ads are 9 not at all shown, they seem to be working very 10 differently. All of this seems to suggest that people 11 are comprehending. But I don't really ask people 12 whether they comprehend it. In fact, we are 13 critiquing that style of assessing the advertisements.</p> <p>14 Yes, go ahead.</p> <p>15 AUDIENCE: Hi. This is from the legal 16 perspective.</p> <p>17 DR. NAIR: Yes.</p> <p>18 AUDIENCE: But your statement about, you 19 know, what's deceptive under FTC law and if behavior 20 doesn't change then the ad isn't deceptive. And I 21 would take issue with that because the issue on native 22 advertising is how much weight or credibility 23 consumers will give the message. And that's why the 24 FTC has said it should be identified as advertising. 25 The consumer can understand that it's an ad</p>	96	<p>1 want to give you a theory of how reactivity occurs. 2 DR. NAIR: Yes. 3 AUDIENCE: And particularly in the case 4 where many of your concepts like attention are 5 actually very easily measured not in a field 6 experiment, although increasingly with very cheap 7 iTracking, \$99 in a pin -- you know, a little pin- 8 shaped container, or lots of other techniques that can 9 be. So I want to push back on this statement that 10 you're trying to go against that kind of measurement. 11 DR. NAIR: No, not necessarily as a 12 substitute. I didn't mean to say that this field 13 experimental agenda is a substitute for that kind of 14 measurement. But I wanted to say that it's a 15 complement to that kind of measurement. And I do 16 believe that the actions of consumers when they are 17 actually engaged in the record search for a goal that 18 is very important. Let's say dinner with the family 19 on a Friday evening, when it's really important to 20 find the right restaurant, they could defer a little 21 bit from the in-lab situation where the actions are 22 less consequential. 23 I think if we can find a way to measure 24 consumer beliefs and consumer information sets and 25 attention in the field in a way that does not disrupt</p>

97	<p>1 things, that will be incredibly valuable and we should</p> <p>2 potentially find a way to combine that. Right after</p> <p>3 this talk I'm going to come to you and ask how should</p> <p>4 we do that in the field, and that will be great.</p> <p>5 AUDIENCE: Okay. So I think this is the</p> <p>6 last one. Okay. So this is actually a followup to</p> <p>7 Anne's comment.</p> <p>8 DR. NAIR: Yeah.</p> <p>9 AUDIENCE: So I think maybe the conditions</p> <p>10 she -- we were just talking about it.</p> <p>11 MD. NAIR: That's fine, yes.</p> <p>12 AUDIENCE: So I think the condition that</p> <p>13 would be nice to have -- imagine having 20 different</p> <p>14 listings and one has an ad next to it. So one way to</p> <p>15 think about it is this is a form of disclosure.</p> <p>16 Another way to think about it, this is a form of</p> <p>17 salience. It's calling -- you know, it's kind of</p> <p>18 calling attention to that ad -- to that listing. And</p> <p>19 it is also, you know, an ad disclosure, but it's also</p> <p>20 -- you know, sort of gets your eyeball to go there.</p> <p>21 And so it would be nice to have another</p> <p>22 condition that had something like that, a type of</p> <p>23 salience, but it didn't say ad. Like, for example, it</p> <p>24 had a star.</p> <p>25 DR. NAIR: Mm-hmm.</p>	99	<p>1 a break right now until 10:45. Thank you.</p> <p>2 (Brief recess.)</p> <p>3</p> <p>4</p> <p>5</p> <p>6</p> <p>7</p> <p>8</p> <p>9</p> <p>10</p> <p>11</p> <p>12</p> <p>13</p> <p>14</p> <p>15</p> <p>16</p> <p>17</p> <p>18</p> <p>19</p> <p>20</p> <p>21</p> <p>22</p> <p>23</p> <p>24</p> <p>25</p>
98	<p>1 AUDIENCE: Or just had a box without the ad</p> <p>2 symbol.</p> <p>3 DR. NAIR: Right, right, right.</p> <p>4 AUDIENCE: And so I was wondering if you had</p> <p>5 that -- okay.</p> <p>6 DR. NAIR: I see that data and the short</p> <p>7 answer is no. We'd love to have it, but, no, we don't</p> <p>8 have it yet. Thank you.</p> <p>9 AUDIENCE: And so just kind of -- so do you</p> <p>10 -- so do you feel like in light of that, so another</p> <p>11 way to interpret the salience is to say, you know,</p> <p>12 this shows that salience -- you know, that salience is</p> <p>13 a good thing, as Sridhar was saying as well. So would</p> <p>14 you make a strong statement about disclosure?</p> <p>15 DR. NAIR: That's right, yeah. I don't</p> <p>16 interpret it that way, but if you would like to</p> <p>17 interpret it that way that would be fine. But we</p> <p>18 don't think that salience is what's driving at our</p> <p>19 attention. Our consideration set is what's driving</p> <p>20 it. But rather than belabor the point, let's chat</p> <p>21 offline.</p> <p>22 (Applause.)</p> <p>23 DR. JIN: Thank you for the engagement. It</p> <p>24 seems like we have underestimated your willingness to</p> <p>25 discuss. We're a little behind schedule. We'll take</p>	100	<p>1 SESSION TWO:</p> <p>2 THE BENEFIT OF COLLECTIVE REPUTATION</p> <p>3 DR. JIN: Hello. We'll start the second</p> <p>4 session on papers. Aniko Oery from Yale University</p> <p>5 will talk about The Benefit of Collective Reputation.</p> <p>6 DR. OERY: Thank you. Yeah, thank you so</p> <p>7 much to the organizers for putting together such an</p> <p>8 awesome program, and also for giving me the</p> <p>9 opportunity to present here. I'm very excited that</p> <p>10 we have a session with theory work. So I'm an</p> <p>11 economic -- I shouldn't say economic theorist. I'm a</p> <p>12 marketing modeler theorist. I don't know how we call</p> <p>13 us. And so we -- I will have less to say in terms of</p> <p>14 quantitative results, but hopefully I can give some</p> <p>15 qualitative insights that are relevant for regulation</p> <p>16 as well.</p> <p>17 And I have to apologize actually also to</p> <p>18 Anthony because we changed or added a bunch of results</p> <p>19 that are more relevant maybe for regulators. And so I</p> <p>20 wanted to -- I will focus a little bit more on that in</p> <p>21 this presentation, and I also apologize, but maybe</p> <p>22 that's good for those people who have seen this talk</p> <p>23 already, which I think there are some of you who have</p> <p>24 seen this talk.</p> <p>25 So this is joint work with Zvika Neeman, who</p>

101	<p>1 is an economist at Tel Aviv University, and Junju Yu, 2 who is an amazing student at Yale. And -- well, okay. 3 And let me now jump into what we think about when we 4 talk about collective reputation. 5 So there are a bunch of different types of 6 questions that we can -- that collective reputations 7 can help us answer. One is agricultural appellation. 8 So here, for example, if you think about a brie cheese 9 or a Bordeaux wine, if you go into the wine store you 10 might not know exactly which vineyard the wine comes 11 from but you know Bordeaux, you have some idea about 12 the quality of a Bordeaux wine. And similarly if you 13 buy brie, you know, you have an idea about the quality 14 of a brie, but you might not know the exact brand of 15 the cheese. 16 And so there you have some -- those cheese 17 companies basically collectively build up their 18 reputation or have a collective brand in their 19 agricultural appellation. 20 And maybe more importantly for regulators is 21 the country of origin application. So, for example, 22 TAG Heuer or many other high-end Swiss watchmakers 23 really put very prominently on their ads Swiss-made, 24 or German manufacturers of cars put on. So if you 25 have a Volkswagen, power of German engineering. Here</p>	103	<p>1 weeks. So this is a pretty new paper and still a work 2 in progress, even though now I think we have all the 3 results together at least. 4 And so -- so the country-of-origin labeling 5 is a big issue. I think Ginger also mentioned it in 6 her presentation at the beginning. And there -- it's 7 not clear in which industry we should regulate it, 8 what are the consequences of it, is there actually -- 9 does it help the consumers or does it maybe even hurt 10 them? 11 Okay. So the way we tried to model it, or 12 our contribution is that we think of a country of 13 origin as a collective brand, and we think of a 14 collective brand as something that creates value for a 15 firm and therefore enforces a firm to invest into the 16 production process of the product. 17 And then we also distinguished between two 18 types -- two very different types of industry. So one 19 is industries where we care more about quality 20 control, and one is where we care more about investing 21 into an exclusive technology. 22 I'm always not sure -- so I can also step 23 back a little bit and the mic will still capture it, 24 or -- okay, good. Because I'm just standing here. 25 So the research questions that we tried to</p>
102	<p>1 -- I put this example because I think it's a nice 2 example where you can see that even if you have a 3 brand, if you shirk and don't keep investing then bad 4 things might happen and the reputation might suffer 5 from it. 6 And this is a very important feature of the 7 model that we have that we really think about 8 reputation as something that you can manage, and that 9 might also deter you from -- but there is a moral 10 hazard problem that might lead you to no investment or 11 to shirking. 12 Another -- but then on the other hand in 13 some other industries, we observe firms not really 14 emphasizing it so much, and also it depends on the 15 country that the company is from. So, for example, 16 Bosch doesn't really emphasize the "made in Germany" 17 so much in their ads. And on the other hand, Chinese 18 manufacturers, there are, like, webpages where you can 19 find Chinese manufacturers of some parts advertising 20 together. 21 But then also the question is do they really 22 want to emphasize made in China, let's say, or should 23 the regulators say you have to emphasize made in 24 China. And so that's kind of a question that I added 25 to the paper after -- yeah, in the last couple of</p>	104	<p>1 answer in this paper is on the one hand what are the 2 fundamental differences in reputation building or 3 brand building if we do it by ourselves, if we have an 4 individual brand, and if we have kind of a collective 5 brand like country-of-origin or appellations, for 6 example. 7 But then I think what is more relevant maybe 8 for the audience today is in which industries and 9 countries is country-of-origin legislation or labeling 10 -- sorry, country of origin labeling socially optimal, 11 and when is it actually -- when does a firm actually 12 want to label the country of origin and when does it 13 not want to label the country of origin? And the gap 14 between the two will basically capture who wants to 15 regulate this. So we want to regulate it if it's 16 socially optimal, but not optimal for the firm. 17 And from a theoretical perspective, so the 18 way we think about it is that there's a classic model 19 by Mailath and Samuelson about reputation building. 20 And the difference between individual reputation and 21 collective reputation is the following: So on 22 individual reputation, each firm sells under its own 23 brand name. So the customers know exactly which 24 product has been produced by which firm. 25 But on the other hand, for this brand we</p>

105	<p>1 have fewer observations so there's less output 2 produced by that brand. And if we have a collective 3 reputation on the other hand, now if you buy a brie 4 you might not be aware -- you have an idea about the 5 brie, but you don't know exactly whether your idea 6 about the brie is generated by this particular 7 producer of the brie, or whether it's generated by 8 some other brie manufacturers.</p> <p>9 So this is a weaker signal that you can get 10 about the brand value. And, on the other hand, you 11 have many, many more signals. So as a manufacturer or 12 as a firm, there is some free riding going on. So you 13 might -- that might also -- you might think, okay, why 14 are collective brands beneficial at all then for 15 incentives? Why do we want to have collective brands? 16 Because signals plus free-riding problems seem to be 17 something that -- from a welfare perspective.</p> <p>18 However, what we would like to focus on in 19 this work is an idea that was first introduced by 20 Mailath and Samuelson that there is a moral hazard 21 problem in the context of brand reputation. And this 22 model as a problem comes from the fact that 23 investments are not observed by the regulators or by 24 consumers. So you don't observe the actual 25 investment, but you observe the quality outcome of the</p>	107	<p>1 competent, so it has the ability to invest into the 2 technology or into monitoring with some probability, 3 or it's incompetent otherwise. A competent firm can 4 invest and increase the probability of producing a 5 good product from a low probability π_L to a higher 6 probability π_H, whereas an incompetent firm who just 7 doesn't have visibility to invest always produces a 8 good quality product only with probability π_L. And 9 importantly the investments are not observed by the 10 market.</p> <p>11 And in every period you have some customers 12 arriving and they see the history of realizations of 13 the product and then build some beliefs about how good 14 they think the brand is actually. And then based on 15 that, their willingness to pay will be determined. 16 And if the quality -- for simplification we normalize 17 everything to the value of a customer, of a good 18 quality product being one and of a bad quality product 19 being zero.</p> <p>20 So then we get a very simple equation for 21 when is it optimal to actually invest. It's optimal 22 to invest if the increase in the probability of 23 producing a good quality product is bigger than the 24 cost of investment. So this would be just π_H minus 25 π_L is greater than C.</p>
106	<p>1 product. So you observe the Volkswagen car, you see 2 that it breaks down or that it's not as energy- 3 efficient as they claim it to be.</p> <p>4 So -- but as I said, reputation is an asset. 5 And the nice thing about the model that they 6 introduced is that you can really manage 7 reputation -- but what this leads to is that if 8 reputation is, for example, very high, you might want 9 to milk your reputation and shirk. So that might be 10 the case for Volkswagen that they were just so 11 overconfident because their reputation was so high and 12 they just thought they could get away with shirking.</p> <p>13 And on the other hand, if your reputation is 14 very low, you might just give up. So the question 15 that we ask is when does an equilibrium exist in a 16 game-theoretic sense where a firm really wants to 17 invest in every period.</p> <p>18 And I just want to give you a toy model to 19 give you the main idea behind this and where this 20 tension comes from. But I won't go too much into 21 detail of the theory behind it because the model is 22 quite -- yeah, it's a -- there's a lot of details that 23 I will have to skip today in the interest of time.</p> <p>24 So imagine there's a firm that lives for a 25 certain number of periods and a firm can be either</p>	108	<p>1 And in this type of model, in the last period if 2 there is no future and you don't -- you know, you die 3 tomorrow, a competent firm would never want to invest 4 because there's no value of reputation at all.</p> <p>5 But the fact that you don't invest in the 6 last period means the customer -- it's not useful for 7 the customer at all to know that somebody is competent 8 or has the ability to invest because they know that 9 even if you have the ability, you will never do it 10 because of -- because you don't have incentive to do 11 so. And hence the whole thing will unravel and even 12 in previous periods you don't want to invest at all 13 into reputation, or into your brand.</p> <p>14 And so this is like the classic moral hazard 15 problem, but a little bit more dynamic and dynamic 16 setup, and this will lead to no investment whatsoever 17 and everybody just shirking all the time. So that's 18 just a very extreme case that we are thinking about.</p> <p>19 Now, of course you can say, okay, if you 20 have long life firms and there's no final periods, 21 then the whole thing might be alleviated but still 22 intuitively there is something called the 23 discouragement fact which you still get in a dynamic 24 setup that once you have very high reputation, you 25 don't -- you want to milk your reputation and you want</p>

109	<p>1 to milk your brand value, and if you have a very low 2 reputation or your brand value is very low, you want 3 to just give up and stop.</p> <p>4 And the question is when can -- when might 5 there be some potential value of collective reputation 6 or a country of origin labeling in order to alleviate 7 this problem? Because it will bundle together signals 8 or you cannot distinguish as well between different 9 producers and this might actually give people some -- 10 firms some commitment value to keep investing.</p> <p>11 So the main point of the paper or the main 12 idea of the paper is that country of origin labeling 13 might help against a moral hazard problem. And then another 14 nice feature is that we 15 can really say in which kinds of industries it would 16 help.</p> <p>17 So one type of industry is if we have 18 exclusive technologies, which means it's very hard to 19 actually produce a good quality product, so it's 20 really about innovation. So if you 21 are an incompetent firm you cannot produce amazing 22 cars. But if you're a good type, then you can -- you 23 have the ability to produce a good car if you invest. 24 So that will be the case where an incompetent sub Pi L 25 is equal to zero. But in these industries, collective</p>	111	<p>1 classic lemons problem. I know that there are some 2 good firms, some competent firms, some incompetent 3 firms. I don't know -- there's a certain fraction. 4 And so the willingness to pay = for a product 5 might be lower than the cost of investment, even 6 though the benefit of the investment is higher. 7 Because part of the surplus just goes to the bad firms 8 because I cannot distinguish as a market between good 9 cars and bad cars, good firms and bad firms.</p> <p>10 And so this will create basically the gap 11 between the socially optimal 12 decision of -- or the socially optimal investment 13 decisions and the investment decisions that maybe 14 firms might actually make if they choose to brand 15 together or not.</p> <p>16 Okay. So how long do I have? Until 15 17 past? Ten more minutes. Okay.</p> <p>18 All right. So I will now go a little bit 19 through the model because I would like to give you a 20 flavor of what is going on here, and then I will talk 21 a little bit more about the intuition.</p> <p>22 So, again, we have an infinite rise model, 23 we have a long-lived firm, the incentive is really 24 that the competent firm can increase the probability 25 of producing a good product at a cost C. And here</p>
110	<p>1 reputation can really be useful only if you are at a 2 very high baseline reputation. So you can think of it 3 as very developed countries where you might want to -- 4 yeah, where the commitment value is high.</p> <p>5 On the other hand, if we have more quality 6 control issues where everybody can produce good 7 quality products, but if you shirk, you make mistakes 8 and this will lead to the product not functioning very 9 well. In that case, the commitment value of 10 collective reputation or collective brand or country 11 of origin is high in countries where the baseline 12 reputation is relatively high. So if you think of 13 maybe some developing countries where you might 14 actually -- yeah, where also maybe a regulator might 15 want to enforce a country of origin label.</p> <p>16 And then there's another thing because now 17 so far I've only talked about the social benefit of 18 collective reputation or country-of-origin labeling. 19 But there's also -- of course, now does a firm 20 actually want to advertise it by themselves? Because 21 if they wanted to advertise it by themselves, then 22 there's no point in regulating it at all.</p> <p>23 And so here we have on top of the moral 24 hazard problem, we now have an adverse selection 25 problem in the sense that if I think -- so that's the</p>	112	<p>1 what's the main -- so in every period a new buyer 2 arrives, it produces -- it sees a good quality product 3 with the probability that is determined by the 4 investment in the past period, and the firm just makes 5 a take-it-or-leave-it offer to the customer, 6 which means it extracts basically the entire 7 surplus from the customer. So the customer just pays 8 whatever he believes the product is worth. And this 9 is what creates these reputational incentives and 10 creates this reputational concerns and the whole 11 dynamic problem.</p> <p>12 So it's a very rich dynamic programming 13 problem. We have the -- yeah, we have discounting and 14 the value of the firm is the price minus the cost. So 15 it's a very standard problem. And the long-term 16 tradeoff that you can see here already is that your 17 have to invest today, but the benefit from your 18 investment is only captured later in the future. So 19 the benefit of reputation is a very long benefit, and 20 people can only collect it later, and that's why we 21 get this tension between the socially optimal 22 investment level and the investment level that can 23 actually be achieved in equilibrium.</p> <p>24 And the question -- and now formally 25 mathematically what we do is really to think about</p>

<p style="text-align: right;">113</p> <p>1 when does this reputational equilibrium exist. And 2 there are some difficulties in the sense 3 that we need to make some modeling assumptions in 4 order to reach that. And maybe I'm actually going to 5 -- I'm going to skip part of this and go to the 6 intuition here. 7 So one just followup thing, and I think this 8 also makes into an intuitive sense, is that a 9 reputation equilibrium can only exist if the cost of 10 investment is relatively low. So if the cost of 11 investment is a little bit too -- is a bit too high 12 -- it will be socially optimal to 13 invest, then a reputation equilibrium might not exist 14 despite it being optimal to invest from a social 15 perspective. 16 And, again, I want to now talk about these 17 two extreme cases. So when is it -- sorry. And the 18 comparison between collective reputation and 19 individual reputation stems from the fact that this 20 cost level at which you can guarantee the existence of 21 these good equilibria might be different, and in the 22 collective case it might be higher than in the 23 individual case. Okay? 24 So now we have these two very different 25 setups. So the reason why I said, okay, sometimes in</p>	<p style="text-align: right;">115</p> <p>1 was from that country. 2 And similarly you can make the argument if 3 you have very low ad reputation and quality control, 4 you learn a lot if somebody fails. Because everybody 5 can produce a good product, but if somebody fails then 6 you know for sure that somebody did not invest 7 or is just incompetent. And, again, there you get 8 super discouraged once you observe a bad outcome, and 9 hence, again, your incentives to invest are 10 deteriorated. 11 So that's why -- that's the connection or 12 the intuitive connection between the two. And now if 13 we have a collective brand or country of origin, then 14 you cannot -- the signals are not as strong so you 15 cannot detect it. So you're less likely to reach 16 those extreme beliefs and have incentives to milk 17 reputation or to just give up. 18 So this is just a summary of the results 19 that we have. So depending on the baseline 20 reputation, which would be kind of the reputation of 21 the country of origin, and the different industry 22 types, we give different predictions. So, for 23 example, you should -- Swiss watches have a very 24 strong incentive to brand together while -- or to 25 emphasize the country of origin because Switzerland</p>
<p style="text-align: right;">114</p> <p>1 developed countries or countries 2 that have very high reputation to start with, why can't 3 exclusive technologies, collective reputation help if 4 the following: So -- because individual reputation, 5 individual brands feel very strongly. 6 So if you have high prior, so we think firms 7 are very good with very high probability because it's 8 a country that has a very good reputation, baseline 9 reputation, then after seeing a good signal or seeing, 10 oh, Volkswagen produced a really good car, you believe 11 that this firm is actually a good firm, it becomes 12 extremely high because you know it's super hard to 13 produce a good quality car, and an incompetent firm 14 would never be able to do so. 15 And this basically -- so the reputation, the 16 brand value, becomes extremely high and the firm's 17 incentive to invest deteriorates because you just want 18 to rest on your laurels. 19 On the other hand, if we had a collective 20 reputation or a collective brand, then this whole 21 effect would be alleviated by a lot because now even 22 if you produce something good, you're not sure whether 23 it was produced by Volkswagen or by Mercedes, so maybe 24 it's actually not Volkswagen that has this amazing 25 technology. But you don't remember which company it</p>	<p style="text-align: right;">116</p> <p>1 has a maybe very high baseline reputation, whereas 2 maybe some manufacturers of parts in Switzerland might 3 not want to emphasize the country of origin so much. 4 Okay. And what are the incentives of firms 5 now to invest? So that comes back to the lemons 6 problem that I was talking about before, the adverse 7 selection problem. So now formally speaking, an 8 adverse selection problem is really that your 9 willingness to pay might be very low because of the 10 probability that a firm is a good type, it's very 11 low, you just want to -- your expected value is so 12 low that you don't want to pay for it. So you don't 13 want to -- it doesn't make up for the cost for the 14 firm. 15 So basically this commitment value of 16 country of origin is not internalized by the firm's 17 themselves. And so that's basically the case where 18 there might be some value of regulation and where 19 maybe the Government or the legislator might want to 20 force firms to label the country of origin. Of 21 course, there are many other reasons why you want to 22 label and I skipped a little bit through that slide. 23 So I think most of the regulation is in the 24 food industry or where you might protect the customer 25 for different reasons. But even there it is about</p>

117	<p>1 quality control, and I think it's important to think 2 about the incentives of the firms to actually keep on 3 investing and not being discouraged for these 4 reputational reasons.</p> <p>5 Okay. So the takeaway for today is really 6 that, first of all, collective brands and individual 7 brands work very differently. It's not 8 straightforward to think about how to model these two, 9 and we tried to use the very classic setup by Mailath 10 and Samuelson in order to do. We can distinguish 11 between two types of industries that have more 12 exclusive technology versus that -- where quality 13 control is more of an issue and can address in which 14 types of countries you might want to regulate one or 15 the other. And we can also 16 maybe explain a little bit why we observe so much, 17 emphasis of country of origin for some products versus 18 for others.</p> <p>19 Well, and then there's also an adverse 20 selection problem on top of that. So if the baseline 21 reputation is very low, this adverse selection problem 22 becomes particular high. So in particular for maybe 23 more developing countries, regulation might be useful.</p> <p>24 But, of course then also regulation can be 25 harmful if it is not socially optimal actually to</p>	119	<p>1 to some extent where collective reputations occur in 2 franchises. I don't know if the model applies 3 directly towards issues of franchises, but there is a 4 collective reputation issue going there.</p> <p>5 And then Aniko has a nice example in the 6 paper where she talks about two drivers who belong to 7 the same platform. I was thinking in this sharing 8 economy if we have individual entrepreneurs or 9 individual businesses under a platform, the extent to 10 which they have a collective reputation and maybe milk 11 off of the overall brand.</p> <p>12 What makes this so interesting is we 13 typically think of country of origin or region of 14 origins with a collective reputation as being high 15 quality. All right? And so this immediately 16 suggests, well, then there's an incentive to free-ride 17 on this collective reputation. Right? This is the 18 lemons issue that she's been talking about.</p> <p>19 And so this creates this tension in the 20 whole paper is that there's a high quality and there's 21 an incentive to shirk on quality. And so how do we 22 resolve this tension? When is there going to be 23 investment by these firms?</p> <p>24 And so the question really is about how does 25 collective reputation form and when does it lead to</p>
118	<p>1 invest. So you have to be careful there as well. But 2 this gives you a framework to think about it a little 3 bit.</p> <p>4 All right. I think I'm -- oh, I have still 5 one minute, but I think I will stop here. But if you 6 have questions now already, otherwise I would let 7 Anthony take over.</p> <p>8 (Applause.)</p> <p>9 DR. JIN: Thank you, Aniko. On a related 10 note, FTC does play an active role in the regulation 11 of "Made in the USA." So I will turn the floor to 12 Anthony Duke from the University of Southern 13 California for discussion.</p> <p>14 DR. DUKE: Okay. Thank you. It's my 15 pleasure to discuss this paper. I'm going to focus my 16 comments -- I'm going to tell you a little bit about 17 how I interpret the paper, what I got from the paper, 18 talk about its contribution and how I see it 19 contributing to the broader base of knowledge on 20 reputation. And then I'll offer some critical remarks 21 at the end, maybe some things to think about for 22 future research.</p> <p>23 So the paper focuses on a common phenomenon. 24 When we talk about country or region of origin or 25 agricultural appellation, I was thinking perhaps even</p>	120	<p>1 higher quality. So she's looking at the investment 2 decisions of these firms in a collective -- in a 3 collective group or in an individual group and how 4 they differ. So I see the research objective. The 5 model -- and I'm going to highlight the key features. 6 And when I say the key features, these are really what 7 define the model. And it's done in a very thoughtful 8 way. And so, in essence, I think these features 9 really are well chosen.</p> <p>10 There's dynamics, of course, because you 11 invest now to free ride later possibly. It's a five- 12 period model and the basic model is a five-period 13 model. And I think that's a nice way to look at it. 14 There's a sufficient history, two periods in the past, 15 two periods in the future; there's a short run and 16 then there's a long run. And five periods gives you 17 that, and I think that's a nice feature.</p> <p>18 There's random consumer match so there's no 19 competition. That's by design. We want to keep 20 competition issues out of here so we can really focus 21 on the belief formation and the reputation formation.</p> <p>22 And there's incompetent firms and competent 23 firms. And only competent firms can achieve high 24 levels -- high outcomes, good outcomes. And the fact 25 that there's income in firms here means that consumers</p>

121	<p>1 cannot perfectly anticipate quality. And that's what 2 you need to really study the reputation issue because 3 reputation lies in the consumer's mind. Right? 4 That's really what we're after. And so this is a nice 5 way to do that. And there's some other features. 6 There's no monitoring, for example. We might think of 7 monitoring as a way to deal with this. But we want to 8 figure out how reputations can form without those sort 9 of techniques, and I think that's a nice aspect. 10 What is the basic results of this model? 11 Well, first of all, let me describe how they get the 12 results. They look at -- they focus on one type of 13 equilibrium of reputational equilibrium, and they're 14 looking at conditions, minimal conditions in which you 15 can support equilibria in which everybody invests all 16 the time. Okay? 17 And then they compare individual versus 18 collectives and what are the minimal conditions in 19 terms of investment costs that sustain this 20 equilibrium. And then they can compare these two 21 conditions and say, okay, when is collective 22 reputation perhaps more likely or is there a larger 23 scope for that type of collective versus individual. 24 And the basic results are as given in this 25 table. So you can think of this in two dimensions,</p>	123	<p>1 there might be -- there's some probability that there 2 might be an incompetent firm among us and consumer 3 beliefs from this way -- they say, okay, well, you 4 know, I see good behavior in the past, well maybe I 5 see bad behavior or maybe I see a bad outcome, but I 6 have a -- but there's -- let me say it this way. 7 There -- if cheating is easy to detect, right, and I'm 8 a competent firm, if I shirk it's going to be easy to 9 detect. And then beliefs, consumer beliefs, will 10 react strongly to that because they might expect that 11 there is a competent firm in there cheating. Right? 12 And so this is like this -- this is supposed 13 to be the carrot and the stick. This is what keeps 14 the competent firm investing, because I know if I 15 don't they might think I'm incompetent. And that's 16 the shadow of the doubt that keeps me in good 17 behavior. 18 On the other corner is the benefit of the 19 doubt. So if this a low initial reputation, if being 20 good is easy to detect then consumer beliefs are very 21 sensitive to good behavior because they don't expect 22 much. There's a high likelihood that these firms are 23 incompetent. So the benefit of investing and getting 24 a good outcome is very high because I can change 25 consumer beliefs. And it's the benefit of the doubt</p>
122	<p>1 all right? The base reputation, high or low. So this 2 would be perhaps whether it's, you know, French wine 3 or something that would be a high base, and then she 4 compares these two cases between exclusive knowledge 5 and I think exclusive technology as well where it's 6 easy to detect failure. And then there's quality 7 control and it's easy to identify good behavior. And 8 I've put some -- just pulled off-the-cuff examples of 9 where these might apply. 10 But to get a sense of what this meeting -- 11 what this -- these results say may be more 12 holistically -- and I hope, Aniko, you don't cringe at 13 this, maybe this is too simplistic, but think of it 14 this way: So in these two dimensions we can talk 15 about initial reputation on the left, on the vertical 16 dimension, and on this horizontal dimension whether 17 cheating is easy to detect or being good is easy to 18 detect. Okay? 19 And so the collective reputation occurs in 20 these two corners, and they exploit either a shadow of 21 a doubt or what I like to call a shadow of a doubt 22 with a benefit of the doubt. And so let me elaborate 23 a little bit on that. 24 So the shadow of a doubt is if cheating is 25 easy to detect, the benefit to the collective is that</p>	124	<p>1 because the consumer knows that, well, there could be 2 incompetent firms there; oh, but he's shining out 3 there because he invested. Okay. And so that's how I 4 interpret your propositions one and two. 5 So they have some additional results in the 6 paper that she didn't get a chance to talk today in 7 the short presentation. She talks about arbitrarily 8 long memory. And this is where history of good 9 outcomes may be observable, or bad outcomes, and what 10 this tends to be good for collectives. 11 And what I like about this result -- and I 12 know this is a new version and you'd put that into the 13 appendix, but what I actually like about the result, 14 it might help to explain the strength of some of these 15 older CEOs, I mean, in Europe where they go to great 16 measures to talk about or to protect, you know, 17 regional names from being used in other contexts. 18 Like scotch can only come from Scotland and champagne 19 can only come from Champagne, France. 20 And then there's some results on brand 21 formation about when do you want to join a collective 22 brand. And the cool result about this is sometimes 23 you want to include a competent firm. And this is 24 also to keep the benefit of the doubt or to keep the 25 shadow of the doubt active and helping and encourage</p>

125	<p>1 firms to invest when they belong to a collective. 2 Some critical comments, what does this 3 contribute? Well, there's a good bit of literature on 4 collective branding, co-branding, umbrella branding, 5 guild branding is a name I just came up with. But, 6 you know, what these papers typically do is they focus 7 on a situation where reputation is already established 8 and then what do you do with that. 9 This paper and the point of departure I see 10 is where these reputations come from. I know there's 11 some work in micro-theory, but not from a collective 12 standpoint. And so this really gets into the 13 microfoundations of where beliefs come from for a 14 collective reputation. I think this is a nice 15 contribution. 16 And obviously it has relevance for marketing 17 should firms join and how to regulate, which Aniko 18 talked about today. 19 So the positives, it's a meaningful 20 research, it's carefully constructed and it provides 21 some novel insights. Going forward, I broke up my 22 going forward into T plus one and T plus two, just 23 like in the paper, with T plus one meaning maybe think 24 about for the -- as this paper develops and the T plus 25 two more forward looking.</p>	127	<p>1 importing grapes from Napa Valley to Texas to make 2 grapes, or you can send your recipe to Belgium and a 3 monastery there and they'll make the beer for you and 4 ship it back and then you can say it comes from 5 Belgium -- from a monastery in Belgium and sell it in 6 the U.S. 7 But I think I'm out of time so I'll stop 8 there. And I just want to say it's a nice paper with 9 lots of cool insights, and I look forward to seeing 10 the next version. 11 (Applause.) 12 DR. JIN: Thank you, Anthony. We can take a 13 few questions. 14 AUDIENCE: Could you tell us a little bit 15 more about how free-riding works in the model? Does 16 it affect either of these cases more than the other? 17 DR. OERY: Yes. So it definitely helps the 18 individual case. The individual brand benefits 19 because it's a problem of having too many firms 20 there, and so you kind of want to free ride on other 21 people's investments as well. So it kind of -- yeah, 22 it goes -- and I think we focus mostly on the case 23 where collective reputation can be useful because when 24 do we want to maybe enforce labeling of country of 25 origin. And that's why I included it, because even</p>
126	<p>1 The papers are a bit tedious to read, but 2 it's worth it because of these insights. I have some 3 thoughts on maybe how to get around that. Maybe it's 4 not possible, but we can discuss them later. 5 The brand formation, which I think is a good 6 direction to go and is a nice start, so when do firms 7 -- and the brand formation is when do firms join a 8 collective and when they don't. My concern a little 9 bit, or at least I think the one concern you'll need 10 to think about is whether the decision to join is 11 potentially informative for the reputation. Okay? 12 And does that decision -- you've probably already 13 thought about that, but when I was reading I was 14 thinking that might be something you might have to 15 deal with. 16 I think you're safer basically on the 17 regulations side, on the labeling versus not labeling, 18 and whether regulatory bodies want to grant that sort 19 of collective demarcation. 20 Going forward, two plus two if you will, I 21 think this brings up new questions about when you have 22 a collective, what are some of the incentives to 23 invest when outside firms try to sponge off of a 24 collective reputation. Like, I don't know if you 25 heard the story recently about this guy who's</p>	128	<p>1 then it has a great value. We wanted to make sure 2 that there we were robust to this. 3 AUDIENCE: So there's some -- I think some 4 of the reasoning that firms are interested in country 5 of origin and appellations of origin is for 6 competitive reasons as well as reputational reasons. 7 Have you -- obviously for trackability you assume no 8 competition here. Do you have any more thoughts, 9 though, on how that would affect your results? 10 DR. OERY: It would -- no, I don't know at 11 which direction it would go. We have thought about it 12 a little bit and it just becomes a mess once you -- 13 because then you have to make assumptions about, okay, 14 how does reputation really enter the firm's profits, 15 because then, yeah, you have also these competitive 16 concerns so the pricing becomes much more messy. 17 Right now we just assume the firm can extract 18 everything from the consumer. 19 So the consumer in our model doesn't get any 20 surplus, basically. And we really want to purely 21 focus on the incentives of the firms. But it would be 22 nice if we can find a nice way to model it, that would 23 be great. I don't want to make statements about how 24 it would affect it. But, again, because we have so 25 many differences, we have collective versus</p>

129	<p>1 individual, and then also difference between 2 industries. 3 DR. JIN: Any more questions? 4 (No response. 5 DR. JIN: Okay. Thank you. 6 DR. OERY: Thank you so much. 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>	131	<p>1 also going to talk a little bit about privacy and 2 welfare implications. 3 So we're going to consider a very simple 4 model. So competition, again, between two parties. 5 There is a persuader and there's a receiver, and the 6 persuader has the ability of sending a message to the 7 receiver. Very, very simple. 8 Moreover, the persuader also can collect 9 information about the receiver's preferences before 10 sending a message. There's going to be two extra 11 assumptions. So the receiver, at least to start with, 12 the receiver is going to be able to observe the 13 quality of the information collected by the sender. 14 And I'll qualify this a little later. 15 Moreover, the receiver is going to be 16 strategic. So the receiver understands that whenever 17 she gets a message -- I'll be using a male sender, 18 female receiver, just to make it simple. So whenever 19 she gets a message, she may think, well, that's great, 20 this is great for me. On the other hand, it may be 21 too good to be true. So we're going to allow that. 22 The receiver is going to be strategic. I haven't 23 introduced my receivers into this, but whatever 24 happens to strategic receivers it will probably work a 25 little worse for naive receivers.</p>
130	<p>1 TAILORED CHEAP TALK 2 DR. JIN: Our next paper will be presented 3 by Pedro Gardete from Stanford University about 4 Tailored Cheap Talk. 5 DR. GARDETE: All right. Thank you very 6 much for having me. It's a real pleasure to be here. 7 This is a co-authored paper with Yakov Bart, who is a 8 professor of marketing at Northeastern University. 9 And he's teaching marketing as we speak, so he 10 couldn't be here. He's very sad about that. But I'll 11 do the best I can without him. 12 So the title of the paper is Tailored Cheap 13 Talk, and the starting point for the paper is the fact 14 that lots of matching markets rely on communication to 15 make those matches occur. And a relatively new trend 16 that's happening is this process of tailoring. So the 17 fact that I can acquire information about consumers or 18 whoever it is that I'm trying to persuade for a given 19 behavior and use that information to customize my 20 communication to those consumers. 21 So this paper is going to investigate the 22 role of communication and matching. I'm going to talk 23 a little bit about the process of data collection and 24 whether I should want to disclose that I'm collecting 25 this data, for example, to consumers. And then we're</p>	132	<p>1 So we feel our model applies to a number of 2 matching markets, whenever you have one of the parties 3 trying to induce an action from the other side of the 4 market. So, for example, in the job market you can 5 think -- in the job market world you can think that a 6 job applicant wants to persuade the potential employer 7 to hire him or her. And so in that case the persuader 8 is actually the applicant to this market. 9 And this persuader also has the ability to 10 acquire information on this company. And, moreover, 11 there's a job post so that is also relevant 12 information. And so there's information acquisition 13 from the applicant's side. On the other hand, there's 14 information disclosure on the hiring side. 15 The bidding market, if you think there's a 16 persuader and the persuadee, then one of the parties 17 is trying to convince the other of very high match 18 values. And, of course, you know, if you were 19 thinking of online dating, of course we'll use the 20 profile of the other person as sort of information 21 they can use. 22 And the first person actually can devise 23 when they're designing their profile, they're also 24 understanding that this information can be used for 25 persuasion. School admissions is another case, that</p>

133	<p>1 is very similar to the case I just talked about.</p> <p>2 And then if you think about relations</p> <p>3 between companies and other companies or relations</p> <p>4 between companies and consumers, and in procurement</p> <p>5 contracts, sales, advertising, we have situations</p> <p>6 where a company is trying to basically persuade a</p> <p>7 potential client that it has the right product or the</p> <p>8 right service to satisfy their needs.</p> <p>9 Given our setting, I'm going to add a couple</p> <p>10 of comments about advertising in particular, although</p> <p>11 the model applies to other settings as well. One way</p> <p>12 to think of this model is maybe not what's happening</p> <p>13 right now today in advertising, but in a sense we're</p> <p>14 peeking a little bit into the future and looking at</p> <p>15 the consequences of some trends that are occurring</p> <p>16 right now.</p> <p>17 So if you think of what's happening in terms</p> <p>18 of information acquisition and how easy it is to get</p> <p>19 information about consumers, that's just becoming</p> <p>20 easier. I have here a number of points of realtime</p> <p>21 acquisition of consumer data, you can get this data</p> <p>22 across multiple channels, across multiple devices.</p> <p>23 It's never been easier to store and acquire this</p> <p>24 information than store it. And there is this whole</p> <p>25 emergence of a new industry. This industry has</p>	135	<p>1 That could be one form. Or you could think of the</p> <p>2 sender trying to use the infinite possibilities of</p> <p>3 language to imply certain things that, you know, are</p> <p>4 not strictly said but they're meant. Or you can also</p> <p>5 think if you talk to Upender and I and our purchasing</p> <p>6 -- car purchasing decisions, you can also just think</p> <p>7 of situations where with 99 percent probability the</p> <p>8 salesperson told you something that may not exactly</p> <p>9 have been true. And Upender was immune to that. I</p> <p>10 just fell for it. But that's -- that can happen.</p> <p>11 So you can think of this spectrum. And this</p> <p>12 -- it's good -- in this model, the receivers are still</p> <p>13 strategic. So no one is being fooled, but despite</p> <p>14 that there may be issues about communication and</p> <p>15 persuasion.</p> <p>16 So you can think of this paper as uniting</p> <p>17 this literature with the one on the top right corner</p> <p>18 on information acquisition and one-to-one advertising.</p> <p>19 So we're basically giving a particular mechanism of</p> <p>20 persuasion to this literature.</p> <p>21 I also want to contrast it with two other</p> <p>22 literatures that occur. One is on the bottom left</p> <p>23 corner, it says Persuasion through Disclosure. So in</p> <p>24 that case it's a little different because I can decide</p> <p>25 whether to disclose or not certain attributes, but if</p>
134	<p>1 existed for a while, but now has expanded tremendously</p> <p>2 with data brokers.</p> <p>3 So the first trend is it's easier and</p> <p>4 cheaper to collect better information about consumers.</p> <p>5 And the second trend is the ad delivery technology.</p> <p>6 So I never know exactly how many milliseconds</p> <p>7 advertisers have to bid for a particular impression.</p> <p>8 But in that set amount of time they can also decide</p> <p>9 the ad copy that they would like to deliver to a</p> <p>10 different consumer.</p> <p>11 And so this is also a highly automated</p> <p>12 process right now and we're in the -- I think right</p> <p>13 now in the situation where the technology is -- the</p> <p>14 trend is to connect these two. So more and more we're</p> <p>15 seeing the information acquisition about a particular</p> <p>16 consumer being used to -- in terms of -- in the form</p> <p>17 of a dynamic creative to be used to give this consumer</p> <p>18 a different message.</p> <p>19 All right. I also want to situate the</p> <p>20 paper a little bit in the literature. And so we will</p> <p>21 be on this top row in the literature. So we'll be</p> <p>22 looking at persuasion via cheap talk, which means that</p> <p>23 we're going to allow the sender to engage in</p> <p>24 misrepresentation. This could be lawful or unlawful.</p> <p>25 So you can think of persuasive puffery.</p>	136	<p>1 I disclose an attribute I have to be 100 percent</p> <p>2 correct about that disclosure. So we're not going to</p> <p>3 be looking at those cases. And those cases have</p> <p>4 received more attention in the past.</p> <p>5 Another case is the case of Deceptive</p> <p>6 Advertising. So it's this very old intuition that I</p> <p>7 may just use the costs of the message or how much my</p> <p>8 investment was in advertising to say that, well, I must</p> <p>9 have a great product otherwise I would not advertise</p> <p>10 as much. And we're actually right now working on</p> <p>11 that. So I'll have a little bit to say. We're</p> <p>12 actually incorporating the cost of advertising into this</p> <p>13 and we can replicate some of the results but have also</p> <p>14 some intermediate results as well.</p> <p>15 So I won't have enough time to go through</p> <p>16 the specifics of the model, but I wanted to give you</p> <p>17 an overview of what's going on. There's two parties</p> <p>18 in this model, there's a sender and the receiver. And</p> <p>19 they're going to be located at different locations</p> <p>20 possibly. The sender, I'm going to call the location</p> <p>21 of the sender Q, and the receiver is going to be</p> <p>22 theta. And they're going to be located along some</p> <p>23 preference circle. It's a very standard horizontal</p> <p>24 differentiation case.</p> <p>25 And these agents may match in the market.</p>

137	<p>1 So if they match they get some utility. So the sender 2 gets this utility vs, but then has this utility for 3 being matched with receivers that are very far away. 4 So we have to be penalized by this distance. And the 5 receiver is actually the same thing. So if there's a 6 match and they get some utility, but I would rather be 7 matched with someone who is closer to my preferences. 8 Not all cases produce matches. So I'm going 9 to normalize the payoffs for not matching to zero 10 because that could also happen. 11 This is just a graphical -- basically a 12 graphical restatement of what I just said. So in this 13 example -- so in this 14 example there is a sender and a receiver. So the 15 receiver could be over here at theta, which is equal 16 here at $\frac{\pi}{4}$. The sender could be at this Q 17 level. So that's $\frac{7\pi}{4}$. And so the distance 18 between the two is -- the linear distance is what I'm 19 -- or the angle between the two is what I'm calling 20 the distance function. 21 So in this case it would be a right angle, 22 it would be $\frac{\pi}{2}$, and then we're just 23 multiplying it by a scale of R just to have a 24 parameter that affects both utilities at the same 25 time. So this distance function operation utilization</p>	139	<p>1 And finally we're going to assume that the 2 cost of acquiring information is cheap as well. If 3 it's high, it's very intuitive, the outcome is 4 trivial. So we're going to look at best case. 5 All right. The setup is also simple. The 6 sender is going to send a message to try to induce a 7 match. That's M. And the message is tailored through 8 information acquisition. So the sender, before 9 sending the message, can engage in information 10 acquisition. And that's going to be this parameter 11 alpha here. That's going to be between 0 and 1. 12 And so the way this technology is going to 13 work is that I'm going to learn the receiver's 14 location with probability alpha. So you can think of 15 if the U.S. has 300 million people and the alpha is 16 half, then with a half probability I have you in my 17 data set, I can customize the message to you. With 18 half probability I don't. 19 The receiver is going to observe alpha and 20 the message, and based on these two pieces of 21 information I'm going to decide whether he should 22 match or not -- she should match or not. So this is 23 the timing of the model. First the agents observe 24 their own locations. Then the sender is going to 25 choose the information level alpha. Then based on</p>
138	<p>1 that is here is just getting us the smallest 2 difference between two locations. So that's very 3 straightforward. 4 I'm going to make a couple of extra 5 assumptions that we thought were appealing. The first 6 one -- actually, then we look at other cases. But we 7 start out by looking at cases where the sender has 8 transparent motives. So everyone knows that this 9 sender would like to match. So the goal of the 10 dealership, for example, when I -- by clicking a 11 banner ad or -- I know exactly what they want. They 12 want me to go to the dealership. 13 And so that's going to be the case where vs 14 is high, meaning even if I have to go to the other 15 side of the circle, that will be a distance π times 16 R, I still want the match. And then we'll look at the 17 other cases. 18 From the receiver side, we're going to 19 assume communication actually has bite. So it can be 20 decisive. So what I mean by that is that if there is 21 a banner ad, on average I'm not going to click it 22 unless it says something interesting, in which case 23 I'm interested in clicking it. So the utility extent 24 of the receiver is not very high, but he or she -- in 25 this case she can be persuaded otherwise.</p>	140	<p>1 that, sender is going to observe the receiver's 2 location with probability alpha and is going to send a 3 message M. The receiver observes alpha, observes M, 4 and decides on an action and payoffs are realized. So 5 it's a very, very simple model to set up. It's not so 6 easy to solve as it turns out, but that's our problem. 7 So we're going to focus on Perfect Bayesian 8 Equilibria, and the only thing I want to highlight 9 here is the left-hand side. To say that the receiver 10 is doing the following, the receiver is trying to 11 understand where the sender is, so that's Q, based on 12 three pieces of information. Her own location, the 13 message she receives and the information level of the 14 sender. So I love red cars. I see a banner for a red 15 car. And I think, wow, that's great, that's exactly 16 what I like. That's theta and the M is equal to 17 theta. That's awesome. 18 On the other hand I think, well, is this too 19 good to be true again because there's a high 20 likelihood that they have data on me. So maybe 21 actually I should think a little bit more about this. 22 So the only thing we're doing here is making sure that 23 the beliefs are consistent to whatever the sender is 24 doing in equilibrium. That's it. So fairly standard. 25 I'll do a little bit of one focal</p>

141	<p>1 equilibrium. It turns out there's more and they're 2 more sophisticated than this. But this is probably 3 what people are doing in real life. We can tell the 4 incentives for the message. So what is the message 5 policy of the sender, right? What happens in 6 equilibrium. And it's going to be the following: If 7 I'm uninformed, I don't know anything about this 8 receiver, I should just tell the truth. 9 So if I'm selling red cars and I'm going to 10 show a banner ad, I have no information about this 11 person, I might as well say I have a red car because 12 if all goes well then this person will visit this and, 13 guess what, I have lots of red cars and they'll find 14 something that they like. So I might as well tell the 15 truth. 16 If I'm informed, on the other hand, I'll 17 pick some message in some set -- and I'm calling this 18 critical set, so we'll see a theta. So I'm in 19 different among messages as long as they convert to 20 consumers. So maybe I know this consumer loves red 21 cars and maybe I'll say that. Of course, cars are 22 much more complicated than color. So, you know, I can 23 instead -- could also present an orange car or a car 24 that has a trim that is similar to the one that this 25 consumer is looking for if I know that also does the</p>	143	<p>1 maximum that I can learn about the receiver before 2 credibility breaking down. 3 Okay. So that's the first result of the 4 paper, is just exploring and uncovering this tradeoff 5 between credibility and information acquisition. 6 In this paper, we can actually change that, 7 but what's going to happen here -- and the idea that's 8 happening here with this particular equilibrium is 9 that I'm learning just as much as I can to still make 10 it worthwhile, this click on this banner. Right? If 11 I learn a little too much then no one will believe my 12 plan. 13 This is the -- this is how this message is 14 implemented. So now we have the preference circle 15 here again. And here I have a receiver at Pi over 16 two, so just on this dot over here. And maybe the 17 sender is over here. So it's maybe Pi over four, 18 it's, you know, nearby. 19 And so what's happening is the following: 20 If the sender is uninformed, there is a matchpoint 21 here. He's just revealing his location. That's fine. 22 And maybe I think, oh, that's great, that's 23 worthwhile. So an orange car is not exactly what I 24 wanted, but it's worth investigating. 25 On the other hand, if the sender is</p>
142	<p>1 trick. So I may be also okay with that message. 2 And so we get into this general -- very 3 general optimal communication policy, which is with 4 one minus all the probability, I'm uninformed and so 5 I'm just going to have a mass point here at two. I'm 6 just going to reveal my type. Without the 7 probability, I could have any density function here. 8 So I could have any function on the message that 9 depends on my location, the location of the receiver, 10 and my information level. 11 All right. So this is the first result for 12 the paper, this central result. It's this letter that 13 we're labeling as willful ignorance and says the 14 following: The level of information acquisition 15 associated with the sender's first best payoff is 16 given by this expression, this alpha bar. Don't worry 17 about right now the expression there. The important 18 part is that this number is always between 0 and 1. 19 So what's happening here is that the sender 20 is facing a credibility tradeoff. On one hand, I 21 would love better information because I can use that 22 to persuade the receiver. On the other hand, if I 23 learn too much the receiver starts understanding that 24 the message has most likely been tailored to appear 25 persuasive, and so there's going to be a cap -- a</p>	144	<p>1 informed, what he's going to do is he's going to mix 2 around this blue line because that's the density for 3 the informed sender. So what's happening there is the 4 following: First of all, with the highest likelihood, 5 this sender is going to say I have the red car that 6 you're looking for. That's the most likely case. 7 But then that becomes too obvious for the 8 receiver. So the sender has to become a little more 9 sophisticated, and sometimes choose things that are 10 similar to what I like, but not exactly what I like, 11 otherwise too conspicuous. And so the sender now has 12 an incentive to mix messages a little bit. 13 The center could also be here at Q prime. 14 So that's very far. That's a terrible deal for me. 15 It's a white car. I hate -- I'm sorry, just colors. 16 So a car that I don't like in which case I'm not 17 interested in that particular model. All right? 18 So what's happening here is if you get 19 attractive news, that could be good or bad. But if 20 you get sort of unattractive news, you're sure that 21 that's bad for sure. Okay? Because bad news is bad 22 news, good news, who knows? 23 All right. I'm going to skip this and skip 24 to the welfare analysis a little bit. So here what 25 they've done also is sort of flipped the problem, and</p>

145	<p>1 instead of thinking of information acquisition from 2 the seller's perspective, we also resolved the model 3 with the receiver choosing the level of information. 4 So the receiver is now choosing the amount of privacy. 5 So that's another way to think of alpha is, 6 well, if I don't do anything, the sender will have all 7 the information that they want. But I may be -- I may 8 want to shade my type to anonymous browsing or 9 whatever through Ad Block in some cases. And so in 10 which case I can decide how much information I'd like 11 to share. Maybe there could be a market for this as 12 well. 13 So what we have here on the X axis is the 14 valuation of the sender. So that's here. And 15 everything I told you up to now is this case of 16 transparent motives, right? So what I'm doing here is 17 I'm actually extending this range and I'm looking at 18 cases where -- some other cases where the valuation of 19 the sender is not so high. So sometimes the sender 20 doesn't want necessarily to match with the average 21 consumer. 22 And on the Y axis, I have the information 23 level as before. In orange, I have the first best 24 information level for the receiver, and in blue I have 25 the first best information level for the sender.</p>	147	<p>1 And so after this threshold, of course you could 2 make it more continuous, but the intuition is the same 3 as -- once communication is ensured, then extra 4 knowledge about my preferences is only used for 5 persuasion. And that becomes bad for me. 6 On the other hand, the blue line, basically 7 what it's saying is the sender is going to engage in 8 as much information acquisition as he is allowed to 9 basically by the receiver. All right? 10 You can actually just add the welfare 11 measures if you think that's a good way to maximize 12 joint welfare. I'm not sure that would be the case. 13 As it turns out, the sender's optimal level of 14 recognition is the same as the one that maximizes 15 joint welfare. There is a given range in the middle 16 that's sort of grayed out or blued, and there is just 17 a pure transfer so there's no effects of utility. Any 18 level is equally good on the joint sense. 19 All right. So we have a few other results, 20 but this is the main thing that I like to highlight. 21 First of all, identifying this tradeoff which is as 22 information acquisition increases, communication loses 23 credibility. And in the limit, suppose that these 24 firms would like to know everything about my 25 preferences. What would happen is I would have a</p>
146	<p>1 And so I won't go through all the 2 information that is happening here, but one of the 3 things that stands out is we get a bang-bang solution 4 for the receiver, meaning I either want to disclose 5 all information or I don't want to disclose any 6 information at all. And the intuition here is the 7 following: If I have very niche tastes, so the S is 8 very low, on average it's not good for a sender to 9 communicate with all possible receivers or with the 10 average receiver. 11 Then I would like to share my information 12 because I need to foster or promote communication. 13 Right? I need to be found, right? I need this 14 really, you know, specific comic book is very hard to 15 find, I would love for people to be able to know that 16 I have that very particular taste. 17 Same thing in the dating market. You can 18 have a very particular thing that you like and you 19 like your partner to also like. You're better off 20 disclosing that thing despite the fact that now maybe 21 people will start using that and say, oh, I also love, 22 you know, this pretty good comic book or something 23 like that. 24 The problem is after a certain threshold 25 information is -- the communication is guaranteed.</p>	148	<p>1 lovely time going online and just seeing everyone 2 telling me things that I would love, right? But the 3 problem is that I cannot believe any of it. So it 4 gets this paradoxical effect. 5 So firms have it in their best interest, if 6 we're thinking of the information part of the 7 communication, to disclose whatever it is that they 8 have about consumers and what's informing a particular 9 message. 10 Moreover, firms are better off if you think 11 that information collection is going to be as good as 12 it can be, then they'll be better off engaging in 13 partial willful ignorance about consumer preference. 14 And the last point that has some regulatory 15 bite is this idea that for consumers it's not 16 indifferent whether they can reveal or protect their 17 data because whatever they reveal can be used to 18 induce matches but can also be used for persuasion, 19 even if they're strategic. 20 So I'll explain a little bit about what 21 we're doing right now and then I'll conclude. So one 22 of the things we're including is the existence of 23 communication costs. Of course, talking to consumers 24 in that particular case is not free. And so we can 25 replicate the effect that as costs goes up a lot, we</p>

149	<p>1 get exactly this thing that just the fact that you're 2 advertising to this scale is enough. You don't have 3 to tell me anything else. That's a credible signal. 4 But we also found an interesting 5 intermediate region that is sort of counterintuitive. 6 And what happens there is that if you're interested in 7 communicating and paying that communication cost, 8 you're more likely to be informed about my 9 preferences. So you're also more likely to then try 10 to persuade me through the content to buy, or more 11 technically you cannot pull with attractive uninformed 12 types anymore. So your ability to credibly convey 13 that you're attractive decreases. So there's an 14 intermediate region that's actually quite interesting 15 that we're exploring right now. 16 About the observability assumption that I 17 talked about in the beginning, I'd like to mention it 18 a little bit more. So the first thing is this is a 19 very, very standard result. If the information level 20 is completely unobservable, so the receiver has no 21 idea what type of information the sender has, then 22 there's no credibility. The market breaks down or the 23 informative part of communication breaks down. I 24 could be naive. 25 So in this case, actually the sender has an</p>	151	<p>1 settings. 2 You'll have a -- and you'll have to 3 incorporate a holdup problem, but the good side is 4 that consumers will actually get some utility in these 5 markets. So it could be worth exploring. 6 So just a punchline that I want you to 7 hopefully sort of provoke a little thought is that 8 there is a tradeoff between information acquisition 9 and credibility. Senders prefer more information 10 because of persuasion ability, but they understand 11 that more attractive claims now, the receivers will 12 understand that they're more likely to be tailored. 13 And the receiver either prefers complete privacy or 14 complete information. Thank you very much. 15 (Applause.) 16 DR. JIN: Thank you, Pedro. Our discussion 17 will be Upender Subramanian from UT Austin. 18 DR. SUBRAMANIAN: Okay. Hello, everyone. 19 My name is Upender. I'm from UT Dallas. So thanks to 20 Ginger, thanks to Avi and thanks to everyone else who 21 has organized this conference. Really excited to be 22 discussing this paper. 23 In the interest of time, let me just quickly 24 get to the idea in a nutshell, what this paper is 25 about. So you can think of many different situations.</p>
150	<p>1 incentive to transmit alpha as best as he or she can 2 in a credible way. The nice thing about this paper is 3 that there's theoretical results that immediately 4 apply to our setting that say that in the Schelling 5 sense if -- with a certain probability, I don't 6 observe alpha, but with a given other probability I do 7 observe it. 8 Or in the next stream of literature if we 9 pick up the van Damme and Hurkens paper, that also 10 says something very similar. If I have a very -- if I 11 have a noisy signal of alpha, so I sort of know what 12 companies are doing but I'm not exactly sure, the 13 results there are that as these signals become better, 14 those results will be exactly our results. So if 15 consumers have a relatively good idea of what's 16 happening in terms of information acquisition, what it 17 means, which is a big question, then our results will 18 hold. We don't need to calculate those cases. 19 And one thing I won't talk about except 20 mention it now is that it's actually easy to 21 incorporate vertical competition into the same 22 setting. It doesn't mean that we're doing it just 23 because it's easy, but just claiming that it will be 24 easy. And you can incorporate -- yeah. I've done 25 that and Bagwell and Ramey have done that in different</p>	152	<p>1 I'm going to talk about one particular situation. 2 There's a seller, like I'm going to say it's me, and 3 then there's a buyer, that's you. So I'm trying to 4 convince you to buy something. So I'm trying to 5 convince you to buy something, I'm going to make some 6 claims. And these are unverifiable claims. So that's 7 kind of what sets up the cheap talk in this situation. 8 An interesting twist in this paper is before 9 I make the claim to you, I can actually try to get 10 some information about you. All right? And so that's 11 essentially what they are studying. So what that 12 means is I can find out what is it that you really 13 like before I tell you what is it that I'm able to 14 provide. And so that's essentially the setting that 15 we have here. 16 And you might assume that in this kind of 17 setting sort of the first-order effects should be as a 18 seller, I can try to get as much information as I can 19 about the buyer. So that would be sort of the 20 straightforward effect. 21 The punchline of the paper or what's the 22 interesting effect on the paper is that that's not 23 always true. And why is that not always true? The 24 reason is that the more I know about you, the more I 25 know about you, the less you are going to believe what</p>

153	<p>1 I say. All right? And the important thing here is of 2 course you must know that I know about you, right. 3 And that's kind of the observability assumption that 4 Pedro was talking about. 5 And the underlying intuition is this: the 6 more I know about you, the more I'm going to pander. 7 So instead of actually telling you objective 8 information about myself, I'm going to tell you what I 9 think you want to hear. Okay? 10 Now, as the buyer, if you realize that this 11 is what is happening, that as I get more information 12 about you I'm just going to be pandering, maybe you 13 think of the current election cycle as people try and 14 figure out what voters want to hear, then what I say 15 is actually going to be less informative. And if what 16 I say is less informative, it's going to be less 17 influential or less credible. And that, in a 18 nutshell, is the main focus. That's a cultivating 19 force and that's what you need a model to analyze. 20 The straightforward effect is you get more 21 information, you can make more claims, but the more 22 strategic effect is the fact that as I get more 23 information the credibility goes down because the 24 receiver or the buyer understands the motivation. 25 And then so the main result is that I don't</p>	155	<p>1 Now, that does not work at the airport 2 security, right? So if I go to the airport security 3 guy and say that I'm Kanishka, he's going to say, very 4 nice to meet you, Kanishka, now show me your driver's 5 license. Right? And so it's important that it's not 6 verifiable, the message should not be verifiable. And 7 finally it should not be binding, which means that in 8 this case if I say I'm Kanishka, Ginger might later 9 come and say why don't you do the next presentation? 10 And I don't want to do the next presentation. So 11 there's some commitment that I don't want to get 12 involved in. Right? 13 And so cheap talk means three things, that 14 all messages are equally cheap or equally costly, that 15 it's not verifiable and it's not binding. And we want 16 to make sure that finally when you go to the 17 application, all these three things are met. And 18 there are different literatures speaking to different 19 situations depending on which of these assumptions I 20 make. 21 So Pedro talked about some of these. If you 22 can verify it, then it becomes a disclosure 23 literature. If the message is not equally costly, 24 it's a signaling literature. And if it's binding, 25 then it becomes a mechanism design on contract</p>
154	<p>1 want to appear or I don't want to know too much about 2 you. If I get too much information about you, I'm 3 actually going to lose my power over you. And 4 therefore I don't want to get too much information. 5 And, in particular it's important that I maintain 6 appearances. So I have to maintain the appearance 7 that I don't know enough about you. And in the model, 8 of course the assumption is that it's transparent. 9 Whatever information I collect about you is known to 10 you and therefore appearances are maintained. 11 So quickly what I like about the paper, it's 12 a novel addition to the cheap talk literature. 13 There's actually a lot of closely connected 14 literature. This one specifically speaks to the cheap 15 talk literature. For those of you who are a little 16 bit rusty, you've kind of heard this jargon before. 17 Cheap talk means three things, right? So you must be 18 able to easily misrepresent yourself, right? 19 So, for example, those of you who have not 20 met Kanishka, I would just come up here and say I'm 21 Kanishka. And it's equally costly for me to say I'm 22 Kanishka -- it's equally easy for me to say I'm 23 Upender as it is for me to say Kanishka. Right? And 24 so that's what it means when I say that the message is 25 cheap.</p>	156	<p>1 literature. And so you have these kind of very 2 closely related literatures. 3 What is very novel about this paper is that 4 it focused on something that's not being cited in the 5 cheap talk literature, which is that the seller, for 6 example, or the sender, persuader, can collect some 7 information about the receiver before they engage in 8 cheap talk. And that was really cool. 9 They have a really nice model. There's 10 another test and a cheap talk model that is something 11 that the authors had to come up with to deliver the 12 insight. And so now they've got a mathematical 13 formulation and I really like that. And finally, of 14 course, it has a nice insight for sort of this big 15 data-big brother era. Right? 16 And this is literature, trying to understand 17 is it always the case that given how costs of 18 collecting and storing information are going down, are 19 we going to find a lot of information being collected 20 and used? And there's kind of -- Pedro's paper as 21 well as other papers just kind of speak to the fact 22 there are countervailing strategic effects as to why 23 firms might self-regulate. And so I think that's 24 interesting from that point of view. 25 Having said that, I had some suggestions,</p>

157	<p>1 mainly trying to kind of push this paper into the 2 practical domain and trying to see how it might be 3 relevant or where it might be relevant, and maybe some 4 ideas that would strengthen the paper. Sometimes in 5 discussion, sometimes in the actual model. 6 So the first thing is as you might remember, 7 position on a circle, so technically it means that we 8 are looking at what are known as horizontal 9 preferences, meaning some of us might like red cars, 10 some of us might like white cars, and so we are not 11 all the same. Right? So that's what horizontal 12 means. 13 I guess I thought initially when I was 14 reading the paper the motivating examples were 15 actually about best restaurant in town, and typically 16 many product claims are of this nature, that I'm the 17 best in town, I'm the best game in this particular, 18 you know, something. And so that's what you would 19 call as vertical. So it will be interesting to at 20 least have some discussion or maybe an extension which 21 talks about what happens when you have product claims 22 of a vertical nature, does that still hold, when they 23 might hold. 24 More specifically, the key assumption in the 25 paper when it comes to horizontal is to say that if I</p>	159	<p>1 authors discuss in the paper, so one example is, for 2 example, Google collects information about you. Maybe 3 they're going to tell you that we collect such and 4 such information. 5 Now, in practice, of course -- and I think 6 this might have been discussed in yesterday's forum as 7 well -- just disclosing what information is collected 8 may not really communicate to people what firms are 9 able to do with that information. And within the 10 model, you need to know exactly what the firm is able 11 to do, the position with which they are able to do, 12 but at least in practice may not necessarily happen. 13 And I think that's an important theoretical 14 question. I mean, it's a difficult theoretical 15 question to address, but I think as we're taking this 16 cheap talk literature into some of these domains, I 17 think it becomes interesting to understand how might 18 firms actually use current mechanisms to change 19 beliefs. 20 From a regulator point of view, it also 21 throws up this question like we were talking about 22 yesterday, maybe firms actually want to, for example, 23 work with the FTC or other people to make disclosures 24 about how precisely they can use this information 25 public. Right? This is actually in the interest of</p>
158	<p>1 make a claim that I'm good at making red cars or I 2 have a red car, it automatically means that I suck at 3 providing any other color of car. Okay? And that's 4 kind of the underlying forces for some of the results. 5 At least that's what I think is the underlying force. 6 It's for the authors to clarify whether the results 7 will also survive, for example, if claims are neutral. 8 Right? 9 So you can imagine that there are some 10 product spaces where making one claim doesn't 11 automatically rule you out from serving other customer 12 segments. Right? So you might say, for example, soy 13 milk will appeal to people for different reasons. 14 Some people look for health, some people look for 15 taste. Just because you make a claim that soy milk is 16 healthy doesn't automatically rule you out in terms of 17 taste. And so it will be interesting to know if the 18 same results would also extend to the case where 19 claims are neutral. 20 Coming to the observability assumption, 21 right? So basically for local (indiscernible) how do 22 you know, right, if I'm the seller and you're the 23 buyer, how do you know what I know about you? Right? 24 How is it exactly that you get to know that? 25 A couple of different things that the</p>	160	<p>1 the firm. So one of the key implications of the 2 current analysis is to say if firms have a vested 3 interested to make it very precisely clear how they 4 can use this information. Right? They don't want to 5 hide that. By making that public, it actually acts as 6 a commitment device and then that can actually help 7 firms. 8 And from a regulation perspective, we can 9 actually contrast this with a different type of 10 regulation. You can either say you have to truthfully 11 disclose what position you have, or you have to be 12 truthful in the claims you make. And these are very 13 two different types of regulation. The authors don't 14 currently look at that, but I think they can have some 15 nice implications by saying actually one kind of 16 regulation might work well, or from more of a market 17 welfare point of view whereas the other might not. So 18 that I thought was interesting. 19 The other question is also how is this 20 information being collected. Right? So if I'm a 21 sales guy, if I'm trying to sell you a car and then I 22 come and ask you what do you like, usually if you're 23 not as naive as Pedro, you would kind of sit back and 24 say, well, whatever I'm going to say is going to be 25 used against me. Then you can become more strategic.</p>

161	<p>1 So in sort of the online setting, this goes to kind of 2 ad blocking or covering your tracks. You know that 3 people are tracking you. How does that affect your 4 privacy concern? 5 And here I think an interesting result would 6 be that allowing for people to use ad blockers might 7 kind of be a blessing in disguise because that also 8 regulates how much information is available to the 9 firm. Firms may not be able to commit to how much 10 they can collect, but we are allowing people to cover 11 their tracks. Maybe it sets up a healthy equilibrium. 12 Right? So that's kind of another interesting 13 direction to look at. 14 Finally, I think it's important to 15 understand whether talk is really cheap or what exact 16 context does this apply to. As I said, as you utilize 17 each of the assumptions in the cheap talk model, you 18 can get into different domains. 19 For example, whenever there is asymmetric 20 information, meaning that I, as a seller, know more 21 than the buyer, then there are many standard remedies. 22 Right? So if you want to be careful about do these 23 remedies apply here, if they apply does cheap talk 24 really have bite. 25 So, for example, a seller can back up claims</p>	163	<p>1 and there's no -- 2 DR. JIN: Actually, I have a question -- 3 DR. GARDETE: Oh, okay. Please. 4 DR. JIN: -- if you don't mind. I would 5 just use this microphone. So your model, my 6 understanding is there's no price. So my question is 7 what if you introduced a price, and if the seller 8 knows my willingness to pay, the price would be used 9 against me, for example, and how that sort of changed 10 your model. 11 DR. GARDETE: I think that's a great 12 question. We wanted to keep the model relatively 13 generic because in some -- you know, buying a car, 14 there's a negotiation. If there is a posted price, 15 there's another posted price. But, of course, if I'm 16 buying a car, again, I'm naive, so I can be 17 discriminated against in a good way for the seller and 18 I may be convinced to pay more. 19 So there are situations where different -- 20 you know, a seller, if he has different information 21 about different consumers, he may be able to apply 22 differential prices. So that's a good question. 23 So the idea -- the intuition isn't 24 following: So we have a model that we can introduce 25 that, but the intuition isn't following. On top of</p>
162	<p>1 with a satisfaction guarantee or the fact that I have 2 custom information about you, I'm not only going to 3 tailor the ad I show you but I could also give you a 4 more specific offer. I could tailor the price. And 5 sometimes that can act as a signal of what information 6 I have. 7 And so we want to kind of understand in what 8 situations might cheap talk be sort of a fire starter 9 problem. Again, we spoke a little about -- me and 10 Pedro spoke a little bit about it yesterday. And so I 11 think in markets where you can argue that there are 12 significant holdup costs or surge costs, then meaning 13 once you click, once you visit a dealer, the cost of 14 visiting another dealer is too costly. That would be 15 what I would call as a holdup problem or a surge cost 16 problem. So markets where this would a significant 17 problem, then I think cheap talk would apply and these 18 results would really apply. 19 And so in the interest of time, let me just 20 stop here. And if you have more questions, Pedro can 21 handle them. Thank you. 22 (Applause.) 23 DR. JIN: Thank you. We'll take a few 24 questions. 25 DR. GARDETE: Maybe everyone is enlightened</p>	164	<p>1 being able to persuade this consumer, now the seller 2 can also use that information to inform price. And so 3 what happens is that this requirement becomes even 4 more stringent in the sense that I can learn even less 5 about the consumer because the consumer understands 6 that, well, if it's a red car and they know my 7 information on top of it, I will suffer an even higher 8 holdup problem when I do visit the seller. 9 So, you know, we haven't done that, but we 10 can explore that further. So the tradeoff being 11 communication credibility then becomes more 12 accentuated. 13 AUDIENCE: So the intuition -- I guess the 14 takeaway if we add competition to this, is the firms 15 are less likely to acquire information. Is that 16 right? 17 DR. GARDETE: I'm not sure. It's very 18 complicated. So it depends a little bit on what you 19 assume these firms know about each other. So you can 20 have -- actually, it's called a little bit the number 21 of combinations. So it's hard to tell exactly what 22 may happen. Can you give me your intuition of why you 23 think that would happen? 24 AUDIENCE: Sure. So why exactly -- I don't 25 know if I can explain that in -- but it seems like --</p>

165	<p>1 so if there's a bunch of firms out there, I very much 2 want to -- I really need this match. And there's 3 going to be some firm that's really close to the 4 position of the buyer. If I can commit to not having 5 any information, then my message is going to be most 6 credible. And if I know there's a bunch of other 7 people out there making similar statements, I'm going 8 to be competing on credibility basically. 9 DR. GARDETE: Right. 10 AUDIENCE: And let me just add, it seems 11 like there would be an interesting joint paper between 12 the previous paper and this one in terms of collective 13 information -- or collective reputation for not 14 collecting information. 15 DR. GARDETE: All right. Here we go. Thank 16 you. The matchmaking. So that's true, except now I 17 know that there is a firm out there that has -- you 18 know, is likely to have a great product. And so it 19 can either become -- it depends a little bit of how we 20 model it. It can even become more credible if I say, 21 oh, I have exactly that product. I can imitate that 22 firm as well. 23 The other thing that I've been a little 24 concerned with, and it's not clear as well, is could 25 we get into a slippery slope in which, you know, I</p>	167	<p>1 customer, and the existence of competition is a pretty 2 clear extension in some sense. But let's suppose that 3 you're on your circle model and that in our world 4 you're going to have to declare a price -- I'll call 5 it a price -- or a characteristic, whatever if your 6 characteristic that determines demand. Here's the 7 problem. If the competitor, you're sitting here at 8 2:00, your competitor is at 5:00, right, and you'd 9 like to get the customer who's at 4:30, but in order 10 to get the customers who's at 4:30 you have to set 11 such a low price or such a degree of redness, or 12 whatever it is, that you then lose all the surplus you 13 can get from the people close to you. Right? 14 So I think then you're -- you're in an 15 interesting world where the specification of the 16 nature and demand and the nature of your model, I'm 17 not even bringing in dynamics and the revelation of 18 type for the future. 19 DR. GARDETE: Right, right. 20 DR. COUGHLAN: But there's a ton of 21 possibilities. 22 DR. GARDETE: I think -- you know, the nice 23 project will be -- because it's significant enough, 24 but we will have to introduce prices so it will be a 25 different analysis in part.</p>
166	<p>1 need more information to compete, and so given that 2 there's another firm that already has some consumer 3 information, I would like to compete with this firm. 4 And so to improve my chances, I should even gather a 5 little more information. 6 So can we get to a situation where it's sort 7 of all stuck in the corner -- in a bad corner in terms 8 of decisions. As it turns out, probably these 9 outcomes depend on very sort of fine assumptions. So 10 it's hard to think about these things sometimes up 11 front. But it's interesting, too. I mean, I think 12 that's part of the theory, in part, to think of, okay, 13 what would happen now if we shut this off or we turn 14 that on. And so that's the real -- 15 AUDIENCE: Thank you. 16 DR. GARDETE: That's interesting. I hadn't 17 thought about that. 18 Yes? 19 DR. COUGHLAN: I think if you put in 20 competition, you have to start thinking carefully 21 about the nature of demand and buyers in the market. 22 So think about an example where all of your business 23 is request for proposals, it's bid business. Okay? 24 DR. GARDETE: Mm-hmm. 25 DR. COUGHLAN: Then every customer is a single</p>	168	<p>1 DR. COUGHLAN: But price is isomorphic with red 2 in some sense, is it not? 3 DR. GARDETE: It depends a little bit if you 4 want to model in a holdup problem or not. So -- so it 5 depends a little bit on sort of the strategy. Yeah, 6 it's interesting enough, but first we had to take this 7 step of being able to solve it if we have this model, 8 then we can get there. Thank you. 9 AUDIENCE: This is just a quick thought, 10 Pedro. But it seems that if you allow for many firms, 11 competition, there could be a so-called adverse 12 selection program that jumps in. If another firm 13 knows that -- other firms have more information about 14 this ad opportunity, let's say. And then I might 15 wonder that the observations for which ads were not 16 served actually are the worst ones. 17 DR. GARDETE: Right, yes, yes. 18 AUDIENCE: And then that might make me 19 afraid about this rating. So then false observation, 20 things can happen to the monitoring. 21 DR. GARDETE: I agree. So that's what I was 22 trying to say a little bit. For the competition 23 assumption, it's crucial -- the crucial assumption is 24 to understand whether the senders know the locations 25 of the other senders. That turns out to be very</p>

169	<p>1 important because I don't know the end locations of 2 the other senders then, you know, it's sort of an 3 independent problem. But if I do know where the 4 others are located, I may not acquire much 5 information, get credibility, but now I'll imitate a 6 lot of people who do know a lot about consumers. So 7 it does become a very complex world, but we'll get 8 there. So that's another aspect. 9 All right. Thank you very much for your 10 time. 11 (Applause.) 12 DR. JIN: That will conclude our sessions in 13 the morning. We have lunch available for you just out 14 of this door. We request you just quickly grab the 15 lunch and come back because we have a very interesting 16 lunch panel. We'll start at 12:30. Thank you. 17 18 19 20 21 22 23 24 25</p>	171	<p>1 So immediately to my left is Jan Pappalardo. 2 She is the head of the Division of Consumer Protection 3 Economists at the Federal Trade Commission in the 4 Bureau of Economics. And then I have Eric Johnson, 5 who is a professor at the Columbia Business School, 6 Columbia University. Next to him is Dina Mayzlin at 7 the University of Southern California Marshall School 8 of business; and then finally Avi Goldfarb, professor 9 of marketing at the University of Toronto Rotman 10 School of Management. 11 So we will have Jan start us off with 12 some -- a little bit more background, a little bit 13 more granular detail than what Ginger gave us this 14 morning to kind of set the stage, and then each of the 15 other researchers will present about ten minutes of 16 their take on the research of interest. And then 17 we'll open it up to some questions after. I certainly 18 have some discussions -- excuse me, some questions, 19 but I suspect that all of you will have interesting 20 questions as well. So we will have a nice little 21 discussion right at the end. 22 So without belaboring the point anymore, 23 Jan. 24 DR. PAPPALARDO: Well, thank you, Andrew. 25 It's a pleasure to be here today to be part of this</p>
170	<p>1 LUNCH PANEL: CAN MARKETING GO TOO FAR? 2 DR. JIN: Hello? We're going to start the 3 panel soon. If you can sit down, that will be great. 4 Hello? Thank you. 5 Thank you. We have a proactive name for the 6 lunch panel, which is Can Marketing Go Too Far? We'll 7 figure out the answer in an hour. So, Andrew Stivers 8 will be the moderator of this panel. 9 DR. STIVERS: Thank you, Ginger. 10 So good afternoon. I'm Andrew Stivers. I 11 am the Deputy for Consumer Protection in the Bureau of 12 Economics, so I serve under Ginger. So if you need to 13 step out -- let me cut to the chase -- the answer is 14 yes, at least from the perspective of the FTC. But I 15 think we're going to take the opportunity here to hear 16 from researchers across a pretty broad range of issues 17 that are relevant to the FTC. And these are going to 18 include information disclosure, privacy, behavioral 19 choice, and social media. 20 Let me just briefly introduce our panelists. 21 I don't want to take up too much of the time because 22 there are more interesting things to talk about. But 23 if you're interested, all of the biographies of our 24 speakers are up online. So please feel free to look 25 them up.</p>	172	<p>1 wonderful conference. Before I say anything of any 2 consequence, I begin with a disclaimer. The views 3 expressed today are my own and do not necessarily 4 reflect the views of anybody else at the Federal Trade 5 Commission, that said. 6 So I wanted to give you some overview of the 7 role of consumer protection economics and marketing 8 research at the Federal Trade Commission. I'll give 9 you a little background on my perspective. I've been 10 here for 30 years, came straight out of graduate 11 school. And talk about some puzzling recent findings 12 about the rare use of consumer research by the Federal 13 Government to improve information remedies, and also 14 talk about some challenges and opportunities for 15 marketing researchers going ahead. 16 So my perspective. Consumer protection 17 economics is really a relatively new kid on the block, 18 young relative to antitrust. The Division at the 19 Federal Trade Commission was launched in the mid 20 1970s. We borrow from many fields in economics, and 21 also have borrowed quite heavily from marketing 22 research through the years. 23 The Division blends research skills from 24 consumer research with traditional economics, and I 25 have to say that I'm really excited to see so many</p>

173	<p>1 people interested in our area because I think there's 2 a lot of room for collaboration going on. We're 3 really eager to learn from you, and it's great that 4 you're here today.</p> <p>5 There's a really rich history of 6 collaboration between marketing researchers and folks 7 at the Federal Trade Commission. And if you have not 8 seen it, I would recommend a series of essays that 9 were published in the Journal of Public Policy and 10 Marketing in 2014, and there's a lookback by many 11 people in the marketing field about their time at the 12 FTC and their experiences here.</p> <p>13 We use a lot of research techniques that we 14 have borrowed from marketing researchers over the 15 years. One example is using controlled quantitative 16 copy test techniques to try to understand how 17 consumers comprehend marketing messages. Classic 18 cases where there's actually quite a bit of literature 19 in the academic realm is a classic case, <i>FTC v. Kraft</i> 20 and <i>FTC v. Stouffer Foods</i>.</p> <p>21 We worked with and learned from consumer 22 research and marketing researchers and have used -- 23 the agency has relied on marketing researchers and a 24 lot of their cases using consumer surveys. An example 25 of that is <i>FTC v. Dolby</i>, evaluating customer success,</p>	175	<p>1 understand how advertising regulation actually 2 affected the types of health messages that firms gave 3 to consumers in marketing. And I was lucky enough to 4 have been at a marketing conference and tell some 5 folks that this was something I was interested in. 6 And they said, oh, if you're interested in content 7 analysis, you should pair up with Debra Ringold to do 8 some research in that area because she had specialized 9 in content analysis.</p> <p>10 We did research that was later published in 11 the Journal of Public Policy and Marketing, and then I 12 worked with another colleague to do some content 13 analysis. And that other colleague is Pauline 14 Ippolito.</p> <p>15 We've done surveys and experiments to study 16 consumer fraud. I think Ginger mentioned earlier 17 today that Keith Anderson has taken the lead on doing 18 many surveys to try to estimate the incidents of 19 consumer fraud in the United States and something 20 about the characteristics of people who are likely to 21 be fraud victims.</p> <p>22 We've done a lab experiment. Folks have 23 worked on trying to understand the characteristics of 24 folks who are likely to be deceived. We've done 25 controlled experiments to assess disclosures,</p>
174	<p>1 and <i>FTC v. TransUnion</i>, evaluating consumer attitudes 2 toward the use of information from credit files to 3 compile marketing lists.</p> <p>4 We've used empirical analysis of consumer 5 behavior increasingly in our cases. And increasingly 6 it's become more sophisticated with more availability 7 of granular data and bigger data sets about what firms 8 are doing and the overall marketplace. An example of 9 that is a finite mixture modeling piece that was 10 recently made public in RIO. It was worked on by 11 Devesh Raval to identify types of content providers 12 largely responsible for cramming in the T-Mobile and 13 AT&T case.</p> <p>14 And one thing I would mention is that a lot 15 of our work is private, right? So you see the tip of 16 the iceberg of what the FTC does. There's quite a bit 17 of work that's done behind the scenes and 18 investigations that incorporates a lot of very -- 19 demand analysis, consumer research, really quite a 20 range of things. And I wish we could bring it all to 21 your attention, but the nature of the beast is that 22 the publicly available cases are the ones where you 23 get a sense of what's going on behind the scenes.</p> <p>24 We've done content analysis. Many, many 25 years ago, I was very interested in trying to</p>	176	<p>1 appliance energy labeling and mortgage disclosure 2 research, and I'd like to talk a little bit about that 3 in more detail.</p> <p>4 The energy labeling question was one about 5 what type of label the FTC ought to use to convey to 6 consumers accurately what types of energy features 7 there are on appliances. And at the time, Congress 8 suggested that we might want to go to a star or a 9 categorical label. At the time, we were using a label 10 that featured kilowatt hours. So we said, well, why 11 don't we test that.</p> <p>12 And we worked with colleagues in the Bureau 13 of Consumer Protection, and we did an online panel 14 study, controlled, randomized experiment. And it was 15 a very interesting study, because in addition to doing 16 the star label and the kilowatt-hour-featured label, 17 we decided to test one that featured a dollar metric.</p> <p>18 So what were the bottom-line findings? What 19 we found was that overly simplistic metrics, such as 20 stars, can actually hinder consumer understanding. 21 People seem to think that the star meant something 22 more than the energy efficiency attribute of the 23 product and applied to other features of the product. 24 In the end, based on this research and public comments 25 and analysis by FTC staff, the Commission decides to</p>

177	<p>1 go to a label that featured dollars as a key metric. 2 We found that dollar amount metrics are meaningful, 3 and this is intuitive, because people can use dollars 4 to compare across all kinds of goods and services. 5 They're trying to figure out how to optimize utilities 6 subject to their budget constraints. 7 We did mortgage disclosure research because 8 we found in cases at the Federal Trade Commission that 9 consumers could be totally clueless about the features 10 of their mortgages, even if they had received the 11 federally required mortgage disclosures. And we were 12 wondering, is there something about the disclosures 13 themselves that could be a problem, and is there 14 something about the disclosures themselves that could 15 be improved to help people make better decisions. 16 So we did a two-part study. We used in- 17 depth consumer interviews for the first part. We 18 talked to recent mortgage borrowers. And we also did 19 a quantitative randomized, controlled experiment, 20 testing what were then the current disclosures, and 21 good versions of the current disclosures, I might add, 22 against a prototype developed here at the FTC. 23 What did we find? Well, the qualitative 24 research was fascinating. We found that many people 25 were unaware of or did not understand key costs or</p>	179	<p>1 that government agencies rarely use consumer research 2 in their decision-making. Fraas and Lutter found that 3 although federal mandates to disclose information 4 underpin a number of flagship regulatory initiatives 5 and sundry major regulations, we've only found a very 6 few exceptional cases where there's any evidence that 7 the responsible regulatory agencies conducted 8 research. 9 So here's a question for all of you in the 10 marketing field. Why is consumer research not a 11 routine part of consumer policy development? Do 12 policymakers not recognize that well-meaning 13 disclosures can mislead? Do policymakers understand 14 the potential benefits of consumer research but think 15 the cost generally does not outweigh them? And what 16 are the costs and benefits of alternative 17 methodologies? 18 A few hot research questions for you guys to 19 think about: how to provide reliable estimates of 20 consumers' willingness to pay in markets without 21 market prices. This is very important for the world 22 of privacy and data security. 23 How do we translate established techniques 24 for advertising disclosure testing in traditional 25 media to newer media? There was a discussion of that</p>
178	<p>1 features of their loans. And even worse, we found 2 that some of the mandated terms were actually 3 misleading to consumers. People thought a discount 4 fee was not really what a discount fee was. 5 We developed a prototype disclosure; we did 6 controlled testing. We found that people did 7 substantially better if we created a document with the 8 first principles of what would you want your best 9 friend to know if your best friend was shopping for a 10 mortgage. And we used features from consumer research 11 to try to say what is clear, what -- how do you layer 12 the information so the most important information is 13 on the first page and so forth. 14 We got substantial improvements with the 15 prototype versus the alternative. We found that 16 extraneous information with additional details can 17 confuse consumers; descriptors can be misleading; and 18 controlled, quantitative consumer research can 19 substantially improve disclosures and may be necessary 20 to avoid inadvertent deception from well-meaning 21 disclosures. So we know this. I think people have 22 known this for 30 or 40 years. You really need to 23 test in controlled settings consumer understanding as 24 possible consumer behavior in field experiments. 25 Here's the puzzle. A recent study found</p>	180	<p>1 yesterday and I think today as well. Very important 2 question. 3 There are many opportunities to try to 4 collaborate with folks at the FTC. In the past, we've 5 had people work jointly on projects. We've had people 6 come for sabbaticals. And I think it's really helpful 7 to just talk to people at the FTC who are on staff 8 working in your area as you develop research projects 9 outside of the Federal Trade Commission to make sure 10 that you understand the nuance of the policies, of the 11 law, the regulations, and the policy questions to make 12 sure that your hard work is as relevant as possible to 13 the real world. And I thank you very much. Oh, I 14 have some references if you want references. 15 (Applause) 16 DR. STIVERS: Great. Thank you, Jan. And 17 now we have Eric. 18 DR. JOHNSON: Thank you. It's nice to know 19 I can still talk IBM if I need to. I have to say one 20 thing because Jan said it well. I've been spending 21 the last years as a senior visiting scholar at -- sort 22 of across town at the Consumer Financial Protection 23 Bureau, and that's been wonderful, but that means I 24 have to use the same disclosure. So what she said. 25 The best version of that is someone who adds</p>

181	<p>1 "and it's not even the opinion of the United States, 2 but somewhere there's a country that approves of what 3 I'm about to tell you." 4 What I'm going to say -- essentially three 5 things. One is I want to introduce why regulation 6 should take a behavioral perspective. The second 7 thing I want to do is offer an example, a contrast 8 example, for mortgage decision-making partly inspired 9 by some great work that Jan just talked about that she 10 was involved in. And, finally, I want to start with 11 some -- stop with some observations about disclosure. 12 Okay. So I think now the field has matured, 13 that we actually have some good empirically grounded 14 models of how people behave that are departures from 15 the standard analysis. One of these is basically 16 models, and I'm going to think particularly of beta- 17 delta or quasi-hyperbolic discounting of time 18 preferences. And I'll come back to that because I 19 think it makes all the difference in the world when 20 you talk about mortgages. 21 Another example is we know a lot about risk 22 preferences, and we know about, a lot about loss 23 aversion. And, finally, you know, we can put a quick 24 view of it, I'll call it limits on information 25 processing. They're very clean models that people do</p>	183	<p>1 commonly called a 2/28. For two years, you get a 2 great rate, and after that two years, you have a 3 terrible rate. Okay? 4 Typically this has -- and this is important 5 -- no money down. So, it's a great rate, no money 6 down, and you get to move into the house immediately. 7 The other is, of course, the classic old, boring, 30- 8 year fixed-rate mortgage. Now, if you think about 9 this from a principal agent problem, this was a 10 beautiful device. Okay, people who were creditworthy 11 who get 30-year mortgages did, but there are people 12 out there who know they're going to have good credit 13 ratings in two years. 14 So what they're going to do is take the 15 2/28. And if I'm not good, I won't buy a mortgage. 16 Sounds like a beautiful separating equilibrium, right? 17 Now, what else could the 2/28 mortgage be? What is 18 the kind of person who it might appeal to? Imagine 19 you believe in present-bias or hyperbolic discounting. 20 What happens in this analysis is very simple. The 21 2/28 becomes a present-bias magnet. 22 And I don't have to tell you how this story 23 ends, you know, not well. And if you've seen a couple 24 of recent movies, you might know. We did an analysis 25 of this where we essentially did two ways of data</p>
182	<p>1 not necessarily think all the way down the tree. 2 There is a notion of K-level reasoning -- we don't go 3 to the bottom. 4 I'm only going to talk as an example about 5 time preferences. The reason I think this is so 6 critically, critically important is because if you 7 don't include these models, you're going to end up 8 with not only results that are wrong but that can hurt 9 social welfare and actually hurt social welfare in a 10 way that hurts the most vulnerable people. 11 And I'll illustrate that in two examples, 12 but you can imagine just one quick thought, if I'm 13 doing disclosure and you think that people have costs 14 of processing information, those costs might be 15 correlated with education or socioeconomic status. 16 Disclosure might actually be harmful or at least not 17 as helpful for people who are not as well off. 18 Okay, so, let me give you my favorite 19 example, and this is a paper that's in press in the 20 Journal of Marketing Research with Steve Atlas, who 21 was a Ph.D. student at Columbia, and you might know 22 who this guy, John Payne, is. So, there are two kind 23 of mortgages in my world. Not only am I going to tell 24 you about our toy model, all we have is a toy model. 25 But essentially imagine the two mortgages. What is</p>	184	<p>1 collection. One is we actually managed to get 2 questions about loss aversion and time preference in a 3 nationally representative sample, which actually turns 4 out to be done by the industry together, three hours' 5 worth of survey data about people's finances. 6 And the other thing is we actually did our 7 own survey using DEEP, which is a technique that 8 Olivier Toubia and a bunch of us have developed, which 9 gives you basically -- it can give you time 10 preferences in a beta delta model in about eight 11 questions or actually parameters from a cumulative 12 prospect theory model in about eight questions. So 13 it's way cool, I think. 14 And basically our little toy model says 15 three things. First is present-bias and impatience 16 will make people choose adjustable 2/28 mortgages. I 17 mean, that should be clear as an intuition. Second, 18 if there's a shock -- and here I'm talking about a 19 negative shock -- to house prices, because they have 20 less money in the mortgage, they will, in fact, be 21 more likely to be under water, okay? 22 And the standard analysis, if you read the 23 press in 2008 and '09 is many, many people would walk 24 away from such mortgages. It would be cheaper for 25 them to move and rent and leave the balance. But our</p>

185	<p>1 analysis, and we borrow this largely from Dellavigna 2 and Pollet who've talked about it in labor 3 markets, is, think about it, if I bought the mortgage 4 because it didn't hurt me at all to get it at first, 5 think about walking away. Walking away has huge 6 costs. You know, many of them nonpecuniary, but, you 7 know, I have to move, I have to find a rental, like 8 change kid's school, et cetera, et cetera. And the 9 benefits are delayed.</p> <p>10 So what this suggests is actually the 11 reverse to what -- you'll not only more likely get 12 into the bad mortgage, but you're more likely to stay 13 in the bad mortgage, which is essentially the analysis 14 from labor that Dellavigna and Pollet basically did 15 using these two data sets and lots of controls, we 16 basically showed that present-bias leads you to get 17 adjustable rate mortgages and keeps you from walking 18 away.</p> <p>19 And I just want to contrast this very pretty 20 model, the 2/28 separates people into creditworthy and 21 non-creditworthy to what I think is the reality, which 22 basically became not only a magnet for people with 23 present-bias but they were condemned to that situation 24 over a long time. Now, I've just pointed out the 25 observation. The first version of the Household</p>	187	<p>1 unquote, revealed.</p> <p>2 Okay, two last comments about disclosure. 3 One is I want to remind you of the work of George 4 Loewenstein and many other people who show that 5 disclosure can have perverse effects. They looked at 6 the setting where a doctor will disclose I own the lab 7 and I'm sending you for a test.</p> <p>8 What they find reliably is that people say, 9 oh, he's a nice guy, he didn't have to tell me that. 10 In fact, people are not more suspicious; they're, in 11 fact, less suspicious. So in that particular 12 disclosure framework -- and disclosure is much more 13 complicated than that -- it's problematic.</p> <p>14 The second thing I want to point out is it 15 raises processing costs. As I said earlier, if 16 processing costs are differentially available to 17 different folks, and I'll use an article -- an example 18 from Ben-Shahar and Schneider, who have a nice book 19 called The Failure of Mandated Disclosure. Actually, 20 that's a law review article, which is cheaper than the 21 book and has all the good content.</p> <p>22 But if you read the law review article, they 23 close by what is the effect of hospital quality 24 disclosures. Yeah, they're kind of hard to read and 25 hard to find, but they say basically what they believe</p>
186	<p>1 Affordable Refinance Program, called HARP, which put 2 in \$7 billion to try and get about 7 million people to 3 refinance is largely considered a failure because only 4 2 million refinanced. So, I mean, it's consistent 5 with this story.</p> <p>6 Okay. Now I'm going to shift from talking 7 about mortgages to talking a little bit about privacy 8 and disclosure. One thing I want to point out, I 9 think the notion that people have a utility for 10 privacy is probably a little naive. It's what I call 11 an assembled value. For those of you who know the 12 term "constructed value," it's my substitute for that 13 because assembled means I have lots of things. I want 14 to have customized products, but I also don't want you 15 to sell my information. And how those get thrown 16 together is a function of how I ask the question.</p> <p>17 We did some research that was published in 18 the Communications of the ACM, where we essentially 19 did the old opt-in/opt-out, which we have done with 20 organ donation and other things. If you have people 21 having to check in to get more mail surveys, in this 22 case only 48 percent of people did. If they opt out 23 not to get them, 98 percent of the people would get 24 these surveys. So, you know, the same standard story. 25 How you frame it is how -- what will be, quote,</p>	188	<p>1 happens is that wealthier and more educated people, in 2 fact, find the good hospitals, go to them, and as a result 3 what beds are left over? The ones at the not-so-good 4 hospitals. And that disclosure actually does maybe 5 improve consumer welfare for some people but not for 6 everybody.</p> <p>7 So I just want to point out disclosure gets 8 to be kind of interesting and complicated as soon as 9 you assume information is costly to process.</p> <p>10 Finally, the solutions, and this is -- I'm 11 writing a book on choice architecture, so I'm going to 12 make a plug for this, which is lowering processing 13 costs through choice architecture. And that's a whole 14 other talk, so I won't talk about that much now, but 15 I'd be glad to talk to you about that later. Thank 16 you very much.</p> <p>17 (Applause)</p> <p>18 DR. STIVERS: Thank you, Eric. That's going 19 to be followed by Dina.</p> <p>20 DR. MAYZLIN: So, my name is Dina Mayzlin. 21 Thank you very much for having me. So I'm going to 22 talk about consumer welfare and regulation of social 23 media. I'm the shortest speaker here. And I'm 24 primarily going to -- basically I'm going to talk 25 about two papers that I've done on this topic, and</p>

189	<p>1 then I'll talk about some other things that I haven't 2 worked on and not that many people have worked on, but 3 I think are sort of interesting and intriguing. 4 So what is social media? So some of you may 5 think of social media as the platforms. I actually 6 have my Facebook friends -- Eric Johnson is one of 7 them. His picture is there. So I think of social 8 media as -- so the medium are the consumers, okay? So 9 instead of sort of a firm advertising on -- you know, 10 on TV or on print, here the consumers are talking to 11 each other. 12 And, so, you can, of course, think about the 13 platforms as well. And, so, you know, usually when I 14 give this talk I talk about the role that the firm can 15 play in managing social media. But, of course, here, 16 we have a slightly different perspective because -- 17 and this actually -- I don't know, the first time I'm 18 interacting with the Federal Government so, you know, 19 we're more worried about perhaps consumer welfare. 20 So since we're worried about consumer 21 welfare, let's think about consumers and how they use 22 social media. So I'm going to -- you know, I usually 23 talk about the three Cs of social media, so 24 connection, curation, and content, where content is 25 like the stuff you read, perhaps it could be blogs,</p>	191	<p>1 research stream, because I've been -- you know, when I 2 was in the market in 2001, I was kind of worried 3 about, you know, oh, the Government has cracked down 4 on this whole review manipulation, but thankfully it 5 has not. So... 6 (Laughter) 7 DR. MAYZLIN: So I was able to get more 8 papers out of it. All right. 9 So the idea is that, you know -- so, again, 10 I usually talk to firms about managing social 11 interactions. And, again, the idea is that in their 12 management of social interaction some may be legal, 13 some may not be, you know, ethical or unethical. You 14 may have negative impact in consumer welfare, and 15 we'll talk about that. 16 And the second thing, which I haven't done 17 research on and I don't think a lot of people have 18 done research on, is that, you know, I think the thing 19 that worries me a lot now as a parent and also as a 20 researcher is what is happening with social media -- 21 misuse of social media. 22 And there's sort of two things I've observed 23 in the past year that's been a big deal. The first 24 one is this idea of incitement of political -- and 25 some of it has to do, you know, may have to do with</p>
190	<p>1 word of mouth. There's also connection where you're 2 connecting with friends. 3 And curation is the idea that, well, I'm 4 going to follow someone on Twitter because this person 5 knows a lot about interesting things that I should be 6 reading about. And different platforms have these 7 kind of different uses, so I would argue that, you 8 know, Facebook is largely about connection; Twitter is 9 about curation; things like blogs are about content. 10 Okay. So why should we worry about 11 regulation? And I have to say that this area has not 12 been well regulated, I think it's okay to say. There 13 has been some regulation by the FTC, but it's kind of 14 pathetic. 15 (Laughter) 16 DR. MAYZLIN: Pathetic in a good way, in a 17 good way, in the most positive use of the word. I 18 mean, there is reasons why it's -- I mean, pathetic in 19 the sense that there are some -- basically, if you 20 don't disclose your connection there may be a fine you 21 can pay. Very few people have been fined. And, so -- 22 and there are reasons why it's so hard to do it, there 23 are all these different players, you know, it's kind 24 of a nightmare. 25 And it's also been good for me, my own</p>	192	<p>1 terrorism or kind of racial incitement. And the 2 second is this misuse of social media by minors and 3 the long-term consequences that can have for kids. 4 And, so, you know, our Government usually 5 worries about -- the Government usually worries about, 6 you know, the area of, you know, minors, and so I 7 think it's kind of a big deal. It's actually, I 8 think, one of the biggest issues that schools now face 9 is the use of social media by children -- schools and 10 parents. 11 Okay, so just kind of a few more frameworks 12 on this. So there's usually -- I think about sort of 13 three different roles that the firms can play in 14 managing social interaction. So one is very passive, 15 which is listening. And I think a lot of sort of what, 16 you know, we've talked about, collecting information, 17 you know, tracking; not necessarily really acting on 18 this information is being done, so it's being done, 19 you know, all the data is being scraped, multiple 20 companies, and, you know, ostensibly, you know, 21 anything that's online is scrapable, and so that's 22 then collected. 23 You can also think about more kind of active 24 roles. So one is engagement, where you try to get 25 people to talk about your product. Another, and the</p>

193	<p>1 most kind of aggressive one, is promote, where you try 2 to sort, you know, get people to buy stuff through 3 social media. And, again, some of it may be done with 4 disclosure by the firm; and some if it may be done 5 without disclosure. And, so, that's what I'm going to 6 talk about.</p> <p>7 So I have these two papers on this topic of 8 what happens when firms try to manufacture word of 9 mouth, so basically try to pretend, to enter the 10 conversations but not reveal that they're -- that they 11 are there. And, so, that can be done under -- you 12 know, because virtual space provides you anonymity.</p> <p>13 All right. So I have -- so, my -- you know, 14 it's a long time ago. My job market paper was on 15 this, and it's this idea of promotional chat. So, 16 it's this idea that, you know, we saw -- you know, I 17 saw back in the day that people started to talk about, 18 you know, CDs, music, movies on online forums, and 19 there was a case of a singer that basically her 20 representative is one in these online forums and 21 pushed -- pretended to be kids.</p> <p>22 This is one of the cases that Ginger talked 23 about, right, with the Sony case. It was basically 24 that, just, you know, a few years later. And, so, you 25 know, I started -- when I saw a case like that back in</p>	195	<p>1 that the worst firm would promote more, would invest 2 more into this.</p> <p>3 And, then, you know, if you think about 4 welfare, I think by the end the paper was published, 5 there wasn't much welfare left, but initially there 6 was more welfare. They have to make it short, so 7 there was a bigger section of welfare and you could 8 look at consumer welfare, so you can kind of look 9 at -- you know, so, of course, if -- so basically one 10 of the results is that as it becomes more costly to do 11 this, there will be less kind of fake reviews in 12 equilibrium, and so you're going to have, you know, 13 more consumer welfare.</p> <p>14 Also, the extent of the real chat matters. 15 So if, you know, there's not enough, then there's 16 going to be a lot of noise and signals, so you're 17 going to be making, you know, kind of bad decisions 18 all the time.</p> <p>19 But, I mean, so I think -- so one thing I 20 want to highlight is this idea that, you know, of 21 course we don't want there to be bad reviews out there 22 or fake reviews out because people are going to be 23 making wrong choices.</p> <p>24 But I think even a more important kind of, 25 you know, negative consequence that could happen is</p>
194	<p>1 -- I think it was about '99, 2000, started to wonder 2 about, you know, so what does that mean. So we 3 basically have advertising where we can no longer tell 4 if it's real word of mouth or advertising content or 5 paid content.</p> <p>6 And, so, you know, so I think the 7 interesting thing was to look at the equilibriums. So 8 if you think about the consumers now know that this is 9 going on, so they know that these -- in my model 10 they're competing firms doing this, do they -- you 11 know, does it still work? Can you still be persuaded 12 if you think that people have these bad incentives, 13 does it just fall apart?</p> <p>14 And, so, we find that in equilibrium you 15 still have an informed equilibrium, so it basically 16 kind of -- what happens is that this basically adds 17 noise, so sometimes you're going to be making wrong 18 decisions because some of the -- some guys are getting 19 messages that are false, that are just promotion.</p> <p>20 And, also, an interesting thing is that the worst 21 product is going to be doing more of this.</p> <p>22 So, but despite this, because of real word 23 of mouth, there is kind of truth-telling that happens 24 in equilibrium. So, on average, you're okay. But if 25 you actually saw how much firms promote, you would see</p>	196	<p>1 that the whole thing could fall apart, right? So if 2 these things become so spammed that nobody wants to go 3 there, which I would argue would happen to IRC -- I 4 don't know if you guys remember IRC back from my -- 5 nobody remembers, okay. It was this online channel 6 kind of chatrooms way back in the day, basically they 7 got spammed and disappeared. How many of you remember 8 IRC? All right, all right.</p> <p>9 Okay, yes, yeah. So those things became 10 much less popular, and so, you know, I think you think 11 in terms of welfare, you could think about the noise 12 added to the -- but I also think, well, you know, is 13 this something that will destroy online forums, online 14 communities. And I think by now we're sort of -- you 15 know, I feel like it hasn't destroyed. You know, we 16 can say with more confidence that it's not going to 17 destroy it, but it's definitely going to add noise.</p> <p>18 Okay. And then another paper, kind of a 19 more recent paper I have with Judy Chevalier at Yale 20 and Yaniv Dover at Hebrew University in Jerusalem is 21 actually an empirical paper of the same topic. You 22 know, it took us a while to write the followup 23 empirical paper, and the reason is that you kind of, 24 you know, couldn't -- I don't know, I and probably 25 other researchers sort of couldn't think of a way to</p>

197	<p>1 really study this phenomenon because sort of by 2 definition you're saying you can't tell it apart, 3 right? 4 So part of the kind of setup of that model 5 was you don't know if it's coming from a consumer, 6 it's coming from an interested party. So if you don't 7 know by definition, then how do you study this thing, 8 you know, it just becomes sort of -- completely 9 unobservable by definition. 10 And, so, this paper, what it does is it 11 exploits a variation in platform design. So as -- you 12 know, as the space has evolved, Tripadvisor and 13 Expedia have very different design features. And one 14 of the design features is that Tripadvisor allows 15 everybody to post a review; and Expedia verifies the 16 authenticity of their reviewers. So they basically -- 17 they just make sure you booked the hotel through 18 Expedia. Okay, and if you didn't, they're not going 19 to post your review there. 20 And, so, we use that, along with variation 21 in kind of organizational structure. So some hotels 22 have small owners; some hotels have large owners; some 23 hotels happen to be right next to a competitor that is 24 a small owner, large owner, independent or chain. And 25 we have sort of -- basically assumptions on, you know,</p>	199	<p>1 then we see the extent to which we see fakery. And, 2 so, let me give you kind of an example of what we 3 found that summarize our results. 4 So you can compare -- so, again, we don't 5 know -- we can just tell the difference. We don't 6 know the absolute level of fakery, but we can compare 7 Hotel A that's a branded chain and a large owner, so 8 sort of less likely to fake. Hotel B is an 9 independent and small owner that we think is more 10 likely to fake. And what we see is in the data, that 11 Hotel B will have seven more five-star reviews on 12 Tripadvisor, and the average number of five-star 13 reviews on Tripadvisor is 37. 14 Okay. So, and this is sort of like a 15 reasonable result, I think, because it's not like 16 overwhelming, right? Like it doesn't kill it. But at 17 the same time, you know, it seems pretty big. You 18 know, it's -- so it's adding noise to the signal. 19 Then if you look at I think a more 20 interesting result is this faking negative reviews for 21 a competitor, which seems even kind of more, you know, 22 aggressive. So, if you can look at -- if you look at 23 Hotel C that's located next to again this kind of, you 24 know, a bigger, less aggressive faker, branded chain, 25 a large owner, versus Hotel D that's located next to a</p>
198	<p>1 who has -- using literature, kind of economics 2 literature, organizational structure literature on, 3 you know, who has more of incentive to fake. 4 And, so, we know which hotels have more 5 incentive to fake; we know who is collocated next to 6 whom; and then we also know kind of -- we look at the 7 difference in the -- so we don't look at each review 8 because by definition we don't know how to do it; we 9 can't tell it apart. But what we can do is we can 10 look at the difference in the distribution of reviews. 11 So we basically look at the same hotel; look at the 12 distribution of reviews it has on Tripadvisor; and 13 compare it to the distribution of reviews on Expedia. 14 And we see the extent to which they differ. 15 So, for example, what we would hypothesize is when 16 you're next to this very aggressive competitor that's 17 small and independent, then you're going to start to 18 see -- you're going to pop -- you're going to have 19 more negative reviews on Tripadvisor relative to 20 Expedia because it's easier to fake, and Expedia is a 21 bit harder to fake. And, so, that's our methodology. 22 So we basically, you know, use this kind of, 23 you know, where we use this to kind of -- we propose 24 as a mechanism to detect review -- to detect some sort 25 of fakery, these differences in distributions, and</p>	200	<p>1 more aggressive faker, you -- we find that Hotel D has 2 six more one- and two-star reviews on Tripadvisor. 3 And the average number of one- and two-star reviews on 4 Tripadvisor was 30. 5 Okay, so it's a pretty significant amount 6 of, you know, negative reviewing as well. But, again, 7 it doesn't kill it, but it seems like, yeah, kind of a 8 big deal. 9 So, all right. And I don't want to suggest, 10 you know, there's been some other papers. I know that 11 Michael Luca has a paper that's either forthcoming or 12 about to be forthcoming on also fake reviews, or it 13 already came out. So there's a few other kind of 14 recent papers on this. But I just, you know, just 15 want to talk about my own stuff. 16 So the last thing I want to talk about that 17 -- actually wanted to show you guys a video, but the 18 reason I couldn't show it is that the Federal 19 Government allows, like, sharing sites to be accessed 20 through their computers, so I couldn't share -- I 21 didn't think of that. 22 So -- but the video was -- okay, so let me 23 talk about the first point. The first one first, and 24 it's really just kind of speculative, like I don't 25 have a model to show this and, you know, but the</p>

201	<p>1 concern is that -- so I saw this -- I mean, I think 2 you see this in elections, right, during the election 3 season. 4 You just see these kind of, you know, crazy 5 conspiracy theories, you know, kind of spinning out of 6 control, and you notice that, you know, people seem to 7 be just in different worlds, you know, like the -- 8 depending on whatever your political affiliation is, 9 you're just getting different news, and news just 10 seems to get very, very extreme. You know, 11 news/opinions/conspiracy theories. 12 And, so, what is going on? So one 13 hypothesis is that if you have homophily in social 14 networks, you kind of have this amplification effect 15 of social media. And it seems like, you know, extreme 16 content seems to propagate. And I -- you know, I 17 think it would be an interesting thing to show -- to 18 show that in a model. 19 And I think it's a big deal. You know, it's 20 a big deal if you think about, you know, our role in 21 the Middle East or perhaps, you know, what is said 22 about -- you know, think about the -- but you also 23 think about the kind of local domestic policy, you 24 know, the fact that people get so much of their news 25 from social media, and they seem to be getting kind of</p>	203	<p>1 troubling is that the electronic footprint doesn't get 2 destroyed. So your fear -- you know, this interview I 3 was going to show you was an 11-year-old saying from 4 my kid's school, you know, I interviewed them for my 5 class, saying how sexting is very popular in sixth 6 grade. 7 And, so, these are basically 11-year-olds, 8 you know, kind of texting pictures of themselves, you 9 know, naked pictures of themselves to boys. You know, 10 it's usually -- it's usually girls to boys to kind of 11 impress them. But that stuff, you know, basically, as 12 soon as the boy gets it, he forwards it to everyone 13 else in his circle. 14 And, so -- and I think part of the reason 15 that happens is that sort of the normal pressures of 16 growing up and trying to kind of fit in and the fact 17 that social media is about connections, but part of it 18 is also there's kind of false sense of -- you know, 19 Snapchats, the stuff is supposed to disappear after a 20 few seconds, but you can take a screenshot, right? 21 So you don't -- you know, as soon as you get 22 that picture, take a screenshot, and so it doesn't 23 quite disappear. So, you know, first of all, they're 24 too young to probably understand, but also, they don't 25 quite understand the technology.</p>
202	<p>1 very, you know, twisted version of the truth, you 2 know, has a big effect on, you know, our country and 3 how elections run and how, you know, public and 4 foreign policy develops. 5 The second point is a point about use of 6 social media by minors. And, so, I mean, how many of 7 you have kids who are, like, between the ages of, you 8 know, 11 and 18? Okay, so a few of you. So, you 9 know, it turns out that this is kind of a big deal. 10 And, you know, and I blame Snapchat, one of the 11 platforms. 12 And, so, what happens in -- these social 13 platforms are very popular among very young children, 14 so starting, I would say, with the age of 10 or 11, 15 kids get their smartphones; they get these apps; and 16 there's very little monitoring by parents. You know, 17 they're basically on their own. 18 But the problem with that is, you know, and 19 you could imagine that kids of that age don't -- you 20 know, they basically don't realize the implications of 21 their behavior. They gauge their behavior for 22 themselves or for their friends. And, then, you know, 23 there are like these sort of things that spin out of 24 control. 25 The other thing that I think is very</p>	204	<p>1 And, so, I'm not sure exactly what the 2 solution is. I mean, one solution is just to be 3 stricter about not allowing minors to use it, you 4 know. I know my kid's school basically they this year 5 outlawed the use of smartphones during school hours. 6 But I have to tell you, I talked to the principal or 7 the superintendent of the district, and he said it's, 8 like, one of the biggest issues they face -- sexting, 9 cyber bullying, and bomb threats. So social -- there 10 was -- my district had three or four bomb threats last 11 year using the site Yik Yak, which provides anonymity. 12 You can post anonymously and just like -- they just 13 went out of control. So I'll just leave you there. 14 (Applause) 15 DR. STIVERS: Thank you, Dina. And we will 16 finish up with Avi. And, unfortunately, we may be 17 running out of time, so this may turn into more of a 18 lightning round than a panel discussion, but maybe we 19 can grab a little bit of time. So we'll see. 20 DR. GOLDFARB: Okay, so, before I start, I 21 should say that all -- pretty much all these ideas, 22 including many of the slides, were developed in 23 collaboration with Catherine, so actually there's a 24 couple papers that are hers and not mine that I will 25 be citing. Okay.</p>

205	<p>1 So what's privacy? Privacy is the right to 2 be left alone -- left alone and the right to no 3 unauthorized intrusion. This is a hundred-year-old 4 definition, and in the law, up until the last few 5 years, privacy was something different. Privacy was a 6 public versus private life distinction. Public 7 figures had the expectation of having their picture 8 taken in certain places, and private -- you know, 9 private figures, if you were not a public figure, you 10 didn't have to worry about that kind of thing, and 11 there was a distinction in the law.</p> <p>12 Or there was a sense of privacy and 13 security, whether you're going to be wire-tapped or 14 whether -- and it's very much about government 15 surveillance of individuals, which is still there, but 16 privacy is now a business issue as well.</p> <p>17 And, so, what's happened to make privacy a 18 business issue? It's that data is now key to 19 innovation in lots of industry. So, you know, I 20 quoted a couple of leading economists on this, one who 21 tends to be very much thinking about the future, Erik 22 Brynjolfsson; another who is an historian, thinks 23 about the past, but also says, hey, if we look at 24 digital age, data is fundamental and it seems to be 25 changing things in a deep way in terms of innovation.</p>	207	<p>1 we look at the consequences of a lot of the 2 regulations that we do have; they restrict innovation, 3 and they hurt outcomes in the context of health.</p> <p>4 So underlying all this, I think, is an idea 5 that privacy and openness are both positive values. 6 So we want privacy, but we want openness. And in 7 particular in an innovation world, we think about how 8 do we facilitate innovation, how do we foster 9 innovation, openness is fundamental to that.</p> <p>10 But privacy and openness are opposites. 11 And, so, we have two positive values that in many ways 12 conflict. So this suggests we're going to have some 13 kind of tradeoff between privacy protection and 14 innovation. And, so, this is pretty bleak from the 15 point of view of thinking about privacy regulations, 16 and consumers seem to care about this, or at least 17 they say they care about this, but we -- are we really 18 willing to hamper our economy in some way in terms of 19 innovation?</p> <p>20 And, so, there's a question of, you know, 21 maybe we should just have a free market and why 22 regulate this thing at all. So I'm going to start 23 with the premise that consumers actually do care. So 24 consumers do react negatively to some kinds -- not all 25 kinds but some kinds of privacy-intrusive advertising.</p>
206	<p>1 And it turns out that the use of data 2 requires data. And that means that privacy 3 regulation, if you think about it, is about explicitly 4 restricting the collection and use of data. Privacy 5 regulation is about restricting data flows. And if we 6 need data for innovation, this could be difficult.</p> <p>7 But it turns out that consumers and 8 governments, as, you know, we've heard the word 9 "privacy" a lot today, and I heard it a bunch 10 yesterday, are concerned with threats to privacy. So 11 companies can use data to harm consumers by charging 12 higher prices or denying service. There's also this 13 big element that it's hard to really define, even when 14 you push people, that it's creepy or repugnant that 15 companies know more about their life than they do.</p> <p>16 So, as a consequence, we've seen some 17 regulatory attention, sectoral in the U.S. and more 18 general in Europe and to some extent in Canada. Okay.</p> <p>19 But then when you look at what people do, 20 and this is related to what Dina just said, is maybe 21 people don't care as much about privacy as they seem 22 to. And, so, how do we reconcile these issues and how 23 do we think about privacy when we acknowledge that 24 maybe people don't care in certain situations or 25 people are revealing a lot about themselves, and then</p>	208	<p>1 Catherine and I showed that in a paper about five 2 years ago, and we've seen more evidence of this, is 3 that if you violate privacy in the wrong way as a firm 4 consumers get really angry at you, or at least they 5 stop buying from you and they behave differently.</p> <p>6 Second, over time, consumers are becoming 7 more reluctant to share data. So if you fix the 8 context of sharing data, in this case it's do you give 9 your income in a survey, people over time are becoming 10 less likely to share. So what's changed is that the 11 benefits of sharing have grown so much relative to the 12 cost. So even though people in a given setting share 13 less, maybe there's -- the benefits to sharing and 14 social media are sufficiently high and have grown so 15 much that we seem to see more of these -- more 16 sharing.</p> <p>17 So how do we think about privacy regulation? 18 I think the -- one privacy regulation that seemed to 19 foster both innovation and consumer protection was the 20 Fair Credit Reporting Act. Okay, so, this, at the end 21 of the day, is privacy regulation. It is about how do 22 we regulate consumer information about credit. And an 23 important aspect of it was there was a centralized 24 repository where consumers could go and figure out if 25 information was accurate, and that actually helped</p>

209	<p>1 firms, too. This was sort of a really nice win/win. 2 Consumers could figure out what firms knew about their 3 credit; and firms could have some verification when 4 that was wrong. 5 So I think one of the most useful things to 6 think about in the context of privacy regulation is to 7 try and figure out if there's some kind of regulatory 8 model around clear and consistent disclosures that's 9 like this Fair Credit Reporting Act in the context of 10 online. And I don't have a good answer. I mean, 11 that's just a question, okay? 12 But, so, now what do we do? I think we have 13 to -- when we think about privacy policy, we think 14 about consumer protection, but we also think about 15 innovation. And it can't be too strict or else it's 16 going to stifle data-driven innovation, and that's the 17 work that Catherine and I had started working on about 18 five years ago, or at least published five years ago. 19 But at the same time -- we worked on it a little bit 20 before that. 21 But at the same time, privacy regulation 22 can't be too lax. And this is what we're starting to 23 see, or else consumers will be unwilling to provide 24 data, and again it's going to stifle data-driven 25 innovation. And getting the balance right is going to</p>	211	<p>1 DR. GOLDFARB: Yeah. 2 AUDIENCE: -- why do you think they should 3 disclose before they are ready for a new product or 4 whatever? 5 DR. GOLDFARB: Why do I think they should 6 disclose? 7 AUDIENCE: Yeah, I don't know what you are 8 saying there. 9 DR. GOLDFARB: Oh, so, I think there's 10 potential for consumer harm from use of data, in 11 particular the fact that data is -- information is 12 non-rival and so the firm can collect it and then the 13 consumer might have very few reached rights on what 14 happens to the data after it's been collected. That's 15 a potential aspect of harm. 16 So at the same time, all of these 17 regulations we have, at least the ones we've seen so 18 far, primarily in Europe but a little bit here, are 19 not just hurting the firms' ability to profit from 20 data but also hurting the ability of the firms to help 21 consumers, and in the hospital case, save lives. 22 So to the extent that there's some way to 23 think through letting consumers know what's happening 24 with the data -- okay, so I should be clear that I 25 don't have -- I don't know what the right policy is.</p>
210	<p>1 be the key challenge in the future. And, so, we might 2 think about, to the extent that we want to think about 3 the Fair Credit Reporting Act, is there some way we 4 can enable disclosures and almost have more openness 5 about privacy. Thanks. 6 (Applause) 7 DR. STIVERS: All right, so how are we doing 8 on time, Ginger? 9 DR. JIN: Fifteen minutes. 10 DR. STIVERS: We have 15 minutes? 11 DR. JIN: Laura says 15 minutes. 12 DR. STIVERS: Oh, great, okay. Well, then, 13 first let me thank our panelists. Let me go ahead and 14 open it up to the audience first and see what 15 questions we have. 16 AUDIENCE: Avi, when you talked to your 17 comment on innovation, are you thinking of private 18 innovation? Innovation is coming in firms, right, or 19 is it public U.S.-based? What are you referring to in 20 your context? 21 DR. GOLDFARB: So, I was thinking firms, but 22 it also is related to universeness. So if you think 23 about all the research -- 24 AUDIENCE: Okay. My question is for these 25 firms --</p>	212	<p>1 I know the right policy isn't -- I know it's not a 2 good policy to say you can't use data. Okay? And, 3 so, given that in the presence of knowledge the 4 consumers seem to care about this in certain 5 situations, how can we make them able to make informed 6 decisions so that we can still have innovation and the 7 consumers are still willing to provide data to firms 8 so that firms can better serve the consumers. 9 AUDIENCE: Avi, I'm just curious to know, 10 I'm having a difficult time understanding where the 11 market failure is that we need to have some regulation 12 to actually correct this market failure in the 13 innovation. 14 DR. GOLDFARB: Okay. So that's fair, I 15 skipped that. So the fundamental market failure is 16 that information is non-rival. So once the 17 information -- once a consumer provides information -- 18 the potential for market failure, I should say, is 19 that information is non-rival. So once a consumer 20 provides information to a firm, that firm can share 21 that information and keep it. And it doesn't need to 22 tell the consumer about that. 23 So that can lead to a variety of 24 interrelated market failures. So one, for example, is 25 that we can get complete unraveling of markets, so</p>

213	<p>1 that consumers are unwilling to buy from firms because 2 they're afraid that that firm is going to share 3 information about their preferences with other firms. 4 AUDIENCE: But won't the firm then realize 5 that and then just start to close that -- 6 DR. GOLDFARB: But if there's no way to 7 commit -- so if there's no credible way to commit -- 8 because the information is non-rival, then it gets -- 9 so this is -- there was a handful of papers, Curtis 10 Taylor has a paper on this and Alessandro Acquisti and 11 others, in a paper on this that came out around the 12 same time showing that markets can unravel, and we 13 have some sense of that. 14 DR. STIVERS: And I should be clear, given 15 this is a panel, everyone else up here is welcome to 16 jump in to answer. 17 DR. JOHNSON: Just one small point, which is 18 that assumes people have a known preference, they 19 understand the problem. And if you see that they 20 change their preferences depending upon whether we 21 checked the box or not, that would make that 22 assumption questionable. 23 DR. MAYZLIN: So I'm going to add this. 24 It's not actually my research, but Alessandro Acquisti 25 has this really cool paper that shows that even, you</p>	215	<p>1 process people are using when they're answering a 2 question, can I gather personalized data. 3 So to use your example, it's known that zip 4 code, plus birthday, you know, you know who I am. Do 5 you think most consumers know that? So that's a case 6 where there's a market failure and perhaps regulation 7 is necessary. And to say people have a utility for 8 privacy when they don't even know the basic facts 9 about how the information is used seems -- I want to 10 be polite here -- seems perhaps inaccurate. And not 11 the basis of good analysis. 12 DR. GOLDFARB: Can I react to that? 13 DR. JOHNSON: Please. 14 DR. GOLDFARB: Okay. So, there is a 15 difference between saying the utility of a full- 16 information model and saying there's a fundamental 17 thing called privacy that we care about. And we're 18 mixing a little bit about privacy and security here, 19 and we'll get to that in a second, but let's just talk 20 about privacy and not worry about fraud and security, 21 okay? 22 So there is a fundamental thing called 23 privacy, perhaps, that people may or may not care 24 about, and that is a utility construct. I don't know 25 how to think about it in any other way. I'm an</p>
214	<p>1 know, just having someone's image is enough to connect 2 -- you know, to connect your data to your, you know, 3 birthday, and once you know your birthday and 4 hometown, I can get your Social Security number, and 5 once I can get your Social Security number, I can do 6 all kinds of things. 7 And, so, like this information is very basic 8 that's shared on Facebook, which people like to do 9 because they like to get happy birthday wishes. The 10 birthday and your hometown actually is, you know, 11 incredibly useful information if you want to know 12 someone's Social Security number. 13 DR. SUBRAMANIAN: My question is for Eric. 14 Eric, you mentioned that, you know, we should not 15 specify your utility function, for privacy that it's 16 an assembled construct. I think a big question is to 17 -- from the researcher's perspective is to understand 18 what is the demand for privacy, so at some point we 19 have to specify some utility for privacy, so how 20 should we do it? 21 DR. JOHNSON: Tough question. So I would 22 say the following. I think your presumption is that 23 you have to specify the classic economic utility 24 function. And you can go ahead and do that. I'm not 25 going to stop you. You just won't be describing the</p>	216	<p>1 economist; I accept that. But, you know, we're at the 2 Bureau of Economics; I'm allowed to say that. And the 3 -- that's different from saying consumers have full 4 information. 5 And we have good models of thinking about 6 information -- pretty good models of thinking about 7 information. And, so, just because we don't know how 8 to construct a full-information utility function 9 doesn't mean we should throw out the idea that there's 10 utility to privacy. 11 DR. JOHNSON: One last response. Years ago, 12 there were 13 proposals that you asked people what do you want to 14 happen in certain situations. And, so, rather than 15 every time I go to a website I have to sort of decide 16 what boxes to check -- I think one was called EPIC, I 17 forget what it stood for -- I was at FTC, maybe the 18 2000 conference. 19 So basically I say do you want other 20 companies to know -- to sell your Social Security -- 21 your birth date to other people, which, by the way, if 22 you get the zip code, it's the same thing. But, you 23 know, and you basically would make that decision once 24 with information, and then that would be captured in a 25 profile that would be carried to every website you</p>

217	<p>1 went.</p> <p>2 Now in a world of assembled preferences,</p> <p>3 that seems like a much better way of intervening than,</p> <p>4 you know, assuming that I can regenerate that every</p> <p>5 time I visit one of the 30 websites, 50 websites I</p> <p>6 visit every day. So part of it is it does matter when</p> <p>7 you come into action what are the interventions. And,</p> <p>8 so, if you help people assemble functions -- utility</p> <p>9 functions in a way they won't regret, I think that's</p> <p>10 sort of one of the interventions.</p> <p>11 AUDIENCE: I think the problem with that, I</p> <p>12 mean, that's why Facebook is so popular. It acts as</p> <p>13 just a gateway. And --</p> <p>14 DR. STIVERS: If you can wait for the --</p> <p>15 AUDIENCE: Oh, sorry. I'm still recovering,</p> <p>16 so this helps. The problem -- I mean, this is one of</p> <p>17 the reasons, you know, Facebook has become so popular</p> <p>18 for the sign-in because you don't need your</p> <p>19 credentials, right? You just use Facebook.</p> <p>20 But then the problem is people don't know</p> <p>21 that they need to go through those arcane menus to</p> <p>22 uncheck and they're passing a lot more than their zip</p> <p>23 code and their birth date, right, and all their</p> <p>24 preferences. And, you know, I'm sure you do this, and</p> <p>25 when we talk about this in our digital and social</p>	219	<p>1 that. Just my little idea.</p> <p>2 AUDIENCE: That's actually happening in the</p> <p>3 credit card industry now. Third-party -- third</p> <p>4 parties are being created that are allowing all</p> <p>5 these banks and credit cards acting as the</p> <p>6 intermediary to -- and stores can share their</p> <p>7 information into this database to then -- it's all</p> <p>8 anonymized, but then you can pull it out, just exactly</p> <p>9 what you're doing.</p> <p>10 AUDIENCE: So you were just saying, doing</p> <p>11 that, yeah.</p> <p>12 DR. STIVERS: I think in both of these --</p> <p>13 with the credit and credit cards, one of the issues</p> <p>14 that I think was hinted at -- or maybe even said</p> <p>15 explicitly by both Eric and Avi -- is this idea that</p> <p>16 accuracy is actually something that consumers care</p> <p>17 very much about.</p> <p>18 So if you have my information, if you're</p> <p>19 going to be acting on my information in some sense --</p> <p>20 and credit is one of these issues where you basically</p> <p>21 are going to be acting on that -- that's going to be,</p> <p>22 I think, potentially a way to, A, make consumers pay</p> <p>23 attention to, hey, what is this information going to</p> <p>24 have, but also to alleviate some of this, well, hey, I</p> <p>25 want to be really private. Well, but I also want you</p>
218	<p>1 media classes, students are -- have no idea this</p> <p>2 information is being shared. But then after you tell</p> <p>3 them, they don't change it.</p> <p>4 AUDIENCE: I was just thinking about what</p> <p>5 you were saying, Avi, when you talked about the Fair</p> <p>6 Credit Reporting Act and its beneficial purposes. And</p> <p>7 this is a little different than what we've just been</p> <p>8 talking about for the last minute or so. Could it be</p> <p>9 that one of the interesting differentiating aspects of</p> <p>10 that is the existence of some third-party non-</p> <p>11 individual-aligned entity where data resides?</p> <p>12 You know, as sort of an electronic ombudsman</p> <p>13 or intermediary? I was keen here on your idea about</p> <p>14 innovation. If firms want to innovate services and</p> <p>15 products that actually people want, they do need to</p> <p>16 know more about people and what they want, but maybe</p> <p>17 individuals don't want to reveal that.</p> <p>18 So if we could have third-party ombudsman</p> <p>19 like repositories of information about cohorts of</p> <p>20 people who are willing to be -- to put their</p> <p>21 information in, you know, that might create</p> <p>22 organizational structures where some data could flow.</p> <p>23 It's just a crazy little idea, but it would create an</p> <p>24 anonymized database in the same way that we benefitted</p> <p>25 from Nielsen data forever and ever and things like</p>	220	<p>1 to be really accurate in terms of how you address your</p> <p>2 decisions toward me.</p> <p>3 AUDIENCE: So, people have been talking</p> <p>4 about privacy as if it were a light switch almost. Do</p> <p>5 I want companies to have my information or not? And</p> <p>6 something I'm curious as to why nobody has mentioned,</p> <p>7 either on the panel or in the audience, I might say,</p> <p>8 do I want companies to have my information, no; but I</p> <p>9 might be willing to sell it to them, depending on --</p> <p>10 depending on the type of information.</p> <p>11 Even in the extreme case of security, I</p> <p>12 probably wouldn't sell my Social Security number to</p> <p>13 anybody, but I might sell my medical records. And --</p> <p>14 for a higher price than I'd sell my favorite color,</p> <p>15 but the issue of consumer willingness to charge, I</p> <p>16 just -- I want to open -- anyone want to comment on</p> <p>17 that?</p> <p>18 DR. MAYZLIN: I mean, Alessandro Acquisti</p> <p>19 has done some experiments on the value of privacy, and</p> <p>20 I think often it looks -- I think in the lab people</p> <p>21 say that they care a lot, but when they -- you know,</p> <p>22 revealed preference says they don't care at all. I</p> <p>23 mean, when people, you know, put all these things up</p> <p>24 online, you know, and don't have very good privacy</p> <p>25 controls set up, they act as if they don't really</p>

221	<p>1 care.</p> <p>2 So I think there's -- right, there is a big</p> <p>3 disconnect between what -- you know, what -- like if</p> <p>4 how much you want to pay for your medical records, you</p> <p>5 know, is \$100,000, but then you'd basically put it --</p> <p>6 you know, you talk about every time you're sick; you</p> <p>7 talk about -- you know, so -- so I think that's the</p> <p>8 kind of weird thing about this field.</p> <p>9 DR. GOLDFARB: So I would add a couple</p> <p>10 things. First, so we can think about a property right</p> <p>11 to the information, and that's where this would go.</p> <p>12 And you say the property right lies with people, and</p> <p>13 then they can sell it or not. If we take Garrett's</p> <p>14 results or his speculative -- you know, his ballpark</p> <p>15 numbers seriously, it's hard to think</p> <p>16 of the transaction costs of thinking through that</p> <p>17 market being sufficiently low that we can justify that any</p> <p>18 trade will happen.</p> <p>19 Maybe, you know, there's lots of great</p> <p>20 technologists in the world, and maybe eventually we'll</p> <p>21 get there, but that's, I think, a first-order</p> <p>22 challenge. And there's a second challenge, which is</p> <p>23 because information is non-rival, it becomes, once</p> <p>24 again, hard to enforce that property right in a way</p> <p>25 like you try to enforce copyright and it's hard</p>	223	<p>1 be this kind of very big gravity center, so we always</p> <p>2 -- or often tend to go there. There's a number of</p> <p>3 other topics that I would have loved to delve into</p> <p>4 that were brought up by our panelists, but we're out</p> <p>5 of time. So thank you very much.</p> <p>6 (Applause)</p> <p>7 DR. JIN: Thank you. We'll be back at 1:50.</p> <p>8</p> <p>9</p> <p>10</p> <p>11</p> <p>12</p> <p>13</p> <p>14</p> <p>15</p> <p>16</p> <p>17</p> <p>18</p> <p>19</p> <p>20</p> <p>21</p> <p>22</p> <p>23</p> <p>24</p> <p>25</p>
222	<p>1 enough. And there the incentives -- the commercial</p> <p>2 incentives are much, much higher.</p> <p>3 DR. STIVERS: Eric, if you have a quick --</p> <p>4 DR. JOHNSON: Very quick. So if this is an</p> <p>5 assembled value, the following should be true, and I</p> <p>6 bet you it is. I say you're going to buy the right to</p> <p>7 keep your information private versus you're going to</p> <p>8 sell the right. We know that from mugs</p> <p>9 that's two to one. For taboo tradeoffs, that's zero</p> <p>10 to infinity. I expect it's going to be closer to zero</p> <p>11 to infinity than it will be to one.</p> <p>12 So I don't think that value exists, although</p> <p>13 this idea is great and Esther Dyson was talking about</p> <p>14 it in 2002, and just -- the market never has happened</p> <p>15 for reasons I think Avi's right.</p> <p>16 DR. STIVERS: Well, I want to thank our --</p> <p>17 AUDIENCE: In the case of medical records,</p> <p>18 for example, there is a black market that's -- in the</p> <p>19 case of medical records, I know, for example, that</p> <p>20 there is a black market on which any of our medical</p> <p>21 information could be bought and sold that was hacked</p> <p>22 from our insurer.</p> <p>23 DR. STIVERS: Okay. Unfortunately, I do</p> <p>24 need to cut us off. I do want to thank our panelists</p> <p>25 for participating. Privacy and data security seem to</p>	224	<p>1 SESSION THREE:</p> <p>2 ALGORITHMIC BIAS? A STUDY OF THE DATA-BASED</p> <p>3 DISCRIMINATION IN THE SERVING OF ADS IN SOCIAL MEDIA</p> <p>4 DR. JIN: Hello, everyone. We're going to</p> <p>5 start.</p> <p>6 Thank you for coming back. I know the room</p> <p>7 is freezing, and we're trying to correct that. Okay,</p> <p>8 just give us a little more time. Hopefully, we'll be</p> <p>9 able to get it right.</p> <p>10 So our next session has three papers. The</p> <p>11 first one will be presented by Catherine Tucker from</p> <p>12 MIT on algorithm bias.</p> <p>13 DR. TUCKER: Okay, so thank you very much.</p> <p>14 So, this is joint work with Anja Lambrecht, who is</p> <p>15 sitting there wrapped up in multiple cardigans. And</p> <p>16 we're incredibly excited to present this today. This</p> <p>17 is the first -- a very new paper, first time we're</p> <p>18 presenting. So I'm going to try and go quite fast --</p> <p>19 it's a very simple paper -- so we can get lots of</p> <p>20 feedback.</p> <p>21 Now, what is this paper? Basically, we're</p> <p>22 going to use data from a field test and then go on to</p> <p>23 delve into whether or not it's suggestive of</p> <p>24 algorithmic bias. Before I go any further, I should</p> <p>25 say that -- I mean, I'm a marketing professor and</p>

225	<p>1 therefore very, very proud of having worked with many 2 industry associations, and, all the tech firms, 3 apart from Apple. Now because this is the FTC, I 4 should also make clear that this research was not 5 funded by anyone apart from the NSF.</p> <p>6 Okay. So let's go onwards. So our research 7 question is to basically delve into the why and to 8 start to present -- I think present -- some evidence 9 about why it is that an ad- serving 10 algorithm might appear biased. Now, why are we doing 11 this? Well, we're doing this, like you heard during 12 the panel, my gosh, we saw the privacy debate there, 13 and I was recently at FTC PrivacyCon, and let me tell 14 you, marketing professors, we should all be there, 15 it's a wonderful conference. I feel we've got a lot 16 to say.</p> <p>17 But one thing which really struck me about 18 that conference was the extent to which -- although 19 the privacy debate hasn't -- is not just focused on 20 the question of whether companies should be allowed to 21 amass data; it's also now concerned with the question 22 of, well, what harms potentially could firms do if 23 they do amass data. And one of the most highlighted 24 harms that could happen is basically the potential for 25 firms to use their algorithms and all their data to</p>	227	<p>1 So we have that result. We've sort of got 2 this headline effect, 20 percent less likely to be 3 shown to women. The question is why, and that's why 4 we think we're different in what we're doing in this 5 paper in that we show it's not to do a click 6 propensity; it's not the case that women just don't 7 click on the ad and the algorithm is reacting to it. 8 It's not the case that there was less opportunity to 9 show the ad to women because they're on social media 10 as much. And it's not the case that the algorithm had 11 learned some kind of underlying sexism from the host 12 country.</p> <p>13 Is that what we show, that in some sense 14 what we're seeing is very much unintentional bias in 15 that young women are a valuable demographic for 16 advertisers? As a result, it costs more to show ads 17 to them. And, so, if you have an ad algorithm, which 18 is just trying to minimize costs, then that can lead 19 to a situation where the algorithm shows fewer ads to 20 women.</p> <p>21 So why does this matter? Well, it matters - 22 - well, what we claim is that we're the first paper to 23 really sort of look at the why of why we might see 24 these adult-serving algorithms serve ads in what 25 appears to be a biased way. And what we show, which I</p>
226	<p>1 potentially act in a discriminatory way against 2 individuals.</p> <p>3 And, indeed, at that Privacy Con conference, 4 there were two papers which looked at ads, and they 5 both suggested that perhaps ads which might be 6 desirable were often less shown to women. And there 7 was also a paper which looked potentially at ads being 8 served less -- certain different ways depending on 9 race.</p> <p>10 Now, those papers were basically documenting 11 a pattern. And what we aim to do is build on that 12 literature and actually look at why. Why is it 13 there's an ad-serving algorithm that might produce 14 effects that make us feel uncomfortable? So what we 15 do is we have data from a field test on an ad which 16 promotes job opportunities in the STEM sector -- for 17 those of you who are not familiar with that term, 18 that's science, technology, engineering, math -- and 19 this ad is going to be shown across 190 countries.</p> <p>20 And the ad was set up as being gender- 21 neutral; however, it ended up being shown to more men 22 than women. And we might think, well, is that a 23 desirable outcome? No. Especially given that the 24 STEM sector is a set in particular which has struggled 25 to attract women.</p>	228	<p>1 think is quite intriguing, is it's not the case that 2 we have an evil ad algorithm. Instead, we have an ad 3 algorithm behaving in a way which might look biased on 4 the face of it which is the result of a series of 5 completely independent advertiser actions.</p> <p>6 And one thing I just want to take, and I'm 7 going to riff off Avi's talk earlier, is that, as 8 you've seen, the way we've always thought about 9 privacy in the legal debate at least and the legal 10 conceptualization of privacy is so often focused on 11 the individual. And as you saw the definitions of 12 privacy have focused around an individual. And I 13 think one thing this paper does is highlight the 14 extent to which we should think of privacy online as 15 often -- or the potential of privacy harms as often 16 being the result of integrated decisions.</p> <p>17 Now, why is this important? Why did we send 18 this paper, even though it was new to the FTC? The 19 reason we sent it is that we know that the FTC -- this 20 is something they're worried about. This is an 21 article from PC World where they talk about this as 22 being a -- you know, we've got people in the FTC in 23 the room who can say if this is right or not -- that 24 this has actually been a big topic of concern, 25 especially among the technologists at the FTC.</p>

229	<p>1 And why do we think it's going to be 2 hopefully somewhat useful for people thinking about 3 algorithmic bias at the FTC is that at least has been 4 discussed various policy solutions for algorithmic 5 bias; one of which I heard a lot about is a solution 6 called algorithmic transparency. And this has been 7 sort of a big slogan, I think, for a lot of tech 8 advocacy groups. And the idea is, well, maybe we 9 could stamp out bias if tech companies just made their 10 algorithms public, put them on the internet and we 11 could study them.</p> <p>12 You know, if you study this ad-serving 13 algorithm, it wouldn't help you predict that it was 14 going to react in this way which led to apparent 15 gender bias. And, so, our paper certainly suggests 16 that algorithmic transparency is not going to be a 17 complete solution.</p> <p>18 Another solution which is often discussed is 19 potentially algorithmic auditing. That is seeing what 20 algorithms are up to and just measuring the outcomes. 21 Again, I think our paper emphasizes there needs to be 22 a little bit of nuance there in that you could just do 23 the algorithmic audit, but unless you try and 24 understand why apparent algorithmic bias happens, you 25 might, I think, unconsciously, unintentionally think</p>	231	<p>1 the inspiration of this.</p> <p>2 And what they did was they basically found a 3 website that talked about careers in science, 4 technology, engineering, maths and created an ad that 5 linked up with it. And the ad was very simple. You 6 know, it's not going to win any prizes for 7 advertising. It just said there were STEM careers; 8 find out about them. That's the ad.</p> <p>9 And the ad's going to be the same. We're 10 not going to do any fancy things to the ad. All 11 that's going to vary, and I want to emphasize, I've 12 got to make sure I call this a field test, not a field 13 experiment, because we don't vary that much, but we're 14 going to target it at 191 different countries, 15 basically the entire world.</p> <p>16 We're going to make sure that the ad was 17 shown to at least 5,000 people in each country. And, 18 now, one thing I should just highlight is that when we 19 set it up, we worked very carefully to set it up to 20 say that we're going to target both men and women. We 21 didn't say men or women; we said all. And the aim was 22 to sort of try and at least choose something which on 23 the face of it was meant to be gender-neutral.</p> <p>24 Now, the only thing, as I say, that is 25 actually changing in all our settings is just the</p>
230	<p>1 there was more bias perhaps than there actually is in 2 the real market case.</p> <p>3 All right, so, that's the basic motivation. 4 Now I'm going to tell you about the field test, and I 5 actually want to tell you a little bit about the 6 origin of the test because it's quite a wonderful 7 story. So after the FTC Privacy Con conference, Anja 8 and I were inspired to basically try and echo some of 9 the results that we saw. And we sent a huge team of 10 undergraduates, and we sent them to work basically on 11 gathering data about ad serving.</p> <p>12 And now we had two groups of undergraduates. 13 One was sort of the MIT group; the other group from 14 Wellesley. And the MIT group did a wonderful job 15 basically building something very complicated to scrape 16 data; and the Wellesley team did something completely 17 different, which was really their own initiative, and 18 they did a field test. And as yet, we haven't quite 19 worked out what to do with all the wonderful MIT 20 workings, but the Wellesley thing is like brilliant 21 and, like, you know, so straightforward, simple.</p> <p>22 And, you know, we learned a lot from what 23 they did. So that's the origin, and I want to give 24 full credit to this bunch of 18- and 19-year old 25 passionate girls from Wellesley who really sort of are</p>	232	<p>1 location. We're going to have 190 different 2 locations, different countries, and we did this 3 because we wanted to sort of delve into the question 4 of whether an algorithm can unintentionally pick up on 5 the bias of the country concerned. That's been 6 discussed a lot. We're not going to find any evidence 7 of it, but that's why we did just so many countries.</p> <p>8 Now, I just want to emphasize, you know, as 9 you can tell, a wonderful team of Wellesley students 10 that, you know, they didn't have much money. NSF gave 11 them a little bit of money, but we didn't spend much 12 money on this. Why is that? Well, a lot of these 13 countries, it just doesn't cost that much to show ads 14 to them, right? It's not America. We have a little 15 bit of a tail in terms of how much we are paying to 16 show these ads, and that tail is basically driven by 17 English-speaking, rich countries.</p> <p>18 So let's now get -- I'm going to just point 19 this out. This paper, it doesn't need complex 20 analysis. I'm going to show you everything I really 21 have to say in a series of just tables. I'm going to 22 show you two tables to get cunning, but it's going to 23 be quite simple. These are basically -- this is 24 overall what happened. And you can see these are the 25 number of impressions, and you can see there's a</p>

233	<p>1 contrast between the number of times the ad was shown 2 to men and women. And you can also see how many times 3 the men and women clicked. 4 Now, I want you to notice three things from 5 this. First of all, it is the case, this ad was 6 definitely shown to fewer women than men. And that 7 difference is particularly pronounced, I would say for 8 sort of quite young women. I would also say that, you 9 know, if you look at the click figures, they look 10 quite similar right on the face of it. I could show 11 you this table in a different way. 12 And this table, you know, I could go per 13 country. You know what you should see there is just 14 basically the same pattern. It looks a little bit 15 different on the country level just because the small 16 countries tended to have fewer older people in them. 17 They were a lot of Caribbean countries. But basically 18 those three patterns hold. 19 So from the broad data, what you should see 20 is that men see more ad impressions than women, 21 headline result, particularly among younger, if you 22 look at younger ad cohorts. But the clicks appear 23 similar. 24 Okay. So, I just said this paper doesn't 25 need any complex analysis, but because we're</p>	235	<p>1 Okay. So, those are the three big results. 2 You know, they're very straightforward, just there in 3 the raw data. We're more interested in the why. Now, 4 when I have discussed this paper, you know, sort of 5 excitedly with people, you know, when you're trying to 6 tell them your research, but they never let you get to 7 the end and tell you what your result is before you 8 finish, what they always said is they've always said, 9 aah, I know why that happens; it's because women don't 10 click on the ad. Right? This is a universal sort of 11 idea that women are bringing this on themselves 12 because they're just uninterested in STEM careers. 13 Now, let me tell you, that is not what 14 happened. You saw it in the raw data. Actually, it's 15 not the case that the ad algorithm's just reacting to 16 the fact that women dislike this ad. Instead, if 17 women see this ad, they are far more likely to click 18 on it. Now, this isn't really moderated by age, but 19 we do see in general that women do click more on this 20 ad. So it's not an explanation; it's not the case 21 that simply the ad algorithm is optimizing based on 22 click totals. 23 So another potential explanation is okay. 24 Well, maybe there are just fewer women out there to 25 show the ad to on social media. Let me tell you, we</p>
234	<p>1 economists, it doesn't mean we didn't try and do a 2 regression; we did. And, so, the question is going to 3 be incredibly simple. And basically what we're going 4 to be focusing on, just in a regression format, is how 5 both the binary indicator for female affects how an ad 6 was displayed and also the interactions between that 7 binary indicator and age. 8 Now, I'm going to make you squint a little 9 bit because this is going to be our first results 10 table, and it's going to be very like what you saw in 11 those tables, but at least you get sort of an idea of 12 statistical significance. We are going to find 13 profound effects as indeed women do see less ads than 14 men. And it is particularly pronounced among women of 15 the 25 to 34 age group potentially. 16 Now, the other thing I wanted to highlight 17 is that if we just look -- you know, you can see ad 18 impressions just means the number of times an ad was 19 shown. In some ways you might be a little bit more 20 interested in the number of unique users we reached. 21 If we look at that, in fact, actually our results are, 22 I would say, almost stronger. And the reason they're 23 almost stronger was there's this odd thing that if you 24 were a woman who happened to see an ad, you tend to 25 see it more than a man.</p>	236	<p>1 have looked long and hard and we can tell you every 2 single piece ever written on this says women spend 3 more time on social media. We will get -- you know, 4 we will, if you like, pay lots of money to comScore to 5 confirm that and MicroData, but really, you know, it's 6 sort of a known fact that women spend more time on 7 social media. So we don't think it's sort of 8 constrained-ish. 9 Now, what we're interested in and why we did 10 the 190 -- that's sort of one of the original ideas 11 was this idea that unintentionally algorithms can pick 12 up the bias of their host countries. And the idea is 13 that maybe they have a training set; they've learned 14 that over time that for whatever reason women don't 15 click on this ad and so, therefore, that bias is how 16 they show ads in the future. That's the idea, and 17 that's what we're really interested in. 18 But you know what, we didn't find any 19 evidence of this going on. Instead, when we put in 20 interactions for -- at least sort of World Health 21 Organization data about female labor market 22 participation, it didn't pick up anything. So whether 23 or not women were more likely to participate in the 24 labor force, whether or not women -- I've got the 25 result, but primary education in general, whether</p>

237

1 women were more educated, that doesn't affect our
2 results. And, also, if we just take one of these
3 indices, which the World Health Organization
4 constructs for female equality, nothing changes.

5 So it's not the case that what we're picking
6 up is some lingering bias in the algorithm. Instead,
7 the result is going to be -- the actual reason we
8 think this is happening is so prosaic and a lot more
9 straightforward in some sense, which is that we think
10 it's really to do with pricing in a world where
11 advertisers are bidding on an individual eyeball.

12 Now, if you look at a lot more data, you
13 wouldn't really see this simply because we sort of see
14 the same price we're paying per click for women and
15 men, but remember, we weren't actually bidding that
16 much. And, so, there's still the potential that
17 actually what we're picking up is that we just didn't
18 bid enough to reach women.

19 And, so, to investigate this possibility,
20 what we did was we got the same wonderful team of
21 Wellesley girls to go out and actually collect lots of
22 data about bidding for women and men on Facebook. And
23 this is something Avi and I have used before, but
24 basically all social media platforms -- advertising
25 platforms basically give you data on what you should

238

1 bid. They give you some suggestions. And, you know,
2 we've made arguments in the past, at least Avi and I
3 have; we got the paper published, that this is -- you
4 know, it tells you something, right, at least about
5 what the ad algorithm wants if you look at suggestive
6 bidding.

7 So we got this suggestive bidding data
8 figure for each of our countries. And this is what we
9 found when we got this bidding data, and it was quite
10 interesting. If you just collect this bidding data on
11 average, women cost five cents more per -- five cents
12 more. That's interesting. What's also interesting is
13 that we wondered if this was actually perhaps itself
14 echoing something about the value of women, so we also
15 looked to see whether this was the result of cultural
16 prejudice. This is actually more pronounced in rich
17 countries. Women cost more in rich countries.

18 And then we went and, you know, we also got
19 this data, so basically women cost more. Women sort
20 of in these mid-tier younger sort of age groups in
21 general cost quite a bit more. And, you know, that's
22 particularly the case -- you saw -- look at the
23 maximum bid, and you might think of the maximum bid
24 here as picking up, well, what you have to do if you
25 really want to reach that demographic.

239

1 So we think maybe our result was actually
2 driven by the fact that women are just more expensive
3 to advertise to than men, and so if you tell an
4 algorithm that you're neutral and the algorithm wants
5 to save you money, it's going to inevitably end up
6 showing the ad to fewer -- to fewer women than men.
7 And that's what we think is going on.

8 Now, the next question, of course, is why.
9 Well, why do women cost more money? You know, we sort
10 of started off this paper just waving our hands and
11 saying, well, that's always been so. Women get
12 married, have babies, those things cost a lot of
13 money, maybe that's why. But then we realized we
14 actually had some data which can help us sort of think
15 about this. And this is data -- we basically got this
16 huge data set of ads from social media, and this time
17 this is consumer items, so it's an entirely different
18 data set again.

19 And we're going to see how women behave
20 about basically purchasing a wide variety of consumer
21 items, ranging from vases to sort of decorative art.
22 And when we look at this, we see some intriguing
23 things which suggest we don't just need to wave our
24 hands about why advertisers might pay for women; we
25 actually see on social media platforms that women do

240

1 seem actually likely to exhibit behavior which might
2 make them more profitable.

3 And, so, what I want you to notice here is
4 it's not the case in general that women or young
5 women, in particular, are more likely to click on ads.
6 Now, remember, on our ad, they loved the ad. They
7 liked clicking on our STEM ad, but in general, at
8 least if you show them a picture of a vase, they're
9 not more likely to click, particularly. On the other
10 hand if they do click, they're more likely to buy.

11 In other words, in a world where you're
12 paying for a click, if women are more likely to
13 convert, they're going to be more profitable. And
14 that gives us some rationalization about why it is
15 that advertisers in general may be willing to pay more
16 to advertise to a woman. So, in other words, what
17 we're picking up may be something completely rational
18 in terms of bidding behavior by advertisers.

19 Okay, so, let's get to the implications.
20 So, there's a lot of limitations, of course. This is
21 a simple field test, right? Very simple,
22 straightforward field test. And this, you know,
23 brings a descriptive to the words descriptive paper,
24 right? It's very, very descriptive, intentionally so.
25 What we do is we presented some evidence which we

241	<p>1 think -- we rule out some things, and then we present 2 some evidence in support of what we think is going on. 3 Another limitation, you know, we've got an 4 ambitious title about algorithmic bias, but we only 5 look at gender. And another big sort of limitation is 6 there are lots of big -- what I would call the non- 7 economist questions, which we don't tackle, in that, 8 you know, I use the word "bias," but is it really bias 9 when we have a world where an algorithm is simply 10 responding to a lot of competitive bidding behavior? 11 Should we call that bias? Should we think of it as 12 bias? 13 That strikes me as a wonderful ethical 14 question for a law professor. You know, also, should 15 we think of this as discrimination? Again, I know at 16 the FTC we probably have a lot of lawyers in the room, 17 right, that's the sort of questions we don't try and 18 tackle. 19 So, punchline -- it's not quite a punchline 20 because it's going to have some policy implications 21 later, but basically what we have done is we have this 22 cross-national field test. And this field test, it 23 was for a STEM ad. We tend to think of STEM as a 24 desirable thing to show at least in a gender-neutral 25 way if not trying to just because we worry about women</p>	243	<p>1 advertisers in London about this result, and they were 2 like, wow, we never thought of that. As soon as they 3 thought of it, she said, don't worry, you can solve it 4 quite easily, just run two campaigns for men and 5 women. And they were like, we never thought of that. 6 And, so, it was actually -- you know, so as you soon 7 as say it, the solution is quite obvious. 8 So, good news, managers, there's something 9 you can definitely do. But having said that, I do 10 want to raise the question. You know, we do this 11 because in some sense this is easy to do. Gender is 12 an easy thing to look at, but there may be other types 13 of bias that we worry about, such as race or economic 14 marginalization, where we may see the same unequal 15 distributions, but they're a little more difficult to 16 measure and a little bit more difficult to know what 17 to do about; so we want to highlight that. 18 Now, for policy, again, you know, we think 19 this is an interesting case study where at least if we 20 just looked at the algorithm it would just look like 21 it's profit maximizing, trying to be cost-effective, 22 no -- nothing about gender at all in it. So I'm not 23 sure if, in this case at least, algorithm transparency 24 would be helpful. 25 The other thing we want to emphasize is if</p>
242	<p>1 in the field; however, it ended up not being served to 2 women. Instead, it ended up being served to men by 3 sort of a figure of 20 percent. 4 We show -- but we show -- what's interesting 5 about the paper is not just that result. But what we 6 try and do to show why this happens, and that we show 7 it's not to do a click propensity; it's not to do with 8 local prejudice or the algorithm picking out local 9 prejudice; instead, it just simply seems to reflect 10 the fact that perhaps very rationally other 11 advertisers consider younger women -- younger female 12 cohorts to be a particularly profitable segment, and 13 as a result are willing to pay more for them. And as 14 a consequence, a algorithm which tends -- is intending 15 to make cost-effective decisions on the part of the 16 advertisers might end up showing fewer ads to women. 17 So here we have a nice -- I think a good 18 example of a case where we have apparent algorithmic 19 bias, but it's just simply an unintentional 20 consequence, what I'm going to call external behavior. 21 So what are the implications for managers? You know, 22 some marketing business school professors have to say 23 what managers should do. 24 Well, first of all, you know, since -- we've 25 actually -- Anja was talking to some people -- some</p>	244	<p>1 we go down to a world where policy is focused on auditing 2 algorithms, then I think our study does emphasize that 3 often what might look like it's a discriminatory 4 outcome can be actually the consequence of potentially 5 completely external or exogenous behavior. 6 So, with that, I will say thank you, and I 7 look forward so much to our discussant. 8 (Applause) 9 DR. JIN: Thank you, Catherine. We love 10 those creative Wellesley girls. And our discussant is 11 Kanishka Misra from UCSD. 12 DR. MISRA: Thank you very much for the 13 organizers. Thank you for having me as a discussant. 14 And thank you for sending the paper. It was really 15 fun to read. It's very simple and it's also as a 16 discussant something you appreciate. 17 I am Kanishka, and this has been verified as 18 a vendor, were trying to pose as me earlier; my ID was 19 checked on my way up, so I'm definitely Kanishka. All 20 right, so what I'm going to do is go quickly over the 21 paper and then sort of pass on some thoughts. 22 There's been a lot of discussion in the 23 popular press where it sort of headlines like STEM is 24 a huge problem. Huge -- lots of articles in all the 25 popular press about the under-representation and the</p>

245	<p>1 gender bias in STEM careers. And recently in the 2 U.K., there was a -- there was a finding that when 3 looking at college applications, if it was a female 4 name versus a male name, people viewed the application 5 differently. And they're piloting a program where 6 they're removing gender from applications, especially 7 for the STEM careers.</p> <p>8 In this paper, they're going to talk about 9 algorithmic bias, and algorithmic bias here is defined 10 as a advertising campaign that's meant to be gender- 11 neutral, but it unintentionally was not gender- 12 neutral. There were, again, another very sort of 13 popular press algorithmic bias that came out recently.</p> <p>14 This was from The Seattle Times, where 15 someone found that if you go on LinkedIn and write 16 Stephanie Williams, and actually it's true for many 17 women's names, they come and say, well, do you really 18 mean Stephen Williams, right? And that's -- again, 19 the reason why that's happening is because there are 20 just more Stephen Williams in LinkedIn's data set, and 21 that's causing sort of this apparent gender bias.</p> <p>22 All right, quickly, what does this paper do? 23 This is a field test. It's a very simple ad. That's 24 it, right? So it's a very simple ad which has do you 25 think about careers in STEM. It was targeted to 18-</p>	247	<p>1 All right, I just want to make a very 2 minor point here. All right, so, and this is more 3 the econometrician in me than what I believe, so I 4 think -- I don't believe this was driven by interest, 5 but econometrically you can say, well, perhaps the 6 women who saw the ad are the women who are really 7 interested in STEM and perhaps every other woman who 8 didn't see the ad was not interested in STEM.</p> <p>9 To truly get about interest, you have to get 10 about, well, would the people who did not see the ad 11 have clicked, and there's no way to get that answer, 12 right? But I think it's completely fair to say that 13 there's a continuous distribution of interest and 14 there is not this huge dichotomy of it, as a 15 conversion (indiscernible).</p> <p>16 What they find is if you break down this 44 17 percent by age group, you actually see enormous 18 differences across different age groups. The 19 particular age group where women tend to be under- 20 represented in their data were the 25- to 55-year- 21 olds. And the question they're after is why. So what 22 is happening? What's causing this? And why, even 23 though an ad is clearly gender-neutral and targeted 24 gender-neutral, why is this happening.</p> <p>25 Interesting, they find no differences by</p>
246	<p>1 to 65-year-olds, not by gender. So if any of you have 2 ever tried something like Facebook advertising, you 3 input where you want to show your ad, the demographics 4 you want to go after, you can go after different 5 interests. You can also go in to say, well, which -- 6 do you want to do men, women, or nothing.</p> <p>7 They said the minimum bid was 20 cents, and 8 as Catherine alluded to, English-speaking, rich 9 countries and Switzerland had about three times higher 10 sort of bid values there to do. Beyond that, they 11 collected some good data from the U.N. about sort of 12 gender equality in different countries. From that, 13 what they found is women represented less than 50 14 percent. The numbers I'm going to show in my slides 15 are for total impressions, I think, where what 16 Catherine had was for reach. The reason I have total 17 impressions is because they had that data in the 18 paper.</p> <p>19 So the main point is that even though this 20 is -- they wanted to be gender-neutral, less than 50 21 percent of women saw -- less than -- women represented 22 less than 50 percent of the reached audience. They 23 said this is not driven by interest, and the data to 24 support that is women represented 50 percent of the 25 people who actually clicked on the ad.</p>	248	<p>1 sort of this median split on the U.N. measure for 2 gender equality, education, labor market 3 participation. One thing I would really like to see 4 in the paper, you always have -- create an amount of 5 data, right? You have 191 countries, a huge 6 representation of the globe.</p> <p>7 It would be great to see more of the raw 8 data than just a regression with a gender split, just 9 to see sort of is there variation across countries. 10 And, well, I actually don't even know -- is there 11 enough variation across countries, and can something 12 else explain it, if not a median split.</p> <p>13 In order to find out more about it, they 14 collected a different data set. This is a data set 15 which looked at just the average price. Again, I 16 don't know the platform they used, but again, if you 17 order Facebook, you click whatever demographic you 18 want to go after, and then once you do that, Facebook 19 has a suggested bid or a minimum/maximum suggested 20 bid. They looked at something similar to the 21 suggested bid, and they find that's higher for women 22 and particularly higher in the range of 25 to 44, 23 which is exactly where they're under-represented in 24 their data.</p> <p>25 I went to some websites which suggest how</p>

249	<p>1 you should advertise in Facebook, and I got this 2 quote, and look, if lots of people want to reach 3 someone, prices go up, not shocking, economic free 4 market. If not lots of people want -- so it's very 5 consistent with what they're saying. 6 They go one step further and ask to say why. 7 Why is this happening, that women in sort of this 8 particular age group are targeted by so many different 9 advertisers. And for this, they collected even a 10 third data set from a U.S. retailer, and they find the 11 reason is because in this women in this age group are 12 more likely to click on an ad -- or, sorry, from a 13 click, add something to their basket and make a 14 purchase. And that's what people should ultimately 15 care about. 16 All right. Some comments. Firstly, the 17 main results are very convincing. They're very clear 18 in their raw data. They're very clear in their 19 regressions, and it's very, very convincing, right? 20 And they have multiple reasons for it. The answer -- 21 the paper is very well written. It's sort of -- it's 22 great that they collected sort of multiple data sets 23 to make their point. And there's lots of sort of face 24 validity to it. This is -- it's again the pricing 25 argument, suggestive price is exactly similar.</p>	251	<p>1 social media. 2 I will make one sort of side note about 3 this. So I did -- so for TV advertising, there are 4 some planning -- there's some sort of suggestive 5 planning websites. Thumbnail is one which I had data 6 from, but my data are about 12 years old. Twelve 7 years ago, when Thumbnail suggested how much you 8 should spend to get a woman's eyeball versus a man's 9 eyeball is exactly the same. So perhaps it's not 10 true, but it's worth looking at. 11 The second thing they look at said -- they 12 say sort of this -- and when we think about this as 13 data-based biases, the data-based biases in this paper 14 are unique to gender, but actually if you look at that 15 data, there's more than just gender in the data. 16 So I told you when I was presenting sort of 17 about what they did, they actually tripled their bid 18 prices for three countries -- or four countries. So 19 let's take a word where you do not have different -- 20 mirrored campaigns by country. You have one campaign 21 where you run it for the entire world. 22 What does this mean? Well, if you don't -- 23 if you didn't triple your bids for these four 24 countries, these four countries would be under- 25 represented, right? And that's probably not data-</p>
250	<p>1 I found a white paper which had a similar 2 result but a very different headline. The result that 3 women -- that men were cheaper to reach on Facebook. 4 Their big headline was "men are cheap," which I don't 5 know how I feel about that. They also cite other 6 papers, which other sort of white papers would suggest 7 that costs per clicks are higher -- higher for women. 8 Just some other thoughts of other reasons 9 why more advertisers might go about -- go after 10 targeting women. When I talk to advertisers, the 11 number one reason I'm always given is women are 12 decision-makers. This is true in a bunch of popular 13 press. There's an HBR article about it, and this is 14 purely saying that women make more purchase decision 15 than men; therefore, more advertisers try and target 16 women than men. 17 One thing you can potentially look at, and 18 this is sort of a question which I had in reading the 19 paper, that is this finding unique to social media or 20 is this a gender finding? Do you find this in all 21 forms of advertising? If it's driven purely by this 22 nature of women make more purchase decisions, you 23 should find it everywhere; if it's driven by something 24 inherent about women more likely to click, then 25 perhaps there's something different about sort of</p>	252	<p>1 based bias. Like, we're probably willing to accept 2 that. But, yes, it is more expensive to reach people 3 in these four countries. 4 Also, I looked at that data. So I looked at 5 their data. The orange bars here are just the 6 impressions that they had by different age groups. I 7 looked at the world population, and that's the blue 8 bar, and then I took the world population adjusted by 9 Facebook penetration. And, again, I don't know 10 Facebook by website. I'm just taking an example of 11 Facebook. 12 And what you do find is, yes, there is -- 13 their population doesn't fully represent sort of the 14 Facebook population and the world population. And is 15 that a bias, or is that something that we're sort of 16 accepting because of free market prices and they 17 aren't bidding sort of very high amounts in their 18 particular origin. So it's sort of an interesting 19 question of, well, what do we consider bias and what 20 do we -- or what are we willing to accept. 21 In terms of sort of main takeaways from the 22 study and why I think what we can learn, for 23 advertising firms, as Catherine suggested, yes, there 24 are differences. If that's important to you, you 25 should mirror your campaigns, just like they mirrored</p>

253	<p>1 campaigns for different countries, if you want to 2 reach the same number of men and women, you should 3 have a mirrored advertising campaign or you have a 4 different campaign to men, different campaign to women, just 5 because the advertising prices are 6 going to be different. 7 This problem is actually a very similar 8 problem to what people face in surveys, what people 9 face in polling, that it's just harder to reach some 10 populations than others. 11 The second question is one for the 12 advertising platform. So I actually asked some of my 13 friends who work in advertising platforms, why don't 14 you sell a way to buy ads where I can say rather than 15 going after this demographic, I want this balance of 16 demographics. The answer is they do sell it, but it's 17 part of their consulting services; it's not part of 18 the free thing you get access to. 19 For policymakers, I think the one big 20 takeaway is that if -- and I think this is important 21 and interesting to look at -- if you look at raw data 22 and something looks like bias, it's really important 23 to dive a little bit deeper to understand what's 24 causing it, and maybe it's not biased, right? Maybe 25 it's just something else, something in the algorithm</p>	255	<p>1 men, same number of clicks, right? Is that -- isn't 2 that neutral? I think the way we've been thinking 3 about it is just in terms of equality of opportunity 4 to have that click. 5 Now, I think what we could do about this 6 potentially is there are different -- you know, you 7 can tell an advertising platform to optimize different 8 things, and we could potentially look at that, too. I 9 mean, that's another way of getting at this. 10 AUDIENCE: I had a question about the 11 variation across countries. And I know that you tried 12 to do some of the United Nations index to control for 13 differences across countries. But in the price that 14 serves, you have only four developed countries. Part 15 of me is not that convinced that the cost of reaching 16 women is that high in many underdeveloped countries 17 because the purchase -- right? 18 DR. TUCKER: No, that's exactly right. This 19 is one of the things that -- you know, we had, I 20 think, going into it, this -- you could -- I shouldn't 21 speak for Anja -- but going into it, we had this 22 prejudice that somehow the price for women would be 23 worse in -- would be lower in less developed countries 24 because they were less prized. But that's not really 25 what we see. Poor countries, men and women are equal.</p>
254	<p>1 is causing it. And that's worth sort of thinking 2 about before claiming or suggesting bias. 3 There's an interesting question about 4 privacy, like what should be -- what should be sort of 5 allowed or what should not be allowed. And I think 6 especially when you talk about sort of under- 7 represented minorities, that is something that we need 8 to take a little bit more seriously in saying what 9 should you be (indiscernible). 10 All right, thank you very much. 11 (Applause) 12 DR. JIN: Thank you. We'll take a few 13 questions. Catherine, do you want to come over? 14 AUDIENCE: A very interesting paper. One 15 question I had was if the algorithm didn't take -- 16 reach as the criteria for optimization rather take 17 return on investment, taking the clicks and buying 18 into account, and given the fact that when women click 19 more often -- I mean click they also buy more often 20 than men, would this bias kind of get back to -- you 21 know, minimize this bias because of the different kind 22 of criteria that you are using? 23 DR. TUCKER: Yeah, that is an interesting 24 question because I think one thing you can say that 25 got results is, well, do you really mind that women,</p>	256	<p>1 And it's the richer countries where women are higher 2 priced. 3 AUDIENCE: Right. And, so, then, it has to 4 be very clear that like, you know, in the other 5 countries you won't see this bias, right? And, so, 6 somehow I wasn't sure that I saw that, but it's nice 7 to highlight that you don't see these bias in the 8 countries -- 9 DR. TUCKER: Oh, that's a really nice idea. 10 So, you're saying you don't see this in Rwanda, but on 11 the other hand, if we look at Taiwan, where for 12 example there's almost a dollar premium for women, 13 that's where we see it. That's a really nice idea. 14 AUDIENCE: Thank you. 15 AUDIENCE: All right, just to clarify, how 16 was the campaign optimized? 17 DR. TUCKER: So it was done -- I'm trying to 18 remember. It was -- we had a manual bid, so we tried 19 to take a bid of it. So we had a manual bid, and we 20 told the social media platform we were trying to get 21 clicks. 22 AUDIENCE: Okay, click on it. 23 DR. TUCKER: Yeah. 24 AUDIENCE: Okay. 25 DR. TUCKER: Well, thank you. And can I</p>

257	<p>1 just say so much thanks for our discussant because 2 what he didn't actually say was that he spent this 3 entire week finding out all the mistakes that we made 4 in the first draft of the paper and telling us, so 5 he's just been amazing. So I just want to sort of 6 give him a big shout-out. Thank you so, so much. 7 (Applause) 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>	259	<p>1 economic students, there is no karma this business. 2 So, you know, so that's great. 3 So what is this paper about? So the paper 4 is about -- 5 (Applause) 6 DR. YOGANARASIMHAN: Yeah. I'll be fine. 7 Oh, okay, it was the mic, not me. 8 Okay, so am I supposed to hold this 9 throughout? 10 (Laughter) 11 DR. YOGANARASIMHAN: I see, okay. So what's 12 the paper about? So it's about the value of 13 information in mobile ad targeting. So we're going to 14 look at what kind of information helps with targeting, 15 how do you effectively measure the value of this 16 information, and a little bit look at what are some of 17 the privacy implications of storing and sharing this 18 information. So that's really the goal here. 19 So let me start by giving you a little bit 20 of background about the smartphone industry. I'm sure 21 all of you probably know these numbers. So for me it 22 was a little bit surprising when I first saw that 23 there are 2 billion smartphone users in the world. I 24 didn't know there were 2 billion people, so this was 25 interesting. There are actually 7 billion people, in</p>
258	<p>1 THE VALUE OF INFORMATION IN MOBILE AD TARGETING 2 DR. JIN: Thank you. We'll switch the order 3 of the next two papers because Hema has a plane to 4 catch. So the next paper will be presented by Hema 5 Yoganarasimhan -- hopefully I got the name right -- 6 from the University of Washington about the value of 7 information in mobile ad targeting. 8 DR. YOGANARASIMHAN: Thank you. No, I was 9 asking around, but no one told me it was actually 10 eventually switched, so that's good. Thank you. 11 Okay, great. Oh, I have to speak in the 12 mic, okay. 13 Okay, so, first of all, thank you to the 14 organizers, both FTC and Marketing Science, for not 15 just organizing this conference but also taking this 16 paper. So it's still in pretty early stages, so, you 17 know, this is a good opportunity for me to -- okay, 18 mic. Okay. 19 So I'm hoping to get a lot of good feedback. 20 I'm not good at this. So I'm hoping to get a lot of 21 good feedback which might be helpful to the paper 22 going forward. And I should say this was joint work 23 with my first-year Ph.D. student, Omid, who has really 24 been amazing in the kind of work that he's been doing. 25 Faces are looking shocked and annoyed, but with</p>	260	<p>1 case you guys didn't know. 2 So and the average, 18 percent, about 2.8 3 are on the iPhone, so that's quite a bit of, you know, 4 internet usage through mobile phones. And much of 5 this usage is coming not through browsers, as you 6 might expect, but it's through programs which are 7 known as applications or apps. Okay, and just to give 8 you some numbers, again, there are about 25 billion 9 iOS apps which have been at least downloaded once and 10 around 50 billion Android apps. 11 So as you can imagine, then, given that this 12 app usage is really driving this industry so much, 13 both development as well as monetization of these apps 14 is of interest to many players in this industry. So 15 there are three really main or broad monetization 16 strategies out there for apps. So what are they? The 17 first is the paid model. So if you want an app, you 18 go pay \$4, \$5, whatever when you download it and you 19 can use it. 20 The second is, you know, what's known as now 21 the freemium model where you can download a free 22 version of the app which is basic, and if you want 23 some extra features or a premium version, you're going 24 to pay some extra money. 25 And the third is what we're going to focus</p>

261

1 on, which is in-app advertising, and probably the most
2 popular way to monetize ads where what you are going
3 to do is you can go download the app, and it's free
4 and you can use it, but every time you're going to use
5 it you're going to be shown some ads. And that's how
6 the developer is monetizing that.

7 Okay. Okay, so, let's talk a little bit
8 more about in-app advertising, because that's what we
9 are going to be really looking at. So I'm sure all of
10 you have seen in-app ads. In case you haven't, here
11 is an example. That little diamond that you see in
12 the bottom is really the in-app ad. It's quite small.
13 If you click on it, it takes you to the advertiser's
14 website.

15 And, you know, just again some numbers about
16 mobile ad space, it's about \$13 billion, and I don't
17 have the exact -- I don't have the exact number on how
18 much of this is in-app advertising, but quite a big
19 chunk is. So who are some of the key players in the
20 industry here? So the first is, of course, the
21 publishers who are the people making these apps and
22 hosting them and looking to monetize them. And these
23 are the people who are going to host the ads
24 eventually.

25 And there are also the advertisers who are

262

1 going to bid and place ads. And most important player
2 probably who is not visible to consumers is really the
3 ad network, which is this two-sided platform which is
4 going to match publishers and advertisers.

5 So one common goal all of them have here is
6 that to increase ad response rates if they could,
7 keeping everything else constant. So I wouldn't say,
8 you know, these other things change, so it's sort of
9 always the case that even if prices go up you don't
10 want necessarily ad response to go up, but everything
11 else being held constant, each player has some
12 interest in seeing ad response increased. And how do
13 we do that? We, you know, in marketing obviously the
14 answer is that we do that with targeting.

15 So what is targeting specifically in this
16 context? So targeting is basically you have an
17 impression, which is a user who is looking at an app
18 at a given point in time, and you have a set of ads
19 that you can show this user, and which ad do you
20 actually show them. So that's really the question
21 that they're grappling with.

22 And, you know, there's been a lot of
23 research in marketing, especially, you know, in the TV
24 world and in the offline world on how to do effective
25 marketing, but in the online or in the mobile setting,

263

1 you know, you can't do really demographic-based
2 targeting or segmentation. So the two main ways to do
3 targeting really is behavioral, which is going to use
4 data on what the user did in the past, so, you know,
5 what kind of apps he or she looked at and what ads
6 they clicked on or what ads they did not click on. So
7 everything about their behavior from the past. So
8 that would be behavior targeting.

9 There's also contextual targeting, which
10 takes into account not so much the behavior of the
11 user but the context in which the impression is
12 happening. So what kind of app they are in and what
13 time of the day are they using the app and so on. So
14 that would be contextual targeting.

15 So those are the variables on which you
16 could be targeting, but there's also another factor
17 which affects how well you can target, and that's the
18 data that you have. So how -- you know, so if you're
19 going to be training these models, what size of the
20 data and at what level of granularity do you have it;
21 is it very fine-grained or is it going to be
22 aggregated, and what is the length of the status, so
23 do you have one month, one year, and, you know, do you
24 really need so long?

25 And, finally, depending on who is actually

264

1 doing this targeting or who is doing the bidding, you
2 also have to worry about whether you can combine data
3 across certain sources. So these are some of the
4 things about targeting from the industry's
5 perspective.

6 From consumers' perspective, of course,
7 targeting can potentially be good because you see
8 relevant ads in that case, but it comes with a certain
9 cost because targeting by definition means that the
10 advertiser and the platform know something about the
11 user and, you know, and that's what they're basing,
12 you know, the ads that they're being shown on.

13 So this is specific to the mobile context.
14 So in the mobile setting, you know, tracking of users
15 is actually very persistent. It's even more
16 persistent than other online settings. So, for
17 example, I don't know how many of you have done
18 this, so if you go to your mobile devices, there's
19 something called Ad-ID, which you can reset, but then
20 you reset it, everything that you're doing through
21 mobile phone can be linked across all the apps and
22 across all the -- even the browser, I think, depending
23 on how it's set up.

24 So a few years back, the system was actually
25 even worse. So there was no way you could reset this

<p style="text-align: right;">265</p> <p>1 Ad-ID, so anytime you -- if you did something on your 2 phone and a few months later you did something else on 3 a completely different ad, these two actions could be 4 linked using the device ID. So then Apple introduced 5 what was known as Ad-ID, which Android also mirrored. 6 So things are a little bit better now. 7 But now there's this question about, you 8 know, apps merging data, advertisers merging data and 9 so on as to whether these should be allowed and, you 10 know, to what extent should even -- you know, we 11 should have Ad-ID, should we even get rid of Ad-ID and 12 not give this access to consumers so to advertisers. 13 So this is some of the background from the 14 consumers' perspective. So what are we going to be 15 doing here given this background? So from a 16 substantive perspective, the first question we're 17 really going to be looking at is we want to understand 18 how much does targeting really improve the 19 effectiveness of mobile ads, in-app ads. 20 So we really want to know -- we want to 21 measure the target, you know, consumer response rate 22 of in-app targeting. And that's from just a, you 23 know, understanding, you know, how much does targeting 24 help, but then we want to look at what if targeting 25 were actually making consumers more responsive, what</p>	<p style="text-align: right;">267</p> <p>1 where the platform is not sharing much data with 2 advertisers in terms of what the user behavior is. If 3 you could allow more and more data sharing between the 4 platform and the advertisers and between advertisers 5 themselves, how much better could they target? Okay, 6 so these are some of the questions we want to 7 understand. 8 Okay, so given that that's what we want to 9 do, what is the most -- the challenges? The first, of 10 course, is that we really -- we really need a model 11 with very high predictive accuracy. And standard 12 econometric models, which focus on causality, don't 13 necessarily work very well in this case, right? 14 So because what -- what those kind -- what 15 these models generally do is you have some kind of a 16 model, however nonparametric you might make it, and 17 then given the margin of consumer behavior, you try to 18 devise some parametric estimates. And what the 19 problem that you are getting worried about is things 20 like endogeneity concerns and so on because you're 21 trying to make counterfactual predictions. 22 But when you are looking at a prediction 23 problem, so we are not really trying to understand why 24 you were targeting the effect there, right? So we are 25 to some extent, but we are not really saying -- you</p>
<p style="text-align: right;">266</p> <p>1 is driving that, right? You know, what is 2 substantive. Is it contextual information? Is it 3 behavioral information? Is it a combination of both, 4 and what kind of information? 5 And we also want to look at what's the value 6 of data really and what's the value of more or better 7 data in this context, right? And that's really for 8 the standard perspective. From a methodological 9 perspective, we want to really understand what kind of 10 models perform well if you want to measure the returns 11 to advertising. We want to look at econometric 12 models, some of the standard ones, and compare them to 13 some of the machine-learning methods and see are they 14 better at being able to predict those. 15 And, finally, once we have some results in 16 that, we want to then go and make a few changes in the 17 system and look at two kinds of -- two broad kind of 18 questions. One is what if tied into privacy 19 regulations? What if you got rid of Ad-ID and you 20 told advertisers on the platform that there is no more 21 Ad-ID, you know, use some other metric to track 22 consumers if you could. And how much worse off would 23 we be in our ability to target? 24 And the other thing we want to look at is 25 something which is not happening on the platform now</p>	<p style="text-align: right;">268</p> <p>1 know, our bigger goal is to measure the effectiveness 2 of targeting. So we are trying to make the best 3 possible off-sample prediction that we can, right? 4 So in that case, when you need high out-of- 5 sample predictive accuracy, your search space, from a 6 modeling perspective, it's not just over parameters 7 given model, but it's over actually the models 8 themselves, right? So that's really a tricky problem. 9 Then you're running into things like bias-variance, 10 tradeoff and so on. 11 So what this translates to is like when you 12 want prediction, you have really working with a very 13 large number of attributes, and when you fix the 14 function of form and try to estimate parameters, 15 you're going to get mediocre results. You want to 16 also look at, you know, input for the function and 17 form and the parameters, and even when you have 18 something as simple as 38 features allowing two-way 19 interactions is going to blow this problem up and make 20 it into 1,600 features, right? So in the computer 21 science language, you would call this an NP hard 22 problem. It's not part of linear time. 23 So, you know, so those are some of the 24 things that, you know, the problems that we run into, 25 and that's why you see we turned to some of the</p>

269	<p>1 mission-learning algorithms.</p> <p>2 Okay, so, there's a lot of related</p> <p>3 literature here, and many of the people who have all</p> <p>4 done this are all in this room, so that's good. So --</p> <p>5 but unfortunately because of time constraints, I'm not</p> <p>6 going to get into all of them. But it was -- but it</p> <p>7 was interesting for me to notice that so many of the</p> <p>8 people who have worked on this are here. And</p> <p>9 especially I think Avi and Catherine. I think we were</p> <p>10 exciting because it was like A, B, C, D. I'm like,</p> <p>11 wow, how many papers, like, you know, in the same year</p> <p>12 and by the same authors.</p> <p>13 Okay, so, with that, let me move on and talk</p> <p>14 a little bit about the data itself. Okay, so, the</p> <p>15 data comes from actually the major in-app advertising</p> <p>16 platform, as well as the App Store in Iran. Again,</p> <p>17 this is, you know, because of my very enterprising</p> <p>18 Ph.D. student, usually when I ask for data people</p> <p>19 always just say no. But it looks like when he asks</p> <p>20 for data, people always say yes.</p> <p>21 So this -- as you might know, in Iran,</p> <p>22 American, you know, companies are not allowed to</p> <p>23 operate, but it's a very high-tech country, which</p> <p>24 means they have a very wide range -- local IP system.</p> <p>25 So think of this as a pattern of Google Play in Iran.</p>	271	<p>1 all the history from one month before, and that is</p> <p>2 about 135 million impressions that we work with.</p> <p>3 Okay, and that's what we use to generate the features.</p> <p>4 So what does the data actually look like?</p> <p>5 So the data is -- if you looked at the raw data, it's</p> <p>6 basically going to be for each impression it's going</p> <p>7 to tell you this Ad-ID, which is the user-resettable,</p> <p>8 device-specific ID. So until the user resets it, we</p> <p>9 know that this is this person, okay? And every time</p> <p>10 they reset it, it's a completely new ID.</p> <p>11 We also know what is the app in which the</p> <p>12 impression happened, what was the ad that was shown.</p> <p>13 And we also have interesting education, which is the</p> <p>14 IP address of the person or the phone, which was being</p> <p>15 used. And we know of the time at which the impression</p> <p>16 happened, as well as the click indicator.</p> <p>17 Okay, so, now let me talk a little bit about</p> <p>18 the framework. So that's the data, and that's what --</p> <p>19 you know, we talked about the data now let me</p> <p>20 tell you a little bit more about what we do. So</p> <p>21 before I talk about the model, I just wanted to define</p> <p>22 the problem formally. So the problem is one of</p> <p>23 prediction, which is to accurately predict the</p> <p>24 property that an impression I, by a user U, in app B</p> <p>25 for an ad A at a given point in time with some global</p>
270	<p>1 So this is -- they're both selling apps, as well as</p> <p>2 selling ads, selling, you know, have this platform to</p> <p>3 sell ads and our data is from the ad platform.</p> <p>4 So it's about -- you know, I think it's one</p> <p>5 of the top three IT companies in Iran, and it sells</p> <p>6 over 50 million ads daily in mobile apps, so that's</p> <p>7 quite a lot of ads. And they have about 25,000 apps</p> <p>8 and 250 ads, and this ad site is growing quite a bit.</p> <p>9 Okay, so, let's talk about the data and</p> <p>10 sampling. So what we do is we focus on the top 50 ads</p> <p>11 and the top 50 apps, which is approximately about 80</p> <p>12 percent of the impression. And because of the model</p> <p>13 that you see, what we need -- we use, we need to</p> <p>14 sample the data. We are not going to use all of it,</p> <p>15 but the sampling is going to be over first -- or with</p> <p>16 users on a three-day framework. So we are going to</p> <p>17 take two days for training and one day for testing,</p> <p>18 and that's over about -- about 27,000 users. And</p> <p>19 which translates to about 17.7 million impressions for</p> <p>20 training in these two days, and about 9 million</p> <p>21 impressions for testing.</p> <p>22 But to actually do this training and</p> <p>23 testing, you need a history of information, right,</p> <p>24 which is the features that you're going to target</p> <p>25 these people on. And for that, we go back and look at</p>	272	<p>1 history H will lead to a click, right? So this is</p> <p>2 what you're trying to do.</p> <p>3 So, then, the goal is to devise an algorithm</p> <p>4 that takes as input a set of preclassified data,</p> <p>5 right? So this is the data for which you know that</p> <p>6 this is -- these are the impressions and at least some</p> <p>7 led to clicks, some did not lead to clicks, right?</p> <p>8 And to generate an output probably which is as close</p> <p>9 as possible to the true click property as in the test</p> <p>10 data, which is a completely different data from the</p> <p>11 training data.</p> <p>12 So if you want to write this algorithm --</p> <p>13 sorry, then what do you need basically? You need, I</p> <p>14 think, three sets of input apart from the data. So</p> <p>15 one is you need an evaluation method. You need</p> <p>16 something to tell you how well you are doing, right?</p> <p>17 And you could come up with many different evaluation</p> <p>18 methods.</p> <p>19 The second is you need a feature set, and</p> <p>20 this is the -- what in marketing -- in the standard</p> <p>21 parlance we often call attributes or explanatory</p> <p>22 variables, right? So it's a set of features. And,</p> <p>23 then, finally, you need a classifying algorithm. And</p> <p>24 because we have our training data where we know the</p> <p>25 outcomes, this is basically a supervised learning</p>

273	<p>1 algorithm, right? So that's what it is.</p> <p>2 Okay, so, briefly about each of these. So</p> <p>3 the evaluation metric we use is quite standard. It's</p> <p>4 basically the -- we take the log loss to begin with,</p> <p>5 which is, you know, some people often also call it</p> <p>6 entropy, but comparing log loss even across different</p> <p>7 data sets can be tricky because the baseline measure</p> <p>8 of how many clicks in a given data there is could be</p> <p>9 very different.</p> <p>10 So you want to normalize it by how much --</p> <p>11 you know, if you had to make, like, just average</p> <p>12 prediction, right, out of 101 -- you got one click,</p> <p>13 which was one person, and how much better can you do</p> <p>14 with your model, right? So that's why we do something</p> <p>15 like relative information gained which, you know,</p> <p>16 normalizes and based on like a completely uninformed</p> <p>17 guess that you could make.</p> <p>18 So that is the evaluation metric we use.</p> <p>19 And to generate the features, we use a framework for</p> <p>20 feature generation, and this is something that I based</p> <p>21 on one of the papers that I worked on in the past.</p> <p>22 When you generate features, you run into this problem</p> <p>23 of, like, exponentially like expanding number of</p> <p>24 features, so you have to keep track also instead of</p> <p>25 that, that's why I used this functional framework.</p>	275	<p>1 Okay, wow, five minutes. I'll be quick.</p> <p>2 So obviously there is OLS, there is logistic</p> <p>3 regressions, and the one we use is boosted trees,</p> <p>4 which I'll explain</p> <p>5 in the next slide is a boosted version of CART --</p> <p>6 classification and regulation trees -- and I've used</p> <p>7 it before in an earlier paper, and it worked very</p> <p>8 well. I could beat a bunch of -- beat out a bunch of</p> <p>9 Kagglers in the prediction context. So I</p> <p>10 assumed that if I could pick out a bunch of like</p> <p>11 computer science Kagglers that you don't -- this has</p> <p>12 worked well, it turns out my hunch was right.</p> <p>13 And we also have a chapter on using machine-</p> <p>14 learning methods in marketing where we explain this a</p> <p>15 lot more, in case you are interested.</p> <p>16 So what is the brief one-slide overview of</p> <p>17 MART? So it takes classification and regulation</p> <p>18 trees, which are essentially just trying to classify</p> <p>19 the data in very, very simple way, multi-</p> <p>20 conventionally, and tries to boost them, which is like</p> <p>21 add more and more of them to reduce the prediction</p> <p>22 error as we add more.</p> <p>23 The nice thing about MART is that it does</p> <p>24 automatic variable selection. You know, you're not</p> <p>25 working with the 1,600 variables. It does</p>
274	<p>1 And this functional framework works where it takes</p> <p>2 this input -- each function basically takes three or</p> <p>3 four inputs, which it relates to something about the</p> <p>4 data -- the user, the ad, or the ad or the time in</p> <p>5 which the impression happens, right?</p> <p>6 And we had these features based on the</p> <p>7 impression, based on clicks, based on click-through</p> <p>8 rate, based on the variability in all the variants and</p> <p>9 how many ads people have seen or how many apps they</p> <p>10 are using. So this is one way to actually generate</p> <p>11 the features, but once you've generated them, what's</p> <p>12 useful to do is to classify them as behavioral</p> <p>13 features or contextual features or potentially both,</p> <p>14 right?</p> <p>15 So, behavioral features are features which</p> <p>16 are based simply on user behavior with pure behavior</p> <p>17 features are ones which are based on user behavior</p> <p>18 with absolutely no contextual information, like</p> <p>19 contextual features that I'm going to get contextual</p> <p>20 features which might not necessarily have behavioral</p> <p>21 information, and then there are, you know, features</p> <p>22 which can do both.</p> <p>23 Okay, so, now let's talk briefly about the</p> <p>24 classifying algorithm. So you can -- you know, there</p> <p>25 are zillions of classifying algorithms out there.</p>	276	<p>1 automatic variable selection, and it can incorporate,</p> <p>2 like, lots and lots of variables in a nonlinear way.</p> <p>3 And it has been empirically shown to be the best</p> <p>4 classified in the world, so that's -- so that's one of</p> <p>5 the reasons we use it.</p> <p>6 Okay, so, that's the framework we use. Let</p> <p>7 me talk briefly about the results. So what this table</p> <p>8 shows is on the rows it shows the different methods of</p> <p>9 classifying algorithms. And on the -- in the columns,</p> <p>10 it shows what are the features it takes as input,</p> <p>11 okay? So the top row is all from MART. And you can</p> <p>12 see that basically MART outperforms, you know, the</p> <p>13 baseline prediction, and the logit models and OLS</p> <p>14 models, by a very significant amount, so margins --</p> <p>15 you know, completely like, you know, beats them, so</p> <p>16 that's -- so that's one thing.</p> <p>17 The second thing is when you look at the</p> <p>18 features, then, so what you know is that behavioral</p> <p>19 targeting is much more than just even pure behavior</p> <p>20 targeting which is the first column where you throw</p> <p>21 out all the contextual information; it's still much</p> <p>22 better than, you know, this pure contextual targeting.</p> <p>23 Of course, when you combine both, you are</p> <p>24 much better off, but what it's telling you is that</p> <p>25 user-specific information is more valuable than</p>

277	<p>1 context-specific information. And within context-</p> <p>2 specific information, we find that app-specific</p> <p>3 features are much more valuable than ad-specific</p> <p>4 features, which means that what's -- ad -- you know,</p> <p>5 one interesting thing about this platform, which I</p> <p>6 didn't have time to talk about, is that all ads end up</p> <p>7 being shown in all apps. So the ad itself is not</p> <p>8 necessarily very informative. We also thought maybe</p> <p>9 because the ad is very small and there is not much</p> <p>10 information in the ad, maybe that's why the ad itself</p> <p>11 is not giving too much information.</p> <p>12 But, you know, apps seem very informative.</p> <p>13 And overall model prediction is pretty good, so you</p> <p>14 see about a 15.2 percent improvement in predictive</p> <p>15 accuracy compared to like a baseline where you are</p> <p>16 just making an average guess.</p> <p>17 Okay, so, now let's take this model and try</p> <p>18 to think about some of the questions that we had</p> <p>19 earlier. So first question we really had is what if</p> <p>20 you got rid of Ad-ID, which is always a discussion</p> <p>21 which is happening, right? Why do you want to track</p> <p>22 people using this special ID, in which case they will</p> <p>23 be forced to rely on IP addresses, right? So that's</p> <p>24 the first question.</p> <p>25 The second question we wanted to ask is,</p>	279	<p>1 So, now, the next one, if platforms are</p> <p>2 allowed to share data with advertisers what would</p> <p>3 happen. We considered what would -- what's the best</p> <p>4 case scenario now because as we get data on what is</p> <p>5 the ad-specific CTR. So we look at what happens if</p> <p>6 they had access to better data, which is ad-app-</p> <p>7 specific CTR. They told you, okay, in this app, this</p> <p>8 is your click-through rate.</p> <p>9 And what if we actually gave them all your</p> <p>10 individual-level data for all the ads that are shown</p> <p>11 to you, for your ad. And then if we gave them -- this</p> <p>12 is the scenario for which is I think the most</p> <p>13 interesting, when you give them data from their own</p> <p>14 ads and give them some kind of cookie kind of</p> <p>15 information, with just your like history, without the</p> <p>16 actual individual-level data, right? And the fifth</p> <p>17 one is what, of course, advertisers really want. They</p> <p>18 want access to all the data, right? So, there will be</p> <p>19 an outcome there, what happens in this case?</p> <p>20 So, of course, what's interesting is that we</p> <p>21 find -- well, we find that at least privacy-preserving</p> <p>22 arrangements are the best in terms of targeting, we</p> <p>23 get very close to it by preserving ad user privacy,</p> <p>24 which is that the scenario in which we give -- as you</p> <p>25 can see, if you compare scenarios 4 and 5, they are</p>
278	<p>1 okay, now what if you actually weaken privacy</p> <p>2 regulations, which the platform has put in place,</p> <p>3 which is that as the platform, if I want to allow the</p> <p>4 sharing of data with advertisers at different levels of</p> <p>5 granularity, what would happen. And once you start</p> <p>6 allowing -- once you start sharing data with</p> <p>7 advertisers, they could share it among each other.</p> <p>8 Then what would happen? Okay, so, that's the second</p> <p>9 question.</p> <p>10 Okay, so the first thing is the value of</p> <p>11 users identify as Ad-ID versus IP address. So we do</p> <p>12 notice that if you moved from Ad-ID to IP addresses,</p> <p>13 you are going to be worse off. And significantly</p> <p>14 worse off. Unlike ad IDs, IP addresses change</p> <p>15 automatically. These ad IDs, you have to go to reset;</p> <p>16 for IP addresses, that's not the case. You move from</p> <p>17 one network connectivity to another, that's going to</p> <p>18 naturally change.</p> <p>19 They are also going to be masked people</p> <p>20 behind VPNs are all going to show up under the same IP</p> <p>21 address, which means that you're -- you know, pooling</p> <p>22 all these users together, which is bad. So we find</p> <p>23 that actually getting rid of Ad-ID would be bad from a</p> <p>24 targeting perspective. And it goes from about, like,</p> <p>25 you know 5 percent loss is what we find.</p>	280	<p>1 very similar. So very few actually hold back the</p> <p>2 individual-level data from advertisers across ads but</p> <p>3 give them their own advertising data and give them</p> <p>4 this feature set, which really does not tell them much</p> <p>5 about the user once they go out of the system.</p> <p>6 Actually, you do get reasonably close to the first</p> <p>7 best scenario. So if you're able to do -- show that</p> <p>8 you can, you know, maintain privacy at the same time,</p> <p>9 maybe, you know, get reasonably good targeting.</p> <p>10 And we also look at which advertisers</p> <p>11 benefit. We find that large advertisers actually</p> <p>12 benefit the most from these, followed by smaller and</p> <p>13 medium advertisers. The ones who control for the size</p> <p>14 of the data, the variation in the data is what it has.</p> <p>15 So even if you're a small advertiser, if you see a lot</p> <p>16 of clicks in your data, that tells that your data is</p> <p>17 more informative. So it's not just, you know, if</p> <p>18 you're large then you benefit more from this; if</p> <p>19 you're small and then you have a lot of variation, you</p> <p>20 might actually benefit more from this.</p> <p>21 Okay, so, finally, we asked this question of</p> <p>22 what if you allowed advertisers to share data now. So</p> <p>23 each advertiser has access to their own data and now</p> <p>24 if they could share data with each other what happens.</p> <p>25 And then we look at the sharing past. We take each --</p>

281	<p>1 you know, the top 50 advertisers and we pair them with 2 each other and say now if you pool together our data, 3 how much better could we do compared to just, you 4 know, using our own data.</p> <p>5 And, again, we find that larger -- so, here 6 we find that larger advertisers gained less from 7 sharing because their own data is reasonably 8 informative. But -- and -- but we also find that when 9 both advertisers are advertising in similar contexts, 10 their sharing is much more valuable. But one of the 11 things we persistently find is that incentives of the 12 sharing pairs are not perfectly aligned. So one 13 always benefits, you know, significantly more than the 14 other, which means that even if you allow this kind of 15 data sharing they might choose not to do it because 16 that is not an incentive-compatible payment system out 17 there.</p> <p>18 Okay, so, I think I'm out of time. 19 Actually, I can see you're nodding vigorously. So 20 what does this -- I think we can all agree that 21 targeting is an important decision in mobile 22 advertising, and what we are really trying to look at, 23 you know, it comes with significant privacy concerns, 24 and we are trying to look at this and find some 25 answers on how do you actually do targeting, how do</p>	283	<p>1 literature and so on.</p> <p>2 So first I'll go through a quick overview of 3 the paper, then kind of try and kind of give a very 4 brief intuition for some of the algorithmic part, 5 which Hema didn't talk about at a pretty high level 6 and then go into some comments and some suggestions.</p> <p>7 So here's the research questions that this 8 paper is trying to tackle. So ad networks have a lot 9 of information, historical information, and they can 10 share this information at different levels, and they 11 have either based on regulation or internal policies, 12 they have -- you know, different networks have 13 different levels of sharing of information with 14 advertisers.</p> <p>15 So the question is, you know, what is the 16 value of this information, both to the network, to the 17 advertisers, and specifically, you know, what this 18 paper is trying to ask is specifically looking at the 19 question of, you know, in terms of prediction of 20 clicks by consumers, right? So what kind of 21 information is valuable, and what kind of aggregation 22 of that and so. And finally to whom, right? And, so, 23 those are the kind of broad set of questions that this 24 paper is trying to -- trying to answer, the standard 25 questions.</p>
282	<p>1 you measure the value of targeting, what helps, and 2 we're also trying to look a little bit more at 3 incentives.</p> <p>4 Some of those, you know, unfortunately I 5 could not present a little bit more on whether the 6 platform wants to share data with advertisers. And, 7 again, that also we find that it doesn't. So that's 8 pretty much what I had to say. Thank you so much. 9 (Applause)</p> <p>10 DR. JIN: Thank you. Our discussant is 11 Sridhar Narayanan from Stanford.</p> <p>12 DR. NARAYANAN: I'll just use this.</p> <p>13 Okay, full thanks to the organizers for 14 putting together a wonderful conference and 15 specifically for asking me to be a discussant on this 16 paper. Kanishka mentioned that it was, you know, fun 17 to discuss the paper because of how clearly and easy 18 it was to read. In this case, it was -- for me, you 19 know, I'm not saying it wasn't clear. The additional 20 thing for me was that it also made me, you know, sent 21 me on this journey of reading lots of papers in the 22 media that I wasn't -- you know, I knew a little bit 23 about it, but I'm kind of vague on the details of it, 24 so it was fun to do this. Okay, all right, and 25 specifically referring to all the machine-learning</p>	284	<p>1 The overall approach is going to be to build 2 a prediction model for predicting clicks by consumers. 3 And then use this historical information, in this case 4 a month's information, to build a set of predictive 5 variables. Hema didn't talk about this, but they 6 actually did some work to try and figure out how much 7 and look at the volume of information. Does adding 8 more information actually help in any significant way. 9 And the broad conclusion -- I'm jumping ahead a little 10 bit here -- but is that, you know, that there's a lot 11 of value in relatively limited information.</p> <p>12 All right. And, so, the next step is that 13 they're going to take -- compare different approaches, 14 specifically a couple of, you know, common, go-to 15 econometric approaches with a couple of -- with one 16 basic machine-learning algorithm, MART. And I'll come 17 back to that in a moment. And then compare different 18 kind of information-sharing scenarios, you know, using 19 the kind of model that they've used to predict clicks. 20 So that's going to be the broad kind of overall 21 approach.</p> <p>22 Now, I'll kind of do a little bit of a 23 detour talking about CART and MART specifically 24 because, you know, partly because this was kind of -- 25 I'd read about it, but it was good to get refreshed,</p>

285	<p>1 and I thought I'd share just kind of broad intuitions 2 that I gained from that.</p> <p>3 So the problem that these kinds of 4 algorithms are trying to solve, or at least one of the 5 problems that they're trying to solve is that there's 6 potentially a very large set of predictive variables. 7 And we want to predict some outcomes from them. So if 8 you try to kind of use some kind of linear or 9 polynomial regressions, one of the kind of underlying 10 assumptions is that there is a globally kind of valid 11 relationship between these predictive variables and 12 these outcomes, right?</p> <p>13 And, you know, if you kind of tried to make 14 it such that, you know, such that this assumption is 15 relaxed, you have an incredibly large set of potential 16 interactions, not just two-way, but three, four, five, 17 1,500-way interactions potentially that you have to 18 kind of think about. And, so, it kind of becomes and 19 an impossible problem to solve using those traditional 20 approaches. Okay.</p> <p>21 So in reality, in different sub-spaces of 22 the data, you might have very different relationships 23 that exist between the predictive variables and 24 outcome variables. So what does CART do? Basically 25 it recursively partitions the data space based on a</p>	287	<p>1 candidates is in terms of preferences of workers is 2 potentially this, and, you know, maybe -- I mean, I'm 3 not basing this on any data. This is just pulled out 4 of, you know -- pulled out of my hat.</p> <p>5 But, basically, this is -- you know, if you 6 look at, you know, one of the major discriminators 7 might be race, so you might argue that, you know, if 8 you're non-white then, you know, your preferences are 9 very strong for one of the two candidates.</p> <p>10 But within that, you know, the 11 differentiation within the non-white category might be 12 based on -- first on, you know, the biggest 13 differentiator might be whether you live in a red 14 state or a blue state, and then other factors might 15 start matching.</p> <p>16 On the other hand, if you look at those who 17 are white, maybe which state you belong to is not the 18 primary factor after race. The primary factor after 19 race is education, right? And, so, if that's kind of 20 the relationship, you know, capturing it through some 21 kind of linear function or a polynomial function or 22 even interactions will lead to -- you know, will 23 quickly blow up into a very, very large set of 24 inflections, so that's why, you know, these models are 25 relevant.</p>
286	<p>1 variable at a time. I'll walk through a simple example 2 to show this. And what is the aim of this 3 partitioning? Basically to kind of differentiate data 4 such that the outcomes -- you know, when you do a 5 partition, you want to kind of find a partition such 6 that you have relatively homogenous set of outcomes 7 within each partition but kind of different across 8 partitions, okay?</p> <p>9 It does this by looking forward without 10 revisiting the prior partitions, and that's what is 11 referred to as the greedy part of this algorithm. 12 But, you know, the reason it's done is because this is 13 actually -- it has been shown that this is an NP- 14 complete problem; in other words, you cannot find a 15 globally optimal solution, so you have to use some 16 kind of approximations for this. So, basically the 17 sequence of locally optimal solutions gets you, you 18 know, hopefully close to that globally optimal 19 solution.</p> <p>20 So just kind of giving an example of how 21 these relationships differ in different parts of this 22 space is an example from, say, the presidential race, 23 and I'm not taking any names of who aligns where, but 24 if you think about, say, you know, one of the key 25 variables that differentiates the two major party</p>	288	<p>1 Now, what does a MART specifically or more 2 generally this class of decision trees called boosted 3 decision trees do? Basically what problem that it's 4 trying to solve is that classification trees have 5 pretty high bias, right? Even though, you know, 6 what are called shallow classification trees, which 7 means that, you know, the number of steps that you are 8 going down is actually small, you know, how you stop 9 going -- before I go there -- how do you stop kind of 10 going any further is by the setting of please set 11 criterion of how many branches you're going to have or 12 some rule based on kind of optimizing some function, 13 some kind of cost function or something of that sort.</p> <p>14 But what boosted decision trees do -- the 15 additional kind of problem is that of overfitting, so 16 you have a high bias, you have an overfitting problem. 17 So what the boosted decision tree does is relatively 18 straightforward, even though in implementation it's 19 hard to do, is that it -- the basic inclusion is that 20 averaging across multiple decision trees helps you out 21 by kind of reducing the bias but also kind of reducing 22 some of these overfitting problems.</p> <p>23 And specifically MART, what it does, is that 24 it kind of fuses kind of a data-based approach to kind 25 of finding -- you know, going through the steps of</p>

289	<p>1 going through multiple decision trees from one to the 2 next. The basis for which one you go to next is based 3 on kind of finding the path of where the descent and 4 gradient of some kind of cost function is the highest. 5 All right. What are the main results of the 6 paper, and this is pretty high level, but I think that 7 it's a fascinating literature overall, very, very vast 8 literature, something anybody who's interested in 9 this, you know, can spend a lot of time going into it. 10 All right, what are the main results over 11 here? If you look at the ad networks problem, first 12 it wants to find -- you know, one problem might be 13 finding a good way to even kind of -- or a good 14 algorithm to kind of classify this information, and 15 what the paper shows is that MART does better than the 16 alternatives and, you know, that's -- you know, that's 17 a pretty straightforward result, something you would 18 expect. 19 The other kind of results are that while, 20 you know, putting together all the information on, you 21 know, who the user is, the app, that they saw the ad 22 in the ad itself, other information obviously is very 23 valuable within that kind of work. Hema referred to 24 it as behavioral targeting variables; things that kind 25 of identify the user and their exact behavior is</p>	291	<p>1 additional feature which Hema didn't talk about is 2 that there is -- the specifics of the auction 3 mechanism of this Iranian ad platform kind of induces 4 its own set of randomness. I won't go into detail of 5 that, but I'll come back to the consequence -- or one 6 of the consequences of this in terms of interpretation 7 of the results later. 8 The empirical work is very competent and the 9 results are kind of interesting, even though they are 10 kind of intuitive as a summary. So, you know, some of 11 the suggestions, first of all, you know, in this 12 paper, the first part kind of compares different 13 algorithms, and I wondered whether it cannot be more 14 comprehensive than this. 15 Now, one of the rationale given by the 16 authors is that there is private empirical work 17 establishing the superiority of MART. In specific, 18 there is one paper that is referred to, but -- and 19 there are more that I looked at as well. But all of 20 those refer to very specific conditions and typically 21 average across multiple metrics, right? So they're 22 better but not necessarily for the kind of context 23 that you're looking at. 24 So there's several other promising 25 candidates, and I won't go into all of them but</p>
290	<p>1 actually more valuable than the contextual behaviors. 2 So that was kind of useful. 3 Now, the other kind of problem that this 4 paper is trying to tackle and, to my mind the bigger 5 substantive issues, that about information sharing. 6 Okay, and so what they find is that there's the 7 highest gain in prediction happens when advertisers 8 are provided impression-level data on their own ads. 9 And, you know, if they're provided 10 information across competitors, actually the gains go 11 -- I mean the gains are lower because of the simple 12 reason that when advertisers get information about 13 their competitors it softens competition. So from the 14 ad networks point of view, it's actually a worse-off 15 idea to share all the information. So that makes -- 16 it makes sense that ad networks, therefore, don't 17 share information across competitors. 18 I'll kind of jump to some of the comments. 19 First of all, it's an important problem from the ad 20 networks' perspective, there's a live problem, you 21 know, what kind of information they're to share. It's 22 also public policy problem because of what privacy 23 issues some of the marketing efficiencies that, you 24 know, different sources of information causes. 25 Okay. The data are nice and rich. An</p>	292	<p>1 there's a large literature in this, and we can talk 2 offline about some of those. But I think that that 3 can kind of -- one of the objectives of the paper is 4 to kind of demonstrate an algorithm, and for that -- 5 from that objective perspective, I think there's -- it 6 can become a little bit more comprehensive. 7 The second point relates more to positioning 8 and phrasing. I wondered whether this is really value 9 of information, right, because all the focus is on 10 clicks, but more clicks need not imply value. After 11 the clicks, there is conversion, and so if you really 12 take it to the ultimate goal of the advertisers or the 13 networks, the data is, I'm guessing, not there. But I 14 think to say anything beyond clicks, but I think it 15 can be more carefully worded so that expectations are 16 clearly set up about what you can and can't do. 17 The third point relates to this point about 18 the randomization that is done in this auction 19 mechanism. And basically what it does is typically in 20 Google and other kind of platforms there's an auction 21 mechanism where there's a ranking and, you know, a 22 score which is generated, and the highest score gets 23 to place their ads. In this case, what happens is 24 that it's not -- and that's deterministic. In the 25 case of the auction that the data is from Iran was</p>

293	<p>1 for, it is probabilistic.</p> <p>2 So if you have a high score, you have a</p> <p>3 higher probability of winning an auction, of getting</p> <p>4 your targeted ad. If you're a lower score, the</p> <p>5 probability is lower. That on the one hand is nice</p> <p>6 because it induces this kind of, you know, random</p> <p>7 variation, which is one of the critiques of the</p> <p>8 machine-learning algorithms, whether on causality and</p> <p>9 kind of alleviate some of that concern.</p> <p>10 But on the other hand, one of the main</p> <p>11 results is that, you know, bigger advertisers kind of</p> <p>12 -- and smaller advertisers differ in terms of the</p> <p>13 value of information, but they also differ in the</p> <p>14 probability of their targeting rule actually being</p> <p>15 applied because let's imagine that the limits,</p> <p>16 somebody who has an incredibly high score, has a</p> <p>17 probability very close to one of their targeting</p> <p>18 mechanism working, and at extreme, somebody close to</p> <p>19 zero is entirely random.</p> <p>20 So I wonder if, you know, there's</p> <p>21 differences across big and small that they're picking</p> <p>22 up is also not picking up these fundamental</p> <p>23 differences in how much I can interpret it as a causal</p> <p>24 versus noncausal effect. So I think kind of a little</p> <p>25 bit more care in interpreting these results would be</p>	295	<p>1 of, well, how long do we have to track someone, right?</p> <p>2 When should data die? You could also tell us so much</p> <p>3 about, well, why is it that an IP address is working</p> <p>4 so poorly. Is it to do with the fact that there's</p> <p>5 multiple people in the household. Some really --</p> <p>6 well, anyway, listen, I'll tell you, I'll email you</p> <p>7 all this, but I think there's a wonderful privacy</p> <p>8 paper to be written sort of secondary, which can</p> <p>9 really answer lots of important policy points.</p> <p>10 DR. YOGANARASIMHAN: Thank you. Those are</p> <p>11 great ideas. I hadn't even thought of any of them.</p> <p>12 AUDIENCE: All right. It's a great paper,</p> <p>13 Hema, and to continue with the question raised by --</p> <p>14 or suggestion raised by Catherine, I think if you talk</p> <p>15 about the behavior in a contextual targeting in in-app</p> <p>16 ads, if your data can have some user-level or app-</p> <p>17 level when they define context, it means the time and</p> <p>18 location, most of the literature, so the app may have</p> <p>19 some tracking users, longitudinal on that, to do some</p> <p>20 kind of location profiling.</p> <p>21 DR. YOGANARASIMHAN: When I mean contextual,</p> <p>22 I'm talking about three kind of things. One is the</p> <p>23 app, where the impression is happening. The second is</p> <p>24 the ad that is being shown, you know, (indiscernible)</p> <p>25 presents the context, and the third is the time, and I</p>
294	<p>1 useful.</p> <p>2 So overall, this is a nice paper. It brings</p> <p>3 in, you know, you know, it's sort of an expanding</p> <p>4 literature and using machine-learning tools, but I</p> <p>5 think it's a very relevant area, relevant policy</p> <p>6 question that it applies it to. The data are great,</p> <p>7 and, you know, applied in a careful way. I just think</p> <p>8 a little bit more comprehensive analysis on model</p> <p>9 comparison, a little bit more care in terms of</p> <p>10 interpreting the results will make this a really nice</p> <p>11 contribution.</p> <p>12 Thank you.</p> <p>13 (Applause)</p> <p>14 DR. JIN: Thank you. We're about 20 minutes</p> <p>15 over our scheduled agenda, so we can pick up probably</p> <p>16 just a couple of quick questions.</p> <p>17 DR. TUCKER: Okay, I just wanted to say, so</p> <p>18 this is such awesome work. I actually think it should</p> <p>19 be two papers, and I think this should be --</p> <p>20 DR. YOGANARASIMHAN: I should get an A and a</p> <p>21 B.</p> <p>22 DR. TUCKER: -- that's right. I would say</p> <p>23 the second paper should be about privacy, because you</p> <p>24 could just do so much with some of your simulations,</p> <p>25 especially you can answer questions along the lines</p>	296	<p>1 know you have done some other work in the context</p> <p>2 like, you know, where the impression happened and, you</p> <p>3 know, how crowded it is and so on. And so we don't</p> <p>4 have that kind of data.</p> <p>5 AUDIENCE: Right. So the related question</p> <p>6 would be the targeting, do you know what's the</p> <p>7 targeting rule of the app? Maybe it's different from</p> <p>8 the --</p> <p>9 DR. YOGANARASIMHAN: So they don't actually</p> <p>10 -- so at this point, what the platform is doing is</p> <p>11 they actually have this ad specific to it, so actually</p> <p>12 they're not talking any -- so they're doing a very --</p> <p>13 almost you could say not that they're targeted except</p> <p>14 like an average of ads that they click to read. So</p> <p>15 they're not taking anything with the app or the time</p> <p>16 in which the click is happening.</p> <p>17 And that's one of the reasons why they</p> <p>18 started working with us because they really wanted to</p> <p>19 look at, you know, if they did more targeting, how</p> <p>20 would things change; should they be doing more</p> <p>21 targeting. That's a bigger -- I mean, that's</p> <p>22 something I didn't get to, which is a really big</p> <p>23 question because it could soften competition if --</p> <p>24 like a bunch of sharing data has shown.</p> <p>25 DR. JIN: Any other questions? Okay, thank</p>

297	<p>1 you so much. 2 DR. YOGANARASIMHAN: Thank you. 3 (Applause) 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>	299	<p>1 So in '97, the FDA clarified its policy and 2 essentially said that the drug companies could 3 advertise on television and provide a major statement, 4 just kind of like a one or two-line statement about 5 the major risks and benefits, and then provide some 6 other outlet for these companies to provide more 7 detailed information, whether that be a 1-800 number, 8 pamphlets in an office, you know, go to the library, 9 or, you know, more and more to go online just to a -- 10 to the drug companies or usually the drug itself would 11 have its own website. 12 So following that change, prior to '96, DTCA 13 was about \$660 million, and as of 2010, it's now over 14 \$4 billion. It's actually about \$4.5 billion today. 15 It's leveled off. Some of the drugs -- some 16 blockbuster drugs have gone off patent, which is why 17 it's leveled off. 18 The FDA aims for a fair and balanced 19 disclosure, you know, with this policy. So there's 20 been a lot of research assessing whether that's being 21 met, that goals' being met. There's also a lot of 22 research looking at how DTCA affects patient visits, 23 drug choice, patient compliance. A lot of authors are 24 in the room that have worked on those papers. 25 So at the same time all of this happening,</p>
298	<p>1 DIRECT-TO-CONSUMER ADVERTISING AND ONLINE SEARCH 2 DR. JIN: Thank you. The third paper will 3 be presented by Matthew Chesnes from FTC. 4 DR. CHESNES: Okay, thanks for including 5 this paper in the conference. This is joint work with 6 Ginger looking at direct-to-consumer advertising and 7 online search. The usual disclaimer applies here as 8 well. These are our opinions and not those of any of 9 the Commission. 10 So, first a bit of motivation. The U.S. is 11 actually one of only two countries in the world that 12 allow direct-to-consumer advertising of prescription 13 drugs. And what I'm talking about are sort of the 14 ubiquitous, you know, commercials you see on pretty 15 much every commercial break anymore on TV as well as, 16 you know, in magazine ads and newspapers and 17 increasingly on the internet. 18 Prior to 1997, you were allowed to do this 19 in the U.S., but you had to provide what was called a 20 brief summary. And that brief summary was really not 21 that brief, and the drug companies really didn't find 22 it advantageous to advertise on television because you 23 had to provide all the risks and benefits in a certain 24 way. And it just -- it didn't really -- it was too 25 cumbersome or too costly for them to do so.</p>	300	<p>1 of course, internet -- the use of the internet for 2 health information has grown dramatically. There's a 3 recent Pew research study which shows that, like, over 4 70 percent of the survey recipients use the internet 5 for health information, to find health information, 6 and 78 percent use search engines to start that search 7 process. So, you know, this is all happening, growing 8 kind of at the same time. 9 So drugs are kind of unique because the 10 typical consumer may have limited information about 11 drugs. They're complicated. There's a lot of 12 different sides to them. So maybe getting them -- 13 getting the information from multiple sources, 14 including online, from their doctor, and from peers. 15 So we're trying to look at that link between 16 advertising and search. Catherine has a paper that is 17 closest to this area where we're trying to kind of 18 determine, you know, how that -- how those advertising 19 are affecting search, are consumers actually going 20 online to find more information, and then is the 21 FDA's, you know, policy, is it really -- is it really 22 being -- is it really succeeding. 23 So there's this active debate on DTCA on the 24 two sides of it. So, you know, DTCA, of course, is 25 just, you know, informs consumers about the existence</p>

<p style="text-align: right;">301</p> <p>1 of drugs, maybe prompts them to do research, talk to 2 their doctor, and maybe eventually seek beneficial 3 treatment, which maybe they weren't aware of. 4 But then, of course, the other side of it is 5 that the advertising itself may be biased and 6 emphasizing the benefits over the risks. You also 7 have the fact that consumers -- you know, they don't 8 directly choose their medicine. They have to go and 9 get a prescription, so it may lead to overprescribing 10 in the end. 11 So our paper tries to sort of shed light on 12 both sides of this debate, and we're just going to 13 look at -- it's going to be a fairly basic paper. We 14 just want to kind of get an idea of does DTCA 15 actually, you know, encourage consumers to search for 16 this information and then dig deeper into that and 17 say, well, what are they actually looking for, what 18 are they actually finding. Are they looking on -- you 19 know, on -- are they going to FDA.gov and getting that 20 information? Are they going to the drug companies' 21 websites? What are they actually -- what are they 22 seeking? 23 And then we'll do something at the end where 24 we'll look at heterogenous effects. So I'm going to 25 look at different drug types and searcher types. So</p>	<p style="text-align: right;">303</p> <p>1 provides searcher demographics for each of these 2 terms. 3 So, importantly, a big caveat of the paper 4 is we're only observing that one channel, right? 5 We're only getting that search channel. We're not 6 getting direct navigation or any other way that 7 someone may land on a certain website, but we -- you 8 know, we have some evidence that, you know, the search 9 engine is the gateway to the internet. So hopefully 10 that's not too strong of an assumption. 11 Advertising data comes from Kantar. We've 12 got ad spending by -- on prescription drugs by month 13 for that sample, and actually even longer than that 14 sample. Overall spending and then also by media, so 15 it's broken out very finely. We're going to look at 16 essentially broadcast, print, and internet aggregated 17 up, because that's -- those are going to be kind of 18 the main categories that we're going to be focusing 19 on. 20 And then some others, other sources of drug 21 information from the Orange Book, National Drug 22 Directory, and the MEPS to get information on 23 prescription rates, insurance coverage, drug age, 24 things like that. 25 So what does the search data look like? So</p>
<p style="text-align: right;">302</p> <p>1 drug types, you know, the main things I'll stress 2 today, we'll look at what type of condition do the 3 drugs treat, you know, chronic or acute conditions, 4 the age of the drug, and then the insurance coverage. 5 And I'll briefly talk about searcher demographics, but 6 I'll probably run out of time before I get to that. 7 So what do our data look like? They're 8 coming from the comScore search planner tool, three 9 years of data, 373 prescription drugs. So we started 10 with the Orange Book listing of all drugs, and then we 11 essentially selected a sample of drugs that were 12 either -- had some volume of search or some 13 advertisements in our sample. And that really just 14 cuts off the -- both of those limitations would cut 15 off the long tail of drugs that just get no search or 16 no advertising. 17 We cover the five large search engines. 18 Monthly data on clicks, on searches, clicks separate 19 for organic clicks and paid clicks or sponsored 20 clicks. And what we observe is the overall number of 21 clicks on a -- like on a given month or a given drug, 22 and we also observe how that's broken out by entity, 23 so comScore calls these things entities. Think of 24 them as websites, but sometimes they're aggregated to 25 a higher level. And then there's also comScore</p>	<p style="text-align: right;">304</p> <p>1 on the left-hand side of this pie chart is just the -- 2 just looking at the organic clicks that we see. And 3 you can see that general health websites like WebMD, 4 places like that, they get the largest fraction, over 5 50 percent of the organic clicks, the brand name is 6 large, there are some -- the producer site would be, 7 you know, Pfizer.com; the brand site would be 8 Lipitor.com, right? So that's the distinction between 9 those two. 10 EDU tends to be health -- medical sites of 11 universities. The dot-govs tend to be -- tend to be 12 FDA and NIH. And then there's other sites which are 13 just -- we classify as they look like nonhealth sites, 14 that they're just things that don't go into these 15 categories. 16 So what we do, and this is not a strict 17 definition by any means, but we classify the 18 pharmacies, the brands, and the producers as 19 promotional sites. So, you know, they -- obviously, 20 there's some information on promotional sites and 21 there's promotional activity maybe on informational 22 sites, but we think that the primary focus of these 23 sites is promotion; and the primary focus of general 24 health, dot-govs, and dot-edu sites is more 25 informational; and leaving the other out.</p>

305	<p>1 Okay. And you can contrast that with the 2 paid-click destinations, and of course, you see a lot 3 more paid clicks on the brand sites and online 4 pharmacies. General health is still fairly large on 5 the paid side, so you're still getting WebMD and those 6 sites are buying those sponsored links. And there are 7 even some, you know, 0 percent for the dot-govs, but 8 even the FDA does -- for certain drugs, they do 9 actually appear in the sponsored links.</p> <p>10 Okay, so, just -- it's a little bit 11 misleading the way I drew these two circles. There's 12 -- one of them is actually much bigger than the other, 13 of course. So organic is about 91 percent of all 14 clicks; paid are the rest. The informational clicks, 15 96 percent of them are from organic links, whereas the 16 promotional clicks are -- a quarter of them are going 17 to come from the paid links, which is -- you know, I 18 think that that's intuitive.</p> <p>19 So the reason I point these out is when I 20 show the effects and regressions, you know, the 21 marginal effects may show one thing, but when you put 22 them in terms of actual clicks in the absolute amount, 23 that's going to tell a totally different story.</p> <p>24 And then, finally, if you just aggregate 25 over organic and paid, 32 percent of those clicks are</p>	307	<p>1 So I'm sorry, this table is pretty small, 2 but I'll just -- I just want to highlight a couple 3 things on this. This just gives you an idea of by 4 drug type what sort of search activity are we seeing. 5 So a couple quick things. For the type of drug, you 6 see that there's slightly more search for acute drugs, 7 you know, drugs that a patient's not, you know, taking 8 all the time, maybe they're searching a little bit 9 more. But the advertising actually is the opposite. 10 There's actually about 50 percent more advertising on 11 chronic drugs compared to -- compared to acute.</p> <p>12 If you look at insurance coverage, you know, 13 you see that drugs that have lower coverage, so this 14 is just below the median coverage, tend to be searched 15 and clicked more. So the story there might be that 16 these consumers might be searching for an alternative 17 source of supply if their insurance company is not 18 covering -- not covering their prescription.</p> <p>19 So these columns are the percent of clicks 20 on paid, promotional, and informational sites. And I 21 really don't see anything systematic across this by 22 drug type. So there doesn't seem to be much going on 23 here. And if you look at searcher demographics, age 24 and income of the searcher, again, we didn't see much 25 -- just in these descriptive tables -- about people</p>
306	<p>1 going to be on informational websites and 16 percent 2 are on promotional. Again, that's going to -- that's 3 important when we look at the -- interpret the 4 results.</p> <p>5 So just a quick graph of advertising over 6 time. We can see the television advertising in red 7 really picks up after 1997 and then sort of levels off 8 in sort of the late 2000s. And the internet is a 9 growing fraction of DTCA. So television is about 60 10 percent; magazines are about 30 percent; and then the 11 internet, I think currently, as of 2011, is about 6 12 percent of DTCA.</p> <p>13 So just some drug attributes I'll just 14 briefly mention. This is the typical drug in our 15 sample, is about seven years old. Thirty-five percent 16 are classified as chronic, and the threshold we use 17 for chronic is more than five prescriptions per 18 patient per year. And we've done some robustness on 19 that -- on that number.</p> <p>20 Insurance coverage, 76 percent, so about a 21 quarter of these drug costs are coming out of pocket. 22 That's coming from the MEPS data. And then on -- the 23 average drug has about four prescriptions per patient 24 per year. Okay, so just to give you an idea of what 25 the sample of drugs looks like.</p>	308	<p>1 clicking more, less into paid versus organic or 2 informational versus promotional. So that's why, you 3 know, looking at these numbers alone, it was kind of 4 hard to discern stories, so that's why we -- you know, 5 the regression framework which we'll present now 6 hopefully will tell a better story or a more 7 convincing story.</p> <p>8 So like I said, this is a very basic 9 framework, so we're just going to regress log search 10 on own drug DTCA and also DTCA and that drug's class 11 in the previous month; and we'll control for drug 12 fixed effects and month fixed effects. When I say 13 search, we'll look at separately searches, clicks, and 14 then break it out by organic and paid clicks. And 15 then also in the second set of results we'll look at 16 informational versus promotional websites.</p> <p>17 Okay, yeah, so I'm controlling -- we've got 18 fixed effects for month and drugs throughout all of 19 these. So the first set of results, just look across 20 the top line here. So these are all elasticity 21 estimates, so we see about -- for a 10 percent 22 increase in DTCA, between a .2 and .3 percent increase 23 in search in clicks. There's a little bit of a bump 24 for paid clicks, so, you know, .8 percent increase in 25 paid clicks.</p>

309	<p>1 But, again, we know that because organic 2 clicks are about, you know, 10 times as big as paid 3 clicks, if you actually do the magnitudes, it turns 4 out that the organic effect is even -- is about twice 5 as big as the paid effect in absolute number of 6 clicks, okay? So that's -- just be careful when you 7 interpret those coefficients.</p> <p>8 And we do see some spillovers from the 9 class. So this is all DTCA in the class pulling out 10 the drug itself, right? So this is just any kind of 11 spillover from -- for drugs in the same class. And, 12 so, you do see some effects, particularly on the 13 clicks regressions.</p> <p>14 And then we break out the different media, 15 the DTCA across the different media. And, again, 16 we're just going to look at broadcast, print, and 17 internet. And here you see that the DTCA effect is 18 really coming mostly from broadcast and internet. 19 There is some positive effects on print ads, but most 20 of it is coming from, you know, television ads and 21 internet ads. And it's a little bit noisier when you 22 look at the class effects. But, again, a stronger 23 effect for the paid links relative to the organic 24 clicks, and that difference is statistically 25 significant from each other.</p>	311	<p>1 drug. If you just focus on the interaction lines, it 2 appears that the effect of DTCA on clicks is lessened 3 for older drugs, so stronger for younger drugs. It's 4 lessened for chronic drugs, so, you know, so 5 strengthened maybe for acute drugs. If you'll 6 actually compare the coefficients on chronic to the 7 overall log DTCA coefficient, they almost cancel each 8 other out. So really all the effect is coming from 9 acute drugs.</p> <p>10 And then we get a positive effect on the low 11 insurance indicator. So this is, again, just the 12 binary below or above the median for insurance. So, 13 again, this is consistent with that story that 14 consumers are searching for maybe an alternative 15 supply source to -- if their prescription is not 16 covered by their insurance.</p> <p>17 Okay, when we look at searcher effects, 18 since I have a little bit of time, so these 19 interactions are searcher age and searcher income, so 20 this is provided by comScore. So here we see that 21 older searchers. You know, some of the results are 22 mixed. Older searchers are -- the effects of DTC are 23 larger for promotional, less for informational, and 24 then income goes the other way essentially. So it's 25 lower income leads to less promotional and higher</p>
310	<p>1 Okay, so, then we're going to break it up 2 into promotional and organic, based on that 3 classification that I showed you. So here what we see 4 is we see stronger marginal effects, if you will, on 5 the promotional sites compared to the informational. 6 But, again, because informational is larger than 7 promotional, the effects on total number of clicks is 8 about the same, between promotional and informational. 9 And, again, larger -- slightly larger effects on paid 10 promotional and paid informational clicks.</p> <p>11 AUDIENCE: In all of these regressions, 12 there are direct fixed effects (off microphone)?</p> <p>13 MR. CHESNES: Yes, yes. Direct fixed 14 effects and year/month fixed effects. Yeah, so when 15 we say query, that's really what we're talking about. 16 It's all just drug queries.</p> <p>17 Okay, so then in terms of heterogeneous 18 effects, I'm just going to add one term to this 19 regression, where we'll add interactions between own 20 drug DTCA and some set of covariates, whether they're 21 covariates, whether they're drug covariates or 22 searcher covariates. So that's the gamma terms that 23 are up here. So same fixed effects for month and for 24 drug.</p> <p>25 Okay, so, let me just show you the ones for</p>	312	<p>1 informational.</p> <p>2 So we were a little bit surprised by the 3 income result. The age result, I think, is a little 4 bit more intuitive if you think that, you know, older 5 searchers may be more responsive to DTCA. They may be 6 taking more medicine and things like that.</p> <p>7 So just to summarize, then, so this is -- 8 all the results are really right on this slide. So 9 DTCA is associated with more frequent searches and 10 subsequent clicks for both the advertised drug and we 11 see some spillovers. And the effect is larger for 12 paid relative to organic, broadcast and internet 13 relative to print and promotional relative to 14 informational. But, again, if you do it in absolute 15 number of clicks, then the effects are much -- are 16 much more similar between these different categories.</p> <p>17 And then the heterogeneous effects show that 18 the effects are stronger for younger drugs, drugs that 19 treat acute conditions. So, you know, maybe this has 20 something to do with chronic drugs and older drugs 21 being more -- you know, these are drugs that are more 22 familiar to searchers. Maybe they don't -- they're 23 not as responsive to DTCA because of that. And then 24 we get these results on stronger for low insurance and 25 older populations and higher incomes.</p>

<p style="text-align: right;">313</p> <p>1 So overall, you know, we don't do a full- 2 blown welfare and welfare analysis because we're only 3 observing the clicks. We don't see what -- you know, 4 what goes on after. We don't do the conversion part 5 of it either. We don't observe that. But we think 6 that these results are at least somewhat supportive of 7 the FDA's original contention when they came up with 8 these guidelines for certain drugs and for certain 9 sub-populations. 10 But it's not all good news. We still see 11 some -- we see some clicks that are going towards 12 these, you know, either paid or promotional websites. 13 So it's a little bit mixed, but I think it's in 14 general supportive of their intention. So thank you 15 very much. 16 (Applause) 17 DR. JIN: Our discussant is Jura Liaukonyte 18 from Cornell University. 19 DR. LIAUKONYTE: Hello, everybody. My name 20 is Jura Liaukonyte, and I'm from Dyson School at 21 Cornell University. First of all, let me start my 22 talk by thanking the organizers for this wonderful 23 conference and for inviting me to discuss this very 24 interesting paper. 25 So let me start by first summarizing what</p>	<p style="text-align: right;">315</p> <p>1 question to be asking and very important question to 2 be seeking answers to. 3 Another thing that wasn't pointed out but I 4 just looked it up, it was very recently -- less than a 5 year ago -- AMA came out with a very strict statement 6 encouraging to ban DTCA. So this just sort of 7 highlights this ongoing discussion and the ongoing 8 policy relevance of the DTCA advertising that exists. 9 So just to summarize, the paper finds 10 evidence that indeed DTCA is associated with internet 11 search, and some people go to informational websites; 12 some people go to the promotional websites. One thing 13 that I did notice is that authors are very cautious 14 throughout the paper, at least the way I read the 15 paper, not to explicitly label anything as causal, but 16 implication is there. So the reader is sort of left 17 to wonder whether the results represent marginal 18 causal advertising-induced search lift. 19 So I think this is really a low-hanging ball 20 -- a low-hanging fruit is to sort of strengthen the 21 discussion and to focus on the causality. So in what 22 follows, I will try to be helpful in giving some 23 suggestions for how to set up this discussion and 24 maybe how to try some alternative specifications to 25 strengthen the causal argument.</p>
<p style="text-align: right;">314</p> <p>1 the paper intended to accomplish and what are the main 2 results and why do we care about that. So the main 3 question that the paper attempts to ask is whether 4 exposure to DTCA advertising drives consumers to 5 search online. And then sort of derivative, second- 6 order questions are -- is what kind of information are 7 consumers thinking and whether that varies by drug 8 type and demographics. 9 Why do we care? I think this paper sets up 10 the discussion really well by highlighting sort of the 11 two sides of the DTCA debate. So one side is claiming 12 that DTCA is bad, essentially that there are no 13 incentives for the advertisers to highlight the risk 14 and it tends to overemphasize the benefits and mislead 15 the consumers. 16 On the other side of the debate are the 17 people who are arguing that DTCA is actually good 18 because information is always good. This type of 19 advertising provides information about the existence 20 of the drug; and then consumers can self-diagnose, 21 match their own symptoms with the symptoms that are 22 highlighted in the ad and then seek treatment. 23 So, if DTCA is biased, then having people to 24 seek further information online is actually good. So 25 from the policy perspective, this is a very important</p>	<p style="text-align: right;">316</p> <p>1 So I imagine that the -- I imagine the 2 authors might face the typical endogeneity taliban, as 3 we call it, during the review process. So let me try 4 to set up the -- let me try to set up the standard 5 advertising endogeneity concern that arises in the 6 advertising literature. So, essentially, intuitively, 7 we have the situations where brands may plan 8 advertising timing with partial knowledge of the 9 unobserved category or time effects, essentially 10 something that is really important for the consumer 11 behavior that brands observe but the researchers, 12 econometricians do not observe. 13 So is it something that we should be 14 worrying in this case? So let me sort of give you an 15 example. I do not have the advertising data that you 16 guys have, but I did have a free source of U.S. Google 17 Trends. So we would be worried about the endogeneity. 18 For example, here, I am graphing Chantix, which is a 19 smoking cessation -- prescription smoking cessation 20 drug, and I'm also graphing quit smoking search term 21 on the Google Trends. And you can see that they're 22 rather correlated. It seems like quit smoking is one 23 of the new year's resolutions, right? All peaks 24 correspond to January. 25 The part that I highlighted with a rectangle</p>

317	<p>1 is the part that I know the advertising expenditure 2 was the highest for the Chantix drugs. How do I know 3 it? Because that's the only one that was mentioned in 4 the paper for that month as like an outlier. It was 5 one of the maximum spends in your data set. 6 So if you're really regressing the search on 7 advertising, you might be picking up just the fact 8 that there is -- there is an interest in the market 9 and the advertisers know that and so on. So should we 10 be worried about that? Fortunately, this is actually 11 something that is observed, right? So we could just 12 include -- I'm sorry -- so we should just include as 13 many fixed effects as possible. 14 So my understanding from reading the paper 15 is that the authors stack everything on the left -- 16 stack all of the searches on the left-hand side and 17 then include one -- one vector of essentially month 18 fixed effects. What I was wondering if you do have 19 enough degrees of freedom to include drug-specific 20 time fixed effects or direct category-specific time 21 fixed effects, so essentially fixed effects for 22 category and month interactions. 23 Why is it important? If you look at -- 24 again, I'm looking at the Google Trends, and here I'm 25 plotting searches for quit smoking and hypertension.</p>	319	<p>1 really skeptical to -- I'm really skeptical that 2 actually advertisers do do things optimally. 3 And I have worked with some companies, and I 4 do know that they do not know what they're doing 5 sometimes when it comes to advertising optimality. 6 And we also have this paper in the QJE that is telling 7 us that really the information is not there for people 8 -- for advertisers to have the information of what is 9 -- when the ads are optimal and not. The signal is 10 just too weak. 11 And on top of that, there is -- there are 12 severe contractual and institutional challenges that 13 complicate the seamless optimization. So, really, I'm 14 a believer that what you are picking up is actually 15 causal, and I think you can develop that argument that 16 it is causal. 17 So another couple of things. I think the 18 paper would be much stronger if it had a little bit 19 more of model free evidence. So one of the things 20 that I was thinking is whether if you could employ 21 diff-in-diff approach in any way by juxtaposing, let's 22 say, search in the United States where you have -- 23 where you have DTCA versus search for the same brand 24 of drug in Canada, where you do not have the DTCA and 25 whether sort of those deltas are informative for your</p>
318	<p>1 And you can see that they're kind of -- almost 2 perfectly negatively correlated. So what your month 3 fixed effects are picking is just an average of that. 4 So if you could include the time-specific sort of 5 drug-specific time fixed effects, I think that would 6 absorb all of that endogeneity. 7 By the way, I have no idea why people do not 8 -- are not searching about hypertension on -- during 9 January. That's a very interesting empirical 10 observation. 11 Another thing that -- so, again, let's try 12 to put in as many controls as possible. Another idea 13 that I had maybe -- and I don't know the extent of 14 your data -- maybe market fixed effects would be 15 possible to include. Presumably, the data is 16 available, but I don't know how important it is in 17 your setup. 18 So remaining endogeneity. So once we have 19 control for all of these fixed effects, is there 20 another endogeneity remaining in the (indiscernible) 21 that we should be worried about? So as an economist, 22 I've been trained to think that advertisers are 23 actually placing their ads optimally, trying to 24 maximize the profits. But now having really done a 25 lot of thinking about the advertising endogeneity, I'm</p>	320	<p>1 causal inferences. 2 Another idea whether you could look into 3 juxtaposing branded searches versus the generic 4 searches. And, again, just sort of anecdotally it 5 looks like there is a variation that could be picked 6 up that might support this. And, then, I have a 7 couple -- I will just summarize it really quickly. 8 I think it would be also nice to talk a 9 little bit about the microfoundations of causality. 10 So you could develop the argument more carefully that 11 shows these microfoundations. So we actually know, 12 and it has been convincingly shown in multiple papers, 13 that especially TV advertising, which the biggest 14 effect that you're picking up is the broadcast 15 advertising, actually causes almost immediate 16 searches. 17 And we have several papers that show that, 18 and you can see I have included one very telling graph 19 that just sort of shows these huge spikes in searches 20 right after the ads have been aired. So we know that 21 this is causally happening, but because your data is 22 so aggregated in the month level, you could sort of 23 develop that argument to really convince the reader 24 that it is causal. 25 And the last thing I'm going to say, I am a</p>

321	<p>1 little bit interested in the advertising content and 2 how that affects consumer outcomes. And one of the 3 things that we know about the ad content is that 4 informative ads tend to be not that interesting and 5 tend to lead to lower overall searches, but 6 informative ads lead to higher overall searches online 7 for people who are interested in the advertised 8 products, so for people who are in the market for that 9 advertised product.</p> <p>10 And one thing that I just did, I looked at 11 my data which sort of has this variable for 12 advertising mood, and it just seems very striking that 13 the prescription ads are labeled -- the prescription 14 ads are about 10 times more likely to be labeled as 15 informative. So here's yet another mechanism for you 16 to sort of have this causality story unravel.</p> <p>17 So, overall, I think you could -- I really 18 like the paper, but I would encourage you to sort of 19 strengthen the causality story because I think 20 causality is there, but it's just -- I haven't read -- 21 I haven't really found the word "causes" in your 22 paper.</p> <p>23 So the encouragement is also to perhaps add 24 a case study where you are looking at the more 25 granular data to show the causation mechanism, and I</p>	323	<p>1 our discussant, too, for excellent comments. Cheers. 2 (Applause) 3 DR. JIN: Okay, well, we'll break now for -- 4 let's see -- ten minutes, and then we'll come back at 5 4:05. Thank you. 6 (Recess.) 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25</p>
322	<p>1 know that Google Trends is now realtime, minute by 2 minute; and I know that Kantar data is available at 3 the second level, and both have market-specific 4 variation.</p> <p>5 All right. Thank you very much. 6 (Applause) 7 DR. JIN: Thank you so much. I really 8 appreciate the suggestions for endogeneity, which is a 9 problem that Matthew and I struggle with a lot, and I'm 10 hoping our future referees are in this room so that we 11 -- we'll see the argument on our endogeneity problem is 12 not such a problem in our paper. So, with that, 13 probably just for a few questions?</p> <p>14 DR. TUCKER: Yeah, I was just going to say 15 with all respect to your discussant advisor, I just 16 wonder if the informative versus persuasive 17 distinction here is masking some really interesting 18 stuff in that in particular what strikes me about your 19 period is it was a period of an explosion of social 20 media, user-generated content, all of these things. I 21 would -- you know, we've seen various hypotheses in 22 the literature, the advertising interacts with social 23 media in a very different way. You have the data to 24 look at it. It might be wonderful. 25 DR. CHESNES: If I could thank my -- thank</p>	324	<p>1 SESSION FOUR: 2 MIGHT I INTEREST YOU IN AN EXTENDED WARRANTY 3 DR. JIN: Thank you. Thank you for staying 4 here for the whole day. We have the last two papers. 5 The first one is going to be presented by Sriram 6 Venkataraman from the University of North Carolina- 7 Chapel Hill, who is going to talk about extended 8 warranties. Thank you. 9 DR. VENKATARAMAN: First and foremost, thank 10 you to the committee for the opportunity to present. 11 And thank you to Ginger and her team here for being 12 such great hosts. And thanks in advance to the 13 discussant, Matt, for his comments. I realize it's 14 Friday, and I tend to have this reaction when I take 15 the podium, I clear the room, but I'm attributing it 16 this time to a treatment effect, which is a Friday 17 treatment as opposed to my presence here. 18 So, what am I going to be talking to you 19 about? First and foremost, this is work with a 20 doctoral student of mine at UNC. The research 21 questions that we're going to be exploring, I'll 22 formalize it in a few slides, but I'm going to be 23 looking at certain substandard questions around 24 extended warranties, and the empirical context for 25 this particular study is going to be the U.S. auto</p>

325	<p>1 industry.</p> <p>2 I've been told, and there's a well known</p> <p>3 saying that is imitation is the best form of flattery,</p> <p>4 and I'm going to embellish it a little bit and say</p> <p>5 plagiarism is an even better form of flattery. So no</p> <p>6 better way to describe what I mean by extended</p> <p>7 warranties for some of us who are less familiar than</p> <p>8 to cut and paste directly from the FTC's website. I'm</p> <p>9 assuming that if it's on FTC's website it's kind of</p> <p>10 pertinent -- a topic that's pertinent and dear to many</p> <p>11 of the folks here in this room.</p> <p>12 And I'd like to draw your attention to a</p> <p>13 couple of components of the blurb that you see up on</p> <p>14 the screen. First of which is I'd like to draw a</p> <p>15 contrast between what I mean by extended warranties</p> <p>16 versus what I mean by traditional warranties. So</p> <p>17 traditional warranty is often referred to as</p> <p>18 manufacturer-backed warranties or factory-installed</p> <p>19 warranties. These are warranties that come installed</p> <p>20 with your car, and you don't have to pay additional</p> <p>21 monies for it.</p> <p>22 Extended warranties, on the other hand, or</p> <p>23 extended service contracts in my particular setting,</p> <p>24 these are again insurance products that you buy, and</p> <p>25 these are optional. And you buy it at an extra cost,</p>	327	<p>1 important to the U.S. economy. It's the -- one of --</p> <p>2 as far as an industry goes, it's a huge contributor to</p> <p>3 the national GDP, employs tons and tons of people.</p> <p>4 And for better, for worse, I've been drawn to this</p> <p>5 particular industry for a couple of years. I've been</p> <p>6 fortunate to get some papers through, not always, but</p> <p>7 we try, right? We continue trying.</p> <p>8 The reason I studied the auto industry in</p> <p>9 this particular context is because it has a lot of</p> <p>10 similarity with the blurb that we just saw in the</p> <p>11 previous screen, okay? So to kind of draw out what I</p> <p>12 mean by that, so my far right, your far left, is the</p> <p>13 set of -- or the menu of manufacturer-backed</p> <p>14 warranties that you get with your product. So every</p> <p>15 new vehicle comes with two types of manufacturer-</p> <p>16 backed warranties -- bumper-to-bumper warranty and</p> <p>17 powertrain warranty, okay?</p> <p>18 So bumper-to-bumper, on average, what it</p> <p>19 does is it covers all parts associated with the</p> <p>20 vehicle, hence the name bumper-to-bumper, apart from</p> <p>21 the parts that are responsible for or susceptible to</p> <p>22 natural wear and tear. Okay? On average, it covers</p> <p>23 the vehicle up to 36,000 miles or three years,</p> <p>24 whichever comes first. Once the bumper-to-bumper</p> <p>25 warranty expires, the powertrain warranty kicks in.</p>
326	<p>1 and I'm going to show you in a little bit the premiums</p> <p>2 that on average people pay for these products.</p> <p>3 Much like traditional warranties, extended</p> <p>4 warranties are also insurance products. The key</p> <p>5 distinction between traditional insurance product and</p> <p>6 an extended warranty product is going to be that there</p> <p>7 is going to be some overlap in what's covered.</p> <p>8 There's going to be some non-overlap in what's</p> <p>9 covered, the specifics of which we're going to be</p> <p>10 exploiting for the empirics that will follow.</p> <p>11 Last but not the least, I'm not necessarily</p> <p>12 going to bias our opinion or, you know, expectations</p> <p>13 on what you're likely to see in today's presentation,</p> <p>14 which is the blurb says it might not necessarily be</p> <p>15 worth the price. I'm not going to be studying the</p> <p>16 question about why people buy extended warranties.</p> <p>17 I'll still speak to that in some handwaving way, but</p> <p>18 I'll tell you why that particular question will</p> <p>19 naturally fall out of the research that I'm</p> <p>20 undertaking today or showcasing today.</p> <p>21 The empirical context, as I mentioned, is</p> <p>22 the auto industry. And why the auto industry? Well,</p> <p>23 I think given the composition of whoever is left in</p> <p>24 the room right now, I think it suffice to say you</p> <p>25 don't need any convincing that the auto industry is</p>	328	<p>1 As the name suggests, powertrain warranty is</p> <p>2 responsible for all parts that are responsible for</p> <p>3 moving the vehicle. Okay.</p> <p>4 On average, it's 72,000 miles or five years,</p> <p>5 whatever -- whichever comes first. So these are</p> <p>6 things that come directly with the product. If you</p> <p>7 want to buy supplemental insurance, i.e., extended</p> <p>8 warranties, they come in a menu of -- you have a menu</p> <p>9 of offerings to choose. I'm going to kind of group all</p> <p>10 of them as basically forming two flavors of extended</p> <p>11 warranties, one of which is regular warranties and the</p> <p>12 other one being comprehensive warranties.</p> <p>13 The regular warranty is one -- and both</p> <p>14 warranties, for the most part, what they do is they</p> <p>15 extend your bumper-to-bumper warranty past the expiry</p> <p>16 of the manufacturer's expiry period. So if you buy</p> <p>17 the regular extended warranty, it takes you from</p> <p>18 36,000 miles to 72,000 miles, three years to seven</p> <p>19 years. If you buy a comprehensive, it takes you up to</p> <p>20 100,000 miles and seven years, whichever comes first.</p> <p>21 Okay. Again, going back to the blurb that</p> <p>22 we had on the previous screen, it's basically</p> <p>23 extending your bumper-to-bumper warranty. So it</p> <p>24 overlaps in terms of what products are covered with</p> <p>25 the manufacturer-backed warranties as well. Okay.</p>

329	<p>1 And that's going to be critical for the exercise that 2 will follow. Okay.</p> <p>3 So why do we care about extended warranties 4 in the auto setting? So here are the numbers that I 5 wasn't privy to until I started researching this 6 topic. So in 2014 alone, \$14 billion was spent on 7 purchasing extended warranties in the auto space. If 8 I took a poll of people, and going back to the panel 9 that we had at lunch, I'm told that the best way to 10 frame a question is to ask people if you don't want to 11 bias a question, then ask them would you refer this 12 particular product or service to your friend, assuming 13 that you are a better citizen if you're responding in 14 support of a friend.</p> <p>15 I'm sure if I posed that poll here in this 16 particular room, most of you would say no chance in 17 hell should anyone be buying extended warranties. Yet 18 if you look up on the screen, 40 percent of the people 19 purchase extended warranties. And when I say 40 20 percent, I mean in the context of the auto industry 21 alone.</p> <p>22 So naturally this is a question that's going 23 to be pertinent to policymakers, and as marketing 24 managers, this is a huge business opportunity for us. 25 So I'm hoping these numbers alone should suffice as</p>	331	<p>1 file a single claim. Amongst those who do file 2 claims, the premiums do not necessarily -- or the 3 savings are not necessarily commensurate the premiums 4 that they're paying. So naturally from a policy 5 standpoint, these statistics should warrant the 6 question, why are people buying extended warranties in 7 the first place.</p> <p>8 I'm not here to claim that it's a bad 9 investment. I might at some point, but not today, 10 right? But think of this as insurance products, 11 right? When we spend monies on our health care and we 12 buy and invest in premiums, we have no expectations 13 that at the end of each year we're going to be 14 recouping the cost of our premiums. It's basically a 15 peace of mind investment that we hope that it insures 16 us against large cost shocks, unanticipated cost 17 shocks in the future. So I'm going to take exactly 18 the same position even in today's presentation.</p> <p>19 So given the numbers that you see up on the 20 screen, no surprise that auto dealers and underwriters 21 are aggressively marketing extended warranties to us. 22 So I suspect many of us in this room have been 23 recipients of conversations at the end of closing a 24 deal at the dealership or have received a place or 25 something like this where they're trying to induce you</p>
330	<p>1 evidence for some interest in this particular kind of 2 research.</p> <p>3 What's going to be very important for us for 4 the empirics is going to be 86 percent of all sales of 5 extended warranties happen at the point of purchase of 6 this particular vehicle. Okay? That's the consumer 7 side story.</p> <p>8 So -- Tim?</p> <p>9 AUDIENCE: Do you lump in the used cars 10 warranties?</p> <p>11 DR. VENKATARAMAN: Actually, this is -- to 12 preview what lies ahead, all this is going to be used 13 cars. The entire exercise is going to be used cars. 14 There's a specific reason why I do that. Okay?</p> <p>15 When it comes to the perks for the firm, 20 16 percent of margins or profits realized for auto 17 dealers are through selling extended warranties. So just 18 to put these numbers in perspective, the average 19 profits that a dealership realizes through sale of a 20 car, which has been the bulk of the interest of 21 academic research, at least on the academic side, the 22 average retail margins are around 2 to 3 percent. So 23 we are looking at several-fold here.</p> <p>24 When it comes to underwriters, 50 percent of 25 the people who buy extended warranties never, ever</p>	332	<p>1 into purchasing extended warranties. Okay?</p> <p>2 So to formalize the research questions, I'm 3 going to be answering the following two questions. 4 One is when the auto buyers of extended warranty -- 5 auto buyers purchase extended warranties, and when I 6 say when are they more likely to purchase it before 7 the manufacturer warranty expires or more likely to 8 purchase it after the manufacturer warranty expires, 9 okay?</p> <p>10 Why is this question important? Well, it 11 could possibly inform or provide us some kind of 12 inclusion or understanding of what underlying 13 mechanisms might justify these choices or rationalize 14 these choices. Once we have a good handle on possible 15 mechanisms that drive these choices, as a policymaker, 16 I might be interested in kind of using that as an 17 input to assessing whether there's a need for a policy 18 intervention, and if there were a need for a policy 19 intervention, what kind of policy intervention might I 20 design, and when might I actually introduce this 21 policy, time the policy intervention.</p> <p>22 From a dealer standpoint as marketeers, 23 clearly this is going to be directly relevant for 24 targeting marketing because as a dealership I can 25 figure out should I be aggressively targeting extended</p>

333	<p>1 warranties to consumers before the warranty expires -- 2 manufacturer warranty expires or after. How soon 3 before and how soon after? 4 So the empirical setting, going back to the 5 question that Tim asked, the empirical setting that we 6 are going to be taking to the exercise is going to be 7 the used vehicle market. So why this particular 8 choice of data? Well, go back to our question. I'm 9 interested in studying whether people are more likely 10 to buy before or after the expiry of the manufacturer 11 warranty. So if I look at the new vehicle market, the 12 entire manufacturer warranty is intact, so there is no 13 variation that I can exploit. So I am left with no 14 other choice, and naturally I'm going to be using the 15 used vehicle market. 16 It so happens from a substandard standpoint 17 as well, the used vehicle market actually forms the 18 lion's share of all sales, at least in the U.S. So 19 depending on which resource you trust, anywhere from 20 55 percent to 79 percent of all auto sales in the U.S. 21 happen through the used vehicle channel. 22 For the purpose of this -- of this 23 particular exercise, the used vehicle market offers us 24 nice, rich variation -- natural variation that we're 25 going to be exploiting for identification. And</p>	335	<p>1 warranty side. So I need to figure out a way to also 2 control for those kind of possibilities in the 3 empirics that follow. 4 So given the question, given the empirics, 5 and given the threats to identification, the empirical 6 strategy that I'm going to be taking to my data is 7 going to be the sharp regression discontinuity design. 8 So I feel like this design is almost tailor-made for 9 this particular question that I'm going to be 10 studying. Why? Because the sharp regression 11 discontinuity design requires the assignment to the 12 treatment condition to be exogenous and 13 nonmanipulatable, right? I'm sure I'm butchering that 14 word, so just bear with me. 15 So in terms of the used car market, think of 16 what the treatment condition is. The treatment is 17 whether the vehicle has expired manufacturer warranty 18 or non-expired manufacturer warranty. And the 19 decision -- your assignment rule to the treatment 20 condition, which in this case is expired, is purely 21 deterministic. So once you hit the age mark or you 22 hit the mileage mark, you're in the treatment 23 condition. Okay? 24 Second, it's completely exogenous. Why 25 exogenous? Because it's predetermined -- even well</p>
334	<p>1 specifically what I mean by that is there are some 2 used vehicles that are almost in pristine shape that 3 have all -- almost all of the manufacturer's 4 warranties in place. Some are really, really old and 5 have nothing. And then you have everyone in between. 6 And that variation is something that we're going to be 7 exploiting. 8 However, with used vehicles, unlike new 9 vehicles, it also introduces a set of econometric 10 challenges for us, first of which is no two used 11 vehicles are alike. Right? So we have to figure out 12 a condition -- try to control as much as possible the 13 role of unobservables. 14 Second, there could be strategic sorting on 15 the part of buyers. And what I mean by that is the 16 composition of people who buy younger vehicles could 17 be very different than the composition of people who 18 buy older vehicles. And I need to find a way to 19 tackle that as well. 20 Going back to the numbers that I outlined a 21 few slides ago, if dealerships and underwriters are 22 making tons of money on extended warranties, perhaps 23 it's possible that the dealerships could be offering 24 more attractive terms on the vehicle to kind of get 25 you -- or get to win your business on the extended</p>	336	<p>1 before it got out of the factories. And we're looking 2 at used car markets, so we're looking at several years 3 after these levels were set. However, going back to 4 what I said on the previous slide, regression 5 discontinuity design also affords us a nice way to 6 control for these threats to identification, one of 7 which is the role of unobservables. 8 And for some of us who are familiar with 9 regression discontinuity design -- I see many in this 10 room who have worked in this space -- by the choice of 11 bandwidth, which is local region around the treatment 12 condition, allows us to almost make the unobservables 13 random -- as if it is random to the treatment 14 assignment. Okay? 15 And I'm going to kind of try to provide some 16 evidence and try to do as much convincing as possible 17 with the data that I have that those conditions are 18 being met. 19 AUDIENCE: Does the supply also vary around 20 that cutoff, though? 21 DR. VENKATARAMAN: Supply of vehicles? 22 AUDIENCE: Supply of vehicles you have is -- 23 DR. VENKATARAMAN: Yes, yes. And I'm going 24 to find a way to convince you that that's not 25 necessarily at work or that's not driving necessarily</p>

337	<p>1 the outcomes here. But it's a great point. 2 Okay. Validity tests. Remember, the 3 threats to identification, I need to take into account 4 the notion of sorting, manipulation, so all these 5 things that are several tests that have been proposed 6 in the literature to kind of allay some of these 7 concerns, as I've been told and I've come to 8 understand through the review process now that none of 9 these tests are foolproof, which -- fine, right? 10 However, if I can show a battery of tests, all of 11 which reject these concerns, I'm hoping that this 12 allays some of your concerns, right, otherwise, 13 there's another journal, right? 14 So I have multiple editors here. I 15 shouldn't be saying these things. Right? 16 But last but not the least, one of the 17 limitations with this approach is, of course, external 18 validity, right? Which is I can make a lot of fairly 19 precise statements within the local region, and I'm 20 going to refrain from making any statements outside 21 this local region. Okay, so, if I say anything that's 22 more preachy outside this region, call me out on that. 23 Okay, so the data set that I'm going to be 24 using in this particular exercise, I got very lucky. 25 I have 50 randomly chosen dealers across five states.</p>	339	<p>1 bumper-to-bumper and a powertrain expiry. And then I 2 have data past powertrain expiry. And that variation 3 is what I'm going to be exploiting to the fullest. 4 So the first step to regression 5 discontinuity design is going to be coming up with the 6 local bandwidth. So we tried two approaches. Both of 7 them seemed to be the de facto -- almost de facto 8 standards in this particular area of research, one of 9 which is the Imbens and Kalyanaraman paper and the 10 Calonico Econometrica 2014 paper. 11 So I have multiple cutoffs. So I have the 12 bumper-to-bumper; I have powertrain -- and powertrain 13 could be either shorter powertrain or longer 14 powertrain. So for each of those mileage markers I 15 run -- I select my bandwidth, so I have a compact 16 bandwidth around each of those markers. Once I had 17 those markers, at this particular point, I'm going to 18 be basically estimating -- running a regression. And 19 this regression is going to be nothing but I'm trying 20 to run logit -- not trying -- I'm running a logit 21 transformation of the conditional choice probability. 22 So it basically becomes a simple linear progression -- 23 or nonlinear regression. 24 So what we have, the key parameters of 25 interest for me, are going to be beta-one -- I should</p>
338	<p>1 If you can -- if you have your geography right, these 2 are states that border my state, North Carolina. And 3 I have data spanning 2009 to 2014. For every vehicle 4 that was sold at these dealerships, I have all the 5 information. 6 So I know the purchase price, the list 7 price, I know the profits that are realized from each 8 sale, both from the sale of the vehicle as well as 9 add-ons, as well as gains from extended warranties 10 alone as well. But my NDA precludes me from exporting 11 any of that information for the empirics or reporting 12 any of those numbers. So my hands are somewhat tied. 13 For the purpose of the analysis, I'm going 14 to limit all this analysis to B2C transactions. I'm 15 going to be focusing on the top 15 make/model 16 combinations which account for around 85 percent of 17 all sales. Estimation sample boils down to 20K-odd 18 observations. What I need is variation in the 19 residual manufacturer warranties. So, as I said, 20 there are those two types of manufacturer warranties, 21 so here is a distribution of observations that I have 22 across the entire mileage spectrum. 23 So I have 47 percent of the data resides in 24 the region before the bumper-to-bumper warranty 25 expires. I have 36 percent that resides between</p>	340	<p>1 walk you through the subscripts. So I is the 2 consumer; J is the vehicle; D is the dealer; T is 3 time. So D is an indicator variable that takes 4 on value 1 if the vehicle is past manufacturer expiry 5 for that particular mileage marker. 6 Notice that I have a slope in the region 7 pre-manufacturer warranty expiry; and then I have a 8 slope that is interacted with the indicator variable. 9 So that allows me to pin down the variation in choice 10 probabilities before and after. And the indicator 11 variable is going to be allowing me to pin down the 12 discontinuity at the point of expiry of the vehicle or 13 manufacturer warranties. Okay. 14 How do I allay some of the threats to 15 identification? So first of which is the strategic 16 sorting between -- under composition of customers for 17 one. Second, and this is a related point, and this is 18 thanks to Matt for bringing this up, it's very 19 possible one of the things that I don't observe in the 20 data is the marketing effort by the dealerships to 21 these individuals, right? 22 So suppose dealerships had perfect foresight 23 and they had access to the analysis that we've 24 undertaken. If I can show that the likelihood is 25 higher pre-expiry and if the dealerships knew that,</p>

341	<p>1 perhaps they are more likely to market more 2 aggressively to those people pre-expiry than 3 otherwise.</p> <p>4 So one way for that to manifest in the 5 results or in the data should be if that were true we 6 should see more bunching of observations in the pre- 7 expiry than the post-expiry. So we should just -- we 8 should see more observations before the expiry than 9 after the expiry of the manufacturer warranty.</p> <p>10 It so happens that the McCrary test -- not a 11 foolproof test -- but it's one test that everyone's 12 employed, that shows -- that allows you to test 13 whether there is discontinuities in the density of 14 their data. Okay, so that's what we employ.</p> <p>15 Two, and it comes to endogenous selection of 16 the marketing mix elements. So one thing that we do 17 is we run regression discontinuity designs on all the 18 continuous covariates that we have in our model. That 19 allows me to assess whether there are departures to 20 the left or to the right of the expiry of the 21 manufacturer warranties.</p> <p>22 And last but not the least, to ensure that 23 I'm actually pinning down what I claim to be pinning 24 down, I run a bunch of placebo tests. And what I mean 25 by that is can I quantify or can I recover any</p>	343	<p>1 could be driving choice probabilities. So once we 2 include all these other covariates that I mentioned a 3 few slides ago, instead of reporting the parameters, 4 I'm going to simply highlight the -- graphically 5 highlight the findings.</p> <p>6 Okay, so this is what we find. So we see 7 almost a linear increase in the likelihood of purchase 8 of extended warranties leading up to the expiry of the 9 manufacturer-backed -- manufacturer warranty, in this 10 case the bumper-to-bumper warranties. And the point 11 of departure or point of expiry of the manufacturer 12 warranty -- in this case bumper-to-bumper -- we see a 13 3 percent drop in purchase rates. Then we see a 14 constant attachment rate, a purchase rate, from that 15 point onwards going forward. So if I were a 16 dealership and I had access to this data, the first 17 set of people that I'm going to be targeting are the 18 folks who are between 35,200 and 36,000 [sic], because 19 they had the highest likelihood of purchase.</p> <p>20 The next possible candidates that I'm going 21 to be targeting are any -- are all the individuals who 22 are within my local bandwidth from the point of expiry 23 of the manufacturer warranties all the way up to 24 48,000-odd-miles. The third best candidates are going 25 to be folks south of 35,000. The further out you get,</p>
342	<p>1 departures or discontinuities in my results in regions 2 where I shouldn't be expecting any of these 3 discontinuities. So we do it across several bins, and 4 we are able to rule out the possibility of these 5 departures or discontinuities happening anywhere else 6 but where it's supposed to happen.</p> <p>7 I'm hoping through -- and in the interest of 8 time, I'm not going to walk you through the technical 9 details of each of these things, but they're all in 10 the paper. So the front end of the paper is actually 11 much shorter than the back end of the paper because we 12 have a lot more battery of tests than the actual 13 formal main model itself.</p> <p>14 Okay. So this is the regression 15 discontinuity plot without any covariates. So the 16 only indicator -- the only variable that we have on 17 the right-hand side is whether it is pre or post- 18 expiry of the vehicle, okay -- expiry of the 19 manufacturer warranties. So as you can see, for the 20 people in the back, you might not be able to see this 21 clearly, but there is a very small discontinuity on 22 the far left panel on the top, but there are a lot 23 more noticeable departures on the other two panels. 24 Of course, this is without covariates. 25 So clearly there could be other things that</p>	344	<p>1 the less attractive they become.</p> <p>2 Tim?</p> <p>3 AUDIENCE: What do the prices look like for 4 these warranties over time? Is there a price 5 discrimination feature associated with these?</p> <p>6 DR. VENKATARAMAN: Yes. We have that. So 7 we have prices in the model. So, most often, prices 8 are increasing, as you get closer -- as we go closer 9 to the extended warranty -- manufacturer warranty.</p> <p>10 AUDIENCE: And what about after the --</p> <p>11 DR. VENKATARAMAN: It's almost flat. You 12 see step function. You see step functions, but the 13 step -- yeah, you see step functions at 30,000 miles.</p> <p>14 Okay. So, what might I be able to glean 15 from this finding? Okay, so powertrain warranty we 16 get just the opposite result. In the interest of 17 time, I'm going to focus on what insight policy 18 development as well as marketing relevant insight 19 might I be able to glean from this result alone. So 20 if those of us who are familiar with the warranty 21 literature, the literature advances four mechanisms 22 that drive warranty choice, as well as provisioning, 23 first of which is insurance provisioning, right, 24 insurance motive.</p> <p>25 So think of this as an insurance. If I'm</p>

345	<p>1 risk-averse, I'm drawn to products that have more 2 insurance. I'm more likely to purchase insurance 3 products. So if the residual on my automobile is 4 high, then I feel like that is less a risky product 5 for me to commit to. Since I'm a risk-averse 6 consumer, I'm going to be drawn to that particular 7 product and but since I'm also risk-averse, I'm also 8 more likely to purchase extended warranties. 9 So you should see more people committing to 10 younger vehicles pre-expiry, and these very people are 11 also more likely to purchase extended warranties. If 12 it is signaling, think of signaling as the more 13 insurance you have, it's almost equal to having higher 14 quality product. If you have a better quality 15 product, it reduces the need to purchase extended 16 warranties. So the predictions from insurance motives 17 and signaling are just the opposite. 18 Incentive motives, these have got nothing to 19 do with consumers; it's got to do more with the firm 20 side. So these have no bearing whatsoever on our 21 results. 22 Sorting mechanism is the risk-averse 23 consumers are going to be -- the more risk-averse you 24 are, the younger the vehicle you're going to commit 25 to; the less risk-averse you are, the more likely to</p>	347	<p>1 concerns of -- concerns that need to be allayed, or 2 kind of promote additional purchase of these 3 particular products if it is actually economically 4 prudent to do so. 5 Okay. That's pretty much all I have to say. 6 So, happy to take any questions and refer to our 7 discussant at this point. Thank you. 8 (Applause) 9 DR. JIN: The discussant is Matthew Jones 10 from the Federal Trade Commission. 11 DR. JONES: Thanks. I have no slides. I 12 just have a few brief comments, which is mostly 13 because I think it's a very clean and straightforward 14 application of an RD design. So not a whole lot to 15 say, but I do have a few suggestions. 16 But, first, let me just review the punchline 17 of the paper. The main question is, is there a 18 systematic variation in the probability of purchasing 19 an extended warranty around base warranty expiration. 20 And the answer is yes. For the 36,000 mile bumper-to- 21 bumper, the probability of purchase increases up to 22 expiration, at which point there's a discontinuous 23 drop. And then it's constant. And for the 60,000- 24 mile powertrain, it's a constant probability, and then 25 at expiration, there's a discontinuous jump, after</p>
346	<p>1 purchase older vehicles. Okay. 2 So what does this -- if these mechanisms 3 were at work -- and I'm going to be done in a 4 second -- what would they suggest? How might I be 5 able to rationalize those two pictures? This would 6 suggest at least as you're seeing an increase pre- 7 expiry, that would suggest that insurance and sorting 8 motives dominate in the region pre-expiry of the 9 manufacturer-backed warranties when it comes to 10 bumper-to-bumper warranty. However, when it comes to 11 the region for the powertrain warranties, you find the 12 opposite effect, in which case signaling motives are 13 more at work. 14 So from a policy standpoint, this would 15 suggest that in the region pre-expiry for the bumper- 16 to-bumper warranties, the manufacturer-backed 17 warranties and the extended warranties, at least in 18 the minds of the consumers, are being treated -- 19 almost traded off as complements, whereas in the 20 region in the post-powertrain expiry, these two 21 products seem to be treated more as substitutes. 22 So knowledge of these being as -- being 23 either substitutes or complements is going to be 24 directly pertinent to policymakers because based on 25 that they can design interventions to either allay</p>	348	<p>1 which it declines. That's the finding. 2 And the approach, I think, is a very nice 3 application of RD design, given that there's no 4 strategic variation in warranty expiration. So you 5 might worry about -- well, you don't have to worry 6 about manipulation of the mileage on the vehicle, 7 right? It's illegal to tamper with an odometer, so 8 that's not a concern. 9 If you're concerned about strategic offering 10 for sale of vehicles, contingent on, you know, whether 11 you're just before the expiration of the base warranty 12 or just after that, there's a test for, you know, the 13 density. And the finding is that there's no 14 difference in density of offering -- or for up-sales 15 on either side. So it seems to be a very clean 16 implementation. 17 And, you know, the findings, I think there's 18 an intuitive interpretation, which Sri just explained. 19 So you have the sorting by risk aversion to explain 20 the bumper-to-bumper, that more risk-averse consumers 21 are more likely to buy a vehicle that still has a 22 warranty, and also more likely to extend that compared 23 to less risk-averse. 24 For the powertrain, the 60,000-mile 25 powertrain, where reliability might be more of a</p>

349	<p>1 concern, it's an older vehicle, there you might have a 2 signaling thing. So the fact that the manufacturer 3 still has a warranty on this vehicle effectively is a 4 guarantee of quality and makes it less likely that 5 this vehicle is going to break down. So I'm less 6 concerned about buying an extended warranty. And I 7 think that's an intuitive rationale for the opposite 8 finding for the higher mileage warranty. 9 But just a couple of suggestions on the 10 paper. So the statistical significance is brought out 11 in these results. But I think it could be a little 12 bit stronger in explaining the economic significance 13 of the estimates. So if you look at the magnitudes 14 for the bumper-to-bumper -- or, sorry -- yeah, bumper- 15 to-bumper in particular, 36,000 miles, the 3 percent 16 discontinuous drop is less than 1 percent in absolute 17 terms. So less than 1 percent point change in the 18 probability of purchase. 19 It's not obvious to me that that's 20 economically significant in terms of motivating 21 strategic targeting, if the effect is -- or if the 22 curve is relatively flat. That's not to say that it 23 isn't economically significant. But, I think, you 24 know, it would be nice to know some more about in 25 concrete terms about what does this mean for a manager.</p>	351	<p>1 warranty expiration. 2 So one way this could go is the F&I manager 3 says, you know, here is one out of 30 pages you have 4 to sign. This happens to be the extended warranty; it 5 costs \$2,000; do you want to buy it or not. And the 6 consumer just responds, right? And it's presented the 7 same way whether or not there is a base warranty. 8 Another way that it could be presented, it 9 could introduce a framing effect where, you know, they 10 say either your vehicle still has a warranty on it but 11 it almost -- it's almost expired, you might want to 12 extend it, it costs \$2,000. But if you're on the 13 other side of base warranty expiration, your vehicle 14 does not have a warranty; would you like to purchase 15 one? And I think something like that, while you can't 16 observe it, could, you know, produce an effect such as 17 a discontinuous jump at expiration. So that's just 18 one possible limitation. 19 But overall I think it's a very nicely 20 executed and interesting piece, and it's encouraging 21 to see evidence that consumers are responding to 22 real economic incentives and information in this 23 decision -- in this purchase decision, rather than 24 just sales pressure, which I think is something that 25 is adequately tested for. It's just the framing of</p>
350	<p>1 These are tremendously profitable products, so there 2 may, in fact, be evidence that it is economically 3 significant, even if it's a small magnitude. 4 Also on the causality issue, I think there's 5 one limitation, one thing. So if -- you know, an 6 identifying assumption here is that all the covariates 7 might otherwise explain a purchase are smooth around 8 warranty expiration. There's one covariate that isn't 9 measured. 10 And, you know, I think you've done 11 everything you can within the limitations of your data 12 to address these things. So that's one of the things 13 about the paper, I mean, all the tests that you could 14 do with the available data are done, and you get a 15 result that confirms. 16 But there's one thing that isn't observed, 17 and I think that's exactly how is the extended 18 warranty presented to the consumer in the F&I office, 19 right? So, you know, you go in, and if you think 20 about how you would design an experiment, right? A 21 consumer comes in to the F&I office, and the F&I 22 manager presents a series of optional add-on products. 23 And what you would want to have if it was a controlled 24 experiment is you'd want to have those products 25 presented in the same way on either side of base</p>	352	<p>1 the sales pitch may differ in a meaningful way. 2 And that's all I have. 3 (Applause) 4 DR. JIN: Thank you, Matthew. We can take a 5 few questions. 6 Sri, you want to come up? 7 DR. VENKATARAMAN: Sure. 8 DR. MISRA: Just maybe a thought about this. 9 So at 36,000 miles limit, right, so the drop, now -- 10 so there is a sorting argument based on risk aversion, 11 but -- and maybe this does happen, that firms 12 obviously sometimes might have incentives to pre- 13 announce certain kinds of incentive schedules such 14 that they actually preselect everybody before the 15 threshold -- the ones that have to buy, and for the 16 ones that are left behind are the ones who have been 17 kind of endogenously selected for -- so this could be 18 another kind of sorting which probably might be 19 optimal for firms. 20 DR. VENKATARAMAN: Beautiful, Kanish, great 21 point. So the only observations that we are tackling 22 in this particular analysis are the sales that are 23 consummated at the dealership, right? So correct me 24 if I'm wrong, what I could do -- in your setting, 25 you're possibly talking about sales or offerings that</p>

353	<p>1 are presented to consumers post-purchase of the 2 vehicle. So you're sitting at home and you receive 3 these mailers. So perhaps some people were 4 strategically chosen to receive it and possibly even 5 the framing of the message was slightly different. 6 DR. MISRA: Who would receive actually mails 7 from your dealer post -- 8 DR. VENKATARAMAN: Yeah, and I can tell you 9 having spoken to F&I people and underwriters, they do 10 blanket mailing. Everyone receives it, right? Some 11 markets, what they do is they receive multiple 12 messages from the same individual, and the only thing 13 that I've been told that they change is they make the 14 reminder note, sometimes you have seen in the picture 15 as well, this is the last reminder. 16 Apparently, there are some people -- some of 17 our peers who seem to view that as, you know, with a 18 greater sense of urgency when someone says this offer 19 is going to end tomorrow, and they feel like they're 20 going to lose out on something big, and they commit to 21 these products. But great suggestion. 22 DR. JOHNSON: One question in addition as well. 23 Like you were mentioning about sorting. And I was 24 thinking, like, one way to probably tease out a little 25 bit more of the effect might be the gradation and</p>	355	<p>1 DR. VENKATARAMAN: Yeah, so in one of the -- 2 one of the things that we do is we try to assess if 3 the supply of similar vehicles in the local market 4 around this particular dealership has any bearing on 5 the likelihood of purchase of extended warranties. 6 And the thinking is as follows. If you buy really old 7 vehicles, the supply of parts for these vehicles is a 8 stock of existing vehicles in that local market that 9 are going to be, you know, turned in as salvage 10 vehicles. 11 So in order to proxy for that effect, we 12 kind of include the stock of variables of similar 13 type, similar age, similar vintage in that local 14 market. We do have many of that particular vehicle, 15 type of vehicle in that market. We just don't have it 16 in the back lot of this particular dealership. And we 17 kind of test whether that has any way to explain some 18 of this variation, that variable to pick up. 19 DR. JIN: I wonder what role price plays in 20 this whole thing. For example, would the dealer lower 21 the price of the car in order to persuade the buyer to 22 buy extended warranty? 23 DR. VENKATARAMAN: Right. So, we -- yeah. 24 So we actually explore that to the fullest. So what 25 we do is we actually run a regression discontinuity on</p>
354	<p>1 behaviors across different types of models which are 2 different in terms of their reliability, right? So 3 did you explore that at all? 4 DR. VENKATARAMAN: Yeah, so I tried to 5 condition it by having the model fixed effects, right? 6 So one of the things I could do -- 7 DR. JOHNSON: But then you're just absorbing 8 everything. 9 DR. VENKATARAMAN: Yeah. So one thing I 10 could do is get that out and kind of recover the 11 treatment effects across all make/models. We tried to 12 do that. There are a whole bunch of really unreliable 13 vehicles for whom we don't have much data. So much of 14 the action is actually coming from parsing of the 15 variation and the slightly more reliable data. 16 So remember, the more reliable vehicles are 17 also the more expensive vehicles. The more expensive 18 the vehicles, the more expensive it is to repair 19 anything if something were to happen. So we're 20 actually -- much of our identification is actually 21 coming from the higher end set of vehicles. But great 22 observation, great intuition. 23 AUDIENCE: So I might have missed this. I 24 was just wondering, you know, Garrett's question a 25 little about supply. I missed what kind of --</p>	356	<p>1 the transacted value of the vehicle and try to see 2 whether the prices, all else being equal, are 3 systematically lower for that kind of vehicle, pre 4 versus post, and we don't see any difference. We rule 5 that out. 6 DR. JIN: Which is surprising. 7 DR. VENKATARAMAN: Apparently, the outcome, 8 at least what was told to me, is the F&I people are 9 compensated for the extended warranties; the sales guy 10 is compensated for consummating the business deal, so 11 -- which might explain why those two are not 12 necessarily going hand in hand. 13 AUDIENCE: What about certified pre-owned? 14 Sort of a combination between -- 15 DR. VENKATARAMAN: Great. 16 AUDIENCE: Do you exploit that at all, or -- 17 DR. VENKATARAMAN: We don't. 18 AUDIENCE: -- see those -- 19 DR. VENKATARAMAN: We don't. The reason we 20 don't is because most certified vehicles, what it does 21 is the dealership or whoever is certifying the 22 vehicle, you're basically extending the manufacturer 23 warranty. So in the data, all we know is this 24 particular vehicle has been certified. I just don't 25 know how long the warranty has been -- has been</p>

357	<p>1 extended. So in order to kind of mitigate any issues 2 that might arise as a result of those observations, we 3 kind of keep them away from the analysis. 4 Any other questions? 5 AUDIENCE: Yeah, I was just wondering if 6 your study looked at whether there were any massive 7 recalls during the time that you looked at and that 8 were, you know, widely publicized and whether that had 9 any impact on a consumer's decision to purchase an 10 extended warranty. 11 DR. VENKATARAMAN: During the period of our 12 data, we had four major recalls, and we have -- in one 13 of the specifications that we tried, we actually had 14 recall indicator variables for those make/models. I 15 don't remember off the top of my head what we found, 16 but all I know is we decided not to put that in, 17 largely because for the most part it wasn't explaining 18 any of the choice proclivity. 19 Remember, this is pre the big Toyota recall. 20 But thanks for that observation. Thank you. 21 (Applause) 22 23 24 25</p>	359	<p>1 economics and marketing, showing that user reviews 2 affect demand and, in fact, there's a recent paper by 3 Greg Lewis showing that the amount that user reviews 4 affect demand has increased a lot over time, which is 5 consistent with the idea that, as consumers get more 6 comfortable with the 7 internet, they also use the internet more as 8 a source of information. 9 Now, consumer voice can affect a lot of 10 different decisions. So for a consumer, this might be 11 just a measure of product quality. So I'm thinking 12 about going to a restaurant; I look at Yelp to see how 13 good it is. For a platform or a retailer, it may tell 14 you which products to display or stock. So Yelp is 15 going to look at the reviews and then pick things that 16 have high star ratings to show you. And then finally 17 for the manufacturer, it's going to show you how to 18 improve products. 19 So imagine I'm a restaurant and, you know, 20 there's a principal agent problem, I don't know what 21 my staff is doing, I can look at Yelp, the people who 22 are complaining about, say, the waiters or they're 23 complaining about the food, then I know what I need to 24 do to improve. So really this kind of consumer voice 25 can help to improve a lot of different dimensions of</p>
358	<p>1 WHAT DETERMINES CONSUMER COMPLAINING BEHAVIOR 2 DR. JIN: Thank you. We'll continue with 3 the last paper about consumer complaining behavior 4 represented by Devesh Raval from Federal Trade 5 Commission. 6 DR. RAVAL: Thanks. 7 So thank you all for staying until the last 8 paper. I know that I'm -- you guys have better things 9 to do, but I'm glad that you're here. I want to thank 10 the organizers for inviting me and also the people 11 that have been laboring behind the scenes. And I'd 12 also like to thank Anne Miles and Patti Poss, both of 13 whom are by the windows for helping provide the data 14 and also asking me lots of pesky questions that helped 15 develop the paper. 16 So let's start. First is the obligatory 17 disclaimer. What we're interested in in this paper is 18 about consumer voice. We have known at least since 19 the work of Al Hirschman that consumer voice really 20 matters for markets, but the amount that it matters 21 has increased a lot since the advent of the internet. 22 So essentially through things like user reviews, the 23 internet has allowed the effect of consumer voice to 24 be magnified. 25 So there's been a lot of work, both in</p>	360	<p>1 the market. 2 But there's still a question of whose voice 3 do we here. And, so, in general, we know very little 4 about the characteristics of reviewers, and it's 5 likely there's a lot of self-selection. So, you know, 6 for example, I've been using Yelp and Amazon for a 7 long time, but I've never written a review. And I 8 imagine only a certain fraction of you do write such 9 reviews. 10 Self-selection could affect a bunch of 11 different parts of this. It could affect which 12 products are reviewed, as well as how quality is 13 assessed. So I think it's easiest to understand this 14 through a set of examples. I have a couple of 15 examples here. 16 So the first one is to think about franchise 17 hotels. So I am a big hotel chain. I want to know 18 which of my franchisees are, say, performing service 19 adequate to my brand image and which are not. Now, if 20 consumers vary in their complaint propensity, then 21 just looking at the sort of complaints or reviews I 22 receive might be very misleading. So for example, one 23 of the main messages of this paper is that consumers 24 in heavily minority areas complain less. 25 You know, so if I have some hotels that are</p>

361	<p>1 being served -- that are serving mostly white 2 customers, others are serving mostly minority 3 customers, it could be that the ones serving mostly 4 minority customers look better than they actually are. 5 And that's because those consumers are not willing to 6 review. 7 And, so, you know, from the franchise 8 hotel's perspective, it's hard for them to know who 9 are the good managers, who are the bad managers, which 10 is the good franchise, which is the bad franchises. 11 From a customer's point of view, the sort of reviews 12 they see online may not provide a good estimate of 13 quality. 14 Now, the second one I've given here is the 15 Consumer Review Fairness Act. So this is actually 16 recently passed by The House, I think in the past week 17 or two, and what they're trying to do is prevent firms 18 from penalizing people from making complaints online. 19 So if you think about it, if firms are 20 allowed to penalize people that make complaints by 21 threatening to -- by threatening to fine them or 22 something like that, then you might have a lot of 23 selection where the left tail in the distribution is 24 not being voiced because people are afraid that, you 25 know, there will be retaliation if they say something.</p>	363	<p>1 provide some of these cases, or at least told me which 2 I could use. But right now we have a bunch of victim 3 data sets that are matched to complaints from Consumer 4 Sentinel Network. 5 So I don't know if you guys know what the 6 Consumer Sentinel Network is, but it's an organization 7 that's getting complaints both from a lot of 8 government agencies like the Federal Trade Commission 9 and the Consumer Financial Protection Bureau, but also 10 private actors like the Better Business Bureau, which 11 receives millions of complaints a year. 12 So in this, we have a bunch of cases where 13 we have a data set, sort of the customer data set of a 14 company, that's all the victims of a particular scam, 15 and then we have matched all the complaints about that 16 company that we were able to get from Consumer 17 Sentinel Network. 18 Now, what's crucial here is that we have 19 addresses, in general both for the victim data sets 20 and the complaints, and that means we can link these 21 to demographics at the zip code level. And there's 22 actually a very important policy question here, which 23 is, you know, one of the things -- one of the ways we 24 use the Consumer Sentinel Network, it's called a 25 sentinel, and the reason it's called a sentinel is</p>
362	<p>1 So this might be things like, literally, you 2 know, you get sued or you get fined, but I talked to 3 Steve Tadelis when he was chief economist of eBay, and 4 one of the things he was saying is that in general the 5 review stars of buyers and sellers were very 6 uninformative. And the reason is that there's 7 retaliation if I give a seller a one-star rating, then 8 they're going to give me a one-star rating. And so 9 the better sort of informative signal is whether -- 10 you know, what the fraction was of reviews you get 11 rather than the actual star rating. 12 Now, in general, there's kind of a 13 fundamental identification problem here if you don't 14 have consumer experience data. And that's because if 15 you see higher rates of consumer complaints, that 16 could be because those consumers have a higher 17 propensity to complain, or it could be because they 18 have a worse consumer experience. And, in general, 19 it's going to be very difficult to disentangle these 20 two stories because in general we don't have this kind 21 of consumer experience data unless maybe you're a big 22 internet firm that knows who purchased all the 23 products. 24 So I'm able to separate the two stories 25 using a set of legal cases. And Patti again helped</p>	364	<p>1 we're trying to look forward to try to, you know, 2 identify emerging problems in the marketplace and try 3 to solve them before too many people get victimized. 4 And, so, we want to make sure that we learn 5 about problems affecting all communities. And if 6 certain communities are a lot more likely to complain 7 than others, then we might just be responding to the 8 problems of one group of society and not other groups. 9 So this is a big policy question for us at the FTC, as 10 well as places like the CFPB. 11 So let me go over the main takeaways quickly 12 of the paper. So what I find is that there's 13 substantial selection in complaints. So areas with 14 more minorities, the areas with more blacks and 15 Hispanics complain at lower rates, whereas areas of 16 more college graduates complain more. 17 And, crucially, it's really important to 18 control for consumer experience. So if you just 19 compared complaint rates for population, what you're 20 going to find is that heavily black areas complain 21 about the same or maybe more. So you're going to get 22 a very misleading picture of what's going on in the 23 marketplace. And that's because some of those heavily 24 black areas are going to be more -- victimized at 25 higher rates, and so they're complaining more, even if</p>

365	<p>1 their underlying propensity to complain is lower. 2 So let me talk a little bit about the 3 related literature of this paper. So this is sort of 4 in between the literature on customer reviews and the 5 literature on customer satisfaction. So as I said, 6 there's been a lot of work showing that customer 7 reviews affect demand. I've highlighted three other 8 papers. So the first paper Dina was talking about at 9 the panel, which is that there's strategic behavior 10 going on, so, you know, somebody may write false 11 negative reviews of their competitors; they might 12 write false positive reviews of themselves. 13 Second, Ginger has a paper on how to 14 optimally rank given reviews. So if reviewers vary in 15 their mean in variance and other characteristics, you 16 can use that to provide a better ranking than just the 17 average star ranking. 18 And, finally, there's been a little bit of 19 work on how reviewers or reviewer characteristics 20 demand. Now, second, there's been a large literature 21 on customer satisfaction, and there's even a journal 22 dedicated to customer satisfaction, as Jan has pointed 23 out to me multiple times. But the foundation of this 24 literature is from the book Exit Voice and Loyalty by 25 Hirschman. So he sort of started out the theory of</p>	367	<p>1 different attributes of different groups. And, again, 2 this is all at the zip code level. And I also try to 3 discretize all the demographics in order to allow 4 nonlinear effects of demographics. So, for example, 5 really high-income areas might be not any different 6 than low-income areas. 7 And as I said, I have four cases where I can 8 compare victims to complaints. So it's kind of nice 9 in a paper to have a little bit of mystery. So here 10 the mystery is that the first case I can't tell you 11 anything about, so I've called it Case B, and it's 12 nice because it has over 12 million victims and over 13 4,000 complaints, and it's by far the biggest data 14 set. The only thing I can tell you about it is that 15 it's been successfully sued in court by a state or 16 federal agency. So that's -- you know. 17 Now, the second case here is Ideal 18 Financial, so this was an FTC case, and what the 19 company did is bought payday loan applications and 20 then withdrew money from the bank accounts of people. 21 So if you do a payday loan application, you have to 22 give data about yourself, and then they just took 23 money from those people. So here we have 2 million 24 victims and about 1,500 complaints. 25 The third case is Platinum Trust. This is</p>
366	<p>1 this. And then there's been a large empirical 2 literature. 3 But, in general, this empirical literature 4 hasn't really been satisfied -- satisfying. There's 5 not really been a consensus about how different 6 demographic groups vary in their complaint rates. And 7 there's two reasons for this. First of all, in 8 general, the samples have been small. 9 So the sample might be, you know, a 10 thousand-person survey, or it might be data from one 11 local Better Business Bureau. But I think more 12 importantly there's been no control for consumer 13 experience. So you don't really know what's being 14 identified when you just run these regressions, which 15 is part of what I'm trying to do in this paper. 16 So let me go over the demographics first I 17 look at. So I'm matching consumer zip code to ACS 18 2008-2012 demographics. So I look at a bunch of 19 different demographics, and I'm going to be 20 controlling for all of these, but in the paper -- in 21 the presentation, I'm going to focus on percent black, 22 percent Hispanic, and percent college graduates. I 23 also look at urbanization, median household income, 24 unemployment rate, median age, household size. 25 So this is getting, you know, a bunch of</p>	368	<p>1 also a payday loan-related case. So here they took 2 payday loan applicants and they tried to sell them 3 deceptive credit cards, so credit cards that weren't 4 real credit cards but maybe they claimed they were. 5 So this is the smallest data set. We've got about 6 70,000 victims and 500 complaints. 7 And then the last case, WinFixer, is a 8 spyware case. So this company falsely claimed that 9 you had spyware, and then it was going to sell you 10 software to then, you know, remove the spyware. So 11 we've got 300,000 victims and 1,000 complaints. 12 But in general, these cases are all somewhat 13 different from each other. But I think the key thing 14 to note is that the number of complaints is orders of 15 magnitude smaller than the number of victims. So this 16 is telling you that there's a lot of selection in who 17 decides to complain. The average person is not 18 complaining. 19 So the first thing I want to show you is 20 that complaint rates are correlated with victim rates. 21 So here I've just constructed the complaint rate per 22 capita and the victim rate per capita and the zip code 23 level. So as I showed you here, the number of 24 complaints is pretty small, so they're about 25-, 25 30,000 zip codes in the U.S. You know, even the</p>

369

1 biggest case is about 4,000 complaints. So the
2 complaint rate is usually going to be either zero or,
3 you know, there's going to be one complaint or zero
4 complaints divided by the population. The victim
5 rates are going to be much bigger because we've got
6 millions of victims for a lot of the cases.

7 What I do is I try to provide a standardized
8 estimate of, you know, if you increase the victim rate
9 by a standard deviation, what happens to the complaint
10 rate. And what I find is that across these cases we
11 find pretty significant effects. So areas with higher
12 rates of victims also have higher rates of complaints.

13 And the magnitudes are about the same across
14 cases. So it's about -- if you increase the victim
15 rate by one standard deviation, the complaint rate is
16 rising by 12 to 17 percent. So this is actually
17 pretty reassuring. It says that the data isn't crazy.
18 Areas that have more victims in general are going to
19 have more complaining consumers.

20 Now I want to look at demographics. So the
21 first thing you see is that the victim rates across
22 demographics vary widely by case. So the X axis here
23 is the population share that's percent black across
24 zip codes; the Y axis is the victims per thousand
25 population. It's just normalized by the mean, so

370

1 everything fits on the same graph.

2 So the blue and the green line are both the
3 cases that involved payday loan victims. And what you
4 see is that when you go to areas that are 100 percent
5 black, they have complaint -- they have victim rates
6 of about 300 to 500 percent greater than areas that
7 are 0 percent black. And my guess is that that has to
8 do with the kinds of consumers that buy payday loans.

9 The Case B that I can't tell you about has
10 higher rates of victims in heavily minority areas or
11 heavily black areas, but it's only 80 to 100 percent
12 larger. So it's not quite as much as those two cases.
13 And then the WinFixer, the spyware case, is about
14 flat. So areas that have very high percent share
15 blacks have about the same victim rate as low
16 percentage share blacks.

17 If I look at Hispanics, things look more
18 similar. You see sort of an inverse U shape, so it
19 seems like the highest victim rates are in sort of
20 moderate, 25 to 50 percent, Hispanic areas. We find
21 lower victim rates in really high Hispanic areas. And
22 -- but in general the variation here is not quite as
23 large as it was for percent black.

24 So here I'm showing you that if you look at
25 here, the huge differences across cases and victim

371

1 rates, but if you look at the complaint rate -- so
2 this is the number of complaints per thousand victims,
3 again normalized the same way. What you find is
4 across all four cases, you see a decline. So areas
5 with high population of blacks have -- have less
6 complaints relative to the number of victims than
7 areas with low percentage share blacks. So this is
8 about a 40 to 80 percent decline.

9 So this is just the raw data. So I want to
10 copy out this a little bit in that, you know, again,
11 most of the zip codes have zero complaints because we
12 don't have many complaints. And, so, this is
13 nonparametric, but I think if you did a statistical
14 test, it's going to be hard to get non -- strong
15 evidence with this kind of data, but I think this
16 shows you that if you just look at the raw data you do
17 find that heavily minority areas complain less. If
18 you do that with Hispanics, you see the same sort of
19 pattern. And, again, heavily Hispanic areas that are
20 close to 100 percent Hispanic have about 50 to 90
21 percent lower complaint rates than areas that are 0
22 percent Hispanic.

23 So I'm going to then examine this more
24 formally by using an ordered logit on the individual
25 data. So here the Y variable is a latent variable for

372

1 the demographic category. So what I've done is I've
2 discretized the categories. So the five categories
3 for black and Hispanic are sort of 5 percent black, up
4 to 25 percent, 25 to 50, 50 to 75, 75 to 100. Now,
5 the main coefficient of interest is alpha, which is an
6 indicator of whether it's in the complaint data set
7 versus the victim data set. So what I've done here is
8 I've just stacked the different data sets together,
9 and this is trying to compare how do the demographics
10 vary between the complaint data set and the victim
11 data set for a particular case.

12 And then I've put in controls for all the
13 other demographics, as well as the log population. So
14 what this is trying to say is if you go between the
15 victim data set and the complaint data set, how does
16 one particular demographic category vary, even after
17 you control for all the others.

18 So I'm going to point out that because I'm
19 using the ordered logit, that's putting a lot of
20 structure, so that's going to say that there's going
21 to be -- if you go across demographic categories,
22 that's going to be a particular downward or upward
23 pattern. And you need this kind of structure because
24 at the end of the day we don't have that many
25 complaints, which is part of the self-selection

<p style="text-align: right;">373</p> <p>1 problem to begin with. 2 So here I've graphed the confidence 3 intervals for the percent change across categories 4 when you go to the complaint data relative to the 5 victim data. So it's easier just to look at the 6 bottom right corner. So the bottom right corner is 7 areas that are 75 to 100 percent black. What you find 8 is that you find significant negative percent changes 9 in the complaint data across all four cases, and this 10 is about a 25 to 80 percent decrease in complaints 11 relative to victims depending on the case. So this is 12 blacks. 13 If you look at Hispanics, you see a similar 14 picture in the sense that for all four cases you find 15 declines, significant in three of the cases. And 16 these are actually bunched pretty close together at 17 about a 30 to 40 percent fall in the complaint rate 18 for very heavily Hispanic areas. 19 Now if you look at college-educated areas, 20 you find higher complaint rates. So this is about -- 21 if you look at the areas with greater than 60 percent 22 college graduates, you have about 25 to 50 percent 23 higher complaints relative to victims. So the paper 24 has all the other demographic categories, but I didn't 25 want to bore you too much. So I've talked about the</p>	<p style="text-align: right;">375</p> <p>1 to victims. So what this says is that, you know, if 2 you don't have that kind of victimization data, you 3 might have a very misleading picture of what's going 4 on. The percentage Hispanic does decline just as we 5 saw in the victim data. 6 And then you can do this formally and 7 econometrically with that specification. What you 8 find is that the red here is confidence intervals for 9 the entire data set; blue is for the FTC; and green is 10 for the CFPB. So the Y axis is the percent change in 11 the complaint rate. And then we've got four groups, 12 so everything here is relative to 0 to 5 percent black 13 areas. And what you see is that for the entire data 14 and for the FTC, heavily black areas complained a 15 little bit more once you control for all the 16 demographics. 17 So if you don't control for demographics as 18 I showed you in the nonparametric regression, it's 19 about flat. When you control for all these 20 demographics, you find 21 somewhat higher complaint rates for heavily percentage 22 black areas. 23 And the green CFPB, you'll see huge 24 increases. So, you know, for -- in the CFPB data, 25 heavily black areas are complaining about 100 percent</p>
<p style="text-align: right;">374</p> <p>1 ones that I think are the most interesting. 2 So what this says is that there's a lot of 3 self-selection. Heavily black areas and heavily 4 Hispanic areas complain a lot less. Heavily college- 5 educated areas complain a lot more. Now, you get very 6 different patterns if you don't control for customer 7 experience. So this is what the literature has done 8 in the past, and it's sort of a more naive thing where 9 you're going to look at per-capita complaint rates and 10 see how they vary with demographics. 11 So here I take data from the Consumer 12 Sentinel Network from 2012 to 2015. I exclude 13 identity theft data. And the specification here is 14 I'm going to look at the log of the expectation of the 15 complaint rate as a function of demographics, 16 population, and time and state trends. So first let 17 me just show you the nonparametric regression. So, 18 again, here, the X axis is the population share of 19 percent black or percent Hispanic. The Y axis is the 20 number of complainants per thousand people. 21 So for percent black, you see it's pretty 22 flat. So really low percentage black areas complain 23 about the same rate as really high percentage black 24 areas. This is very different than what we saw when 25 we looked at the cases where we could match complaints</p>	<p style="text-align: right;">376</p> <p>1 or more. And I think some of that is that they're 2 complaining about -- heavily black areas are 3 complaining about different things. So let me just 4 show you that quickly. So it's hard to see all these 5 different colors, so I'll just try to summarize what's 6 going on. 7 And we're looking here at the percent change 8 in the share of complaints where I've divided 9 complaints into different categories like auto-related 10 complaints, imposter complaints, debt collection, et 11 cetera. And what you find is that in heavily 12 percentage black areas, you get a lot more complaints 13 on things like banks, debt collection, and auto- 14 related complaints. 15 And I think there's a common theme across 16 all of these, which is finance because I suspect a lot 17 of the auto-related complaints may be related to auto 18 finance. So what this is saying is that heavily black 19 areas are complaining about different issues, and 20 likely that's due to different rates of victimization 21 or things like that. 22 So I guess I have a couple minutes left, and 23 so I'm going to talk about, you know, what can you do 24 with all of this. So how should we account for 25 selection. So I think there are two potential</p>

377

1 answers, and I think there's some complementarity
2 between those answers. So first of all, there's a
3 policy answer, which is sort of outreach. So here we
4 contact groups that typically complain less.

5 So for the FTC, this is things like outreach
6 events, which we do periodically. So we might go to
7 Atlanta or LA and try to hold an event where we talk
8 to local community groups. We might want to talk to,
9 say, non-English-speaking media, and try to get -- you
10 know, first of all, tell them about the FTC, what we
11 do, how they can complain, but also learn from them
12 what their problems are.

13 Now if you're a marketer, this might be
14 something like surveys or incentives. So you could
15 think about running a survey of everyone that's bought
16 your product and, you know, offer them a \$50 gift card
17 and then try to see what their -- see what their
18 comments are. And that might give you a very
19 different picture than just looking at the people that
20 decided to review or decided to complain on the
21 website.

22 And, again, incentives might be some way to
23 get people to complain. So for example, you offer
24 them a raffle ticket, essentially, to complain. And
25 there's also a statistical answer, which is weighting,

378

1 so you could think about overweighting complaints from
2 groups that complain less, but the problem with that
3 is you need data on consumer experience to construct
4 the weights to begin with.

5 So that's something, you know, I could do
6 with this type of data because I have that data, but
7 if you're a marketer, you might need to do sort of a
8 survey or do something like that in order to do the
9 weighting in the first place. But I think -- you
10 know, I've not seen anyone do this in practice, but
11 these are the sorts of things you would need to do in
12 order to deal with self-selection.

13 So that's it.

14 (Applause)

15 DR. JIN: Thank you. The discussant is Anne
16 Coughlan from Northwestern.

17 DR. COUGHLAN: Well, thanks very much. I
18 feel I have great power, and yet you have great
19 coercive power against me if I go long, so I'm going
20 to go short.

21 But thank you for all -- yeah, I like to
22 walk around. Better if I can walk around.

23 So thanks again for this great conference
24 today. I think we've all had a wonderful array of
25 papers and presenters and great discussions, so thanks

379

1 to the organizers and thanks for hosting to the FTC.
2 And it's a pleasure to be here.

3 So I have some comments on Devesh's paper
4 here, which I found very interesting. And, in fact,
5 his presentation helped me a lot. So one of the first
6 comments for Devesh is going to be a little more
7 clarity in writing, please. So you'll see that one of
8 the things that I have to say I think really was due
9 to the fact that I was a little confused about what
10 was being intermixed where in the paper, but we will
11 get to that.

12 I want to emphasize to those of you who are
13 not at the FTC what I found immensely interesting and
14 novel here. There is a novel data set that is
15 available only in the law enforcement community, which
16 is the Consumer Sentinel Network. Now, for those of
17 us not in the FTC, this reminds me greatly of the
18 explosion of papers that I see of academic colleagues
19 with people who work at Google and Microsoft, right,
20 where you really cannot get the quality of data,
21 right, sitting outside of the community.

22 So this is terrific because it compiles lots
23 and lots and lots of different kinds of consumer
24 complaints and very wonderfully it frequently,
25 apparently, includes the complainer's address, thus

380

1 facilitating the entire analysis that's done here that
2 lets you put together zip code data with -- on
3 complainers with the actual nature of the complaints.

4 And, then, there's analysis that combines
5 the demographics of the victims of fraud from this
6 interesting sample of four law enforcement cases and
7 asks whether the propensity to complain correlates
8 with a number and type of victim.

9 So what I saw as the goal of this paper is a
10 much deeper descriptive dive than I've seen before
11 into the nature of who complains, which is super
12 important for us to understand and also show how the
13 demographics of complainers compares to the
14 demographics of victims, which is very important
15 potentially for consumers protection issues that we're
16 concerned with here today.

17 I'm not going to go over again the
18 interesting particulars of the data. You can take a
19 look at this yourself. The interesting thing that I
20 found here is I thought about this -- I thought about
21 the question of why. There's a lot of interesting
22 information here about what, and I was trying to
23 figure out about why, okay? And, in fact, you see
24 some of this in the paper.

25 One of the questions is is this due to

<p style="text-align: right;">381</p> <p>1 differences in people's cost of time? Is it due to 2 differences in people's access to the ability to 3 complain or the knowledge about how to complain? 4 Because the answers to those questions are crucial for 5 helping to get voice out there properly. So, for 6 example, one of the things that wasn't emphasized in 7 presentation but which I found very intuitive is that 8 complaint rates are lower for areas that have higher 9 household size.</p> <p>10 Well, a few of us were talking about being 11 parents of kids, and you know what that one's about, 12 who has time to follow up on complaints when you 13 hardly have time for four cycles of REM sleep per 14 night, right? So that one was very intuitive to me. 15 And the one that I found kind of intriguingly 16 different from what I thought would happen is that 17 complaint rates are higher in areas with a high 18 percentage of college grads.</p> <p>19 Again, if what you believed was the cost-of- 20 time hypothesis, you'd guess this isn't happening, 21 right? So I found some of these actually just very 22 interesting on a univariate analysis, right? There's 23 some very intriguing descriptives here.</p> <p>24 Now, going on to the law enforcement 25 actions, there are four different law enforcement</p>	<p style="text-align: right;">383</p> <p>1 of contemplation. So one of the thoughts that I had 2 is this: What is, so to speak, an equilibrium 3 complaining process? When is it that you would 4 decide, so to speak, that on the margin it just isn't 5 worth it to you to complain about whatever it is that 6 is happening? And in particular, so many people do 7 not complain, and some of these things -- payday loan 8 frauds and so on -- presumably would be notable enough 9 you would expect a lot of people to complain, and yet 10 they don't all. Right?</p> <p>11 So why do people not complain? That was 12 kind of interesting to me. And perhaps on the margin 13 what we want to think about is a sort of an economic 14 model where on the margin the necessary number of 15 complainers to sort of induce action, right, is really 16 of interest here. It doesn't take, you know, however 17 many hundreds of thousands were harmed for action to 18 occur.</p> <p>19 And, so, in some sense, I was thinking, 20 well, perhaps this is really an okay number of 21 complaints. I mean, we don't actually know what the 22 right number of complaints is, do we? Right? The 23 right number of complaints is the number that induces 24 action to occur, and then that brings in my mind 25 another thought, which is -- you may be familiar with</p>
<p style="text-align: right;">382</p> <p>1 actions here, and as I saw it, and I believe that's 2 the way it was presented here, too, relative to the 3 level of victimization, if you're in highly black or 4 highly Hispanic areas, you see fewer complaints. But 5 with higher college education, you see more 6 complaints.</p> <p>7 And, so, the sort of inference that I wanted 8 to draw from this is this, that perhaps the types of 9 complaints in these sub-populations don't reflect the 10 types of victimization of concern in the cases that 11 were presented here. And I think there was a sense of 12 that, that there's lots that people complain about. 13 So is it really just that there's a larger array of 14 issues to complain about in some areas, right? And 15 some of this doesn't really concern victimization due 16 to fraud.</p> <p>17 So I believe some of this was cleared up, 18 but it wasn't clear when I first read the paper 19 whether the complaints database was restricted to 20 fraud complaints. Now I believe from having heard the 21 presentation that that's carefully culled down, but if 22 not, you want to separate out and make sure you have 23 fraud/fraud in the four cases looked at.</p> <p>24 Now, one of the things I thought about was 25 the classic alternative explanations, you know, string</p>	<p style="text-align: right;">384</p> <p>1 this -- the commentary -- I'm not sure how much 2 research was literally done on this -- about what 3 happens when violent crime occurs on the city streets. 4 And when there are only one or two people who observe 5 it, they tend to run and help. And you remember the 6 famous case -- I can no longer remember the name of it 7 -- I think it's -- Kitty Genovese, exactly. And how 8 many people, 30, 50 people later on reported that they 9 had heard about her being attacked, and she was 10 killed, correct?</p> <p>11 AUDIENCE: I believe that story is no longer 12 true.</p> <p>13 DR. COUGHLAN: It is not?</p> <p>14 AUDIENCE: No.</p> <p>15 AUDIENCE: Apparently it was made up by The 16 New York Times reporter.</p> <p>17 AUDIENCE: Yeah.</p> <p>18 AUDIENCE: But it's a good story anyway.</p> <p>19 DR. COUGHLAN: Well, okay. Well, let me 20 state this as a hypothesis, then. 21 (Audience comments off microphone.) 22 DR. COUGHLAN: Thank you. Thank you. 23 So the hypothesis, though, is that if you 24 know that there are many others, your individual 25 impetus to complain goes down, right? And, so, it may</p>

385	<p>1 not really be necessary for us to be seeking more and 2 more complaints, and it could be helpful to understand 3 to do some investigation into, well, what is the 4 necessary number of complaints. Okay? 5 Now, the other thing that I thought I'd say 6 a couple of words about, and then I'll close off, is 7 some more ideas for continued research. We have an 8 intermixture of four different cases here. Two of 9 them are payday loan; one is about spyware; and the 10 other one is -- I don't know what. But the two payday 11 loan ones are similar, and the other two -- well, one 12 of the other, the spyware one, is obviously very 13 different; and the fourth looks different as well. 14 So one of the things I am thinking, and I 15 know how burdensome it must have been to create the 16 information per case, so I'm in dreamland. I'm not 17 worried about the cost of data. But it would be 18 interesting and probably valuable to cluster together 19 like types of cases because then you could pool data 20 and think about the common issues here, but it 21 probably isn't appropriate to pool across these four 22 because those are very different drivers for those 23 cases. 24 And then there are lots of different types 25 of complaints. And you saw some of that in the, you</p>	387	<p>1 So I'll stop with that. Thank you. 2 (Applause) 3 DR. JIN: Thank you, Anne. Any question? 4 DR. RAVAL: Can I give a response to one 5 thing? 6 So I just want to give a quick response to 7 the comments on this slide, actually, which is, you 8 know, to try to think about more detail in what people 9 are complaining about and not just aggregating 10 complaints. So, in general, this is, I think, a 11 machine-learning or text-finding challenge. 12 So we have the complaints; we have a 13 categorization that it's about autos or it's about 14 debt collection or something like that. But to go 15 deeper, you really have to look at the text of the 16 complaints, and I've done some work on that 17 internally, but, you know, we have the free-form text 18 of what people say, and there are some potentially 19 crazy complaints. There are going to be people that 20 complain about each one of the issues you talked 21 about, but the question is, I think, how can you use 22 something like topic modeling and machine-learning to 23 try to do that. 24 DR. COUGHLAN: Exactly. I would totally 25 agree. Yeah, it's not easy to do.</p>
386	<p>1 know, auto and bank -- the categories of products, but 2 there are also different types of complaints. There 3 were customer service complaints; there were "I was 4 overpriced" complaints; there were "I couldn't return 5 my product" complaints; all kinds of complaints out 6 there. 7 And, so, I'm thinking that conceivably this 8 complaining kind of research, whether you do or don't 9 want to go beyond consumer fraud, per se, could 10 produce a whole wealth of interesting research 11 projects, okay? 12 Finally, I've got this just as one small 13 comment, but I don't know how possible it is, but it 14 would be very useful to try to figure out metrics for 15 filtering out spurious complaints because there are 16 complaints that are not real, and that's an important 17 thing to do, too. 18 So in sum, what I found so interesting and 19 quite different from data available that I've seen in 20 other projects is that here there's a degree of detail 21 you just can't find anywhere else. So I would urge 22 keep on going. There's a ton of interesting stuff 23 here, with the possibility of getting a much better 24 judgment on when and where you want to take action on 25 consumer fraud.</p>	388	<p>1 AUDIENCE: So about the machine-learning 2 part on complaining, I think there's some studies, so 3 using Facebook data they can pretty much see how many 4 complaints, and Facebook has a natural policy. They 5 changed the conversation of how a customer can 6 complain, airlines, hotels, so that before the changes 7 the two are not classed together. 8 So after the policy change, all the 9 complaints that you complain about the surveys was 10 bad, and then they cluster together. So there's a 11 very good -- and that your policy can be wrong. 12 You're really tied with your complaint behavior here 13 with social media and machine-learning techniques. So 14 we can talk more offline. 15 DR. RAVAL: No, that sounds like something 16 we should be doing internally. 17 (Applause) 18 DR. JIN: So thank you all. Thank you to 19 all the presenters and discussants and actually the 20 active participation at the whole conference. It's 21 really sweet. 22 So before Sudhir delivers the closing 23 remarks, I just want to mention a few logistics 24 things. One is that transcript of this whole 25 conference will be available soon on our website. So</p>

389	<p>1 if you missed part of that, you will be able to get 2 back to it in the transcript. We're also planning to 3 post the slides on our website, and before doing that, 4 we're going to email the presenters and discussants and 5 make sure that you -- if you want to put some updates 6 into the slides and you will be able to do so. 7 If you have any comments or suggestions 8 about this conference or future activities, then we 9 can organize with your marketing community or even 10 now, other communities; you're welcome to send us an 11 email at the marketingconf@ftc.gov, which is the same 12 email website that you will see in the registration 13 website. That's where we'll welcome your comments. 14 And, finally, I want to thank Laura Kmitch 15 and Constance Herasingh for really running the whole 16 show for the whole day. They not only made sure the 17 computer worked, made sure the lunch worked, made sure 18 the time worked, and the microphone worked, they 19 actually have been helping me from day one, from 20 planning to all of the probably followup work after 21 today. So let's give a round of applause to both of 22 them. 23 (Applause) 24 25</p>	391	<p>1 community, but nobody had role models of papers that 2 were actually targeted towards that -- those set of 3 issues. And, so, we would always have some throwaway 4 lines at the end of a conclusion saying this work 5 would be relevant to policy regulators but with really 6 no specific, you know, particular analysis that was 7 done, a counterfactual that was particularly run or 8 even some dicing and slicing of the data in ways that 9 would be particularly relevant. 10 And I was reminded of that partly when 11 Catherine Tucker was telling Hema, you should actually 12 slice the data and take a very limited slice of data 13 and see whether that would already do things other 14 than privacy -- it would be nice from privacy 15 perspective, you don't have to have a long data set. 16 And as she said that, I was reminded of a paper that I 17 was writing around a very similar issue that Hema was 18 discussing, but it's sort of ad-targeting on price 19 targeting. And one of the counterfactuals that we 20 were doing, what would you do with last visit, last 21 purchase; then Catalina, the company that did it, 22 would keep only 64 weeks of data, and we had 100-plus 23 weeks of data. 24 And, so, we wrote something with 64 weeks of 25 data, but our motivation, sadly enough, now that I</p>
390	<p>1 CONCLUSION/CLOSING REMARKS 2 DR. JIN: So with that, I'm going to turn over 3 the podium to Sudhir. 4 DR. SUDHIR: So, first, let me start by 5 thanking Ginger. As she mentioned, you know, I think 6 just -- I think, if I recall, it was November of 2015 7 I was just taking over as Marketing Science editor and 8 Ginger was -- I saw on LinkedIn that she was taking 9 over the Director of the Bureau of Economic Analysis. 10 And I sent her a note on LinkedIn saying, 11 congratulations; by the way, we should do something 12 with marketing. 13 And I really didn't have any clear idea what 14 I was thinking. And a couple of months later, I get 15 this very detailed proposal to me and Avi saying, hey, 16 you know, we should put together a special issue. And 17 I was just -- I mean, to me, I was thinking about 18 really a special issue and, like, you know, this just 19 seemed to be the ideal special issue, I think, to do. 20 Because partly I think there is a fair amount of 21 latent interest, as was evident from over the 100 22 people who registered and came to this conference. 23 And, so, my sense of it was that there's 24 always this interest in the ability to do work related 25 to consumer protection in the marketing-economic</p>	392	<p>1 think about it, was, you know, data storage is very 2 expensive. Companies don't want to store data. 3 Therefore, you know, let's try what we can do with 64 4 weeks of data. And we -- you know, and we then said, 5 you know, storage is getting cheap; why the hell would 6 you care about this, remove all the stuff from the 7 paper. 8 So I was looking back at the paper today, 9 and as you commented, and I found that we did not have 10 the 64-week description, but if I had written, hey, 11 given privacy concerns, if we had gotten 64 weeks, 12 wouldn't it be wonderful, and everybody would have 13 said we were so far ahead in terms of thinking about 14 this issue. But it was a counterfactual that we had 15 run, but we motivated based on storage cost, which 16 made no intuitive sense to anybody. 17 But my point is that I think there is lots 18 and lots of opportunity if you start doing the data 19 with exactly the same kind of things that we would, 20 but we would be informing people. 21 So, in fact, when Ginger sent us this thing 22 for the special issue, Avi and I talked about it, and 23 one of the things that we said was we should have a 24 conference before we run the special issue because we 25 wanted people to have a melding of the minds, so to</p>

A				
a.m 1:14 5:2	343:16 381:2	93:23 132:3 140:4	75:21,23,25 78:15	277:20 278:11,12
aah 235:9	accessed 200:19	217:7 354:14	78:16 79:7,8 80:5	278:23
Aaron 6:21,22	accommodate 33:13	383:15,17,24	80:9,10,11,12,15	ad-serving 226:13
ability 86:2 107:1	accomplish 314:1	386:24 396:8,12	80:16,17 81:6,18	229:12
108:8,9 109:23	account 46:13	actionable 80:1	83:15,22,24 84:19	ad-specific 277:3
131:6 132:9	254:18 263:10	actionably 79:15	85:13,17 87:17	279:5
149:12 151:10	337:3 338:16	actions 10:14 16:19	88:2,3 89:16,21,22	ad-targeting 391:18
211:19,20 266:23	376:24	56:9,13 62:9,25	89:25 90:14,24	add 69:3 80:17
381:2 390:24	Accountability 10:7	63:8 93:23 94:2	91:1,5,5,7 94:5,20	133:9 147:10
able 5:22 6:6,23	accounting 49:13	96:16,21 228:5	94:25 95:1,18	164:14 165:10
13:12 14:15 16:4	accounts 367:20	265:3 381:25	97:14,18,19,23	177:21 196:17
25:8,20 33:10 35:7	accrued 22:16	382:1	98:1 115:3 134:5,9	213:23 221:9
39:20 41:4 63:23	accuracy 219:16	active 14:21 118:10	138:11,21 141:10	249:13 275:21,22
65:1 79:18 114:14	267:11 268:5	124:25 192:23	145:9 161:2,6	310:18,19 321:23
131:12 146:15	277:15	300:23 388:20	162:3 168:14	add-on 22:19
152:13 154:18	accurate 56:25	activities 11:5 14:20	226:15,19,20	350:22
159:9,10,11 161:9	208:25 220:1	389:8	227:7,9,17 228:2,2	add-ons 338:9
163:21 164:1	accurately 176:6	activity 5:10 20:4	230:11 231:4,5,8	added 100:18
168:7 191:7 212:5	271:23	67:24 304:21	231:10,16 233:1,5	102:24 196:12
224:9 266:14	achieve 36:24	307:4	233:20,22 234:5	adding 199:18 284:7
280:7 342:4,20	120:23	actors 363:10	234:17,18,24	addition 9:2 15:3
344:14,19 346:5	achieved 112:23	acts 160:5 217:12	235:10,15,16,17	67:19 70:14 75:16
362:24 363:16	acknowledge 206:23	actual 16:2 44:11	235:20,21,25	154:12 176:15
389:1,6	ACM 186:18	56:9 68:2,15 76:24	236:15 238:5	353:22
absence 74:17	acquire 130:17	88:9 92:9 105:24	239:6 240:6,6,7	additional 67:16,17
absent 24:12 57:15	132:10 133:23	157:5 237:7	241:23 245:23,24	67:18 71:15 90:3,3
absolute 199:6	164:15 169:4	279:16 305:22	246:3,25 247:6,8	91:1,1 124:5
305:22 309:5	acquired 65:21	342:12 362:11	247:10,23 249:12	178:16 282:19
312:14 349:16	acquiring 139:2	380:3	258:1,7 259:13	288:15 291:1
absolutely 61:24	acquisition 132:12	acute 302:3 307:6	261:12,16 262:3,6	325:20 347:2
86:15 87:12 89:10	133:18,21 134:15	307:11 311:5,9	262:10,12,19	393:13
90:20 274:18	135:18 139:8,10	312:19	265:3 270:3,8	address 18:11 59:7
absorb 318:6	142:14 143:5	ad 3:15 12:23 15:3	271:12,25 274:4,4	117:13 159:15
absorbing 354:7	145:1 147:8,22	23:10,15 26:18	277:4,7,9,10,10	220:1 271:14
Abuse 10:1	150:16 151:8	27:7,8,19 28:6,11	278:14,15 279:11	278:11,21 295:3
academic 173:19	Acquisti 213:10,24	28:17,19,24 30:9	279:23 283:8	350:12 379:25
330:21,21 379:18	220:18	33:24 34:16,18	289:11,21,22	394:24
academics 43:1	ACS 366:17	37:5,6,8,11,12,13	290:14,16,19	addresses 277:23
accentuated 164:12	act 8:1,6 9:16,19,20	37:16,18,19 41:5	291:3 293:4	278:12,14,16
accept 216:1 252:1	9:21 10:2,2,3,6,8,9	44:12,21 45:8	295:24 296:11	363:19
252:20	10:9 162:5 208:20	48:23 49:4,10,11	303:12 314:22	addressing 11:7
acceptable 15:8	209:9 210:3 218:6	54:13 58:16,20,23	321:3	adds 180:25 194:16
accepted 393:23	220:25 226:1	58:23 59:2,4,10	ad's 231:9	adequate 360:19
accepting 252:16	361:15	61:6,12,17 63:15	ad- 225:9	adequately 351:25
access 253:18	acting 10:19 56:1	66:16 68:4 69:1	ad-app- 279:6	adjust 47:22
265:12 279:6,18	77:24 192:17	70:9,14,16 71:5,12	Ad-ID 264:19 265:1	adjustable 184:16
280:23 340:23	219:5,19,21	72:2,2,5,7,21	265:5,11,11	185:17
	action 41:12 92:3	74:20 75:7,19,20	266:19,21 271:7	adjusted 252:8

adjusting 18:3	116:6,8 117:19,21	advertising 2:11,15	50:3 127:16 128:9	334:21 343:3
admin 7:3	168:11	3:19 12:21 13:23	128:24 161:3	agree 168:21 281:20
administrative 8:20	advertise 70:4	14:20 20:24 22:3	237:1 359:2,4,9	387:25
admissions 132:25	110:20,21 136:9	22:10 24:22 27:3,7	360:10,11 365:7	agreed 15:11
adopts 55:18	239:3 240:16	27:21 35:21 41:2,3	affiliation 48:18	agreement 95:10
ads 3:12 13:16 27:5	249:1 298:22	42:21 45:25 53:2,6	201:8	agricultural 101:7
27:10,11,12 28:9	299:3	53:21,22,23 54:2	Affordable 10:8	101:19 118:25
29:7 30:8 37:14	advertised 69:22	54:21,24 55:1,2,4	186:1	ahead 25:9 27:21
40:22,24 42:20,24	70:9 82:14 312:10	55:8,9,10,14,17	affords 336:5	29:11 90:6 94:14
48:25 49:1 58:7	321:7,9	56:5,16,19,22 57:5	afraid 168:19 213:2	172:15 210:13
59:19 69:10,11,12	advertisement	57:23 58:12 60:24	361:24	214:24 284:9
69:21 71:19 72:12	62:23 65:2,4 86:18	61:22 66:11,12,15	afternoon 170:10	330:12 392:13
72:24 76:14 77:1	91:8	66:17,21,24 68:16	age 202:14,19	aim 226:11 231:21
78:14,15,17,24,25	advertisements 56:3	69:9 73:8 75:2	205:24 234:7,15	286:2
83:5,19 84:1,12,24	56:11 70:25 71:1	76:1,4 77:4 79:23	235:18 238:20	aims 299:18
88:13,14 92:20,22	92:18 94:13	79:24 84:9,10	247:17,18,19	Airborne's 79:19
94:1,6,8 101:23	302:13	86:20,22 87:3,13	249:8,11 252:6	aired 320:20
102:17 168:15	advertiser 24:10	89:6,12,14 94:22	302:4 303:23	airlines 388:6
224:3 226:4,5,7	31:12 32:1,18 33:1	94:24 102:19	307:23 311:19	airport 155:1,2
227:16,19,24	44:10,16,24 49:10	133:5,10,13	312:3 335:21	AI 358:19
232:13,16 234:13	69:6 70:2,8,9	135:18 136:6,8,12	355:13 366:24	alarm 19:18,19
236:16 239:16	71:24 75:13 228:5	149:2 175:1	agencies 8:6 13:12	alert 20:4
240:5 242:16	264:10 280:15,23	179:24 189:9	179:1,7 363:8	Alessandro 213:10
253:14 261:2,5,10	advertiser's 75:11	194:3,4 207:25	agency 8:16 15:3	213:24 220:18
261:23 262:1,18	261:13	231:7 237:24	34:18 173:23	algorithm 87:8
263:5,6 264:8,12	advertisers 26:16	245:10 246:2	367:16	224:12 225:10
265:19,19 270:2,3	27:16 30:13 31:18	250:21 251:3	agenda 6:5 43:12	226:13 227:7,10
270:6,7,8,10 274:9	33:13 34:2,7 35:7	252:23 253:3,5,12	96:13 294:15	227:17,19 228:2,3
277:6 279:10,14	35:13 38:1 39:15	253:13 255:7	agent 183:9 359:20	229:13 232:4
280:2 290:8	39:25 44:16 49:5	261:1,8,18 266:11	agents 30:1 136:25	235:21 237:6
292:23 295:16	50:23 52:1 66:14	269:15 280:3	139:23	238:5 239:4,4
296:14 298:16	70:1,3,4 71:22	281:9,22 298:1,6	ages 202:7	241:9 242:8,14
309:19,20,21	73:7 134:7 227:16	298:12 300:16,18	aggregate 305:24	243:20,23 253:25
318:23 319:9	237:11 239:24	301:5 302:16	aggregated 263:22	254:15 272:3,12
320:20 321:4,6,13	240:15,18 242:11	303:11 306:5,6	302:24 303:16	272:23 273:1
321:14	242:16 243:1	307:9,10 314:4,19	320:22	274:24 284:16
adult-serving	249:9 250:9,10,15	315:8 316:5,6,8,15	aggregating 387:9	286:11 289:14
227:24	261:25 262:4	317:1,7 318:25	aggregation 283:21	292:4
adults 11:17	265:8,12 266:20	319:5 320:13,15	aggressive 8:4 193:1	algorithm's 235:15
advance 15:25 26:3	267:2,4,4 278:4,7	321:1,12 322:22	198:16 199:22,24	algorithmic 3:10
324:12	279:2,17 280:2,10	advertising-based	200:1	224:2,24 229:3,4,6
advances 344:21	280:11,13,22	51:1	aggressively 331:21	229:16,19,23,24
advantage 393:14	281:1,6,9 282:6	advertising-induc...	332:25 341:2	241:4 242:18
advantageous	283:14,17 290:7	315:18	agile 38:17	245:9,9,13 283:4
298:22	290:12 292:12	advised 20:6	ago 41:6 174:25	algorithms 29:1
advantages 63:7	293:11,12 314:13	advisor 322:15	193:14 208:2	225:25 227:24
advent 55:1 358:21	317:9 318:22	advocacy 9:9 229:8	209:18,18 216:11	229:10,20 236:11
adverse 110:24	319:2,8	affect 45:18 49:1	251:7 315:5	244:2 269:1

274:25 276:9	Alto 58:16	angle 137:19,21	171:22 298:15	180:15 188:17
285:4 291:13	AMA 315:5	angry 208:4	anytime 265:1	204:14 210:6
293:8	amass 225:21,23	Aniko 100:4 118:9	anyway 295:6	223:6 244:8
aligned 281:12	amazing 101:2	119:5 122:12	384:18	254:11 257:7
aligns 286:23	109:21 114:24	125:17	apart 80:23 194:13	259:5 282:9
alike 334:11	257:5 258:24	Anja 224:14 230:7	196:1 197:2 198:9	294:13 297:3
allay 337:6 340:14	amazingly 48:22	242:25 255:21	225:3,5 272:14	313:16 322:6
346:25	Amazon 360:6	Anne 4:12 91:16	327:20	323:2 347:8 352:3
allayed 347:1	ambitious 241:4	358:12 378:15	apologize 100:17,21	357:21 378:14
allays 337:12	America 14:24	387:3	app 59:8 67:4,5	387:2 388:17
allege 14:5 15:19,23	232:14	Anne's 97:7	68:18,19 260:12	389:21,23 394:19
alleged 14:24	American 269:22	announce 352:13	260:17,22 261:3	395:5
alleviate 109:6	Americans 10:5	annoyed 258:25	262:17 263:12,13	Apple 225:3 265:4
219:24 293:9	amoebas 22:25	anonymity 193:12	269:16 271:11,24	appliance 176:1
alleviated 108:21	amount 22:24 23:6	204:11	279:7 289:21	appliances 176:7
114:21	36:11 48:24 51:10	anonymized 218:24	295:18,23 296:7	applicant 132:6,8
allow 31:5 33:3 36:7	134:8 145:4 177:2	219:8	296:15	applicant's 132:13
41:2 47:9 131:21	200:5 248:4	anonymous 145:8	app- 295:16	applicants 368:2
134:23 168:10	276:14 305:22	anonymously	app-specific 277:2	application 101:21
267:3 278:3	358:20 359:3	204:12	apparent 56:24	155:17 245:4
281:14 298:12	390:20	answer 25:21 37:17	229:14,24 242:18	347:14 348:3
367:3	amounts 252:17	37:17,18 41:20	245:21	367:21
allowed 147:8 216:2	amplification	52:2 74:7 83:8	apparently 37:14	applications 245:3,6
225:20 254:5,5	201:14	98:7 101:7 104:1	353:16 356:7	260:7 367:19
265:9 269:22	analogous 45:14	170:7,13 209:10	379:25 384:15	applied 176:23
279:2 280:22	analogy 42:23	213:16 247:11	appeal 158:13	293:15 294:7
298:18 358:23	analysis 144:24	249:20 253:16	183:18	applies 119:2 132:1
361:20	160:2 167:25	262:14 283:24	appealing 138:5	133:11 294:6
allowing 46:10	174:4,19,24 175:7	294:25 295:9	appear 84:1,2	298:7
161:6,10 204:3	175:9,13 176:25	347:20 377:3,25	142:24 154:1	apply 122:9 150:4
219:4 268:18	181:15 183:20,24	answering 25:4	225:10 233:22	161:16,23,23
278:6 340:11	184:22 185:1,13	42:17 215:1 332:3	305:9	162:17,18 163:21
allows 33:11 49:18	215:11 232:20	answers 48:13 79:4	appearance 154:6	appreciate 51:22
197:14 200:19	233:25 294:8	83:17 281:25	appearances 154:6	244:16 322:8
336:12 340:9	313:2 338:13,14	315:2 377:1,2	154:10	approach 25:4
341:12,19 394:6	340:23 352:22	381:4	appears 227:25	26:22 28:5 44:4
alluded 246:8	357:3 380:1,4	Anthony 2:22	311:2	59:25 70:12 284:1
alpha 139:11,14,15	381:22 390:9	100:18 118:7,12	appellation 101:7	284:21 288:24
139:19,25 140:2,3	391:6	127:12	101:19 118:25	319:21 337:17
142:16 145:5	analyze 153:19	anticipate 121:1	appellations 104:5	348:2
150:1,6,11 372:5	analyzed 68:8	anticompetitive	128:5	approaches 59:15
alternative 45:14	Anderson 175:17	8:18 9:18	appendix 124:13	284:13,15 285:20
47:8 178:15	Andrew 3:7 6:4	antitrust 7:15	applause 6:25 7:2	339:6
179:16 307:16	170:7,10 171:24	172:18	21:3 43:10 48:15	appropriate 385:21
311:14 315:24	Android 66:23 67:4	anybody 91:25	52:7 77:8 85:20	approves 181:2
382:25	260:10 265:5	172:4 220:13	98:22 118:8	approximately
Alternatively 46:9	anecdotally 320:4	289:8 392:16	127:11 151:15	270:11
alternatives 289:16	Angeles 15:4	anymore 149:12	162:22 169:11	approximations

286:16	arrives 112:2	138:19 139:1	268:13 272:21	Austin 151:17
apps 55:16 202:15	arriving 107:12	152:16 164:19	306:13 367:1	Australia 65:24,25
260:7,9,10,13,16	art 239:21	188:9	attributing 324:15	authenticity 197:16
261:21 263:5	article 187:17,20,22	assumed 275:10	auction 2:10 20:23	authorities 9:3
264:21 265:8	228:21 250:13	assumes 38:6	22:2 24:20,22 28:5	authors 79:15
270:1,6,7,11 274:9	articles 244:24	213:18	30:4,11 37:10,12	156:11 158:6
277:7,12	artifact 90:16	assuming 217:4	37:24 38:2 40:7,11	159:1 160:13
April 14:6,8	aside 50:4	325:9 329:12	44:5 291:2 292:18	269:12 291:16
arbitrarily 124:7	asked 8:13 41:8	assumption 10:3	292:20,25 293:3	299:23 315:13
arcane 217:21	59:17,20 74:9 92:4	35:17,23 149:16	auctioneer 33:23	316:2 317:15
architecture 188:11	216:13 253:12	153:3 154:8	38:8	auto 324:25 326:22
188:13	280:21 333:5	157:24 158:20	auctions 25:20	326:22,25 327:8
area 14:21 17:11,20	asking 58:3 89:9	168:23,23 213:22	39:15	329:4,7,20 330:16
22:9,9 34:23 45:9	93:19,20 258:9	285:14 303:10	audience 29:13	331:20 332:4,5
48:1,9 57:18,20	282:15 315:1	350:6	31:10,17,25 32:5	333:20 376:17
58:15 173:1 175:8	358:14	assumptions 34:12	33:7,17 34:14	386:1
180:8 190:11	asks 269:19 380:7	36:3 113:3 128:13	36:23 37:4 40:17	auto- 376:13
192:6 294:5	aspect 47:1 60:10	131:11 138:5	50:2 58:11 63:11	auto-related 376:9
300:17 339:8	121:9 169:8	155:19 161:17	63:17 71:3,7 85:23	376:17
areas 16:12 360:24	208:23 211:15	166:9 197:25	86:24 88:22 94:15	automated 134:11
364:13,14,15,20	aspects 58:2 218:9	285:10	94:18 95:3,8,23	automatic 275:24
364:24 367:5,6	assemble 217:8	asymmetric 161:19	96:3 97:5,9,12	276:1
369:11,18 370:4,6	assembled 186:11	AT&T 174:13	98:1,4,9 104:8	automatically 47:19
370:10,11,14,20	186:13 214:16	Atlanta 377:7	127:14 128:3	158:2,11,16
370:21 371:4,7,17	217:2 222:5	Atlas 182:20	164:13,24 165:10	278:15
371:19,21 373:7	assembly 20:2	attached 33:7	166:15 168:9,18	automobile 345:3
373:18,19,21	assess 56:4 58:3,6	attachment 343:14	210:14,16,24	autonomous 54:16
374:3,4,5,22,24	59:5 60:19,23 61:3	attack 12:11	211:2,7 212:9	54:16
375:13,14,22,25	63:23,25 76:4 86:2	attacked 384:9	213:4 217:11,15	autonomy 54:11
376:2,12,19 381:8	175:25 341:19	attempts 314:3	218:4 219:2,10	autos 387:13
381:17 382:4,14	355:2	attention 14:1 55:16	220:3,7 222:17	availability 174:6
argue 7:16 162:11	assessed 86:12	86:9,11 87:12,14	246:22 254:14	available 7:5 20:8
190:7 196:3 287:7	360:13	87:14,23 88:6,24	255:10 256:3,14	34:1 51:13 67:16
argued 80:14	assessing 2:15 53:2	89:7,19 90:3 96:4	256:15,22,24	161:8 169:13
arguing 314:17	53:6,21 60:2 74:10	96:25 97:18 98:19	295:12 296:5	174:22 187:16
argument 60:19	74:24 92:11 94:13	136:4 174:21	310:11 330:9	318:16 322:2
78:2 79:12 115:2	299:20 332:17	206:17 219:23	336:19,22 344:3	350:14 379:15
249:25 315:25	assessment 56:17	325:12	344:10 354:23	386:19 388:25
319:15 320:10,23	asset 106:4	attenuation 64:7	356:13,16,18	Avenue 394:24
322:11 352:10	assign 44:11	attitudes 174:1	357:5 384:11,14	average 44:22 60:17
arguments 58:5	assignment 335:11	attorney 396:10	384:15,17,18,21	67:13 75:12
238:2	335:19 336:14	attract 226:25	388:1	138:21 145:20
arises 316:5	assistant 6:16	attractive 144:19	audio 7:5	146:8,10 194:24
arrangements	associated 142:15	149:11,13 151:11	audio- 68:7	199:12 200:3
279:22	312:9 315:10	334:24 344:1	audit 229:23	238:11 248:15
array 378:24 382:13	327:19 344:5	attribute 136:1	auditing 229:19	260:2 273:11
arrivable 86:1	associations 225:2	176:22	244:1	277:16 291:21
arrivals 83:22	assume 128:7,17	attributes 135:25	August 66:9,20 67:2	296:14 306:23

318:3 326:2	254:20 264:24	122:1,3 347:19	204:4 216:19,23	82:18 84:2 91:2,9
327:18,22 328:4	270:25 280:1	348:11 350:25	219:20 221:5	91:23,24 92:17,20
330:18,22 365:17	284:17 291:5	351:7,13	224:21 225:7,24	94:19 122:7 123:4
368:17	323:4 328:21	based 3:11 32:4	226:10 230:8,10	123:5,17,21
averaging 288:20	329:8 333:4,8	51:23 53:18 63:7	230:15 231:2,15	130:19 174:5
aversion 181:23	334:20 336:3	107:14 139:20,25	232:16,23 233:14	178:24 202:21,21
184:2 348:19	342:11,20 355:16	140:11 176:24	233:17 234:3	240:1,18 241:10
352:10	389:2 392:8	235:21 252:1	237:24,25 238:19	242:20 244:5
Avi 5:15 6:4 26:14	back- 40:4	273:16,20 274:6,7	239:15,20 241:21	263:7,8,10 267:2
26:17 151:20	backed 327:16	274:7,8,16,17	262:16 271:6	267:17 274:16,16
171:8 204:16	background 37:23	283:11 285:25	272:13,25 273:4	274:17 276:19
210:16 212:9	171:12 172:9	287:12 288:12	274:2 276:12	289:25 295:15
218:5 219:15	259:20 265:13,15	289:2 310:2	285:24 286:3,16	316:11 358:1,3
237:23 238:2	bad 50:7 76:4 102:3	346:24 352:10	287:5 288:3	365:9 388:12
269:9 390:15	107:18 111:7,9,9	392:15	292:19 328:10,22	behavioral 170:18
392:22	115:8 123:5,5	baseline 72:15 110:2	331:14 339:18,22	181:6 263:3 266:3
Avi's 222:15 228:7	124:9 144:19,21	110:11 114:8	356:22	274:12,15,20
Aviv 101:1	144:21,21 147:5	115:19 116:1	basing 264:11 287:3	276:18 289:24
avoid 12:12 178:20	166:7 185:12,13	117:20 273:7	basis 76:14 215:11	behaviors 63:12
avoidable 11:1	194:12 195:17,21	276:13 277:15	289:2	290:1 354:1
aware 90:21 105:4	278:22,23 314:12	basic 32:24 63:6	basket 249:13	belabor 98:20
301:3	331:8 361:9,10	72:20 74:14	battery 337:10	belaboring 171:22
awareness 15:5	388:10	120:12 121:10,24	342:12	Belgium 127:2,5,5
Awe 6:15	Bagwell 150:25	214:7 215:8 230:3	Bay 58:15	belief 120:21
awesome 100:8	balance 184:25	260:22 284:16	Bayesian 140:7	beliefs 41:12 96:24
140:17 294:18	209:25 253:15	288:19 301:13	bear 91:13 335:14	107:13 115:16
axis 145:13,22	balanced 299:18	308:8	bearing 345:20	123:3,9,9,20,25
369:22,24 374:18	ball 315:19	basically 20:24	355:4	125:13 140:23
374:19 375:10	ballpark 47:11	27:21 28:8 29:10	beast 174:21	159:19
	221:14	29:23 32:16 37:6	beat 275:8,8	believe 86:18 96:16
	ballparked 51:6	37:11,16 44:9 46:7	beats 276:15	114:10 143:11
B	ban 39:24 315:6	48:5 79:1 80:13	beautiful 183:10,16	148:3 152:25
B 87:22 199:8,11	bandwidth 336:11	101:17 104:14	352:20	183:19 187:25
269:10 271:24	339:6,15,16	111:10 112:6	becoming 133:19	247:3,4 382:1,17
294:21 367:11	343:22	114:15 116:15,17	208:6,9	382:20 384:11
370:9	bang 73:11	126:16 128:20	beds 188:3	believed 381:19
B2C 338:14	bang-bang 146:3	133:6 135:19	beer 127:3	believer 319:14
babies 239:12	bank 367:20 386:1	137:11 147:6,9	beginning 39:22	believes 57:11 112:8
babysitter 60:5	banks 219:5 376:13	158:21 165:8	103:6 149:17	believing 15:20
back 13:17 31:2	banner 40:22	181:15 184:9,14	behalf 8:7	Bella 69:6,22
42:9,24 43:23	138:11,21 140:14	185:14,16,22	behave 17:25	belong 119:6 125:1
45:22 53:8 58:21	141:10 143:10	187:25 188:24	181:14 208:5	287:17
72:4 73:17 84:14	bar 56:12 142:16	190:19 193:9,19	239:19	bemoans 57:10
91:19 96:9 103:23	252:8	193:23 194:3,15	behaving 94:7 228:3	Ben 6:20 90:11
116:5 127:4	bars 252:5	194:16 195:9	behavior 4:11 17:1	Ben's 90:21
160:23 161:25	Bart 130:7	196:6 197:16,25	60:12 62:2,4,5,19	Ben-Shahar 187:18
169:15 181:18	basal 64:8	198:11,22 202:17	63:1,4,19 68:4	beneficial 105:14
193:17,25 196:4,6	base 72:6 118:19	202:20 203:7,11	74:17,19 78:20,20	218:6 301:2
223:7 224:6				

benefit 2:20 5:12 46:6 100:2,5 110:17 111:6 112:17,19,19 122:22,25 123:18 123:23,25 124:24 280:11,12,18,20	biannual 394:6 bias 3:10 224:2,12 224:24 227:14 229:3,5,9,15,24 230:1 232:5 236:12,15 237:6 241:4,8,8,11,12 242:19 243:13 245:1,9,9,13,21 252:1,15,19 253:22 254:2,20 254:21 256:5,7 288:5,16,21 326:12 329:11	38:1,7,9 39:3,11 39:12 49:7,12 251:23 big 11:19 15:17 17:10 30:3 39:17 41:20 49:23 65:24 73:23 103:5 150:17 156:14 191:23 192:7 199:17 200:8 201:19,20 202:2,9 206:13 214:16 221:2 223:1 228:24 229:7 235:1 241:5,6 250:4 253:19 257:6 261:18 293:21 296:22 303:3 309:2,5 353:20 357:19 360:17 362:21 364:9	214:10 215:4 bit 30:2,10 35:11 37:22 38:17 39:24 40:14,18 47:5 49:21 50:24 65:12 70:10 71:9 72:25 92:5 96:21 100:20 103:23 108:15 111:18,21 113:11 113:11 116:22 117:16 118:3,16 122:23 125:3 126:1,9 127:14 128:12 130:23 131:1 133:14 134:20 136:11 140:21,25 144:12 144:24 148:20 149:18 154:16 162:10 164:18,20 165:19 168:3,5,22 171:12,12 173:18 174:16 176:2 186:7 198:21 204:19 209:19 211:18 215:18 229:22 230:5 232:11,15 233:14 234:9,19 238:21 243:16 253:23 254:8 259:16,19 259:22 260:3 261:7 265:6 269:14 270:8 271:17,20 282:2,5 282:22 284:10,22 292:6 293:25 294:8,9 298:10 305:10 307:8 308:23 309:21 311:18 312:2,4 313:13 319:18 320:9 321:1 325:4 326:1 349:12 353:25 365:2,18 367:9 371:10 375:15	161:24 black 222:18,20 364:20,24 366:21 369:23 370:5,7,11 370:23 372:3,3 373:7 374:3,19,21 374:22,23 375:12 375:14,22,25 376:2,12,18 382:3 blacks 364:14 370:15,16 371:5,7 373:12 blame 202:10 blanket 47:18 353:10 bleak 207:14 blends 172:23 blessing 161:7 Bliss 58:17 block 37:19 145:9 172:17 blockbuster 299:16 blocker 37:5,12,13 37:19 blockers 161:6 blocking 37:6,8,11 37:16 40:24 42:24 161:2 blogs 189:25 190:9 blow 268:19 287:23 blown 313:2 blue 144:2 145:24 147:6 252:7 287:14 370:2 375:9 blued 147:16 blurb 325:13 326:14 327:10 328:21 blurring 54:25 55:10 BMW 35:24 bodies 126:18 boils 338:17 bomb 204:9,10 book 146:14,22 187:18,21 188:11 302:10 303:21 365:24
benefitted 218:24 benignly 23:9,10 best 53:25 58:8 79:15 130:11 139:4 142:15 145:23,25 148:5 150:1 157:15,17 157:17 178:8,9 180:25 268:2 276:3 279:3,22 280:7 325:3 329:9 343:24 bet 222:6 beta 184:10 beta- 181:16 beta-one 339:25 better 16:22 18:13 46:7,8 73:7 93:3 134:4 142:21 146:19 148:10,12 150:13 177:15 178:7 212:8 217:3 265:6 266:6,14 267:5 273:13 276:22,24 279:6 281:3 289:15 291:22 308:6 325:5,6 327:4 329:13 345:14 358:8 361:4 362:9 363:10 365:16 366:11 378:22 386:23 beyond 246:10 292:14 386:9	biased 225:10 227:25 228:3 253:24 301:5 314:23 biases 251:13,13 bid 28:24 29:14,17 29:21,24 30:22,24 31:4,14,24 32:3,13 36:24 38:10,19,25 39:1,7,16 134:7 166:23 237:18 238:1,23,23 246:7 246:10 248:19,20 248:21 251:17 256:18,19,19 262:1 bidder 29:24 38:23 bidders 28:23 29:9 29:11,20 30:5 31:9 35:5,5 38:2,9,12 38:17,20,21 39:7 bidding 12:5 24:21 28:21,22 31:20,21 32:1 35:10 38:24 39:9 44:11,18 48:23 132:15 237:11,15,22 238:6,7,9,10 240:18 241:10 252:17 264:1 bids 29:11,22,23 30:20,25 32:8,9,12 36:20,25 37:25	big- 51:16 bigger 46:5,10 47:2 107:23 174:7 195:7 199:24 268:1 290:4 293:11 296:21 305:12 369:5 biggest 192:8 204:8 287:12 320:13 367:13 369:1 bill 23:20,21 billion 13:13,15 24:4 24:5,6 40:6,9,11 40:12 50:11 186:2 259:23,24,25 260:8,10 261:16 299:14,14 329:6 binary 234:5,7 311:12 binding 30:19 38:11 155:7,15,24 binds 30:23 bins 342:3 biographies 170:23 birth 216:21 217:23 birthday 214:3,3,9	214:10 215:4 bite 138:19 148:15	

booked 197:17	305:3 319:23	brokers 134:2	bureau 5:8,11 9:7	buys 27:21
bookend 79:11	360:19	brother 156:15	11:9,10 43:13	
84:12,14	branded 199:7,24	brought 12:21 14:3	170:11 171:4	C
bookends 79:5,6,17	320:3	14:23 15:17 51:4	176:12 180:23	C 107:25 111:25
79:22 81:20 84:8	branding 125:4,4,5	223:4 349:10	216:2 363:9,10	199:23 269:10
85:8	brands 105:14,15	browser 264:22	366:11 390:9	Café 67:14
boost 275:20	114:5 117:6,7	browsers 260:5	business 8:17 15:22	calculate 150:18
boosted 275:3,5	304:18 316:7,11	browsing 145:8	16:7,13 17:21 21:1	calculation 24:12
288:2,14,17	bread 43:6	brut 36:12	54:12,14,18,19	40:5
Bordeaux 101:9,11	break 99:1 247:16	Brynjolfsson 205:22	66:3 166:22,23	calculations 46:13
101:12	298:15 308:14	buck 73:12	171:5,8 205:16,18	49:2
border 61:12 69:4	309:14 310:1	budget 29:15,18	242:22 259:1	California 118:13
338:2	323:3 349:5	177:6	329:24 334:25	171:7
bore 373:25	breaking 143:2	build 101:17 107:13	356:10 363:10	call 5:25 28:22 61:5
boring 37:11 183:7	breaks 106:2 149:22	226:11 284:1,4	366:11	67:20 68:1 75:13
born 54:14	149:23	building 18:22,22	businesses 10:13	81:25 82:21,22
borrow 172:20	Brett 76:15	19:15,18,24,25	18:2 66:7 119:9	87:25 88:5,25
185:1	brie 101:8,13,14	20:5 104:2,3,19	busy 393:1	91:23 100:12
borrowed 172:21	105:3,5,6,7,8	230:15	butchering 335:13	122:21 136:20
173:14	brief 7:10 99:2	building's 19:16	butter 43:6	157:19 162:15
borrowers 177:18	275:16 283:4	bulk 27:21 28:15	button 22:24	167:4 181:24
Bosch 102:16	298:20,20,21	330:20	buy 15:24,25 27:15	186:10 231:12
bottom 16:8 84:2,4	347:12	bullying 204:9	28:14,15,17 29:6	241:6,11 242:20
87:18 135:22	briefly 170:20 273:2	bump 308:23	34:6 56:2 74:25	268:21 272:21
182:3 261:12	274:23 276:7	bumper 347:21	75:9 79:16 101:13	273:5 316:3
373:6,6	302:5 306:14	bumper- 346:15	105:3 149:10	337:22
bottom-line 176:18	brilliant 230:20	349:14	152:4,5 183:15	called 22:19 28:6
bought 15:12 28:9	bring 8:19,20 34:2	bumper-to- 347:20	193:2 213:1 222:6	58:16 59:16 65:14
42:20 185:3	53:14 67:11 84:14	bumper-to-bumper	240:10 253:14	65:22 87:19 88:24
222:21 367:19	174:20 394:7	327:16,18,20,24	254:19 325:24,25	108:22 164:20
377:15	bringing 167:17	328:15,23 338:24	326:16 328:7,16	183:1 186:1
box 72:16 89:1 98:1	235:11 340:18	339:1,12 343:10	328:19 330:25	187:19 215:17,22
213:21	brings 50:14 126:21	343:12 346:10	331:12 333:10	216:16 229:6
boxes 216:16	240:23 294:2	348:20 349:14	334:16,18 348:21	264:19 288:2,6
boy 203:12	383:24	bunch 37:25 51:24	351:5 352:15	298:19 363:24,25
boys 203:9,10	broad 9:16 170:16	53:18 67:11 68:10	355:6,22 370:8	367:11
branch 14:25	233:19 260:15	73:5,21 100:18	buyer 112:1 152:3	calling 69:18 72:14
branches 288:11	266:17 283:23	101:5 165:1,6	152:19 153:10,24	75:13 82:18 84:18
brand 101:14,18	284:9,20 285:1	184:8 206:9	158:23 161:21	93:25 95:16 97:17
102:3 103:13,14	broadcast 303:16	230:24 250:12	165:4 355:21	97:18 137:19
104:3,4,5,23,25	309:16,18 312:12	275:8,8,10 296:24	buyers 12:5 15:12	141:17
105:2,10,21	320:14	341:24 354:12	166:21 332:4,5	calls 68:9,14 72:24
107:14 108:13	broader 57:20	360:10 363:2,12	334:15 362:5	73:2 81:14 82:3
109:1,2 110:10	118:19	366:18,25	buying 27:2 44:21	84:21 89:21,22
111:14 114:16,20	broadly 55:3 60:24	bunched 373:16	163:13,16 208:5	90:1,4 91:14
115:13,24 119:11	broke 125:21	bunching 341:6	254:17 305:6	302:23
124:20,22 126:5,7	broken 302:22	bundle 109:7	329:17 331:6	Calonico 339:10
127:18 304:5,7	303:15	burdensome 385:15	349:6	campaign 245:10

251:20 253:3,4,4 256:16 campaigns 243:4 251:20 252:25 253:1 Canada 206:18 319:24 Canadian 50:12 cancel 311:7 candidates 287:1,9 291:25 343:20,24 cap 142:25 capita 368:22,22 Capitol 395:1 capture 103:23 104:14 captured 112:18 216:24 captures 20:25 capturing 35:20 287:20 car 12:22 13:2,3,4 13:16,18,19 106:1 109:23 114:10,13 135:6 140:15 141:11,23,23 143:23 144:5,15 144:16 158:2,3 160:21 163:13,16 164:6 325:20 330:20 335:15 336:2 355:21 card 10:7 219:3 377:16 cardigans 224:15 cards 43:22 219:5 219:13 368:3,3,4 care 10:8 17:23 41:9 41:10,16 60:6,15 63:3 65:10 77:22 80:22,24 103:19 103:20 206:21,24 207:16,17,23 212:4 215:17,23 219:16 220:21,22 221:1 249:15 293:25 294:9 314:2,9 329:3	331:11 392:6 careers 231:3,7 235:12 245:1,7,25 careful 118:1 161:22 294:7 309:6 carefully 125:20 166:20 231:19 292:15 320:10 382:21 cares 31:12 Caribbean 233:17 Carolina 338:2 Carolina- 324:6 carried 216:25 carrot 123:13 cars 101:24 109:22 111:9,9 140:14 141:9,13,21,21 157:9,10 158:1 330:9,13,13 CART 275:5 284:23 285:24 case 14:3,23 15:18 16:8 19:13,22,23 30:4,7,12 33:9,10 35:18 45:17 56:6 57:19 74:16 78:12 79:25 80:25 81:19 81:20 83:6 84:11 85:15,15 96:3 106:10 108:18 109:24 110:9 113:22,23 116:17 127:18,22 132:7 132:25 133:1 135:24 136:5,5,24 137:21 138:13,22 138:25 139:4 144:6,16 145:10 145:15 147:12 148:24 149:25 155:8 156:17 158:18 173:19 174:13 186:22 193:19,23,25 208:8 211:21 215:5 220:11	222:17,19 227:6,8 227:10 228:1 230:2 233:5 235:15,20 237:5 238:22 240:4 242:18 243:19,23 260:1 261:10 262:9 264:8 267:13 268:4 275:15 277:22 278:16 279:4,19 282:18 284:3 292:23,25 316:14 321:24 335:20 343:10,12 346:12 367:10,11,17,18 367:25 368:1,7,8 369:1,22 370:9,13 372:11 373:11 384:6 385:16 cases 12:20 17:1 23:9,10,12 32:12 33:13 113:17 122:4 127:16 136:3,3 137:8 138:6,7,17 145:9 145:18,18 150:18 173:18,24 174:5 174:22 177:8 179:6 193:22 362:25 363:1,12 367:7 368:12 369:6,10,14 370:3 370:12,25 371:4 373:9,14,15 374:25 380:6 382:10,23 385:8 385:19,23 cash 15:11 Catalina 391:21 catch 12:16 258:4 categorical 176:9 categories 67:7 303:18 304:15 312:16 372:2,2,21 373:3,24 376:9 386:1 categorization	387:13 category 287:11 316:9 317:22 372:1,16 category-specific 317:20 Catherine 3:12 26:14,17 90:6 204:23 208:1 209:17 224:11 244:9 246:8,16 252:23 254:13 269:9 295:14 300:16 391:11 causal 26:19 293:23 315:15,18,25 319:15,16 320:1 320:24 causality 267:12 293:8 315:21 320:9 321:16,19 321:20 350:4 causally 320:21 causation 321:25 cause 75:1 causes 290:24 320:15 321:21 causing 245:21 247:22 253:24 254:1 cautious 315:13 caveat 303:3 CDs 193:18 cease-and-desist 15:10 center 19:14 144:13 223:1 centers 38:25 central 142:12 centralized 208:23 cents 26:23 32:2 39:9 238:11,11 246:7 century 54:3,5,8 CEOS 124:15 CER 396:16 certain 27:25 30:8,9 31:14 36:11 39:10	42:6 44:18 50:3 106:25 111:3 135:3,25 146:24 150:5 205:8 206:24 212:4 216:14 226:8 264:3,8 298:23 303:7 305:8 313:8 313:8 324:23 352:13 360:8 364:6 certainly 24:1 35:2 41:15 171:17 229:15 CERTIFICATE 396:1 certified 356:13,20 356:24 certify 396:4 certifying 356:21 cessation 316:19,19 cetera 185:8,8 376:11 393:13 CFPB 364:10 375:10,23,24 chain 197:24 199:7 199:24 360:17 challenge 12:10 25:14,16 29:25 32:7,10 34:11 35:1 35:2,3 38:22 39:13 210:1 221:22,22 387:11 challenges 11:6,8 16:14 22:11 25:15 32:6 42:25 172:14 267:9 319:12 334:10 challenging 17:9 18:7 23:24 24:14 36:12 champagne 124:18 124:19 chance 39:1 74:3,12 75:6 86:13 124:6 329:16 chances 166:4 change 17:14 18:5
--	---	--	---	--

38:4 42:19 51:9,14 56:24 60:12 63:19 77:1 78:19 82:17 84:3 91:9 92:19 93:1 94:20 95:3,12 123:24 143:6 159:18 185:8 213:20 218:3 262:8 278:14,18 296:20 299:12 349:17 353:13 373:3 375:10 376:7 388:8 393:11 changed 27:2 28:7 34:25 49:17 54:7 70:14 77:25 100:18 163:9 208:10 388:5 changes 50:21 63:1 65:9 81:25 82:21 91:2,22 92:19 93:20 237:4 266:16 373:8 388:6 changing 63:12 205:25 231:25 channel 196:5 303:4 303:5 333:21 channels 133:22 Chantix 316:18 317:2 Chapel 324:7 chapter 275:13 characteristic 167:5 167:6 characteristics 33:16 82:8,9 175:20,23 360:4 365:15,19 charge 220:15 charging 206:11 Charitable 10:4 Charlie 394:23 chart 304:1 Chartock 6:21 chase 170:13 chat 92:1 98:20	193:15 195:14 chatrooms 196:6 cheap 2:24 96:6 130:1,4,12 134:22 139:2 152:7 154:12,14,17,25 155:13,14 156:5,8 156:10 159:16 161:15,17,23 162:8,17 250:4 392:5 cheaper 134:4 184:24 187:20 250:3 cheating 122:17,24 123:7,11 check 81:8 186:21 216:16 checked 213:21 244:19 Cheers 323:1 cheese 35:25 101:8 101:15,16 Chen 6:21 Chesnes 3:20 298:3 298:4 310:13 322:25 Chevalier 196:19 Chicago 22:18,21 23:2 27:14 chief 362:3 children 192:9 202:13 Children's 10:2 China 102:22,24 Chinese 102:17,19 choice 78:2 170:19 188:11,13 299:23 333:8,14 336:10 339:21 340:9 343:1 344:22 357:18 choices 62:7 64:22 76:12,24,25 195:23 332:13,14 332:15 choose 78:1 111:14 139:25 144:9	184:16 231:22 281:15 301:8 328:9 choosing 145:3,4 chosen 78:5 120:9 337:25 353:4 Chrome 22:19 chronic 302:3 306:16,17 307:11 311:4,6 312:20 chunk 261:19 church 54:17 circle 31:12 136:23 138:15 143:14 157:7 167:3 203:13 circles 305:11 circumstances 10:20 cite 250:5 cited 156:4 cities 65:19 68:20 citing 204:25 citizen 329:13 city 58:18 71:19 384:3 claim 106:3 152:9 158:1,10,15 227:22 331:1,8 341:23 claimed 14:25 368:4 368:8 claiming 150:23 254:2 314:11 claims 13:10 56:24 79:20 151:11 152:6,6 153:21 157:16,21 158:7 158:19 160:12 161:25 331:2 clarification 10:17 53:9 clarified 10:23 299:1 clarify 34:14 51:22 69:10 158:6 256:15 clarity 379:7	class 8:1 203:5 288:2 308:10 309:9,9,11,22 classed 388:7 classes 218:1 classic 104:18 108:14 111:1 117:9 173:17,19 183:7 214:23 382:25 classification 275:6 275:17 288:4,6 310:3 classified 276:4 306:16 classify 274:12 275:18 289:14 304:13,17 classifying 272:23 274:24,25 276:9 clean 12:24,25 45:6 181:25 347:13 348:15 cleaning 13:4 clear 79:24,25 80:7 85:12 88:23 103:7 160:3 165:24 167:2 178:11 184:17 209:8 211:24 213:14 225:4 249:17,18 256:4 282:19 324:15 382:18 390:13 cleared 382:17 clearly 54:23 247:23 282:17 292:16 332:23 342:21,25 clears 29:2 clever 44:3 click 40:24 67:14,24 67:25 74:24 75:9 75:11,20,23,25 76:9 83:19 84:19 84:24 88:1 95:5 138:21 143:10 162:13 227:5,7 233:9 235:10,17	235:19,22 236:15 237:14 240:5,9,10 240:12 242:7 248:17 249:12,13 250:24 254:18,19 255:4 256:22 261:13 263:6 271:16 272:1,9 273:12 296:14,16 click-through 274:7 279:8 clicked 75:10 83:13 233:3 246:25 247:11 263:6 307:15 clicking 72:12 75:2 75:7 76:2,7,8 83:14 138:10,23 240:7 308:1 clicks 68:16 76:3 87:15 88:6,16,19 90:5 91:13,14 233:22 250:7 254:17 255:1 256:21 272:7,7 273:8 274:7 280:16 283:20 284:2,19 292:10 292:10,11,14 302:18,18,19,19 302:20,21 304:2,5 305:3,14,14,16,22 305:25 307:19 308:13,14,23,24 308:25 309:2,3,6 309:13,24 310:7 310:10 311:2 312:10,15 313:3 313:11 client 133:7 close 22:8 84:9 165:3 167:13 187:23 213:5 272:8 279:23 280:6 286:18 293:17,18 371:20 373:16 385:6 closely 154:13 156:2
---	---	--	--	--

closer 40:10,11 58:18 81:19 83:5 84:15 137:7 222:10 344:8,8	192:22 211:14 246:11 248:14 249:9,22	356:14	commented 392:9	186:18
closest 88:11 300:17	collecting 130:24	combinations	comments 18:13	communities 196:14
closing 4:15 331:23	156:18 165:14	164:21 338:16	58:9 77:7 118:16	364:5,6 389:10
388:22	192:16	combine 97:2 264:2	125:2 133:10	community 5:12,14
cloud-based 14:4	collection 130:23	276:23	176:24 187:2	5:19 18:14,15
club 12:6	148:11 184:1	combines 380:4	249:16 283:6	377:8 379:15,21
clueless 177:9	206:4 376:10,13	come 7:8 8:15 19:6	290:18 323:1	389:9 391:1
cluster 385:18	387:14	19:11 27:25 43:20	324:13 347:12	394:11,15
388:10	collective 2:20 100:2	43:21 56:20 97:3	377:18 379:3,6	compact 339:15
co-authored 53:16	100:5 101:4,6,18	124:18,19 125:10	384:21 387:7	companies 15:10
130:7	103:13,14 104:4	125:13 154:20	389:7,13	22:22,23,25 23:2,8
co-branding 125:4	104:21 105:2,14	155:9 156:11	commerce 28:9	46:10 47:22,25
Coca- 27:22	105:15 109:5,25	160:22 169:15	commercial 55:21	101:17 133:3,3,4
code 91:5 215:4	110:10,10,18	180:6 181:18	57:1 222:1 298:15	150:12 192:20
216:22 217:23	113:18,22 114:3	217:7 245:17	commercials 298:14	206:11,15 216:20
363:21 366:17	114:19,20 115:13	254:13 272:17	commission 1:1,18	220:5,8 225:20
367:2 368:22	117:6 119:1,4,10	284:16 291:5	2:1 3:1 4:1 8:6,21	229:9 269:22
380:2	119:14,17,25	305:17 323:4	8:23,25 9:16 171:3	270:5 298:21
coded 91:5,7,8	120:2,3 121:21,23	325:19 328:6,8	172:5,8,19 173:7	299:2,6,10 319:3
codes 368:25 369:24	122:19,25 124:21	337:7 352:6 394:1	176:25 177:8	392:2
371:11	125:1,4,11,14	comes 28:11 58:16	180:9 298:9	companies' 301:20
coefficient 311:7	126:8,19,22,24	64:3 75:19 101:10	347:10 358:5	company 14:4,5,17
372:5	127:23 128:25	105:22 106:20	363:8	14:25 15:19 37:15
coefficients 309:7	165:12,13	116:5 127:4	commit 161:9 165:4	102:15 114:25
311:6	collectively 101:17	157:25 264:8	213:7,7 345:5,24	132:10 133:6
coercive 378:19	collectives 121:18	269:15 281:23	353:20	307:17 363:14,16
cohorts 218:19	124:10	303:11 319:5	commitment 109:10	367:19 368:8
233:22 242:12	collector 9:5	327:15,24 328:5	110:4,9 116:15	391:21
cohosting 6:10	collects 159:2	328:20 330:15,24	155:11 160:6	company's 16:1
Cola 27:23	college 10:3 245:3	341:15 346:9,10	committee 6:3	comparable 42:2
collaborate 180:4	364:16 366:22	350:21	324:10	compare 81:1,4
collaboration 13:11	373:22 381:18	comfortable 359:6	committing 345:9	121:17,20 177:4
173:2,6 204:23	382:5	comforting 82:16	common 10:16	198:13 199:4,6
colleague 53:17	college- 374:4	comic 146:14,22	35:11 118:23	266:12 279:25
175:12,13	college-educated	coming 5:4 20:15	262:5 284:14	284:13,17 311:6
colleagues 176:12	373:19	28:25 31:6 75:25	376:15 385:20	367:8 372:9
379:18	collocated 198:5	158:20 197:5,6	commonly 183:1	compared 68:15
collect 14:5 112:20	color 69:14 141:22	210:18 224:6	communicate 146:9	86:5 93:2 277:15
131:8 134:4 154:9	158:3 220:14	260:5 302:8	159:8	281:3 307:11,11
156:6 159:3	colors 144:15 376:5	306:21,22 309:18	communicating	310:5 348:22
161:10 211:12	Columbia 171:5,6	309:20 311:8	149:7	364:19
237:21 238:10	182:21	339:5 354:14,21	communication	compares 122:4
collected 14:7	column 276:20	commensurate	130:14,20,22	291:12 380:13
131:13 156:19	columns 276:9	50:20 331:3	135:14 138:19	comparing 62:17
159:7 160:20	307:19	comment 19:5 45:21	142:3 146:12,25	64:15 83:10 273:6
	combination 266:3	97:7 210:17	147:3,22 148:7,23	comparison 62:11
		220:16 386:13	149:7,23 164:11	78:13 80:14,17
		commentary 384:1	Communications	113:18 294:9

compelling 57:16	complaining 4:10	265:3 271:10	concerned 24:1	conduct 11:11
compensate 50:23	358:1,3 359:22,23	272:10 273:16	165:24 206:10	conducted 179:7
compensated 356:9	364:25 368:18	276:15 335:24	225:21 232:5	conference 1:5,19
356:10	369:19 375:25	complex 169:7	348:9 349:6	5:20,21 6:11,18,24
compensation 13:18	376:2,3,19 383:3	232:19 233:25	380:16	18:25 19:8,10,14
13:20	386:8 387:9 388:2	compliance 299:23	concerns 23:25	22:5 43:4 53:13
compete 166:1,3	complains 380:11	complicate 319:13	49:21 112:10	54:23 57:8 151:21
competent 107:1,3	complaint 360:20	complicated 141:22	128:16 267:20	172:1 175:4
108:3,7 111:2,24	364:19 366:6	164:18 187:13	281:23 337:7,11	216:18 225:15,18
120:22,23 123:8	368:20,21 369:2,3	188:8 230:15	337:12 347:1,1	226:3 230:7
123:11,14 124:23	369:9,15 370:5	300:11	392:11	258:15 282:14
291:8	371:1,21 372:6,10	component 36:6,17	conclude 11:6 62:21	298:5 313:23
competing 7:14	372:15 373:4,9,17	36:18,21 37:1	62:22 81:18	378:23 388:20,25
165:8 194:10	373:20 374:9,15	56:16	148:21 169:12	389:8 390:22
competition 7:15,20	375:11,21 381:8	components 46:3,17	concluded 395:6	392:24 393:20
7:23 11:2 32:13,20	381:17 388:12	325:13	conclusion 4:14	394:6 395:6
32:21 33:12	complaints 360:21	composition 326:23	284:9 391:4	confidence 10:9
120:19,20 128:8	361:18,20 362:15	334:16,17 340:16	CONCLUSION/...	196:16 373:2
131:4 150:21	363:3,7,11,15,20	comprehend 94:12	390:1	375:8
164:14 166:20	364:13 367:8,13	173:17	conclusions 77:7	confirm 236:5
167:1 168:11,22	367:24 368:6,11	comprehending	concrete 349:25	confirms 350:15
290:13 296:23	368:14,24 369:1,4	94:11	condemned 185:23	conflict 207:12
competitive 32:11	369:12 371:2,6,11	comprehension	condition 61:1,2,5,6	confuse 178:17
128:6,15 241:10	371:12 372:25	93:13	62:12,12,18,18	confused 59:24
competitor 167:7,8	373:10,23 374:25	comprehensive	68:25 69:2,5,20	74:23 84:15 379:9
197:23 198:16	376:8,9,10,10,12	291:14 292:6	70:20,21,24 72:2	confusing 82:24
199:21	376:14,17 378:1	294:8 328:12,19	72:15,16,17,18,19	congested 19:21
competitors 290:10	379:24 380:3	computer 14:24	73:25 74:1 76:7	congratulations
290:13,17 365:11	381:12 382:4,6,9	27:8 29:1 268:20	80:5,10,11,12,18	390:11
compile 174:3	382:19,20 383:21	275:11 389:17	81:15 85:17,17	Congress 176:7
compiles 379:22	383:22,23 385:2,4	computer- 28:8	87:18,20,20 89:10	connect 134:14
complain 360:24	385:25 386:2,3,4,5	computers 29:5	89:11,13,16 97:12	214:1,2
362:17 364:6,15	386:5,15,16	200:20	97:22 302:2	connected 17:10
364:16,20 365:1	387:10,12,16,19	comScore 236:4	334:12 335:12,16	154:13
368:17 371:17	388:4,9	302:8,23,25	335:20,23 336:12	connecting 190:2
374:4,5,22 377:4	complement 93:20	311:20	354:5	connection 15:7
377:11,20,23,24	96:15	Con 226:3 230:7	conditional 90:25	115:11,12 189:24
378:2 380:7 381:3	complementarity	conceivably 386:7	339:21	190:1,8,20
381:3 382:12,14	377:1	concepts 96:4	conditioning 87:7	connections 203:17
383:5,7,9,11	complements	conceptualization	conditions 62:3	connectivity 278:17
384:25 387:20	346:19,23	228:10	68:23 69:15 70:25	connects 38:7
388:6,9	complete 151:13,14	conceptualize 31:15	74:22 80:2,13	consensus 366:5
complainants	212:25 229:17	conceptually 30:16	81:15,16 82:4,12	consequence 13:7
374:20	286:14	concern 55:19,20	82:17,25 83:11	172:2 195:25
complained 375:14	completely 149:20	77:2 126:8,9 161:4	84:13 97:9 121:14	206:16 242:14,20
complainer's 379:25	197:8 228:5	201:1 228:24	121:14,18,21	244:4 291:5
complainers 380:3	230:16 240:17	293:9 316:5 348:8	291:20 302:3	consequences 25:10
380:13 383:15	244:5 247:12	349:1 382:10,15	312:19 336:17	103:8 133:15

192:3 207:1 291:6 consequential 60:4 96:22 consider 46:17 71:15 131:3 242:11 252:19 consideration 47:6 47:17 74:6 88:8 98:19 considered 55:25 186:3 279:3 considering 51:19 considers 47:7 consistent 41:12 73:13 89:23 91:11 93:6 94:2,4 140:23 186:4 209:8 249:5 311:13 359:5 console 15:1,6,13 conspicuous 61:8,10 144:11 conspiracy 201:5 Constance 6:12 389:15 constant 262:7,11 343:14 347:23,24 Constitution 394:24 395:1 constrain 14:17 constrained-ish 236:8 constraints 177:6 269:5 construct 24:23 25:9 60:20 214:16 215:24 216:8 378:3 constructed 125:20 186:12 368:21 constructs 237:4 consulting 253:17 consume 56:3 77:25 consumer 1:7 2:14 4:10 7:11,17 10:1 10:15 11:10 14:2,7 14:9,14 16:2,7,25 17:7,21,24 18:1,3 23:13 24:17 50:9	51:1 53:1,5 59:19 60:12,16,17 66:16 66:25 67:23 74:17 76:6,23,25 85:13 89:14 92:10,11 93:13,14,23 94:25 95:5 96:24,24 120:18 123:2,9,20 123:25 124:1 128:18,19 133:21 134:10,16,17 141:20,25 145:21 148:13 164:1,5,5 166:2 170:11 171:2 172:7,12,16 172:24 173:21,24 174:1,4,19 175:16 175:19 176:13,20 177:17 178:10,18 178:23,24 179:1 179:10,11,14 180:22 188:5,22 189:19,20 191:14 195:8,13 197:5 208:19,22 209:14 211:10,13 212:17 212:19,22 220:15 239:17,20 265:21 267:17 300:10 316:10 321:2 330:6 340:2 345:6 350:18,21 351:6 358:1,3,18,19,23 359:9,10,24 361:15 362:14,15 362:18,21 363:3,6 363:9,16,24 364:18 366:12,17 374:11 378:3 379:16,23 386:9 386:25 390:25 consumer's 10:20 91:23 92:17 121:3 357:9 consumers 7:14,19 7:20,25 8:7 9:1 10:19 11:1,2 12:12 13:15,22 15:4,20	17:15,23 24:13 46:2,13 47:2,9,11 50:4,6,8,17,25 51:7,25 55:21 56:1 59:23 61:4,16,18 62:24 63:8 64:1 65:3,10 69:8,20 72:1,10 73:8,10 74:22,24 75:2 76:8 76:19,21 77:5,23 78:25 80:22 81:25 83:9,18 89:12 92:7 92:12 94:23 95:14 95:18 96:16 103:9 105:24 120:25 130:17,20,25 133:4,19 134:4 141:20 148:8,15 148:23 150:15 151:4 163:21 169:6 173:17 175:3 176:6 177:9 178:3,17 189:8,10 189:21 194:8 206:7,11 207:16 207:23,24 208:4,6 208:24 209:2,23 211:21,23 212:4,7 212:8 213:1 215:5 216:3 219:16,22 262:2 265:12,25 266:22 283:20 284:2 300:19,25 301:7,15 307:16 311:14 314:4,7,15 314:20 333:1 345:19,23 346:18 348:20 351:21 353:1 359:5 360:20,23 361:5 362:16 369:19 370:8 380:15 consumers' 14:15 93:17 179:20 264:6 265:14 consummated 352:23 consummating	356:10 consumption 93:25 contact 377:4 contain 32:17 container 96:8 contemplation 383:1 content 18:19 54:20 55:5,7,8,9,22 57:1 69:14 86:17 149:10 174:11,24 175:6,9,12 187:21 189:24,24 190:9 194:4,5 201:16 321:1,3 322:20 contention 313:7 contested 8:22 context 60:2 66:8 105:21 161:16 207:3 208:8 209:6 209:9 210:20 262:16 263:11 264:13 266:7 275:9 291:22 295:17,25 296:1 324:24 326:21 327:9 329:20 context- 277:1 context-specific 277:1 contexts 124:17 281:9 contextual 263:9,14 266:2 274:13,18 274:19,19 276:21 276:22 290:1 295:15,21 contingent 348:10 continue 74:25 75:21 295:13 327:7 358:2 393:24 continued 3:2 4:2 75:7,10 385:7 continues 83:20 continuing 83:25 continuous 147:2 247:13 341:18	continuously 29:23 35:15 contract 22:14 27:19,22 155:25 contracting 27:23 28:3,3 contracts 27:20 28:2 133:5 325:23 contractual 319:12 contrast 135:21 160:9 181:7 185:19 233:1 305:1 325:15 contribute 125:3 contributing 118:19 contribution 48:7 103:12 118:18 125:15 294:11 contributor 327:2 control 77:14 82:7 84:5 91:6 103:20 110:6 115:3 117:1 117:13 122:7 201:6 202:24 204:13 255:12 280:13 308:11 318:19 334:12 335:2 336:6 364:18 366:12 372:17 374:6 375:15,17,19 controlled 173:15 175:25 176:14 177:19 178:6,18 178:23 350:23 controlling 308:17 366:20 controls 82:5 185:15 220:25 318:12 372:12 controversial 57:4 conventionally 275:20 converge 84:3 conversation 26:7 43:19 388:5 conversations 193:10 331:23
---	--	---	--	---

conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4	162:13,15 179:15 208:12 232:13 238:11,17,19,21 239:9,12 255:15	226:19 231:14 232:2,7,13,17 233:16,17 236:12 238:8,17,17 246:9 246:12 248:5,9,11 251:18,18,24,24 252:3 253:1 255:11,13,14,16 255:23,25 256:1,5 256:8 298:11	240:20 261:20 264:6 267:10 276:23 279:17,20 300:1,24 301:4 305:2,13 337:17 342:24	153:23 164:11 165:8 169:5
convert 141:19 240:13	264:9 288:13 289:4 325:25 331:14,16,16 381:1 385:17 392:15	country 30:11 101:21 102:15 103:12 104:10,12 104:13 109:6,12 110:10,15 114:8 115:1,13,21,25 116:3,16,20 117:17 118:24 119:13 127:24 128:4 181:2 202:2 227:12 231:17 232:5 233:13,15 251:20 269:23	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	credible 68:15 149:3 150:2 153:17 165:6,20 213:7 credibly 149:12 credit 10:7 12:6 15:12 174:2 183:12 208:20,22 209:3,9 210:3 218:6 219:3,5,13 219:13,20 230:24 368:3,3,4 creditworthy 183:10 185:20 creepy 206:14 crime 10:4 384:3 cringe 122:12 criteria 254:16,22 criterion 288:11 critical 118:20 125:2 141:18 329:1 critically 182:6,6 criticisms 59:25 critique 93:20 critiques 293:7 critiquing 94:13 cross 39:10 44:22 394:22 cross-national 241:22 crossing 83:12 crowded 296:3 crucial 32:3 44:25 168:23,23 363:18 381:4 crucially 364:17 Crystal 6:23 Cs 189:23 CTR 279:5,7 cues 88:25 89:5 culled 382:21 cultivating 153:18 cultural 238:15 cumbersome 298:25 cumulative 184:11 cunning 232:22
convey 86:22 149:12 176:5	cost-effective 242:15 243:21 cost-of- 381:19 Cost-Saving 9:21 costly 39:15 154:21 155:14,23 162:14 188:9 195:10 298:25	country-of-origin 103:4 104:5,9 110:18 couple 24:15 59:25 102:25 133:9 138:4 158:25 183:23 204:24 205:20 221:9 284:14,15 294:16 307:2,5 319:17 320:7 325:13 327:5 349:9 360:14 376:22 385:6 390:14	cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
convince 34:6 132:17 152:4,5 320:23 336:24	costs 28:3,3 121:19 136:7 148:23,25 156:17 162:12,12 177:25 179:16 182:13,14 185:6 187:15,16 188:13 221:16 227:16,18 250:7 306:21 351:5,12	course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
convincing 249:17 249:19 308:7 326:25 336:16	Coughlan 4:12 91:17 166:19,25 167:20 168:1 378:16,17 384:13 384:19,22 387:24	country-of-origin 103:4 104:5,9 110:18 couple 24:15 59:25 102:25 133:9 138:4 158:25 183:23 204:24 205:20 221:9 284:14,15 294:16 307:2,5 319:17 320:7 325:13 327:5 349:9 360:14 376:22 385:6 390:14	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
convincingly 320:12	counterfactual 31:23 32:1 36:4 37:4,7 38:3 44:14 44:19 78:10,11 267:21 391:7 392:14	course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
cookie 279:14	counterfactuals 45:7 391:19	course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
cool 85:3 124:22 127:9 156:8 184:13 213:25	counterintuitive 149:5	course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
copy 134:9 173:16 371:10	countervailing 11:2 17:7 156:22	course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
copyright 221:25	countries 65:16 67:9 104:9 110:3,11,13 114:1,1 117:14,23	course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
core 54:10		course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
Cornell 48:21 313:18,21		course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 218:23 369:17 387:19 create 15:5 23:12 111:10 218:21,23 248:4 385:15 created 178:7 219:4 231:4 creates 42:25 103:14 112:9,10 119:19 creating 27:4,10 creative 12:4 16:19 18:10 57:11 134:17 244:10 credentials 217:19 credibility 94:22 95:8,12,19 142:20 143:2,5 147:23 149:22 151:9	conversion 75:17 83:9 87:16 88:9,17 247:15 292:11 313:4
corner 123:18 135:17,23 166:7,7 373:6,6		course 25:14 27:15 28:1 39:16 64:9 108:19 110:19 116:21 117:24 120:10 132:18,19 141:21 147:1 148:23 153:2 154:8 156:14 159:5 163:15 183:7 189:12,15 195:9,21 239:8	court 7:25 8:24 367:15 courts 8:19 covariate 350:8 covariates 310:20 310:21,21,22 341:18 342:15,24 343:2 350:6 cover 16:12 161:10 302:17 coverage 302:4 303:23 306:20 307:12,13,14 covered 311:16 326:7,9 328:24 covering 161:2 307:18,18 covers 44:22 327:19 327:22 cracked 191:3 cramming 174:12 cranking 29:5 crazy 38:14 201:4 	

curation 189:24 190:3,9	data 11:15 17:10 24:21 28:11 29:5,7 29:9,21 30:21 36:1 39:14 40:3 41:4 44:15 45:10 46:19 46:23 56:12 65:25 65:25 67:2 70:5 75:5 76:10,15 82:6 90:15 95:21 98:6 130:23,25 133:21 133:21 134:2 139:17 140:20 148:17 174:7,7 179:22 183:25 184:5 185:15 192:19 199:10 205:18,24 206:1,2 206:4,5,6,11 208:7 208:8 209:24 211:10,11,14,20 211:24 212:2,7 214:2 215:2 218:11,22,25 222:25 224:22 225:21,23,25 226:15 230:11,16 233:19 235:3,14 236:21 237:12,22 237:25 238:7,9,10 238:19 239:14,15 239:16,18 245:20 246:11,17,23 247:20 248:5,8,14 248:14,24 249:10 249:18,22 251:5,6 251:15,15 252:4,5 253:21 263:4,18 263:20 264:2 265:8,8 266:6,7 267:1,3 269:14,15 269:18,20 270:3,9 270:14 271:4,5,5 271:18,19 272:4,5 272:10,10,11,14 272:24 273:7,8 274:4 275:19 278:4,6 279:2,4,6 279:10,13,16,18	280:2,3,14,14,16 280:16,22,23,24 281:2,4,7,15 282:6 285:22,25 286:3 287:3 290:8,25 292:13,25 294:6 295:2,16 296:4,24 302:7,9,18 303:11 303:25 306:22 316:15 317:5 318:14,15 320:21 321:11,25 322:2 322:23 333:8 335:6 336:17 337:23 338:3,23 339:2 340:20 341:5,14 343:16 350:11,14 354:13 354:15 356:23 357:12 358:13 362:14,21 363:3 363:13,13,19 366:10 367:13,22 368:5 369:17 371:9,15,16,25 372:6,7,8,10,11,15 372:15 373:4,5,9 374:11,13 375:2,5 375:9,13,24 378:3 378:6,6 379:14,20 380:2,18 385:17 385:19 386:19 388:3 391:8,12,12 391:15,22,23,25 392:1,2,4,18 393:7 393:12 data- 3:10 251:25 data-based 224:2 251:13,13 288:24 data-big 156:15 data-driven 209:16 209:24 database 218:24 219:7 382:19 date 216:21 217:23 dating 132:19 146:17 daughter 8:12	day 27:25 193:17 196:6 208:21 217:6 263:13 270:17 324:4 372:24 389:16,19 days 27:2 270:17,20 de 339:7,7 deadline 393:8 deal 44:6,19 121:7 126:15 144:14 191:23 192:7 200:8 201:19,20 202:9 331:24 356:10 378:12 dealer 162:13,14 332:22 340:2 353:7 355:20 dealers 330:17 331:20 337:25 dealership 138:10 138:12 330:19 331:24 332:24 343:16 352:23 355:4,16 356:21 dealerships 334:21 334:23 338:4 340:20,22,25 dealing 16:16 44:4 deals 28:8 dear 325:10 debate 57:6 225:12 225:19 228:9 300:23 301:12 314:11,16 Debra 175:7 debt 376:10,13 387:14 decade 42:22 deceived 13:15 15:20 58:4 59:21 59:22,24 60:3,14 95:6,6 175:24 deceiving 80:19,20 84:11 91:19 decentralized 16:19 deception 2:15 10:17 15:22 53:1,5 55:20 56:17 58:1,3	60:2,10,19 61:25 62:9,13,16 64:23 72:22 74:15 76:12 77:19,21 78:1,6,21 79:7,10 80:7,11,18 81:15,20 83:6,10 84:9 85:7,8,15,17 85:19 86:13 87:20 91:21 92:14,16 178:20 deceptions 10:18 deceptive 8:8,8,18 9:17 12:21 13:10 13:23 53:23 55:24 55:25 56:7 59:4,4 59:11,20 61:3 78:18 79:23 80:16 81:12 94:19,20 136:5 368:3 decide 47:16 59:11 64:12 134:8 135:24 139:21 145:10 216:15 383:4 decided 14:8 176:17 357:16 377:20,20 decides 140:4 176:25 368:17 decision 8:21 56:2 71:8 111:12 126:10,12 216:23 250:14 281:21 288:2,3,14,17,20 289:1 335:19 351:23,23 357:9 decision-makers 250:12 decision-making 179:2 181:8 decisions 8:24 111:13,13 120:2 135:6 166:8 177:15 194:18 195:17 212:6 220:2 228:16 242:15 250:22 359:10 decisive 138:20
D				
D 2:2 3:2 4:2 199:25 200:1 269:10 340:2,3 D.C 1:21 daily 270:6 Dallas 151:19 Damme 150:9				

declare 167:4	delve 223:3 224:23 225:7 232:3	describe 121:11 325:6	deter 12:13,17 102:9	286:21 293:12,13 352:1
decline 371:4,8 375:4	demand 16:2 18:4 166:21 167:6,16 174:19 214:18 359:2,4 365:7,20	describing 214:25	deteriorated 115:10	difference 72:17,21 73:17,20,24 74:20 81:14 85:16 89:15 89:17 90:23 91:7 104:20 129:1 138:2 181:19 198:7,10 199:5 215:15 233:7 309:24 348:14 356:4
declines 348:1 373:15	demarcation 126:19	description 392:10	deteriorates 114:17	differences 104:2 128:25 198:25 247:18,25 252:24 255:13 293:21,23 370:25 381:1,2
decorative 239:21	demographic 227:15 238:25 248:17 253:15 366:6 372:1,16,21 373:24	descriptive 240:23 240:23,24 307:25 380:10	determined 107:15 112:3	different 18:8 22:20 26:6 27:11 29:22 30:1 33:4,14,15,21 35:8 42:1 44:5 45:19 52:1 61:14 62:7,10 63:4,18 64:22 72:4 74:18 74:19 78:9,15,16 78:21 81:17 82:3 85:15 91:15 97:13 101:5 103:18 109:8 113:21,24 115:21,22 116:25 134:10,18 135:24 136:19 141:19 150:25 151:25 155:18,18 158:13 158:25 160:9,13 161:18 163:19,20 163:21 167:25 187:17 189:16 190:6,7,23 192:13 197:13 201:7,9 205:5 216:3 218:7 226:8 227:4 230:17 231:14 232:1,2 233:11,15 239:17 246:4,12 247:18 248:14 249:8 250:2,25 251:19 252:6
decrease 373:10	demographic-based 263:1	descriptives 381:23	determines 4:10 28:9 167:6 358:1	
decreased 26:18 39:23	demographics 246:3 253:16 302:5 303:1 307:23 314:8 363:21 366:16,18,19 367:3,4 369:20,22 372:9,13 374:10 374:15 375:16,17 375:20 380:5,13 380:14	descriptors 178:17	deterministic 292:24 335:21	
decreases 149:13	demonstrate 78:20 292:4	design 60:20,21 63:6 65:6 70:12 77:18 79:4 80:8,10 85:11 120:19 155:25 197:11,13,14 332:20 335:7,8,11 336:5,9 339:5 346:25 347:14 348:3 350:20	Deterrence 10:3	
dedicated 365:22	demonstrated 91:22	designing 132:23	detour 284:23	
deep 184:7 205:25	density 142:7 144:2 341:13 348:13,14	designs 341:17	detriment 10:20 93:15	
deeper 253:23 301:16 380:10 387:15	denying 206:12	desirable 226:6,23 241:24	Deutsch 15:4	
default 47:19	departure 125:9 343:11	desktop 16:20 66:11 71:20	develop 180:8 319:15 320:10,23 358:15	
defeat 13:1	departures 181:14 341:19 342:1,5,23	despite 113:14 135:13 146:20 194:22	developed 110:3 114:1 177:22 178:5 184:8 204:22 255:14,23	
defer 96:20	depend 166:9	destinations 305:2	developer 261:6	
define 17:6 120:7 206:13 271:21 295:17	depending 115:19 155:19 201:8 213:20 220:9,10 226:8 263:25 264:22 333:19 373:11	destroy 196:13,17	developing 110:13 117:23	
defined 60:24 245:9	deputy 170:11	destroyed 196:15 203:2	development 179:11 260:13 344:18	
definitely 18:2 63:21 90:21 127:17 196:17 233:6 243:9 244:19	descent 289:3	detail 81:3 82:2 83:16 106:21 171:13 176:3 291:4 386:20 387:8	develops 125:24 202:4	
definition 92:16 197:2,7,9 198:8 205:4 264:9 304:17		details 69:25 70:11 106:22 178:16 282:23 342:9	Devesh 4:11 174:11 358:4 379:6	
definitions 55:2 228:11		detailed 299:7 390:15	Devesh's 379:3	
deflate 49:12		detect 16:15 62:15 73:19 115:15 122:6,17,18,25 123:7,9,20 198:24 198:24	deviation 369:9,15	
degree 167:11 386:20		detectable 76:11	device 13:1 160:6 183:10 265:4	
degrees 317:19		detecting 16:23	device-specific 271:8	
delayed 185:9			devices 133:22 264:18	
deliberate 93:24			devise 132:22 267:18 272:3	
deliberation 75:15			diamond 261:11	
delightful 37:15			dichotomy 247:14	
deliver 134:9 156:11			dicing 391:8	
delivers 388:22			die 108:2 295:2	
delivery 67:10 68:12 68:14 134:5			diesel 12:24 13:10	
Dellavigna 185:1,14			diff-in-diff 319:21	
delta 181:17 184:10			differ 120:4 198:14	
deltas 319:25				

253:1,4,4,6 254:21 255:6,7 265:3 272:10,17 273:6,9 276:8 278:4 283:10,12,13 284:13,17 285:21 285:22 286:7,21 290:24 291:12 296:7 300:12 301:25 305:23 309:14,15 312:16 322:23 334:17 353:5 354:1,2 359:10,25 360:11 366:5,19 367:1,1,5 368:13 372:8 374:6,24 376:3,5,9 376:19,20 377:19 379:23 381:16,25 385:8,13,13,22,24 386:2,19	dimension 45:20 122:16,16 dimensions 121:25 122:14 359:25 Dina 171:6 188:19 188:20 204:15 206:20 365:8 dinner 60:5 96:18 394:21 395:3 direct 303:6 310:12 310:13 317:20 direct-to-consumer 3:19 298:1,6,12 direction 126:6 128:11 161:13 directly 7:19 76:23 85:18 119:3 301:8 325:8 328:6 332:23 346:24 Director 5:7 390:9 director's 5:8 Directory 303:22 disappear 203:19,23 disappeared 196:7 discern 308:4 discipline 17:15 disclaimer 172:2 298:7 358:17 disclose 63:4 130:24 135:25 136:1 146:4,5 148:7 160:11 179:3 187:6 190:20 211:3,6 disclosed 55:22 72:24 75:19 disclosing 146:20 159:7 disclosure 2:14 10:8 13:25 15:6 20:14 53:1,5 56:22 57:7 57:12 58:22 60:12 60:13,23 61:2,5,21 62:6,11,12,17,23 63:1 64:14,16,17 64:19,20 65:3,7,10 68:24 69:2,8 70:15 72:14,16,17 73:3	73:10,12,25 74:17 74:18 76:18,21 77:3 80:22 81:25 83:10,11,20 84:6 84:18,21 87:10,19 89:22 93:2,3,12 95:13,14 97:15,19 98:14 132:14 135:23 136:2 155:22 170:18 176:1 177:7 178:5 179:24 180:24 181:11 182:13,16 186:8 187:2,5,12 187:12,19 188:4,7 193:4,5 299:19 disclosures 72:11 159:23 175:25 177:11,12,14,20 177:21 178:19,21 179:13 187:24 209:8 210:4 disconnect 22:20 221:3 discontinuities 341:13 342:1,3,5 discontinuity 335:7 335:11 336:5,9 339:5 340:12 341:17 342:15,21 355:25 discontinuous 347:22,25 349:16 351:17 discontinuously 39:2 discount 178:3,4 discounting 112:13 181:17 183:19 discouraged 115:8 117:3 discouragement 108:23 discretize 367:3 discretized 372:2 discriminated 163:17 discrimination 3:11	46:12 224:3 241:15 344:5 discriminators 287:6 discriminatory 226:1 244:3 discuss 6:7 77:16 83:3 98:25 118:15 126:4 159:1 282:17 313:23 discussant 2:12,17 2:22,25 3:13,17,21 4:8,12 20:18 43:13 43:23 77:10 244:7 244:10,13,16 257:1 282:10,15 313:17 322:15 323:1 324:13 347:7,9 378:15 discussants 388:19 389:4 discussed 159:6 229:4,18 232:6 235:4 discussing 43:25 151:22 391:18 discussion 20:20 26:20 41:18 42:10 43:9 51:18 118:13 151:16 157:5,20 171:21 179:25 204:18 244:22 277:20 314:10 315:7,21,23 discussions 171:18 378:25 disentangle 31:6 36:13 362:19 disentangled 89:2 disguise 161:7 dish 22:25 dislike 235:16 display 2:10 14:14 20:24 22:3,10 26:12 359:14 displayed 234:6 disrupt 96:25 distance 137:4,17,18	137:20,25 138:15 distinction 91:18 205:6,11 304:8 322:17 326:5 distinguish 17:5 109:8 111:8 117:10 distinguished 103:17 distributed 29:23 39:6 distribution 198:10 198:12,13 247:13 338:21 361:23 distributions 198:25 243:15 distributors 15:24 district 204:7,10 disturb 70:7 dive 253:23 380:10 divide 90:17 divided 369:4 376:8 Division 171:2 172:18,23 Do-Not-Call 10:5 doable 90:10 doctor 187:6 300:14 301:2 doctoral 324:20 doctors 14:6 document 95:11 178:7 documented 95:21 documenting 73:6 92:19 226:10 doing 6:8 22:6 28:20 31:9 37:20 38:13 54:1 59:13 61:11 74:10 76:16 95:24 140:10,22,24 141:3 145:16 148:21 150:12,22 174:8 175:17 176:15 182:13 194:10,21 210:7 219:9,10 225:10 225:11 227:4 258:24 264:1,1,20
---	---	--	---	--

265:15 272:16	95:10 96:2,11 97:8	draft 257:4	312:18,18,20,20	154:22 243:11,12
296:10,12,20	97:25 98:3,6,15,23	dramatic 65:8 87:22	312:21 313:8	282:17 387:25
319:4 359:21	100:3,6 118:9,14	88:5	317:2	eBay 362:3
388:16 389:3	127:12,17 128:10	dramatically 63:1	DTC 311:22	echo 230:8
391:20 392:18	129:3,5,6 130:2,5	300:2	DTCA 299:12,22	echoing 238:14
393:5,11	151:16,18 162:23	draw 325:12,14	300:23,24 301:14	econometric 63:24
DOJ 13:12	162:25 163:2,3,4	327:11 382:8	306:9,12 308:10	266:11 267:12
Dolby 173:25	163:11 164:17	drawbacks 59:14	308:10,22 309:9	284:15 334:9
dollar 38:24 49:10	165:9,15 166:16	drawn 44:5 327:4	309:15,17 310:20	Econometrica
176:17 177:2	166:19,24,25	345:1,6	311:2,7 312:5,9,23	339:10
256:12	167:19,20,22	draws 47:10	314:4,11,12,17,23	econometrically
dollars 26:22 40:9	168:1,3,17,21	dreamland 385:16	315:6,8,10 319:23	247:5 375:7
177:1,3	169:12 170:2,9	drew 305:11	319:24	econometrician
domain 157:2	171:24 180:16,18	drive 332:15 344:22	Dubai 65:19	30:6 247:3
domains 159:16	188:18,20 190:16	driven 17:2 232:16	due 84:21 376:20	econometricians
161:18	191:7 204:15,20	239:2 246:23	379:8 380:25	316:12
domestic 201:23	210:7,9,10,11,12	247:4 250:21,23	381:1 382:15	economic 1:5 12:18
dominant 38:19	210:21 211:1,5,9	driver's 155:4	Duke 118:12,14	46:4 100:11,11
dominate 346:8	212:14 213:6,14	drivers 119:6	Dukes 2:22	214:23 243:13
donation 186:20	213:17,23 214:13	385:22	dynamic 18:6 24:4	249:3 259:1
door 19:21 169:14	214:21 215:12,13	drives 314:4	108:15,15,23	349:12 351:22
doors 19:11	215:14 216:11	driving 98:18,19	112:11,12 134:17	383:13 390:9
dot 143:16	217:14 219:12	260:12 266:1	dynamics 63:21,24	economically 347:3
dot-edu 304:24	220:18 221:9	336:25 343:1	64:9 120:10	349:20,23 350:2
dot-govs 304:11,24	222:3,4,16,23	drop 343:13 347:23	167:17	economics 5:8 9:7
305:7	223:7 224:4,13	349:16 352:9	Dyson 222:13	11:10 25:2 43:14
doubt 122:21,21,22	244:9,12 254:12	drug 298:21 299:2	313:20	79:9 170:12 171:4
122:24 123:16,19	254:23 255:18	299:10,10,23		172:7,17,20,24
123:25 124:24,25	256:9,17,23,25	301:20,25 302:1,4	E	198:1 216:2 359:1
Doug 43:13,17	258:2,8 259:6,11	302:21 303:20,21	E 2:2 3:2 4:2 20:1	economist 101:1
Douglas 2:12	282:10,12 294:14	303:23 306:13,14	eager 173:3	216:1 241:7
Dover 196:20	294:17,20,22	306:21,23 307:4,5	earlier 175:16	318:21 362:3
download 260:18,21	295:10,21 296:9	307:22 308:10,11	187:15 228:7	economists 5:11
261:3	296:25 297:2	309:10 310:16,20	244:18 275:7	171:3 205:20
downloaded 260:9	298:2,4 313:17,19	310:21,24 311:1	277:19	234:1
downloads 66:25	322:7,14,25 323:3	312:10 314:7,20	early 6:20 258:16	economy 119:8
68:19	324:3,9 330:11	316:20 319:24	easier 133:20,23	207:18 327:1
downward 372:22	336:21,23 344:6	drug's 308:10	134:3 198:20	ecosystem 54:25
DR 5:3 7:3 22:4	344:11 347:9,11	drug-specific	373:5	Edelman's 90:11
43:11,15,17,25	352:4,7,8,20 353:6	317:19 318:5	easiest 360:13	editor 390:7
48:16,20 49:8 50:9	353:8,22 354:4,7,9	drugs 298:13 299:15	easily 86:1,12 96:5	editors 337:14
53:3,11 63:16,20	355:1,19,23 356:6	299:16 300:9,11	154:18 243:4	EDU 304:10
64:13,18 71:6,9	356:7,15,17,19	301:1 302:3,9,10	East 201:21	educate 12:12 17:15
73:16,21 77:9,12	357:11 358:2,6	302:11,15 303:12	easy 64:20 78:12	educated 188:1
85:21 86:14,25	378:15,17 384:13	305:8 306:25	89:4 122:6,7,17,17	237:1 374:5
89:9 90:7,9,10,20	384:19,22 387:3,4	307:6,7,11,13	122:25 123:7,8,20	education 182:15
91:17 92:4 93:11	387:24 388:15,18	308:18 309:11	133:18 140:6	236:25 248:2
93:16 94:17 95:2,7	390:2,4 394:20	311:3,3,4,5,9	150:20,23,24	271:13 287:19

382:5	160:10 165:19	319:20 341:14	engine 66:3 303:9	121:15 140:8
effect 17:20 24:9,18	200:11 220:7	employable 85:10	engineering 101:25	equilibrium 49:3
26:19,22 46:1 80:6	283:11 302:12	employed 341:12	226:18 231:4	51:9 70:6,7 106:15
81:9 82:4,11,15	313:5,12 339:13	396:7,10	engines 300:6	112:23 113:1,9,13
86:15,25 93:12	346:23,25 348:15	employee 396:9	302:17	121:13,13,20
114:21 148:4,25	350:25 351:10	employees 15:5	English-speaking	140:24 141:1,6
152:20,22 153:20	369:2	employer 132:6	232:17 246:8	143:8 161:11
153:22 187:23	elaborate 122:22	employs 327:3	enjoy 5:21	183:16 194:14,15
201:14 202:2	elasticity 308:20	enable 210:4	enlightened 162:25	194:24 195:12
227:2 267:24	election 153:13	enacted 9:24	enormous 247:17	383:2
293:24 309:4,5,17	201:2	encourage 46:24	enrich 23:15 42:10	equilibriums 194:7
309:23 311:2,8,10	elections 201:2	124:25 301:15	ensure 341:22	era 156:15
312:11 320:14	202:3	321:18	ensured 147:3	Eric 171:4 180:17
324:16 346:12	electronic 14:4	encouragement	enter 128:14 193:9	188:18 189:6
349:21 351:9,16	203:1 218:12	321:23	entered 14:12	214:13,14 219:15
353:25 355:11	element 206:13	encouraging 315:6	enterprising 269:17	222:3
358:23	elements 33:4 85:11	351:20	Entertainment	Erik 205:21
effective 78:17	341:16	ended 226:21 242:1	14:24	error 275:22
81:12 87:4 262:24	email 295:6 389:4	242:2	enthusiastically	especially 7:10 9:6
effectively 259:15	389:11,12	endogeneity 64:3	5:25	12:14 49:23 55:15
349:3	embellish 325:4	267:20 316:2,5,17	entire 112:6 231:15	57:15 226:23
effectiveness 26:18	emergence 133:25	318:6,18,20,25	251:21 257:3	228:25 245:6
265:19 268:1	emergency 19:13,13	322:8,11	330:13 333:12	254:6 262:23
effects 82:10 90:19	19:17 20:2	endogenous 341:15	338:22 375:9,13	269:9 294:25
147:17 152:17	emerging 364:2	endogenously	380:1	320:13
156:22 187:5	emphasis 117:17	352:17	entirely 239:17	essays 173:8
226:14 234:13	emphasize 76:22	endorsement 14:18	293:19	essence 83:4 120:8
301:24 305:20,21	77:17 102:16,22	endorsements 14:21	entities 302:23	essentially 22:13
308:12,12,18	102:23 115:25	ends 67:1 183:23	entity 218:11 302:22	48:25 56:9 152:11
309:12,19,22	116:3 231:11	energy 176:1,4,6,22	entrepreneurs	152:14 181:4
310:4,7,9,12,14,14	232:8 243:25	energy- 106:2	119:8	182:25 183:25
310:18,23 311:17	244:2 379:12	enforce 8:17,25 9:12	entropy 273:6	185:13 186:18
311:22 312:15,17	emphasized 381:6	9:18 10:11,12	environment 13:5,8	275:18 299:2
312:18 316:9	emphasizes 229:21	110:15 127:24	18:6 25:11,11 38:4	302:11 303:16
317:13,18,20,21	emphasizing 54:10	221:24,25	environments 16:20	311:24 314:12
317:21 318:3,5,14	102:14 301:6	enforcement 8:11	EPA 13:12	316:6,9 317:17,21
318:19 354:5,11	empirical 24:20	8:16 10:6 379:15	EPIC 216:16	358:22 377:24
367:4 369:11	174:4 196:21,23	380:6 381:24,25	equal 109:25 137:15	establish 57:25
efficiencies 290:23	291:8,16 318:9	enforces 103:15	140:16 255:25	established 125:7
efficiency 176:22	324:24 326:21	enforcing 9:10,14	345:13 356:2	179:23
efficient 106:3	333:4,5 335:5	engage 5:22 9:7	equality 237:4	establishing 291:17
effort 340:20	366:1,3	16:21 18:9,13 95:1	246:12 248:2	Esther 222:13
efforts 394:18	empirically 181:13	134:23 139:9	255:3	estimate 11:21
eight 22:22 184:10	276:3	147:7 156:7	equally 147:18	42:12 175:18
184:12	empirics 326:10	engaged 9:25 96:17	154:21,22 155:14	268:14 361:12
either 15:11 106:25	330:4 335:3,4	engagement 95:9	155:14,23	369:8
122:20 127:16	338:11	98:23 192:24	equation 107:20	estimates 45:13
146:4 151:13	employ 29:1,20	engaging 148:12	equilibria 113:21	47:15 55:11

179:19 267:18 308:21 349:13 estimating 45:7 339:18 Estimation 338:17 et 185:8,8 376:10 393:13 ethical 191:13 241:13 Europe 51:19 52:3 124:15 206:18 211:18 European 26:15 evacuation 19:17 evaluate 28:24 evaluating 173:25 174:1 evaluation 14:6 38:21 39:8 272:15 272:17 273:3,18 evening 96:19 evenly 40:1 event 7:4 20:7,9 377:7 events 377:6 eventually 12:13 13:22 37:21 221:20 258:10 261:24 301:2 everybody 33:8 41:9 108:17 110:6 115:4 121:15 188:6 197:15 313:19 352:14 392:12 everybody's 43:19 51:13 393:3 everyone's 341:11 evidence 57:16 62:15 64:23 72:22 74:15 75:4 76:6,11 179:6 208:2 225:8 232:6 236:19 240:25 241:2 303:8 315:10 319:19 330:1 336:16 350:2 351:21 371:15	evident 390:21 evil 228:2 evolved 197:12 evolving 17:22 18:2 18:4 48:11 exact 74:5 81:4 101:14 161:15 261:17,17 289:25 exactly 7:10 11:3 18:10 61:13 75:9 101:10 104:23 105:5 134:6 135:8 138:11 140:15 143:23 144:10 149:1 150:12,14 158:24 159:10 164:21,24 165:21 204:1 219:8 248:23 249:25 251:9 255:18 331:17 350:17 384:7 387:24 392:19 examine 371:23 example 11:9 12:19 12:20 13:23,24 14:18,23 15:14 34:3 60:4 67:3,7 69:22 87:17 95:24 97:23 101:8,21 102:1,2,15 104:6 106:8 115:23 119:5 121:6 130:25 132:4 137:13,14 138:10 154:19 156:6 158:7,12 159:1,2 159:22 161:19,25 163:9 166:22 173:15,24 174:8 181:7,8,21 182:4 182:19 187:17 198:15 199:2 212:24 215:3 222:18,19 242:18 252:10 256:12 261:11 264:17 286:1,20,22	316:15,18 355:20 360:6,22 367:4 377:23 381:6 393:7 examples 10:21 11:3 11:6 16:11 122:8 157:14 182:11 360:14,15 excellent 323:1 393:19 exceptional 179:6 exchange 28:11 41:5 exchanges 27:19 28:6,18,20 33:25 excited 22:5 24:25 100:9 151:21 172:25 224:16 excitedly 235:5 excitement 15:5 exciting 27:1 42:19 43:5,12 269:10 exclude 374:12 exclusive 103:21 109:18 114:3 117:12 122:4,5 excuse 171:18 executable 80:1 executed 351:20 exercise 10:24 31:15 44:13 45:12 51:8 329:1 330:13 333:6,23 337:24 exercises 48:13 exhibit 240:1 exist 106:15 113:1,9 113:13 285:23 existed 134:1 existence 113:20 148:22 167:1 218:10 300:25 314:19 existing 30:14,18 59:13,14 355:8 exists 222:12 315:8 exit 19:24 365:24 exogenous 244:5 335:12,24,25 expanded 134:1	expanding 273:23 294:3 expect 49:9,9,11 51:24 123:10,21 222:10 260:6 289:18 383:9 expectation 73:19 205:7 374:14 expectations 292:15 326:12 331:12 expected 44:21 116:11 expecting 342:2 Expedia 88:13,15 197:13,15,18 198:13,20,20 expenditure 317:1 expensive 239:2 252:2 354:17,17 354:18 392:2 experience 16:16 362:14,18,21 364:18 366:13 374:7 378:3 experienced 90:17 experiences 173:12 experiment 36:14 58:7 64:5,6 65:19 66:1,9,10,18 67:1 67:1,4,9 68:17,20 70:1 78:4,13 85:23 93:13 96:6 175:22 176:14 177:19 231:13 350:20,24 experimental 60:20 60:21 70:12 79:3,9 82:17 96:13 393:13 experimentation 71:10 82:12 85:6 experiments 53:18 53:20 65:13 66:21 79:10 89:4 175:15 175:25 178:24 220:19 expiration 347:19 347:22,25 348:4 348:11 350:8	351:1,13,17 expired 335:17,20 351:11 expires 327:25 332:7,8 333:1,2 338:25 expiry 328:15,16 333:10 339:1,2 340:4,7,12 341:7,8 341:9,20 342:18 342:18 343:8,11 343:22 346:7,20 explain 36:9 73:2 117:16 124:14 148:20 164:25 248:12 275:4,14 348:19 350:7 355:17 356:11 explained 78:3 348:18 explaining 47:4 349:12 357:17 explanation 235:20 235:23 explanations 382:25 explanatory 272:21 explicitly 206:3 219:15 315:15 exploit 122:20 333:13 356:16 exploiting 326:10 333:25 334:7 339:3 exploits 197:11 exploration 87:15 explore 46:25 72:24 84:14 164:10 354:3 355:24 explored 48:2 exploring 143:4 149:15 151:5 324:21 explosion 322:19 379:18 exponentially 273:23 exporting 338:10 exposed 56:25 59:15
--	--	--	--	--

60:8 75:21	113:17 115:16	392:21	327:2,12,12	170:24 196:15
exposure 72:3 73:18	201:10,15 220:11	facto 339:7,7	342:22 367:13	225:15 226:14
76:1,2,14 314:4	293:18	factor 263:16	392:13	250:5 335:8 345:4
expressed 57:5	extremely 43:12	287:18,18	fascinating 85:23	353:19 378:18
172:3	85:9,12 114:12,16	factories 336:1	177:24 289:7	feeling 5:9
expression 142:16	eyeball 33:8,19,20	factors 17:3 287:14	fashion 56:10	fell 135:10
142:17	33:21 97:20	factory-installed	fast 29:4 54:25	felt 39:24 394:8
extend 25:19 158:18	237:11 251:8,9	325:18	224:18	female 131:18 234:5
328:15 348:22		facts 215:8	favorite 182:18	236:21 237:4
351:12	F	fails 115:4,5	220:14	242:11 245:3
extended 4:6 324:2	F&I 350:18,21,21	failure 122:6 186:3	FDA 9:19 299:1,18	fewer 26:13 76:20
324:7,24 325:6,15	351:2 353:9 356:8	187:19 212:11,12	304:12 305:8	93:5 105:1 227:19
325:22,23 326:3,6	face 11:6 12:10	212:15,18 215:6	FDA's 300:21 313:7	233:6,16 235:24
326:16 328:7,10	16:14 47:23 192:8	failures 212:24	FDA.gov 301:19	239:6,6 242:16
328:17 329:3,7,17	204:8 228:4	fair 9:18 208:20	fear 203:2	382:4
329:19 330:5,17	231:23 233:10	209:9 210:3	feature 35:6 102:6	field 17:14 43:7
330:25 331:6,21	249:23 253:8,9	212:14 218:5	109:14 120:17	53:18 58:7 78:3,8
332:1,4,5,25	316:2	247:12 299:18	272:19 273:20	78:13 79:10,19
334:22,25 338:9	Facebook 58:14,24	390:20	280:4 291:1 344:5	80:1 89:4 96:5,12
343:8 344:9 345:8	76:16 189:6 190:8	fairly 26:9 75:14	featured 176:10,17	96:25 97:4 173:11
345:11,15 346:17	214:8 217:12,17	140:24 301:13	177:1	178:24 179:10
347:19 349:6	217:19 237:22	305:4 337:18	features 7:7 15:2	181:12 221:8
350:17 351:4	246:2 248:17,18	Fairness 361:15	120:5,6,8 121:5	224:22 226:15
355:5,22 356:9	249:1 250:3 252:9	fake 195:11,22	176:6,23 177:9	230:4,18 231:12
357:1,10	252:10,11,14	198:3,5,20,21	178:1,10 197:13	231:12 240:21,22
extending 145:17	388:3,4	199:8,10 200:12	197:14 260:23	241:22,22 242:1
328:23 356:22	Facebooks 49:24	faker 199:24 200:1	268:18,20 270:24	245:23
extension 157:20	Faces 258:25	fakery 198:25 199:1	271:3 272:22	fields 53:15 172:20
167:2	facilitate 207:8	199:6	273:19,22,24	Fifteen 210:9
extent 35:20 56:5	facilitating 380:1	faking 199:20	274:6,11,13,13,15	fifth 279:16
65:10 71:23 86:18	faciling 38:24 142:20	fall 25:24 72:24	274:15,17,19,20	figure 33:5 67:12
93:17 119:1,9	fact 44:20 47:23	194:13 196:1	274:21 276:10,18	80:16,18 121:8
138:23 195:14	60:3,6 61:6 68:25	326:19 373:17	277:3,4	153:14 170:7
198:14 199:1	94:12 105:22	false 15:2 79:20	federal 1:1,18 2:1	177:5 205:9
206:18 210:2	108:5,23 113:19	168:19 194:19	3:1 4:1 8:5,6,19	208:24 209:2,7
211:22 225:18	120:24 130:13,17	203:18 365:10,12	9:15 13:6,11 18:21	238:8 242:3 284:6
228:14 265:10	146:20 149:1	falsely 14:25 368:8	171:3 172:4,8,12	332:25 334:11
267:25 318:13	153:22 156:21	familiar 226:17	172:19 173:7	335:1 380:23
external 242:20	162:1 184:20	312:22 325:7	177:8 179:3 180:9	386:14
244:5 337:17	187:10,11 188:2	336:8 344:20	189:18 200:18	figures 205:7,9
extra 131:10 138:4	201:24 203:16	383:25	347:10 358:4	233:9
147:3 260:23,24	211:11 234:21	family 96:18	363:8 367:16	figuring 44:25
325:25	235:16 236:6	famous 384:6	federally 177:11	file 8:1 331:1,1
extract 128:17	239:2 242:10	fancy 231:10	fee 178:4,4	files 68:8 174:2
extracts 112:6	254:18 295:4	fantastic 6:5 53:14	feedback 224:20	filtering 386:15
extraneous 178:16	301:7 317:7 349:2	far 3:6 110:17 137:3	258:19,21	final 8:25 60:11
extreme 61:19,22	350:2 359:2 379:4	144:14 170:1,6	feel 7:22 71:11	108:20
70:21 108:18	379:9 380:23	211:18 235:17	98:10 114:5 132:1	finally 18:12 20:6

74:23 139:1 155:7	250:19,20 257:3	116:4,20 117:2	242:24 257:4	318:19 354:5
155:16 156:13	288:25 289:3,13	119:23 120:2,22	258:13 259:22	fixed-rate 183:8
161:14 171:8	301:18 344:15	120:23,23,25	260:17 261:20	flagship 179:4
181:10,23 188:10	348:1,13 349:8	123:22 124:2	265:16 267:9	flash 43:22
263:25 266:15	findings 83:18	125:1,17 126:6,7	270:15 276:20	flat 344:11 349:22
272:23 280:21	172:11 176:18	126:23 127:19	277:19,24 278:10	370:14 374:22
283:22 305:24	343:5 348:17	128:4,21 147:24	280:6 283:2	375:19
359:16 365:18	finds 315:9	148:5,10 156:23	287:12 289:11	flattery 325:3,5
386:12 389:14	fine 97:11 98:17	159:8,18,22 160:2	290:19 291:11,12	flavor 111:20
finance 376:16,18	143:21 166:9	160:7 161:9	298:10 308:19	flavors 328:10
finances 184:5	190:20 259:6	164:14,19 165:1	313:21,25 324:5,9	flipped 144:25
financial 50:19	337:9 361:21	168:10,13 174:7	324:19 325:14	floor 19:10,11 20:19
180:22 363:9	fine- 27:7	175:2 191:10	327:24 328:5,20	118:11
367:18	fine-grained 263:21	192:13 193:8	331:7 334:10	Florian 76:15
financially 396:11	fined 190:21 362:2	194:10,25 209:1,2	339:4 340:15	flow 218:22
find 5:21 28:13,16	finely 303:15	209:3 210:18,21	343:16 344:23	flows 206:5
30:17 50:16 60:18	fingers 29:4	210:25 211:20	347:16 358:16	flu 79:21
62:18,25 72:22	finish 204:16 235:8	212:7,8 213:1,3	360:16 365:8	fly 12:14
74:2,15,16 75:4,17	finite 174:9	218:14 225:2,22	366:7,16 367:10	focal 140:25
76:18 81:9,14	fire 162:8	225:25 252:23	368:19 369:21	focus 24:17 58:4
82:15,20 87:24,25	firm 17:1,15 24:18	352:11,19 361:17	374:16 377:2,10	91:10 100:20
89:20 91:13 96:20	46:23 64:20,25	361:19	378:9 379:5	105:18 118:15
96:23 97:2 102:19	66:19 103:15,15	firms' 211:19	382:18 390:4	120:20 121:12
128:22 141:13	104:11,16,22,24	first 5:5 11:5,9	first-order 152:17	125:6 127:22
146:15 152:12	105:12 106:16,24	12:19 16:14 20:16	221:21	128:21 140:7
156:19 177:23	106:25 107:3,6	20:21 25:3 32:7	first-year 258:23	153:18 260:25
185:7 187:8,25	108:3 109:21	38:12,17,20,23	Firstly 75:6 249:16	267:12 270:10
188:2 194:14	110:19 111:23,24	39:6 41:23 42:14	fit 35:23 44:7 203:16	292:9 304:22,23
200:1 231:8 232:6	112:4,14 114:11	44:2 48:18 60:1	fits 370:1	311:1 315:21
234:12 236:18	114:11,13 116:10	63:25 64:2 72:2,5	five 20:19 29:8	344:17 366:21
247:16,25 248:13	116:14 123:2,8,11	72:7,10 77:17,22	34:25 71:18,18	focused 156:4
248:21 249:10	123:14 124:23	78:9 80:8 81:1	120:16 208:1	225:19 228:10,12
250:20,23 252:12	128:17 159:10	83:19 85:5 105:19	209:18,18 238:11	244:1
277:2 278:22,25	160:1 161:9 165:3	117:6 121:11	238:11 275:1	focuses 118:23
279:21,21 280:11	165:17,22 166:2,3	132:22 134:3	285:16 302:17	focusing 40:3 78:22
281:5,6,8,11,24	168:12 189:9,14	138:5 139:23	306:17 328:4	234:4 303:18
282:7 286:5,14	193:4 195:1 208:3	142:11,15 143:3	337:25 372:2	338:15
289:12 290:6	211:12 212:20,20	144:4 145:23,25	five- 120:11	fold 59:9
298:21 300:5,20	213:2,4 330:15	147:21 149:18	five-period 120:12	folks 93:9 173:6
334:18 336:24	345:19 362:22	157:6 168:6	five-star 199:11,12	175:5,22,24 180:4
343:6 346:11	firm's 17:3 114:16	177:17 178:8,13	fix 208:7 268:13	187:17 325:11
364:12,20 369:10	116:16 128:14	184:15 185:4,25	fixed 29:13 31:13	343:18,25 393:1
369:11 370:20	firms 7:14,18,21	189:17 191:23	35:19 36:17,18	follow 19:15 190:4
371:3,17 373:7,8	22:12,20 25:17	200:23,23,23	38:5 82:4 83:2	326:10 329:2
373:14,20 375:8	28:6 46:20 50:16	203:23 210:13,14	308:12,12,18	335:3 381:12
375:20 376:11	102:13 108:20	221:10 224:11,17	310:12,13,14,23	followed 52:1
386:21	109:10 111:2,2,3,7	224:17 227:22	317:13,18,20,21	188:19 280:12
finding 73:4 245:2	111:9,9,14 114:6	233:5 234:9	317:21 318:3,5,14	following 57:3

104:21 114:4	250:21 333:17	306:9 360:8	379:24	216:8
140:10 141:6	formulation 156:13	362:10	Friday 1:13 96:19	fullest 339:3 355:24
142:14 143:19	forth 178:13	frame 186:25	324:14,16	fully 33:11 61:17
144:4 146:7	forthcoming 200:11	329:10	friend 178:9,9	62:8 71:11 79:23
163:24,25 214:22	200:12	framed 95:18	329:12,14	252:13
222:5 299:12	fortunate 327:6	framework 118:2	friends 189:6 190:2	fun 244:15 282:16
332:3	Fortunately 317:10	187:12 270:16	202:22 253:13	282:24
follows 12:4 315:22	forum 159:6	271:18 273:19,25	front 8:20 27:24	function 9:4 81:25
355:6	forums 193:18,20	274:1 276:6 308:5	166:11 342:10	137:20,25 142:7,8
followup 24:15	196:13	308:9	frontier 42:21,23	186:16 214:15,24
40:15 97:6 113:7	forward 43:8 58:9	frameworks 192:11	fruit 315:20	216:8 268:14,16
196:22 389:20	77:7 125:21,22,25	framing 351:9,25	FTC 5:5,7,9,19 6:4	274:2 287:21,21
food 116:24 359:23	126:20 127:9	353:5	7:3,6,9,10,13,16	288:12,13 289:4
Foods 173:20	244:7 258:22	France 124:19	7:17 8:10 9:2	344:12 374:15
fooled 135:13	286:9 343:15	franchise 360:16	10:16 13:9,21 20:1	functional 273:25
foolproof 337:9	364:1 394:1	361:7,10	20:13 22:8 23:20	274:1
341:11	forwards 203:12	franchisee 9:23	24:7 43:13,14	functioning 110:8
Football 28:14	foster 146:12 207:8	franchisees 360:18	53:13 54:24 55:23	functions 8:11 217:8
footprint 203:1	208:19	franchises 119:2,3	56:21 77:20 92:15	217:9 344:12,13
force 36:12 116:20	found 26:17 74:20	361:10	93:9 94:19,24	fundamental 104:2
153:19 158:5	83:8 146:13 149:4	franchisor 9:23	118:10 159:23	205:24 207:9
236:24	176:19 177:2,8,24	fraud 10:1,4 11:9,11	170:14,17 173:12	212:15 215:16,22
forced 277:23	178:1,6,15,25	11:17,22,23,24	173:19,20,25	293:22 362:13
forces 158:4	179:2,5 199:3	12:1,3 48:23 49:4	174:1,16 176:5,25	funded 225:5
foregoing 396:4	231:2 238:9	175:16,19,21	177:22 180:4,7	further 20:3 48:2
foreign 202:4	245:15 246:13	215:20 380:5	190:13 216:17	164:10 224:24
foremost 8:11 324:9	250:1 321:21	382:16,20 386:9	225:3,13 228:18	249:6 288:10
324:19	357:15 379:4,13	386:25	228:19,22,25	314:24 343:25
foresight 340:22	380:20 381:7,15	fraud/fraud 382:23	229:3 230:7	396:9
forever 218:25	381:21 386:18	frauds 12:8,11	241:16 258:14	fuses 288:24
forget 216:17	392:9	383:8	298:3 364:9	Fusion 14:3
form 41:3 55:4	foundation 365:23	free 105:12 120:11	367:18 375:9,14	future 5:23 48:3,14
97:15,16 119:25	four 4:5 32:17 80:13	127:20 148:24	377:5,10 379:1,13	50:21 108:2
121:8 134:16	83:11 137:16,17	170:24 207:21	379:17 394:13,17	112:18 118:22
135:1 268:14,17	143:17 204:10	249:3 252:16	FTC's 20:25 57:14	120:15 133:14
325:3,5	251:18,23,24	253:18 260:21	325:8,9	167:18 205:21
formal 342:13	252:3 255:14	261:3 316:16	FTC.gov 20:12	210:1 236:16
formalize 324:22	274:3 285:16	319:19	full 9:11 53:7 61:16	322:10 331:17
332:2	306:23 324:1	free-form 387:17	61:23,25 62:4	389:8 394:3
formally 112:24	344:21 357:12	free-ride 119:16	64:21 69:17 76:13	
116:7 271:22	367:7 371:4 373:9	free-riding 105:16	77:13 79:6,10,11	G
371:24 375:6	373:14 375:11	127:15	79:13,14,24 80:12	gain 39:19 290:7
format 55:18 234:4	380:6 381:13,25	freedom 317:19	80:15,18 81:4,19	gained 273:15 281:6
formation 120:21	382:23 385:8,21	freemium 260:21	83:5 84:15 85:9,14	285:2
120:21 124:21	fourth 11:12 14:18	freezing 224:7	91:2 216:3 230:24	gaining 55:14
126:5,7	385:13	French 122:2	282:13	gains 290:10,11
forming 328:10	Fraas 179:2	frequent 312:9	full- 215:15 313:1	338:9
forms 12:10 27:18	fraction 111:3 304:4	frequently 84:25	full-information	gambling 10:6

game 157:17	370:22 387:10	9:11,12 10:21 11:3	188:15 358:9	goal 7:19 24:9 42:10
game-changing 15:1	generally 44:25 46:2	15:14 53:25 56:7	glass 19:11	96:17 138:9
game-theoretic	46:11 57:10	62:13 66:2 83:16	glean 344:14,19	259:18 262:5
106:16	179:15 267:15	94:23 96:1 100:14	global 271:25	268:1 272:3
gamma 310:22	288:2	106:14,18,19	globally 285:10	292:12 380:9
Ganesh 6:4	generate 10:24,25	109:3,9 111:19	286:15,18	goals 57:22
gap 39:11 104:13	13:6 271:3 272:8	115:17,22 134:17	globe 248:6	goals' 299:21
111:10	273:19,22 274:10	136:16 162:3	go 3:6 7:23 10:18	goes 111:7 127:22
gaps 39:17	generated 46:11	164:22 172:6,8	11:5 14:8 17:6	141:12 148:25
Gardete 2:24 130:3	105:6,7 274:11	182:18 184:9	18:23 19:10 22:18	153:23 161:1
130:5 162:25	292:22	189:14 199:2	36:9 37:2 39:16	278:24 311:24
163:3,11 164:17	generation 273:20	208:8 224:8	52:2 66:20 73:15	313:4 327:2
165:9,15 166:16	generic 163:13	230:23 237:25	80:3,4 81:2 90:6	384:25
166:24 167:19,22	320:3	238:1 257:6 260:7	94:14 96:10 97:20	going 8:2,14 10:23
168:3,17,21	Genovese 384:7	265:12 279:13,14	101:9 106:20	12:11 16:13 17:13
Garrett 2:11 20:22	geographic 90:15	279:24 280:3,3	111:18 113:5	18:22 19:23 24:19
21:2 43:11 44:1,4	geography 58:18	283:3 306:24	124:15 126:6	24:19,22 25:12,18
45:3,24 46:16 47:7	71:19 338:1	316:14 362:7,8	128:11 136:15	25:19 26:9,21
47:21 48:9 73:14	George 187:3	367:22 377:18	138:12,14 146:1	27:16 28:14,15,17
Garrett's 221:13	German 101:24,25	387:4,6 389:21	155:2,16 165:15	28:24 29:1,12,13
354:24	Germany 102:16	given 9:10 12:11	170:1,6 176:8	29:14,15,20,21,22
gas 9:24	getting 5:18 7:4	17:16 18:5 35:19	177:1 182:2 188:2	29:24 30:16 31:5
gateway 217:13	33:14 42:9 49:23	36:1 50:4 73:18	196:2 208:24	31:13,23,24,24
303:9	65:23 79:21 88:7	121:24 130:18	210:13 214:24	32:4,6,8,22,23
gather 12:15 24:21	93:17 123:23	133:9 142:16	216:15 217:21	33:3,10 34:24
166:4 215:2	138:1 194:18	147:15 150:6	221:11 223:2	35:10,12,15,23,24
gathering 230:11	201:9,25 209:25	156:17 166:1	224:18,22,24	35:25 36:4,5,7,13
gauge 202:21	255:9 267:19	208:12 212:3	225:6 233:12	36:19,20,25 37:23
GDP 327:3	278:23 293:3	213:14 226:23	237:21 244:1,20	38:3,3 40:25,25
gender 31:19 229:15	300:12,13 301:19	250:11 254:18	245:15 246:4,4,5	41:17,22 43:15
241:5 243:11,22	303:5,6 305:5	260:11 262:18	248:18 249:3,6	44:21 47:3 48:10
245:1,6,21 246:1	363:7 366:25	265:15 267:8,17	250:9,9 260:18	49:12 52:2,4 55:13
246:12 248:2,8	386:23 392:5	268:7 271:25	261:3 262:9,10	55:16 56:4,6 57:6
250:20 251:14,15	gift 377:16	273:8 291:15	264:18 266:16	58:6,14 60:18,20
gender- 226:20	Gillette 31:20	302:21,21 326:23	270:25 278:15	60:21,25 61:4,10
245:10,11	Ginger 2:6 5:7 41:8	331:19 335:4,4,5	280:5 283:2,6	61:18 62:2,3 63:24
gender-neutral	53:11 55:23 91:19	348:3 361:14	288:9 289:2	67:23 72:6 73:16
231:23 241:24	103:5 151:20	365:14 392:11	290:10 291:4,25	78:23 80:3 81:1
246:20 247:23,24	155:8 170:9,12	393:20	299:8,9 301:8	82:2 84:4 87:22
general 33:11 83:21	171:13 175:16	gives 9:16 11:23	304:14 315:11,12	93:3 95:15 97:3
142:2,3 206:18	193:22 210:8	50:2 53:22 118:2	333:8 344:8	105:12 111:20
235:19 236:25	298:6 324:11	120:16 184:9	350:19 351:2	113:4,5 118:15,16
238:21 240:4,7,15	365:13 390:5,8	240:14 307:3	364:11 366:16	119:4,22 120:5
304:3,23 305:4	392:21 393:18	giving 26:24 54:3	370:4 372:14,21	123:8 125:21,22
313:14 360:3	394:3,12,17	100:8 135:19	373:4 377:6	126:20 130:21,22
362:4,12,18,20	girls 203:10 230:25	259:19 277:11	378:19,20 380:17	131:1,3,10,12,15
363:19 366:3,8	237:21 244:10	286:20 315:22	386:9 387:14	131:21,22 133:9
368:12 369:18	give 6:25 7:9,12	glad 5:20 92:4	go-to 284:14	134:23 136:2,17

136:19,20,21,22	263:21 265:14,17	211:1,5,9 212:14	Gordon 76:15	294:6 295:11,12
137:8 138:4,13,18	268:15,19 269:6	213:6 215:12,14	gosh 225:12	324:12 337:1
138:21 139:1,4,6	270:14,15,16,24	221:9	gotten 392:11	352:20 353:21
139:10,11,12,13	271:6,6 274:19	good 5:3,18 6:2 22:4	government 23:19	354:21,22 356:15
139:19,21,24	278:13,17,19,20	34:21 48:10 53:11	57:10 116:19	378:18,18,23,25
140:1,2,7 141:6,9	284:1,13,20 288:8	63:20 81:8 98:13	172:13 179:1	394:12,14
142:5,6,25 143:7	288:9,10,11,25	100:22 103:24	189:18 191:3	greater 107:25
144:1,1,5,23 147:7	289:1,9 300:19	107:5,8,13,17,23	192:4,5 200:19	353:18 370:6
148:1,11 152:1,2,5	301:12,13,19,20	109:19,22,23	205:14 363:8	373:21
152:25 153:6,8,12	301:24 303:15,17	110:6 111:2,8,9,25	governments 206:8	greatly 5:12 379:17
153:15,16 154:3	303:18 305:16,23	112:2 113:21	grab 169:14 204:19	greedy 286:11
155:3 156:18,19	306:1,2 307:22	114:7,8,9,10,11,13	grade 203:6	green 67:12 370:2
159:3 160:24,24	308:9 309:16	114:22 115:5	gradation 353:25	375:9,23
162:2 165:3,5,7	310:1,18 313:11	116:10 120:24	gradient 289:4	Greg 359:3
167:4 170:2,15,17	320:25 322:14	122:7,17 123:4,16	grads 381:18	ground 6:19,25
172:15 173:2	324:5,7,18,21,22	123:20,21,24	graduate 172:10	11:25
174:23 181:4,16	324:25 325:4	124:8,10 125:3	graduates 364:16	grounded 181:13
182:4,7,23 183:12	326:1,6,7,8,9,12	126:5 131:21	366:22 373:22	group 91:6 120:3,3
183:14 186:6	326:15 328:9,21	135:12 140:19	grained 27:8	230:13,13,14
188:11,18,21,24	329:1,8,22 330:3,4	144:19,22 146:8	grant 126:18	234:15 247:17,19
188:24 189:22	330:12,13 331:13	146:22 147:11,18	granular 171:13	249:8,11 328:9
190:4 193:5 194:9	331:17 332:3,23	148:11 150:15	174:7 321:25	364:8
194:17,21 195:12	333:4,6,6,14,25	151:3 158:1	granularity 263:20	groups 229:8 230:12
195:16,17,22	334:6,20 335:6,7,9	163:17,22 170:10	278:5	238:20 247:18
196:16,17 197:18	336:3,15,23	177:21 181:13	grapes 127:1,2	252:6 364:8 366:6
198:17,18,18	337:20,23 338:13	183:12,15 187:21	graph 11:25 306:5	367:1 375:11
201:12 203:3	338:15 339:3,5,17	188:2 190:16,17	320:18 370:1	377:4,8 378:2
205:13 207:12,22	339:19,25 340:11	190:25 209:10	graphed 373:2	growing 203:16
209:16,24,25	342:8 343:4,15,17	212:2 215:11	graphical 137:11,12	270:8 300:7 306:9
213:2,23 214:25	343:20,24 344:17	216:5,6 220:24	graphically 343:4	grown 24:4 208:11
219:19,21,21,23	345:6,23,24 346:3	242:17 243:8	graphing 316:18,20	208:14 300:2
222:6,7,10 224:4	346:23 349:5	246:11 258:10,17	grappled 92:5	growth 25:1
224:18,22 226:19	353:19,20 355:9	258:19,20,21	grappling 262:21	guarantee 113:20
228:7 229:1,14,16	356:12 359:12,15	264:7 269:4	gravity 223:1	162:1 349:4
230:4 231:6,9,10	359:17 362:8,19	277:13 280:9	gray 59:1	guaranteed 27:18
231:11,14,16,20	364:20,21,22,24	284:25 289:13,13	grayed 147:16	27:20 146:25
232:1,6,18,20,21	365:10 366:19,21	313:10 314:17,18	great 21:1 80:2	guess 12:1 51:6 58:2
232:22 234:2,3,8,9	368:9 369:2,3,5,18	314:24 332:14	85:24 86:14 97:4	64:8 141:13
234:10,12 236:19	371:14,23 372:18	359:13 361:9,10	124:15 128:1,23	157:13 164:13
237:7 239:5,7,19	372:20,20,22	361:12 384:18	131:19,20 136:9	273:17 277:16
240:13 241:2,20	374:9,14 375:3	388:11	140:15 143:22	370:7 376:22
242:20 244:20	376:6,23 378:19	goods 177:4	163:11 165:18	381:20
245:8 246:14	379:6 380:17	Google 58:21 59:17	170:3 173:3	guessing 292:13
253:6,15 255:20	381:24 386:22	66:23 68:18 159:2	180:16 181:9	guidelines 57:14
255:21 258:22	387:19 389:4	269:25 292:20	183:2,5 210:12	313:8
259:13 260:23,25	390:2	316:16,21 317:24	221:19 222:13	guild 125:5
261:2,4,5,9,23	Goldfarb 5:16 171:8	322:1 379:19	248:7 249:22	guy 126:25 155:3
262:1,4 263:3,19	204:20 210:21	Googles 49:24	258:11 259:2	160:21 182:22

187:9 356:9	234:24 235:14	81:23	Heisenberg 93:19	301:24
guys 179:18 194:18	271:12,16 296:2	harm 9:1 17:7 92:8	95:24	Heuer 101:22
196:4 200:17	happening 75:8	92:24 93:1,7	held 39:18 262:11	hey 205:23 219:23
260:1 316:16	85:25 130:16	206:11 211:10,15	hell 329:17 392:5	219:24 390:15
358:8 363:5	133:12,17 142:19	harmed 55:21 91:24	Hello 90:7 100:3	392:10
H	143:8,19 144:3,18	92:8,8,13 383:17	151:18 170:2,4	hi 5:3 43:25 94:15
H 107:6,24 272:1	146:2 150:16	harmful 117:25	224:4 313:19	hidden 13:2
hacked 222:21	153:11 191:20	182:16	help 11:7 16:9 65:9	hide 160:5
hairs 34:17	211:23 219:2	harms 22:15 225:22	77:4,13 89:6 101:7	high 28:4 49:16
half 31:21 39:7,9	237:8 245:19	225:24 228:15	103:9 109:13,16	56:12 65:8 83:25
40:4,9 49:11	247:22,24 249:7	HARP 186:1	114:3 124:14	86:3 106:8,11
139:16,16,18	263:12 266:25	hat 287:4	160:6 177:15	108:24 110:2,4,11
hamper 207:18	277:21 295:23	hate 144:15	211:20 217:8	110:12 113:11
hand 23:25 24:3	296:16 299:25	hazard 102:10	229:13 239:14	114:2,6,7,12,16
27:3 43:21 102:12	300:7 320:21	105:20 108:14	265:24 284:8	116:1 117:22
102:17 104:1,25	342:5 381:20	109:13 110:24	359:25 384:5	119:14,20 120:23
105:3,10 106:13	383:6	HBR 250:13	helped 208:25	120:24 122:1,3
110:5 114:19	happens 23:6 28:12	head 73:23 74:8	358:14 362:25	123:22,24 132:17
131:20 132:13	37:13 51:5 64:5	171:2 357:15	379:5	138:14,24 139:3
140:18 141:16	131:24 141:5	headache 39:17	helpful 6:17 25:13	140:19 145:19
142:20,22 143:25	149:6 157:21	headline 227:2	26:20 42:17 180:6	208:14 252:17
147:6 240:10	164:3 183:20	233:21 250:2,4	182:17 243:24	255:16 267:11
256:11 287:16	188:1 193:8	headlines 244:23	258:21 315:22	268:4 283:5 288:5
293:5,10 325:22	194:16,23 202:12	health 13:8 14:11	385:2	288:16 289:6
356:12,12	203:15 211:14	158:14 175:2	helping 48:8 124:25	293:2,16 345:4
handful 213:9	229:24 235:9	207:3 236:20	358:13 381:5	359:16 370:14,21
handle 162:21	242:6 274:5 279:5	237:3 300:2,5,5	389:19	371:5 374:23
332:14	279:19 280:24	304:3,10,24 305:4	helps 23:4,5 31:3	381:17
hands 31:2 239:10	290:7 292:23	331:11	76:21 127:17	high-end 101:22
239:24 338:12	333:16 341:10	healthy 158:16	217:16 259:14	high-income 367:5
handshake 28:8	351:4 369:9 384:3	161:11	282:1 288:20	high-level 25:22
handwaving 326:17	happy 22:7 70:13	hear 17:11 153:9,14	Hema 3:16 258:3,4	high-rating 82:22
happen 19:23 41:17	91:10 214:9 347:6	170:15	283:5 284:5	high-tech 269:23
91:4 102:4 135:10	hard 6:3 7:25 9:11	heard 7:15 12:22	289:23 291:1	higher 49:5 86:20
137:10 143:7	17:8 30:16 50:18	49:15 126:25	295:13 391:11,17	88:14,15 89:23
147:25 159:12	51:8,15 65:4	154:16 206:8,9	Herasingh 6:13	90:1 93:4 95:15,16
164:22,23 166:13	109:18 114:12	225:11 229:5	389:15	107:5 111:6
168:20 195:25	146:14 164:21	382:20 384:9	Herbalife 15:18	113:22 120:1
196:3 197:23	166:10 180:12	hearings 8:23	16:6	164:7 206:12
216:14 221:18	187:24,25 190:22	heavily 172:21	hereto 396:11	220:14 222:2
225:24 278:5,8	206:13 221:15,24	360:24 364:20,23	heterogeneity 25:18	246:9 248:21,22
279:3 330:5	221:25 236:1	370:10,11 371:17	25:20 30:4,7,12,15	250:7,7 256:1
333:21 342:6	268:21 288:19	371:19 373:18	35:11,16,18 36:6	293:3 302:25
352:11 354:19	308:4 361:8	374:3,3,4 375:14	37:1 82:6,7 90:18	311:25 312:25
381:16	371:14 376:4	375:21,25 376:2	91:11	321:6 340:25
happened 205:17	harder 198:21 253:9	376:11,18	heterogeneous	345:13 349:8
222:14 232:24	Harikesh 53:4 77:9	Hebrew 196:20	310:17 312:17	354:21 362:15,16
	78:3 80:4,14 81:2	Heck 35:3	heterogenous 42:4	364:25 369:11,12

370:10 373:20,23 375:21 381:8,17 382:5 highest 32:13 38:10 144:4 289:4 290:7 292:22 317:2 343:19 370:19 highlight 44:13 61:12 70:22 71:1,4 85:16 89:17 90:1 120:5 140:8 147:20 195:20 228:13 231:18 234:16 243:17 256:7 307:2 314:13 343:4,5 highlighted 61:7 72:18,21 73:18 84:12 88:4 92:20 225:23 314:22 316:25 365:7 highlighting 79:14 86:10 90:3 91:1 314:10 highlights 315:7 highly 14:10 134:11 382:3,4 Hill 324:7 hinder 176:20 hinted 219:14 hire 29:3 132:7 hiring 132:14 Hirschman 358:19 365:25 Hispanic 366:22 370:20,21 371:19 371:20,22 372:3 373:18 374:4,19 375:4 382:4 Hispanics 364:15 370:17 371:18 373:13 historian 205:22 historical 13:13 16:8 283:9 284:3 historically 54:5 history 7:6 10:10 33:7 107:12	120:14 124:8 173:5 270:23 271:1 272:1 279:15 hit 32:9 335:21,22 hold 8:22 36:21 53:8 150:18 157:22,23 233:18 259:8 280:1 377:7 holding 36:17,17 38:4 holdup 151:3 162:12,15 164:8 168:4 holistically 122:12 home 60:6 67:10 68:11 353:2 hometown 214:4,10 homogenous 286:6 homophily 201:13 honest 7:8 honestly 79:2 hope 5:21 11:7 16:8 19:5 40:17 42:7 122:12 331:15 hopefully 19:22 20:19 49:13 57:18 90:10 100:14 151:7 224:8 229:2 258:5 286:18 303:9 308:6 394:14 hoping 258:19,20 322:10 329:25 337:11 342:7 horizontal 122:16 136:23 157:8,11 157:25 hospital 187:23 211:21 hospitals 188:2,4 host 227:11 236:12 261:23 hosted 28:5 hosting 261:22 379:1 hosts 324:12 hot 179:18	hotel 197:17 198:11 199:7,8,11,23,25 200:1 360:17 hotel's 361:8 hotels 88:17 197:21 197:22,23 198:4 360:17,25 388:6 hour 170:7 hours 176:10 204:5 hours' 184:4 house 23:20,21 183:6 184:19 361:16 household 185:25 295:5 366:23,24 381:9 huge 51:12 81:14 185:5 230:9 239:16 244:24,24 247:14 248:5 320:19 327:2 329:24 370:25 375:23 hunch 275:12 hundred-year-old 205:3 hundreds 36:15 383:17 hunts 34:5 Hurkens 150:9 hurt 103:9 182:8,9 185:4 207:3 hurting 211:19,20 hurts 182:10 hyperbolic 183:19 hypertension 317:25 318:8 hypotheses 322:21 hypothesis 201:13 381:20 384:20,23 hypothesize 198:15	ID 244:18 265:4 271:8,10 277:22 idea 9:13 57:21 60:25 63:6 74:24 85:7 101:11,13 105:4,5,19 106:19 109:12 143:7 148:15 149:21 150:15 151:24 163:23 190:3 191:9,11,24 193:15,16 195:20 207:4 216:9 218:1 218:13,23 219:1 219:15 222:13 229:8 234:11 235:11 236:11,12 236:16 256:9,13 290:15 301:14 306:24 307:3 318:7,12 320:2 359:5 390:13 ideal 367:17 390:19 ideas 5:18 18:12 157:4 204:21 236:10 295:11 385:7 identification 30:3 85:6 333:25 335:5 336:6 337:3 340:15 354:20 362:13 identified 94:24 366:14 identify 32:23 36:11 44:8 122:7 174:11 278:11 289:25 364:2 identifying 36:10 37:2 60:16 147:21 350:6 identity 10:3 374:13 idiosyncratic 35:14 36:8 IDs 278:14,15 ignorance 142:13 148:13 illegal 348:7	illustrate 182:11 image 20:11 214:1 360:19 imagine 31:18 45:16 47:25 97:13 106:24 158:9 182:12,25 183:18 202:19 260:11 293:15 316:1,1 359:19 360:8 Imbens 339:9 imitate 165:21 169:5 imitation 325:3 immediate 320:15 immediately 5:17 19:19 43:22 119:15 150:3 171:1 183:6 immensely 379:13 immune 135:9 impact 2:9 20:23 22:2 40:8,12 42:12 56:18 83:20 84:6 191:14 357:9 impacts 42:4 impatience 184:15 imperfect 60:9 impetus 384:25 implement 61:11 64:21,25 65:1,4 66:20 79:18 implementation 288:18 348:16 implemented 58:7 65:13,14,20 66:9 66:18 67:5,9 82:19 143:14 implementing 37:6 implication 315:16 implications 92:2 131:2 160:1,15 202:20 240:19 241:20 242:21 259:17 imply 135:3 292:10 important 7:17 8:5 12:18 18:15 26:1
I				
I's 32:19 33:2,12 i.e 328:7 IAB 57:13 IBM 180:19 iceberg 174:16				

29:19 31:16 41:7	improve 166:4	included 16:6 66:24	incremental 87:2	40:8,13,19,19
42:5,11 43:4 51:16	172:13 178:19	70:15 127:25	independent 169:3	42:13,19 43:2
57:24 58:1 68:14	188:5 265:18	320:18	197:24 198:17	49:22 50:4,11
70:5 73:4 83:4	359:18,24,25	includes 379:25	199:9 228:5	51:11 55:12,18
87:13 92:1 96:18	improved 75:17	including 17:3	index 255:12	56:19 57:5,10
96:19 102:6 117:1	177:15	31:19 69:13 82:7	India 65:18	103:7,18 109:17
142:17 153:1	improvement	148:22 204:22	indicate 14:13	115:21 116:24
154:5 155:5	277:14	298:4 300:14	indicator 234:5,7	133:25,25 184:4
159:13 161:14	improvements	inclusion 288:19	271:16 311:11	205:19 219:3
169:1 178:12	178:14	332:12	340:3,8,10 342:16	225:2 259:20
179:21 180:1	improves 39:2	income 15:21 35:21	357:14 372:6	260:12,14 261:20
182:6 183:4	in- 177:16	120:25 208:9	indices 237:3	325:1 326:22,22
195:24 208:23	in-app 55:16 58:12	307:24 311:19,24	indifference 39:10	326:25 327:2,5,8
228:17 252:24	68:4 261:1,8,10,12	311:25 312:3	indifferent 148:16	329:20
253:20,22 262:1	261:18 265:19,22	366:23	indiscernible 63:14	industry's 264:4
281:21 290:19	269:15 295:15	incomes 312:25	158:21 247:15	industry-wide 9:4
295:9 306:3	in-lab 96:21	incompetent 107:3	254:9 295:24	inertia 75:1 76:7
314:25 315:1	in-stream 58:23	107:6 109:21,24	318:20	inevitably 239:5
316:10 317:23	inaccurate 215:10	111:2 114:13	individual 7:25 8:7	inexperienced 90:12
318:16 327:1	inadvertent 178:20	115:7 120:22	28:24 60:14 104:4	90:18
330:3 332:10	incentive 108:10	123:2,15,23 124:2	104:20,22 113:19	inference 382:7
363:22 364:17	111:23 114:17	inconsistent 17:25	113:23 114:4,5	inferences 320:1
380:12,14 386:16	115:24 119:16,21	incorporate 150:21	117:6 119:8,9	infinite 111:22
importantly 26:5	144:12 150:1	150:24 151:3	120:3 121:17,23	135:2
84:6 85:5 101:20	198:3,5 345:18	276:1	127:18,18 129:1	infinity 222:10,11
107:9 303:3	352:13	incorporates 174:18	228:11,12 237:11	inflections 287:24
366:12	incentive-compati...	incorporating 49:6	353:12 371:24	influential 153:17
imported 68:17	281:16	136:12	384:24	inform 25:9 36:20
importing 127:1	incentives 47:22	increase 73:3 87:23	individual-aligned	52:4 164:2 332:11
imposes 56:12	105:15 112:9	87:25,25 88:4,5	218:11	information 3:15
impossible 285:19	115:9,16 116:4	107:4,22 111:24	individual-level	9:5,21 14:11 17:5
imposter 376:10	117:2 126:22	262:6 308:22,22	279:10,16 280:2	18:21 23:14 25:17
impress 203:11	128:21 141:4	308:24 343:7	individuals 205:15	29:21 30:1,10
impression 27:7	194:12 222:1,2	346:6 369:8,14	218:17 226:2	31:19 33:14,21,22
49:19,20 51:23	281:11 282:3	increased 262:12	340:21 343:21	33:22,23,25 34:1,3
56:25 134:7	314:13 351:22	358:21 359:4	induce 132:3 139:6	34:9,13,16,20
262:17 263:11	352:12 377:14,22	increases 84:18	148:18 331:25	39:19 49:6 50:24
270:12 271:6,12	incentivized 15:23	95:19 147:22	383:15	51:13 61:16,23,24
271:15,24 274:5,7	incidences 11:22	347:21 375:24	induces 291:3 293:6	62:4 64:22 67:16
295:23 296:2	incidents 175:18	increasing 84:21	383:23	67:17,22 69:17
impression-level	incitement 191:24	87:13 344:8	industries 10:13	76:13 79:11,13,14
290:8	192:1	increasingly 33:1	102:13 103:19	79:24 80:12,15
impressions 28:25	include 14:10	96:6 174:5,5	104:8 109:15,25	81:5,19 83:6 84:15
232:25 233:20	124:23 170:18	298:17	117:11 129:2	85:9,14 86:6,17,22
234:18 246:15,17	182:7 317:12,12	incredibly 97:1	industry 9:17 15:17	87:2 91:2,3,4
252:6 270:19,21	317:17,19 318:4	214:11 224:16	16:9 22:13 23:19	96:24 130:17,19
271:2 272:6	318:15 343:2	234:3 285:15	24:2,3 25:23 26:25	131:9,13 132:10
impressive 44:8	355:12	293:16	27:1 35:3 38:14	132:12,12,14,20

132:24 133:18,19	293:13 299:7	218:14	intention 313:14	159:17 160:18
133:24 134:4,15	300:2,5,5,10,13,20	input 46:16 246:3	intentionally 240:24	161:5,12 165:11
135:18 139:2,8,9	301:16,20 303:21	268:16 272:4,14	interact 7:18	166:11,16 167:15
139:21,25 140:12	303:22 304:20	274:2 276:10	interacted 340:8	168:6 169:15
140:13 141:10	314:6,18,19,24	332:17	interacting 189:18	170:22 171:19
142:10,14,21	319:7,8 338:5,11	inputs 274:3	interaction 191:12	176:15 188:8
143:5 145:1,3,7,10	351:22 359:8	inside 8:21 9:2 13:4	192:14 311:1	189:3 190:5 194:7
145:22,24,25	380:22 385:16	93:17	interactions 18:8	194:20 199:20
146:2,5,6,11,25	information-shari...	insight 156:12,14	191:11 234:6	201:17 218:9
147:8,22 148:6,11	284:18	344:17,18	236:20 268:19	238:10,12,12
149:19,21 150:16	informational	insights 46:22	285:16,17 287:22	242:4 243:19
151:8,9,14 152:10	304:21,25 305:14	100:15 125:21	310:19 311:19	247:25 252:18
152:18 153:8,11	306:1 307:20	126:2 127:9	317:22	253:21 254:3,14
153:21,23 154:2,4	308:2,16 310:5,6,8	insignificant 81:17	interacts 322:22	254:23 259:25
154:9 156:7,18,19	310:10 311:23	inspiration 231:1	interest 4:6 53:24	269:7 271:13
159:2,4,7,9,24	312:1,14 315:11	inspired 181:8	56:18 65:12 70:10	277:5 279:13,20
160:4,20 161:8,20	informations 34:8	230:8	77:16 80:2 90:22	291:9 313:24
162:2,5 163:20	informative 126:11	inspiring 393:4	106:23 148:5	318:9 321:4
164:2,7,15 165:5	149:23 153:15,16	install 37:12	151:23 159:25	322:17 351:20
165:13,14 166:1,3	277:8,12 280:17	installed 325:19	162:19 171:16	374:1 379:4,13
166:5 168:13	281:8 319:25	instance 69:5 70:2	246:23 247:4,9,13	380:6,18,19,21
169:5 170:18	321:4,6,15 322:16	74:1	260:14 262:12	381:22 383:12
172:13 174:2	362:9	instituted 54:17	317:8 324:2 330:1	385:18 386:10,18
178:12,12,16	informed 31:22	institution 394:14	330:20 339:25	386:22 393:4
179:3 181:24	41:18 62:8 141:16	institutional 7:7	342:7 344:16	interestingly 82:20
182:14 186:15	144:1,3 149:8	319:12	372:5 383:16	interests 23:14
188:9 192:16,18	194:15 212:5	institutions 34:24	390:21,24 394:9	246:5 394:8
208:22,25 211:11	informing 148:8	53:14	interested 23:18,22	intermediary
212:16,17,17,19	392:20	instruction 20:3	32:14,21 33:15	218:13 219:6
212:20,21 213:3,8	informs 6:10 300:25	instructions 19:15	91:17 128:4	intermediate 136:14
214:7,11 215:9,16	infrastructure	insurance 302:4	138:23 144:17	149:5,14
216:4,6,7,24 218:2	50:19,21	303:23 306:20	149:6 160:3	intermixed 379:10
218:19,21 219:7	inherent 250:24	307:12,17 311:11	170:23 173:1	intermixture 385:8
219:18,19,23	inherently 51:15	311:12,16 312:24	174:25 175:5,6	internal 283:11
220:5,8,10 221:11	initial 122:15	325:24 326:4,5	197:6 234:20	internalized 116:16
221:23 222:7,21	123:19	328:7 331:10	235:3 236:9,17	internally 387:17
258:1,7 259:13,14	initially 63:13	344:23,24,25	247:7,8 275:15	388:16
259:16,18 266:2,3	157:13 195:5	345:2,2,13,16	289:8 321:1,7	internet 10:6 12:6
266:4 270:23	initiative 230:17	346:7	332:16 333:9	23:7 28:17 34:7
273:15 274:18,21	initiatives 179:4	insurer 222:22	358:17 396:11	40:23 90:13
276:21,25 277:1,2	injury 10:24,25	insures 331:15	interesting 5:22 7:7	229:10 260:4
277:10,11 279:15	innovate 218:14	intact 333:12	9:22 14:19 40:17	298:17 300:1,1,4
283:9,9,10,13,16	innovation 109:20	integrated 55:6	42:11 46:22 48:3,7	303:9,16 306:8,11
283:21 284:3,4,7,8	205:19,25 206:6	228:16	48:12 82:1,25 83:8	309:17,18,21
284:11 289:14,20	207:2,7,8,9,14,19	intelligent 39:18	84:17 119:12	312:12 315:10
289:22 290:5,10	208:19 209:15,16	intend 24:15	138:22 149:4,14	358:21,23 359:7,7
290:12,15,17,21	209:25 210:17,18	intended 314:1	152:8,22 156:24	362:22
290:24 292:9	210:18 212:6,13	intending 242:14	157:19 158:17	interpret 82:11

98:11,16,17	177:3 291:10	IP 269:24 271:14	Jin 2:6 5:3,7 7:3	journey 282:21
118:17 124:4	305:18 312:4	277:23 278:11,12	43:11,17 48:16	judge 8:21,22
293:23 306:3	348:18 349:7	278:14,16,20	53:3 77:9 85:21	judgment 7:24
309:7	381:7,14 392:16	295:3	98:23 100:3 118:9	386:24
interpretation 70:18	intuitively 108:22	iPhone 260:3	127:12 129:3,5	Judy 196:19
291:6 348:18	316:6	Ippolito 175:14	130:2 151:16	July 16:5 393:9
interpretations	inverse 370:18	Iran 269:16,21,25	162:23 163:2,4	jump 77:16 101:3
88:21	invest 103:15	270:5 292:25	169:12 170:2	213:16 290:18
interpreting 80:21	106:17 107:1,4,7	Iranian 291:3	210:9,11 223:7	347:25 351:17
293:25 294:10	107:21,22 108:3,5	IRC 196:3,4,8	224:4 244:9	jumping 284:9
interrelated 212:24	108:8,12 109:23	irreversible 25:7	254:12 258:2	jumps 168:12
intersection 26:12	112:17 113:13,14	isomorphic 168:1	282:10 294:14	June 14:16 15:13
394:25	114:17 115:6,9	issue 54:4 73:24	296:25 298:2	Junju 101:1
intertwined 23:8	116:5 118:1	94:21,21 103:5	313:17 322:7	Jura 3:21 48:20
intervals 373:3	120:11 125:1	117:13 119:4,18	323:3 324:3 347:9	313:17,20
375:8	126:23 195:1	121:2 205:16,18	352:4 355:19	jurisdiction 9:16
intervening 217:3	331:12	220:15 350:4	356:6 358:2	justify 57:16 221:17
intervention 57:11	invested 124:3	390:16,18,19	378:15 387:3	332:13
332:18,19,19,21	investigate 130:21	391:17 392:14,22	388:18 390:2	juxtaposing 319:21
interventions 217:7	237:19	392:24 393:9,16	394:20	320:3
217:10 346:25	investigating 143:24	393:24 394:2	job 6:5 8:13 16:22	
interview 203:2	investigation 16:5	issues 43:5,6 60:23	78:22 132:4,5,6,11	K
interviewed 203:4	385:3	62:22 110:6 119:3	193:14 226:16	K 4:15 5:15
interviews 177:17	investigations	120:20 135:14	230:14	K-level 182:2
intriguing 189:3	174:18	170:16 192:8	John 182:22	Kagglers 275:9,11
228:1 239:22	investigative 9:7	204:8 206:22	Johnson 2:11 20:22	Kalyanaraman
381:23	investing 102:3	219:13,20 290:5	22:4 33:9,24 34:17	339:9
intriguingly 381:15	103:20 109:10	290:23 357:1	37:8 49:8 50:9	Kanish 352:20
introduce 163:24	117:3 123:14,23	376:19 380:15	73:16 171:4	Kanishka 3:13
167:24 170:20	investment 102:10	382:14 385:20	180:18 189:6	154:20,21,22,23
181:5 332:20	105:25 107:24	387:20 391:3	213:17 214:21	155:3,4,8 244:11
351:9	108:16 111:5,6,12	items 239:17,21	215:13 216:11	244:17,19 282:16
introduced 105:19	111:13 112:4,18	iTracking 96:7	222:4 353:22	Kantar 303:11
106:6 131:23	112:22,22 113:10	Iyer 6:4	354:7	322:2
163:7 265:4	113:11 119:23		join 15:25 124:21	karma 259:1
introduces 334:9	120:1 121:19	J	125:17 126:7,10	keen 218:13
introduction 2:5 5:1	136:8 254:17	J 340:2	395:4	keep 16:12 18:16
91:20 393:11	331:9,15	Jakarta 65:18	joint 100:25 147:12	51:16 102:3
intrusion 205:3	investments 105:23	Jan 171:1,11,23	147:15,18 165:11	109:10 117:2
intuition 32:24	107:9 127:21	180:16,20 181:9	224:14 258:22	120:19 124:24,24
111:21 113:6	invests 121:15	365:22	298:5	163:12 212:21
136:6 146:6 147:2	invisible 30:17	January 5:9 316:24	jointly 180:5 394:13	222:7 273:24
153:5 163:23,25	inviting 77:15	318:9	Jones 4:8 347:9,11	357:3 386:22
164:13,22 184:17	313:23 358:10	jargon 154:16	journal 6:12 173:9	391:22
283:4 354:22	involve 59:15 67:18	Jason 6:21	175:11 182:20	keeping 83:2 262:7
intuitions 285:1	involved 155:12	Jennifer 6:21 19:1	337:13 365:21	keeps 123:13,16
intuitive 113:8	181:10 370:3	396:3,16	journalism 54:9	185:17
115:12 139:3	iOS 260:9	Jerusalem 196:20	journalists 54:10	Keith 175:17

Keller 6:21	197:21 198:1,6,22	55:12 58:12 82:7	138:11 141:7,20	215:4,4,5,8,24
key 20:25 120:5,6	198:23 199:2,21	109:15 177:4	141:22,25 143:18	216:1,7,20,23
157:24 160:1	199:23 200:7,13	207:24,25,25	146:14,15,22	217:4,17,20,24
177:1,25 205:18	200:24 201:4,5,14	214:6 266:17	147:24 150:11	218:12,16,21
210:1 261:19	201:23,25 202:9	285:3 352:13	152:24,25 153:2,2	220:21,23,24
286:24 326:4	203:8,10,16,18	370:8 379:23	153:6 154:1,7	221:3,5,6,7,14,19
339:24 368:13	205:10 207:13	386:5 394:7	157:18 158:17,22	222:8,19 224:6
kick 20:16 39:11	209:7 221:8 223:1	Kitty 384:7	158:23,23,24	228:19,22 229:12
kicks 327:25	227:11 254:20,21	Kmitch 6:12 389:14	159:10 161:2,20	230:21,22 231:6
kid 172:17	258:24 259:14	knee-jerk 93:24	163:13,20 164:6,9	232:8,10 233:9,12
kid's 185:8 203:4	263:5,12 266:4,9	94:3	164:19,25 165:6	233:13 234:17
204:4	266:17 267:14,15	knew 209:2 282:22	165:17,18,25	235:2,4,5,9 236:3
kids 192:3 193:21	279:14,14 281:14	340:25	167:22 168:24	236:5,18 238:1,4
202:7,15,19	282:23 283:3,3,20	know 5:4 7:8,12	169:1,2,3,6 178:9	238:18,21 239:9
381:11	283:21,23 284:18	11:18 14:19 15:15	178:21 180:18	240:22 241:3,8,14
kill 199:16 200:7	284:19,20,22,24	15:16 17:23 22:21	181:21,22,23	241:15 242:21,24
killed 384:10	285:1,8,8,9,10,13	22:23 23:2,4,17	182:21 183:12,23	243:6,10,16,18
kilowatt 176:10	285:18,18 286:3,5	26:2 29:4 30:5	183:24 185:6,7	248:10,16 250:5
kilowatt-hour-fea...	286:7,16,20	31:16 33:19 34:10	186:11,24 189:9	252:9 254:21
176:16	287:19,21 288:9	34:22 35:1 36:10	189:13,17,18,22	255:6,11,19 256:4
kind 11:19 18:3	288:12,13,15,21	37:9,9,17 38:13	190:8,23 191:1,3,9	258:17 259:2,21
22:15 23:9 24:5	288:21,24,24,24	41:14 44:2,3,9,20	191:13,18,25	259:24 260:1,3,20
30:17 31:1 36:11	289:3,4,13,14,19	45:2,6,11,17,19,24	192:4,6,6,16,17,19	261:15 262:8,13
37:23 38:18 39:5	289:23,24 290:2,3	45:24 46:2,4,6,7	192:20,20 193:2	262:22,23 263:1,4
39:17 40:4 44:6	290:18,21 291:3,9	46:12,15,19 47:13	193:12,13,16,16	263:18,23 264:10
45:5 48:13 49:11	291:10,12,22	47:18,20,22,24	193:18,24,25	264:11,12,14,17
49:21,23 50:3,14	292:3,4,20 293:6,9	48:6 49:17 50:5,10	194:2,6,8,9,11	265:8,10,10,20,21
50:18 51:6 54:14	293:11,24 295:20	50:15,20,22 51:4,5	195:3,9,12,15,17	265:23,23 266:1
55:4,8,10,10,13	295:22 296:4	51:8,15 52:3 56:15	195:20,25 196:4	266:21 268:1,16
62:22 77:24 82:11	299:4 300:8,9,17	59:3 62:22 63:2,14	196:10,12,15,15	268:23,24 269:11
82:16,17 84:15	301:14 303:17	63:17 64:18 65:23	196:22,24,24	269:17,21,22
85:2 88:22 91:17	308:3 309:10	68:3 78:4,11 79:20	197:5,7,8,12,25	270:2,4 271:9,11
96:10,13,15 97:17	314:6 318:1 325:9	79:20 80:21 82:19	198:3,4,5,6,8,22	271:15,19 272:5
98:9 102:24 104:4	327:11 328:9	85:2 88:11 89:3	198:23 199:5,6,17	272:24 273:5,11
115:20 127:20,21	330:1 332:11,16	90:11 91:25 92:12	199:18,21,24	273:15 274:21,24
152:7,16 153:3	332:19 334:24	92:24 93:8,14	200:6,10,10,14,25	275:24 276:12,15
154:16 156:1,20	335:2 336:15	94:19 95:3 96:7	201:4,5,6,7,10,15	276:15,18,22
156:21 157:1	337:6 347:2	97:17,19,20 98:11	201:16,19,20,21	277:4,12 278:21
158:4 160:15,23	352:17,18 354:10	98:12 100:12	201:22,24 202:1,2	278:25 280:8,9,17
161:1,7,12 162:7	354:25 355:12,17	101:10,11,13,14	202:2,3,8,9,10,16	281:1,4,13,23
171:14 182:22	356:3 357:1,3	104:23 105:5	202:18,20,22	282:4,16,19,20,22
183:18 187:24	359:24 362:12,20	108:2,7,8 111:1,3	203:2,4,8,9,9,11	283:12,15,17,19
188:8 190:7,13,23	367:8 371:15	114:12 115:6	203:18,21,23	284:10,14,18,24
191:2 192:1,7,11	372:23 375:2	119:2 122:2 123:4	204:4,4 205:8,19	285:13,14 286:4
192:23 193:1	381:15 383:12	123:14 124:12,16	206:8,15 207:20	286:12,18,24
194:16,23 195:8	386:8 392:19	125:6,10 126:24	211:7,23,25 212:1	287:2,4,5,6,7,8,10
195:11,17,24	393:3,15 394:7	128:10 132:18	212:1,9 214:1,2,2	287:12,20,22,24
196:6,18,23 197:4	kinds 10:14 30:1	134:6 135:3	214:3,10,11,14	288:5,7,8,25 289:9

289:12,16,16,20	147:4 212:3 316:8	292:1 302:17	learn 18:14 39:15	96:18 98:20
289:21 290:9,21	346:22 381:3	304:6 305:4	64:9 66:19 115:4	102:22 167:2
290:24 291:10,11	known 60:1 154:9	331:16 365:20	139:13 142:23	168:14 189:21
292:21 293:6,11	157:8 178:22	366:1 370:23	143:1,11 164:4	215:19 225:6
293:20 294:3,3,7	213:18 215:3	largely 174:12 185:1	173:3 252:22	232:18 240:19
295:24 296:1,2,3,6	236:6 260:7,20	186:3 190:8	364:4 377:11	251:19 261:7
296:19 298:14,16	265:5 325:2	357:17	learned 48:22	270:9 274:23
299:8,9,19 300:7	358:18	larger 71:23 121:22	173:21 227:11	277:17 293:15
300:18,21,24,25	knows 45:3 124:1	281:5,6 310:6,9,9	230:22 236:13	318:11 319:21
301:7,15,19 302:1	138:8 144:22	311:23 312:11	393:15	323:4 358:16
302:3 303:8,8	163:8 168:13	370:12 382:13	learning 63:22	389:21 392:3
304:7,19 305:7,17	190:5 362:22	largest 15:18 66:3	143:9 272:25	letter 142:12
305:20 307:7,7,12	Kraft 35:25 173:19	304:4	275:14	letting 211:23
308:3,4,24 309:1,2		late 306:8	leave 18:22 19:14,19	level 16:10 46:23
309:20 311:4,21	L	latent 371:25 390:21	19:20,24 56:24	58:11 68:22 71:21
312:4,19,21 313:1	L 77:14 107:5,8,25	latest 11:15	184:25 204:13	112:22,22 113:20
313:3,12 317:1,2,9	109:24	Laughter 190:15	leaves 394:12	137:17 139:25
318:13,16 319:4,4	LA 15:4 377:7	191:6 259:10	leaving 19:25 50:4	140:13 142:10,14
320:11,20 321:3	lab 175:22 187:6	launched 66:23	304:25	145:3,23,24,25
322:1,2,21 326:12	220:20	68:18 172:19	led 229:14 272:7	147:13,18 149:19
338:6,7 348:10,12	label 58:20 59:1	Laura 6:12 210:11	left 19:25 61:24,25	199:6 233:15
348:17 349:24,24	69:1,3 70:14,18	389:14	61:25 64:24 69:5	263:20 283:5
350:5,10,19 351:3	74:21,23 104:12	laurels 114:18	69:19 70:21,23	289:6 295:17
351:9,16 353:17	104:13 110:15	law 8:11,16,20	122:15 135:22	302:25 320:22
354:24 355:9	116:20,22 176:5,9	94:19 180:11	171:1 188:3 195:5	322:3 363:21
356:23,25 357:8	176:9,16,16 177:1	187:20,22 205:4	205:2,2 315:16	367:2 368:23
357:16 358:8	315:15	205:11 241:14	317:15 326:23	382:3
359:19,20,23	labeled 321:13,14	379:15 380:6	327:12 333:13	leveled 299:15,17
360:3,5,17,25	labeling 9:19 103:4	381:24,25	341:20 342:22	levels 23:19,22
361:7,8,25 362:2	104:9,10 109:6,12	lawful 134:24	352:16 361:23	57:12 120:24
362:10 363:5,5,23	110:18 126:17,17	laws 8:17 9:10,12	376:22	278:4 283:10,13
364:1 365:10	127:24 142:13	10:11,12	left-hand 140:9	306:7 336:3
366:9,13,25	176:1,4	lawsuits 8:19,20	304:1 317:16	Lewis 359:3
367:16 368:10,25	labor 185:2,14	lawyers 8:3 241:16	legal 10:16,22 12:18	Liaukonyte 3:21
369:3,8 371:10	236:21,24 248:2	lax 209:22	94:15 191:12	48:20,20 313:17
375:1,24 376:23	laboring 358:11	layer 178:11	228:9,9 362:25	313:19,20
377:10,16 378:5	lack 49:14	layout 55:5	legislation 10:5	library 299:8
378:10 381:11	Lambrecht 224:14	lead 102:10 108:16	24:24 25:6 104:9	license 155:5
382:25 383:16,21	land 303:7	110:8 119:25	legislator 116:19	lies 121:3 221:12
384:24 385:10,15	language 10:22	175:17 212:23	lemons 111:1 116:5	330:12
386:1,13 387:8,17	135:3 268:21	227:18 272:1,7	119:18	life 34:6 108:20
390:5,16,18 391:6	laptop 22:18	287:22 301:9	Lending 9:20	141:3 205:6
392:1,3,4,5 394:5	large 55:11,13 56:16	321:5,6	lends 78:2	206:15
394:8,11	57:17 65:15 68:8	leaders 43:7	length 263:22	lift 75:25 315:18
knowing 44:20,23	73:17 197:22,24	leading 205:20	lessened 311:2,4	light 98:10 220:4
knowledge 16:17	199:7,25 268:13	343:8	let's 6:25 31:8,20	301:11
17:21 18:1 25:3	280:11,18 285:6	leads 106:7 185:16	36:25 59:8 67:13	lightning 204:18
118:19 122:4	285:15 287:23	311:25	79:12 80:10 85:10	liked 240:7

likelihood 123:22 140:20 144:4 340:24 343:7,19 355:5	69:13,24 75:13 93:25 97:14	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	199:23,25 location 69:7 71:18 136:20 139:14 140:2,12 142:9,9 143:21 232:1 295:18,20 locations 71:17,23 136:19 138:2 139:24 168:24 169:1 232:2 locking 76:6 Loewenstein 187:4 log 273:4,6 308:9 311:7 372:13 374:14 logistic 275:2 logistical 18:18 logistics 388:23 logit 276:13 339:20 339:20 371:24 372:19 logos 22:7 London 243:1 long 54:2 63:14 108:20 111:16 112:19 120:16 124:8 141:19 185:24 193:14 236:1 263:24 295:1 302:15 356:25 360:7 378:19 391:15 long-lived 111:23 long-term 112:15 192:3 longer 194:3 303:13 339:13 384:6,11 longitudinal 295:19 look 29:21 34:4 36:21,22 41:5,7,11 42:3 43:8 57:23 58:9 62:7 64:22 76:12 77:7,20 80:10 81:14,24 82:2,10 90:15,17 90:21 94:3 120:13 121:12 127:9 138:6,16 139:4	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4
limit 147:23 338:14 352:9 393:20	literally 79:7 362:1 384:2	204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4	
limitation 241:3,5 350:5 351:18	literature 5:13 18:16 25:2 44:5 88:11 125:3 134:20,21 135:17 135:20 150:8 154:12,14,15 155:23,24 156:1,5 156:16 159:16 173:18 198:1,2,2 226:12 269:3 283:1 289:7,8 292:1 294:4 295:18 316:6 322:22 337:6 344:21,21 365:3,4 365:5,20,24 366:2 366:3 374:7	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4	
limitations 240:20 302:14 337:17 350:11	literatures 135:22 155:18 156:2	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4	
limited 17:16 284:11 300:10 391:12	litigation 7:24 8:1	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4	
limits 181:24 293:15	little 30:10 37:22 38:14 39:24 40:14 40:21 45:22 47:5 49:21 50:24 65:12 70:10 71:9 72:25 76:6 82:24 87:11 87:24 92:19 96:7 96:20 98:25 100:20 103:23 108:15 111:18,21 113:11 116:22 117:16 118:2,16 122:23 126:8 127:14 128:12 130:23 131:1,14 131:25 133:14 134:20 135:24 136:11 140:21,25 143:11 144:8,12 144:24 148:20 149:18 151:7 154:15 162:9,10 164:18,20 165:19	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4	
line 54:24 55:9 144:2 147:6 308:20 370:2	live 14:8 287:13 290:20	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4	
linear 137:18 268:22 285:8 287:21 339:22 343:7	lives 106:24 211:21	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 313:13 319:18 320:9 321:1 325:4 326:1 349:11 353:24 354:25 360:3 365:2,18 367:9 371:10 375:15 379:6,9 393:12	158:14,14 160:14 161:13 170:24 194:7 195:8,8 198:6,7,10,11,11 199:19,22,22 205:23 206:19 207:1 226:12 227:23 228:3 233:9,9,22 234:17 234:21 237:12 238:5,22 239:22 241:5 243:12,20 244:3,7 249:2 250:17 251:11,14 253:21,21 255:8 256:11 259:14,16 265:24 266:5,11 266:17,24 268:16 270:25 271:4 276:17 279:5 280:10,25 281:22 281:24 282:2 284:7 287:6,16 289:11 296:19 300:15 301:13,24 301:25 302:2,7 303:15,25 304:13 306:3 307:12,23 308:13,15,19 309:16,22 311:17 317:23 320:2 322:24 329:18 333:11 344:3 349:13 359:12,15 359:21 361:4 364:1 366:17,18 366:23 369:20 370:17,17,24 371:1,16 373:5,13 373:19,21 374:9 374:14 380:19 387:15 lookback 173:10 looked 26:11,11,15 41:25 187:5 226:4 226:7 236:1 238:15 243:20 248:15,20 252:4,4	
lines 294:25 311:1 391:4	load 27:9	165:23 166:5 168:3,5,22 171:12 171:12,20 172:9 176:2 184:14 186:7,10 202:16 204:19 209:19 211:18 215:18 218:7,23 219:1 224:8 229:22 230:5 232:11,14 233:14 234:8,19 243:15,16 253:23 254:8 259:16,19 259:22 261:7,11 265:6 269:14 271:17,20 282:2,5 282:22 284:9,22 292:6 293:24 294:8,9 305:10 307:8 308:23 309:21 311:18 312:2,3 3		

252:7 263:5 271:5	85:4 87:2 91:20	148:2 244:9	34:15,18,18,19	334:22 337:20
291:19 315:4	106:22 114:21	loved 223:3 240:6	Madden 28:13	361:18
321:10 357:6,7	115:4 148:25	lovely 148:1	magazine 298:16	male 131:17 245:4
374:25 382:23	154:13 156:19	loves 141:20	magazines 306:10	Mall 394:23
looking 40:12 44:7	169:6,6 173:2,13	low 64:14 106:14	magnet 183:21	man 234:25
44:14 46:19 50:13	173:24 174:14,18	107:5 109:1,2	185:22	man's 251:8
60:4 120:1 121:14	181:21,22 190:5	113:10 115:3	magnified 358:24	manage 102:8 106:6
125:25 133:14	191:17,19 192:15	116:9,11,12	magnitude 24:8	managed 184:1
134:22 136:3	195:16 206:9,25	117:21 122:1	350:3 368:15	management 14:4
138:7 141:25	207:1 217:22	123:19 146:8	magnitudes 309:3	171:10 191:12
144:6 145:17	220:21 225:15	167:11 221:17	349:13 369:13	manager 349:25
157:8 245:3	229:5,7 230:22	311:10 312:24	mail 186:21	350:22 351:2
251:10 258:25	232:6,12 233:17	370:15 371:7	Mailath 104:19	managers 242:21,23
261:9,22 262:17	237:8,12 239:12	374:22	105:20 117:9	243:8 329:24
265:17 267:22	240:20 241:10,16	low-hanging 315:19	mailers 353:3	361:9,9
283:18 286:9	244:22 258:19,20	315:20	mailing 353:10	managing 189:15
291:23 298:6	262:22 269:2	low-income 367:6	mails 353:6	191:10 192:14
299:22 301:17,18	270:7 275:15	lower 84:25 89:21	main 19:24 25:15	mandated 178:2
304:2 308:3	280:15,19 283:8	111:5 255:23	28:20 42:9 55:20	187:19
317:24 321:24	284:10 289:9	290:11 293:4,5	63:7 72:9 80:25	mandates 179:3
324:23 330:23	299:20,21,23	307:13 311:25	82:10,15 90:22	manifest 341:4
336:1,2 360:21	300:11 305:2	321:5 355:20	106:19 109:11,11	Manila 65:18
376:7 377:19	318:25 322:9	356:3 364:15	112:1 147:20	manipulation 191:4
392:8 394:1	327:9 337:18	365:1 370:21	153:18,25 246:19	337:4 348:6
looks 24:17 26:25	342:12,22 347:14	371:21 381:8	249:17 252:21	manner 19:20
55:8 62:5 74:18	355:16 358:21,25	lowering 188:12	260:15 263:2	manual 256:18,19
85:14 87:20 88:12	359:4,9,25 360:5	Loyalty 365:24	289:5,10 293:10	manufacture 193:8
220:20 233:14	361:22 363:7	Luca 200:11	302:1 303:18	manufacturer
253:22 269:19	364:6 365:6	lucky 175:3 337:24	314:1,2 342:13	105:11 332:7,8
306:25 320:5	368:16 369:6	lump 84:12 330:9	347:17 360:23	333:2,10,12
385:13	372:19 374:2,4,5	lumping 83:11	364:11 372:5	335:17,18 338:19
Los 15:3	376:12,16 379:5	lunch 3:5 169:13,15	maintain 38:22	338:20 340:4,13
lose 154:3 167:12	380:21 383:9	169:16 170:1,6	154:5,6 280:8	341:9,21 342:19
353:20	393:5,6 394:2	329:9 389:17	maintained 154:10	343:9,11,23 344:9
loses 147:22	lots 75:8 96:8 127:9	Lutter 179:2	major 179:5 269:15	349:2 356:22
loss 12:3 181:22	130:14 141:13		286:25 287:6	359:17
184:2 273:4,6	185:15 186:13	M	299:3,5 357:12	manufacturer's
278:25	205:19 221:19	M 139:7 140:3,3,16	majority 9:2	328:16 334:3
losses 77:2	224:19 236:4	396:16	make/model 338:15	manufacturer-
lot 6:19 7:7 8:10 9:8	237:21 241:6	Mac 35:25	make/models	327:15
12:4,20 13:11 14:1	244:24 249:2,4,23	machine- 275:13	354:11 357:14	manufacturer-ba...
14:7 16:12,14,16	276:2,2 282:21	machine-learning	making 6:13 35:23	325:18 327:13
20:25 22:11,14	295:9 358:14	266:13 282:25	46:5,20 68:12 70:5	328:25 343:9
24:21 25:1 26:9	379:22,23,23	284:16 293:8	74:11 140:22	346:9,16
27:2 31:18 34:23	382:12 385:24	294:4 387:11,22	158:1,10 160:5	manufacturers
34:25 35:7 41:10	392:17,18	388:1,13	165:7 194:17	101:24 102:18,19
42:6 44:2,5 53:24	love 98:7 140:14	machinery 44:9	195:17,23 261:21	105:8 116:2
55:14,15 78:14	142:21 146:15,21	Macy's 34:5,5,8,14	265:25 277:16	map 67:18

March 13:9	15:19,21 16:1,10	mass 142:5	317:5	186:13 206:2
margin 267:17	22:8 26:19 53:12	massive 357:6	Mayzlin 171:6	234:18 264:9
383:4,12,14	100:12 125:16	match 83:24 120:18	188:20,20 190:16	269:24 277:4
marginal 60:11,16	130:8,9 170:1,6	132:17 136:25	191:7 213:23	278:21 281:14
305:21 310:4	171:9 172:7,15,21	137:1,6 138:9,16	220:18	288:7 295:17
315:17	173:6,10,11,14,17	139:7,22,22	MBAs 29:4	304:17 363:20
marginalization	173:22,23 174:3	145:20 165:2	McCrary 341:10	393:10
243:14	175:3,4,11 179:10	262:4 314:21	McNaughton 6:22	meant 135:4 176:21
margins 276:14	182:20 224:25	374:25	MD 97:11	231:23 245:10
330:16,22	225:14 242:22	matched 137:3,7	Meadows 6:23	measure 17:7 24:9
Maria 6:22	258:14 262:13,23	363:3,15	mean 10:22 56:8	92:25 96:23
Marilyn 6:22	262:25 272:20	matches 46:8 55:4	77:25 78:18 84:7	243:16 248:1
mark 335:21,22	275:14 290:23	130:15 137:8	84:10 91:24 96:12	259:15 265:21
marker 340:5	329:23 331:21	148:18	124:15 138:20	266:10 268:1
markers 339:14,16	332:24 340:20	matching 46:7	150:22 159:14	273:7 282:1
339:17	341:16 344:18	130:14,22 132:2	166:11 184:17	359:11
market 2:10 12:12	359:1 389:9 390:7	137:9 287:15	186:4 190:18,18	measured 96:5
13:22 16:13 17:4	390:12 394:5	366:17	194:2 195:19	350:9
17:14,19,21 20:23	marketing-econo...	matchmaking	201:1 202:6 204:2	measurement 23:10
22:2 44:6 66:11	390:25	165:16	209:10 216:9	42:19 96:10,14,15
76:2,12 77:3	marketingconf@f...	matchpoint 143:20	217:12,16 220:18	measurements
107:10 111:8	389:11	material 56:2,8	220:23 224:25	95:25
132:4,4,5,8,15	marketplace 16:21	76:11 77:19,25	234:1 245:18	measures 67:23,24
136:25 145:11	25:19 26:12,15	85:6	251:22 254:19	124:16 147:11
146:17 149:22	27:6,11,13,17,17	materially 56:7	255:9 287:2	measuring 23:11
160:16 166:21	27:19 28:4,7 29:2	60:13 77:1	290:11 295:21	86:16 87:4,9 92:9
179:21 191:2	30:17 32:11 34:3	math 226:18	296:21 325:6,15	93:8 229:20
193:14 207:21	42:1 49:14,18,22	mathematical	325:16 327:12	mechanism 38:8
212:11,12,15,18	56:17 174:8 364:2	156:12	329:20 334:1,15	40:20 51:11 75:3
212:24 215:6	364:23	mathematically	341:24 349:25	76:1 135:19
221:17 222:14,18	marketplaces 24:22	112:25	350:13 365:15	155:25 198:24
222:20 230:2	29:7	maths 231:4	369:25 383:21	291:3 292:19,21
236:21 248:2	markets 7:13,13	Matt 324:13 340:18	390:17 393:23	293:18 321:15,25
249:4 252:16	16:24 17:9 68:13	matter 80:9 81:6	meaning 56:24	345:22
317:8 318:14	130:14 132:2	88:6 217:6 227:21	125:23 138:14	mechanisms 159:18
321:8 333:7,11,15	151:5 162:11,16	matters 45:15	146:4 157:9	332:13,15 344:21
333:17,23 335:15	179:20 185:3	195:14 227:21	161:20 162:12	346:2
341:1 355:3,8,14	212:25 213:12	358:20,20	meaningful 125:19	media 3:12 7:4
355:15 360:1	336:2 353:11	Matthew 3:20 4:8	177:2 352:1	20:12 54:4,6,8,16
market-specific	358:20	298:3 322:9 347:9	means 10:18 13:14	54:19,21,22 55:5
322:3	married 239:12	352:4	38:10 39:2 56:9	170:19 179:25,25
marketeers 332:22	Marshall 171:7	matured 181:12	62:9 84:8 95:5	188:23 189:4,5,8
marketer 377:13	MART 275:17,23	maximize 147:11	108:6 109:18	189:15,22,23
378:7	276:11,12 284:16	318:24	112:6 120:25	191:20,21 192:2,9
marketers 42:18	284:23 288:1,23	maximizes 147:14	134:22 150:17	193:3 201:15,25
marketing 1:7 3:6	289:15 291:17	maximizing 243:21	152:12 154:17,24	202:6 203:17
5:10,12,19 6:11	masked 278:19	maximum 36:22,24	155:7,13 157:7,12	208:14 218:1
7:11 9:22 15:15,16	masking 322:17	143:1 238:23,23	158:2 180:23	224:3 227:9

235:25 236:3,7 237:24 239:16,25 250:19 251:1 256:20 282:22 303:14 309:14,15 322:20,23 377:9 388:13 median 248:1,12 307:14 311:12 366:23,24 mediated 28:9 medical 220:13 221:4 222:17,19 222:20 304:10 medicine 301:8 312:6 mediocre 268:15 medium 189:8 280:13 meet 27:16 155:4 meeting 122:10 melding 392:25 memory 124:8 men 31:20,21,21 226:21 231:20,21 233:2,3,6,20 234:14 237:15,22 239:3,6 242:2 243:4 246:6 250:3 250:4,15,16 253:2 253:4 254:20 255:1,25 mention 18:17 48:10 149:17 150:20 174:14 306:14 388:23 mentioned 45:24 55:23 103:5 175:16 214:14 220:6 282:16 317:3 326:21 343:2 390:5 394:3 mentioning 353:23 menu 67:19 327:13 328:8,8 menus 217:21 MEPS 303:22 306:22	Mercedes 114:23 merchant 15:12 merging 265:8,8 mess 128:12 message 89:6,12,14 94:23 95:9 131:6 131:10,17,19 134:18 136:7 139:6,7,9,17,20 140:3,13 141:4,4 141:17 142:1,8,24 143:13 148:9 154:24 155:6,23 165:5 353:5 messages 141:19 144:12 155:14 173:17 175:2 194:19 353:12 360:23 messy 128:16 met 154:20 155:17 299:21,21 336:18 Metcalf 396:3 method 272:15 methodological 266:8 methodologically 48:7 methodologies 66:19 179:17 methodology 198:21 methods 78:12 266:13 272:18 275:14 276:8 metric 68:15 88:20 176:17 177:1 266:21 273:3,18 metrics 176:19 177:2 291:21 386:14 Mia 69:6,22 mic 43:20 103:23 258:12,18 259:7 Michael 200:11 Michigan 77:11 micro- 51:1 micro-awards 50:19 micro-theory	125:11 MicroData 236:5 microfoundations 125:13 320:9,11 microphone 19:2,3 19:6,7 86:24 163:5 310:12 384:21 389:18 Microsoft 379:19 mics 19:3 mid 172:19 mid-tier 238:20 middle 27:17 40:22 61:2,15 68:25 79:6 147:15 201:21 mile 71:18,18 347:20,24 mileage 335:22 338:22 339:14 340:5 348:6 349:8 miles 327:23 328:4 328:18,18,20 344:13 349:15 352:9 358:12 milk 106:9 108:25 109:1 115:16 119:10 158:13,15 million 11:17,21 16:6 66:4,5,5 139:15 186:2,4 270:6,19,20 271:2 299:13 367:12,23 million-ish 50:12 millions 363:11 369:6 milliseconds 134:6 mind 51:17,21 92:9 121:3 163:4 254:25 290:4 331:15 383:24 minds 93:17 346:18 392:25 mine 204:24 324:20 minimal 77:4 121:14,18 minimize 227:18 254:21 minimum 246:7	minimum/maxim... 248:19 minor 247:2 minorities 254:7 364:14 minority 41:13 360:24 361:2,4 370:10 371:17 minors 192:2,6 202:6 204:3 minus 107:24 112:14 142:4 minute 43:16 74:24 118:5 218:8 322:1 322:2 minutes 20:17,17,18 20:19 24:15 53:8 85:22 111:17 171:15 210:9,10 210:11 275:1 294:14 323:4 376:22 394:22 mirror 252:25 mirrored 251:20 252:25 253:3 265:5 mislead 10:19 56:1 78:24 179:13 314:14 misleading 91:18 178:3,17 305:11 360:22 364:22 375:3 misled 15:4 77:23 93:14 misperception 17:1 Misra 3:13 244:11 244:12 352:8 353:6 misrepresent 154:18 misrepresentation 134:24 missed 354:23,25 389:1 mission 7:16,17 mission-learning 269:1	mistakes 110:7 257:3 misuse 191:21 192:2 MIT 224:12 230:13 230:14,19 mitigate 357:1 mitigates 49:20 mix 144:1,12 341:16 mixed 311:22 313:13 mixing 215:18 mixture 32:22 174:9 Mm-hmm 97:25 166:24 mobile 2:16 3:15 16:20 53:2,6,19 55:15 66:12,17,20 66:24 258:1,7 259:13 260:4 261:16 262:25 264:13,14,18,21 265:19 270:6 281:21 mode 13:3 model 25:18,23 29:25 32:23 33:11 33:13 35:6 36:2,10 37:2 38:5,7 39:19 50:6,25 54:12,14 102:7 103:11 104:18 105:22 106:5,18,21 108:1 111:19,22 117:8 119:2 120:5,7,12 120:12,13 121:10 127:15 128:19,22 131:4 132:1 133:11,12 135:12 136:16,18 139:23 140:5 144:17 145:2 153:19 154:7 156:9,10 157:5 159:10 161:17 163:5,10 163:12,24 165:20 167:3,16 168:4,7 182:24,24 184:10 184:12,14 185:20
--	---	---	--	--

194:9 197:4	monotonic 88:17	278:16	245:17 286:23	215:7 383:14
200:25 201:18	month 56:21 64:6	moved 16:18 278:12	Napa 127:1	385:1,4
209:8 215:16	263:23 271:1	movies 183:24	Narayanan 3:17	need 19:23 29:2,5
260:17,21 267:10	302:21 303:12	193:18	282:11,12	34:11 35:17 36:10
267:16 268:7	308:11,12,18	moving 88:2 328:3	national 303:21	46:1,13 56:13 63:3
270:12 271:21	310:23 317:4,17	MP3 68:8	327:3 394:22	63:8 113:3 121:2
273:14 277:13,17	317:22 318:2	mugs 222:8	nationally 184:3	126:9 146:12,13
284:2,19 294:8	320:22	multi- 16:9 275:19	Nations 255:12	146:13 150:18
319:19 341:18	month's 284:4	multi-level 15:15,16	nationwide 11:11	153:19 159:10
342:13 344:7	Monthly 302:18	15:19,21	native 2:15 53:2,6	165:2 166:1
354:5 383:14	months 58:21 265:2	multiple 133:22,22	53:22,23 54:2,24	170:12 178:22
modeler 30:6	390:14 393:10	192:19 224:15	55:1,2 56:5 57:23	180:19 206:6
100:12	mood 321:12	249:20,22 288:20	72:11 75:1 78:15	212:11,21 217:18
modeling 31:1 113:3	moral 102:9 105:20	289:1 291:21	78:16,24 79:6	217:21 218:15
174:9 268:6	108:14 109:13	295:5 300:13	80:11,15,17 81:7	222:24 232:19
387:22	110:23	320:12 337:14	81:18 83:5,19 84:8	233:25 239:23
models 25:19 30:14	Moreover 131:15	339:11 353:11	84:10,12 85:14,17	254:7 263:24
30:18 36:6 49:19	morning 5:3 22:5	365:23	94:21	267:10 268:4
49:20 73:1 181:14	53:11 169:13	multiply 40:6,7	natural 25:5 327:22	270:13,13,23
181:16,25 182:7	171:14	multiplying 137:23	333:24 388:4	272:13,13,15,15
216:5,6 263:19	mortgage 176:1	music 193:18	naturally 278:18	272:19,23 292:10
266:10,12 267:12	177:7,11,18	myriad 25:15	326:19 329:22	326:25 332:17,18
267:15 268:7	178:10 181:8	mystery 367:9,10	331:4 333:14	334:18 335:1
276:13,14 287:24	183:8,15,17		nature 44:13 55:21	337:3 338:18
354:1 391:1	184:20 185:3,12	N	57:1 58:22 69:14	345:15 347:1
moderate 370:20	185:13	N 2:2 3:2 4:2	86:5 157:16,22	359:23 372:23
moderated 235:18	mortgages 177:10	nail 26:4	166:21 167:16,16	378:3,7,11
moderator 3:7	181:20 182:23,25	Nair 53:4,11 63:16	174:21 250:22	needs 48:2 133:8
170:8	183:11 184:16,24	63:20 64:18 71:6,9	380:3,11	229:21
Mom 8:13	185:17 186:7	73:21 86:14,25	Navdeep 2:16 53:17	Neeman 2:21
moment 7:9 284:17	motivated 25:25	89:9 90:9,20 92:4	68:7	100:25
monastery 127:3,5	392:15	93:16 94:17 95:2,7	navigation 303:6	negative 184:19
monetary 13:17,20	motivating 157:14	95:10 96:2,11 97:8	NDA 338:10	191:14 195:25
monetization	349:20	97:11,25 98:3,6,15	near 58:15	198:19 199:20
260:13,15	motivation 153:24	naive 131:25 149:24	nearby 143:18	200:6 365:11
monetize 261:2,22	230:3 298:10	160:23 163:16	neat 77:18 78:22	373:8
monetizing 261:6	391:25	186:10 374:8	84:20	negatively 207:24
money 12:15 54:13	motive 344:24	naiveté 76:6	necessarily 78:18	318:2
79:4 183:5,5	motives 138:8	naked 203:9	87:16 88:7,8,16	negotiation 163:14
184:20 232:10,11	145:16 345:16,18	name 48:18,20	90:1 96:11 145:20	neither 396:6
232:12 236:4	346:8,12	104:23 125:5	159:12 172:3	network 34:16
239:5,9,13 260:24	Motor 9:20	151:19 170:5	182:1 192:17	262:3 278:17
334:22 367:20,23	mouth 190:1 193:9	188:20 245:4,4	262:10 267:13	283:16 363:4,6,17
monies 325:21	194:4,23	258:5 304:5	274:20 277:8	363:24 374:12
331:11	move 18:19 26:9	313:19 327:20	291:22 326:11,14	379:16
monitoring 107:2	51:23 53:3 74:3,4	328:1 384:6	331:2,3 336:25,25	networks 16:19
121:6,7 168:20	183:6 184:25	394:23	356:12	201:14 283:8,12
202:16	185:7 269:13	names 124:17	necessary 178:19	289:11 290:14,16

292:13	nicely 351:19	North 324:6 338:2	374:20 380:8	191:22 317:11
networks' 290:20	niche 146:7	Northeastern 130:8	383:14,20,22,23	350:16
neutral 158:7,19	Nielsen 218:25	Northwestern	383:23 385:4	observes 140:3,3
226:21 239:4	night 12:14 381:14	378:16	numbers 26:2,4,5	observing 36:24
245:11,12 255:2	nightmare 190:24	not-so-good 188:3	42:12 49:16 51:17	303:4 313:3
never 38:25 39:3,12	NIH 304:12	notable 26:14 383:8	55:13 221:15	obtain 41:4
108:3,9 114:14	nine 393:9	note 118:10 251:2	246:14 259:21	obvious 144:7 243:7
133:23 134:6	nine-paper 393:20	353:14 368:14	260:8 261:15	349:19
222:14 235:6	no-disclosure 62:18	390:10	308:3 329:4,25	obviously 35:1
243:2,5 330:25	64:15,16 69:4	notice 14:13 20:4,14	330:18 331:19	45:25 125:16
360:7	72:18 73:25	24:11 72:11 80:24	334:20 338:12	128:7 262:13
new 8:13 9:5 27:14	no-information	201:6 233:4 240:3	nutshell 151:24	275:2 289:22
34:23 56:20 58:3	69:18	269:7 278:12	153:18	304:19 352:12
61:1 66:22 103:1	nodding 281:19	315:13 340:6		385:12
112:1 124:12	noise 194:17 195:16	noticeability 70:18	O	occur 31:21 119:1
126:21 130:15	196:11,17 199:18	noticeable 342:23	object 30:5	130:15 135:22
133:25 172:17	noises 17:4	notion 76:8 182:2	objective 120:4	383:18,24
211:3 224:17	noisier 309:21	186:9 337:4	153:7 292:5	occurred 74:12
228:18 271:10	noisy 150:11	novel 125:21 154:12	objectives 292:3	92:16
316:23 327:15	non 371:14	156:3 379:14,14	objectivity 54:11	occurrences 74:3
333:11 334:8	non- 218:10 241:6	November 390:6	obligatory 358:16	occurring 133:15
384:16 393:25	non-creditworthy	Nowadays 24:6	observability	occurs 19:13,17
newer 179:25	185:21	NOx 13:6	149:16 153:3	69:6 96:1 122:19
news 54:6,8,15,18	non-English-spea...	NP 268:21	158:20	384:3
144:19,20,21,22	377:9	NP- 286:13	observable 124:9	odd 234:23
144:22 201:9,9,24	non-expired 335:18	NSF 225:5 232:10	observation 168:19	odometer 348:7
243:8 313:10	non-overlap 326:8	nuance 180:10	185:25 318:10	Oery 100:4,6 127:17
news/opinions/co...	non-rival 211:12	229:22	354:22 357:20	128:10 129:6
201:11	212:16,19 213:8	nuanced 34:23	observations 32:24	of-the-envelope
newspapers 298:16	221:23	number 11:19,19,20	33:3 105:1 168:15	40:5
nice 33:10 35:6 60:5	non-white 287:8,11	12:1,2,2 26:10	181:11 338:18,21	off-sample 268:3
97:13,21 102:1	noncausal 293:24	33:14,15 47:24	341:6,8 352:21	off-the-cuff 122:8
106:5 109:14	nonhealth 304:13	55:11 68:8 82:3	357:2	offer 33:23 47:23
119:5 120:13,17	nonlinear 276:2	106:25 132:1	observe 17:2 25:16	93:22 112:5
121:4,9 125:14	339:23 367:4	133:20 142:18	30:8,10,19,24,25	118:20 162:4
126:6 127:8	nonmanipulatable	164:20 179:4	32:8,11,14 36:14	181:7 353:18
128:22,22 150:2	335:13	199:12 200:3	37:25 39:4,11	377:16,23
155:4 156:9,14	nonparametric	214:4,5,12 220:12	44:18 56:13 76:24	offering 334:23
160:15 167:22	267:16 371:13	223:2 232:25	102:13 105:24,25	348:9,14
171:20 180:18	374:17 375:18	233:1 234:18,20	106:1 115:8	offerings 328:9
187:9,18 209:1	nonpecuniary 185:6	250:11 253:2	117:16 131:12	352:25
242:17 256:6,9,13	normal 203:15	255:1 261:17	139:19,23 140:1	offers 333:23
275:23 290:25	normalize 107:16	268:13 273:23	150:6,7 302:20,22	office 299:8 350:18
293:5 294:2,10	137:9 273:10	288:7 299:7	313:5 316:11,12	350:21
320:8 333:24	normalized 369:25	302:20 306:19	340:19 351:16	official 57:13
336:5 348:2	371:3	309:5 310:7	384:4	offline 16:17,24 17:8
349:24 367:8,12	normalizes 273:16	312:15 368:14,15	observed 11:16 30:7	28:22 29:9,24 31:8
391:14	norms 54:10	368:23 371:2,6	105:23 107:9	35:5 38:9 40:18

42:8 70:13 98:21	187:2 189:8	311:3,21,22 312:4	228:14 262:25	142:3 147:13
262:24 292:2	190:10,12 192:11	312:20,25 334:18	264:16 298:1,7	286:15,17,18
388:14	194:24 196:5,9,18	346:1 349:1	299:9 300:14,20	319:9 352:19
oftentimes 9:6 34:2	197:18 199:14	olds 247:21	305:3 314:5,24	optimality 319:5
oh 46:18 114:10	200:5,22 202:8	Olivier 184:8	321:6 361:12,18	optimally 318:23
118:4 124:2	204:20,25 206:18	OLS 275:2 276:13	onwards 225:6	319:2 365:14
143:22 146:21	208:20 209:11	ombudsman 218:12	343:15	optimization 254:16
163:3 165:21	210:12,24 211:24	218:18	open 22:19 67:5	319:13
175:6 180:13	212:2,14 215:14	Omid 258:23	68:13 88:20	optimize 177:5
187:9 191:3	215:21 222:23	once 67:11 79:1	171:17 210:14	255:7
210:12 211:9	224:7,13 225:6	108:24 115:8	220:16	optimized 256:16
217:15 256:9	233:24 235:1,23	128:12 147:3	openness 207:5,6,9	optimizing 235:21
258:11 259:7	240:19 256:22,24	162:13,13 212:16	207:10 210:4	288:12
okay 7:21 11:25	258:11,12,13,17	212:17,19 214:3,5	operate 29:10	option 13:19
12:4,15,23,25 15:2	258:18 259:7,8,11	216:23 221:23	269:23	optional 325:25
15:8,15 18:21,24	260:7 261:7,7	248:18 260:9	operation 137:25	350:22
20:2 33:18 48:5	267:5,8 269:2,13	266:15 274:11	operationalized	options 13:16
50:2 54:22 56:3,10	269:14 270:9	278:5,6 280:5	29:16	orange 141:23
56:19 57:2,22 58:5	271:3,9,17 273:2	318:18 327:24	opinion 60:16 181:1	143:23 145:23
59:2,4,5,12 60:17	274:23 275:1	332:14 335:21	326:12	252:5 302:10
60:24 61:4,6,8,22	276:6,11 277:17	339:16 343:1	opinions 57:9 298:8	303:21
62:1,3,6,14,16	278:1,8,10 279:7	375:15	opportunities 48:4	order 14:17 24:7
63:5,9,11 65:11	280:21 281:18	one's 381:11	172:14 180:3	25:24 26:18 39:23
66:1,7,13 67:21	282:13,24 285:20	one- 200:2,3	226:16	50:8 54:15 56:13
68:1,16,20,23 69:1	286:8 290:6,25	one-slide 275:16	opportunity 15:22	56:23 67:20 68:12
69:9,16,21,24 70:8	294:17 296:25	one-star 362:7,8	27:5 100:9 168:14	74:2,3 109:6 113:4
70:16,23 71:17,24	298:4 305:1,10	one-to-one 135:18	170:15 227:8	117:10 167:9
71:25 72:7,9,14,15	306:24 308:17	ones 73:9,11 81:7	255:3 258:17	248:13,17 258:2
72:21,22,24 73:4	309:6 310:1,17,25	168:16 174:22	324:10 329:24	314:6 355:11,21
73:22 74:13 75:20	311:17 323:3	188:3 211:17	392:18 393:14	357:1 367:3
75:23 76:3,5,17,22	327:11,17,22	266:12 274:17	opposed 59:1	371:24 378:8,12
77:5 78:25 79:16	328:3,21,25 329:2	280:13 310:25	324:17	ordered 372:19
80:13 87:21 89:19	330:6,14 332:1,9	352:15,16,16	opposite 307:9	orderly 19:20
95:17 97:5,6 98:5	335:23 336:14	361:3 374:1	344:16 345:17	orders 8:25 15:10
101:2 103:11,24	337:2,21,23	385:11	346:12 349:7	68:2,15 368:14
105:13 108:19	340:13 341:14	ongoing 5:13 11:13	opposites 207:10	organ 186:20
111:16,17 113:23	342:14,18 343:6	16:14 18:6 315:7,7	opt 41:2,23,25 42:1	organic 69:24 75:23
113:25 116:4	344:14,15 346:1	online 2:10 3:20	47:9,12,16,25	83:22 84:1,19,24
117:5 118:14	347:5 380:23	10:2,9,13 14:18,20	51:10,25 186:22	87:8,21 88:14
121:16,21 122:18	383:20 384:19	14:20,20 16:18,23	opt-in 47:13 51:5,23	302:19 304:2,5
123:3 124:3	385:4 386:11	20:24 22:3,9,14	opt-in/opt-out	305:13,15,25
126:11 128:13	old 8:13 27:2 29:8	23:6,11 26:12	186:19	308:1,14 309:1,4
129:5 142:1 143:3	90:12,12 136:6	56:22 68:4 132:19	opt-out 51:5	309:23 310:2
144:21 151:18	183:7 186:19	148:1 161:1	optimal 39:7,11	312:12
153:9 158:3 163:3	230:24 251:6	170:24 176:13	104:10,16,16	organically 83:14
166:12,23 181:12	306:15 334:4	192:21 193:18,20	107:21,21 111:11	organization 236:21
182:18 183:3,10	355:6	196:5,13,13	111:12 112:21	237:3 363:6
184:21 186:6	older 124:15 233:16	209:10 220:24	113:12,14 117:25	organizational

197:21 198:2 218:22 organize 389:9 organized 151:21 organizers 22:6 100:7 244:13 258:14 282:13 313:22 358:10 379:1 organizing 53:13 258:15 Orhun 2:17 77:10 77:12 oriented 54:9,9 origin 30:11 101:21 103:13 104:10,12 104:13 109:6,12 110:11,15 115:13 115:21,25 116:3 116:16,20 117:17 118:24 119:13 127:25 128:5,5 230:6,23 252:18 original 236:10 313:7 origins 119:14 ostensibly 192:20 ought 176:5 out-of- 268:4 outcome 17:2 42:1 75:14 105:25 115:8 123:5,24 139:3 226:23 244:4 279:19 285:24 356:7 396:12 outcomes 17:2 63:25 120:24,24 124:9,9 166:9 207:3 229:20 272:25 285:7,12 286:4,6 321:2 337:1 outlawed 204:5 outlet 299:6 outlier 317:4 outlined 334:20 outperforms 276:12	output 105:1 272:8 outreach 377:3,5 outright 39:24 outside 126:23 180:9 337:20,22 379:21 394:5 outweigh 179:15 overall 119:11 174:8 232:24 277:13 284:1,20 289:7 294:2 302:20 303:14 311:7 313:1 321:5,6,17 351:19 overconfident 106:11 overemphasize 314:14 overfitting 288:15 288:16,22 overlap 32:19 33:12 326:7 overlaps 328:24 overly 57:15 176:19 overprescribing 301:9 overpriced 386:4 overview 23:16 85:2 136:17 172:6 275:16 283:2 overweighed 11:1 overweighting 378:1 overwhelming 199:16 owned 54:7 owner 197:24,24 199:7,9,25 owners 197:22,22	84:18 178:13 pages 69:11 351:3 paid 56:15 58:6 59:19 61:21 69:9 69:12 88:13 194:5 260:17 302:19 305:3,5,14,17,25 307:20 308:1,14 308:24,25 309:2,5 309:23 310:9,10 312:12 313:12 paid-click 305:2 pair 34:4,6 175:7 281:1 pairs 281:12 Palmer 394:23 Palo 58:15 pamphlet 18:20 pamphlets 299:8 pander 153:6 pandering 153:12 panel 3:5 31:5,7 169:16 170:1,3,6,8 176:13 204:18 213:15 220:7 225:12 329:8 342:22 365:9 panelists 170:20 210:13 222:24 223:4 panels 88:11 342:23 paper 20:16,17,21 24:5,18 25:1,2,3 26:14,21 42:14,14 44:1 45:2,2,3,22 47:21 53:4,16,22 57:18,22 58:2 64:4 64:11 72:8,20,23 72:25 73:4,6,24 74:5 77:16,18 78:21 83:16 84:20 85:4,11 87:6,11 88:12 90:12,21,23 90:25 91:6,10 92:6 95:11 102:25 103:1 104:1 109:11,12 118:15 118:17,17,23	119:6,20 124:6 125:9,23,24 127:8 130:2,7,12,13,21 134:20 135:16 142:12 143:4,6 150:2,9 151:22,24 152:8,21,22 154:11 156:3,20 157:1,4,14,25 159:1 165:11,12 182:19 193:14 195:4 196:18,19 196:21,23 197:10 200:11 208:1 213:10,11,25 224:17,19,21 226:7 227:5,22 228:13,18 229:15 229:21 232:19 233:24 235:4 238:3 239:10 240:23 242:5 244:14,21 245:8 245:22 246:18 248:4 249:21 250:1,19 251:13 254:14 257:4 258:4,16,21 259:3 259:3,12 275:7 282:16,17 283:3,8 283:18,24 289:6 289:15 290:4 291:12,18 292:3 294:2,23 295:8,12 298:2,5 300:16 301:11,13 303:3 313:24 314:1,3,9 315:9,14,15 317:4 317:14 319:6,18 321:18,22 322:12 339:9,10 342:10 342:10,11 347:17 349:10 350:13 358:3,8,15,17 359:2 360:23 364:12 365:3,8,13 366:15,20 367:9 373:23 379:3,10	380:9,24 382:18 391:16 392:7,8 paper's 91:13 papers 5:25 6:8 18:19 26:10,13 53:20 100:4 125:6 126:1 156:21 188:25 191:8 193:7 200:10,14 204:24 213:9 224:10 226:4,10 250:6,6 258:3 269:11 273:21 282:21 294:19 299:24 320:12,17 324:4 327:6 365:8 378:25 379:18 391:1 393:22,25 393:25 Pappalardo 93:11 171:1,24 paradigm 37:24 paradoxical 148:4 parameter 137:24 139:10 parameters 184:11 268:6,14,17 339:24 343:3 parametric 267:18 parent 191:19 parents 192:10 202:16 381:11 parlance 272:21 parsing 354:14 part 26:25 30:23 39:17 45:25 51:3 66:18 93:13 111:7 113:5 142:18 148:6 149:23 166:12,12 167:25 171:25 177:17 179:11 197:4 203:14,17 217:6 242:15 253:17,17 255:14 268:22 283:4 286:11 291:12 313:4 316:25 317:1
	P			
	P 74:1,4,5,12 p.m 395:7 PA 19:16 Packaging 9:19 page 2:4 3:4 4:4 27:9,10,24 67:15 75:11 81:10 83:21			

328:14 334:15	136:17 219:4	paying 38:10 149:7	176:21 177:3,15	384:8 387:8,18,19
357:17 366:15	396:7,10	232:15 237:14	177:24 178:3,6,21	390:22 392:20,25
372:25 388:2	partition 286:5,5,7	240:12 331:4	180:5,5,7 181:14	394:7
389:1	partitioning 286:3	payment 16:6 49:19	181:25 182:10,13	people's 13:8 127:21
partial 148:13 316:8	partitions 285:25	49:20 281:16	182:17 183:10,11	184:5 381:1,2
participate 6:7	286:8,10	payments 51:2	184:16,23 185:20	per-capita 374:9
28:19 236:23	partly 181:8 284:24	Payne 182:22	185:22 186:2,9,20	perceive 95:4
participating	390:20 391:10	payoff 142:15	186:22,23 187:4,8	percent 11:16 25:24
222:25	partner 146:19	payoffs 137:9 140:4	187:10 188:1,5	26:18 30:22,23,24
participation	parts 102:19 116:2	pays 112:7	189:2 190:21	39:23 40:6,11
236:22 248:3	286:21 327:19,21	PC 228:21	191:17 192:25	47:11,16,19 48:24
388:20 394:16	328:2 355:7	peace 331:15	193:2,17 194:12	68:11 75:6 135:7
particular 53:22	360:11	peaks 316:23	195:22 201:6,24	136:1 186:22,23
54:7 56:5 57:13,22	party 197:6 286:25	Pedro 2:24 130:3	206:14,19,21,24	227:2 242:3
61:11 65:18 69:21	pass 244:21	151:16 153:4	206:25 208:9,12	246:14,21,22,24
70:1 73:2,6 86:5	passed 361:16	155:21 160:23	213:18 214:8	247:17 260:2
86:11,17 87:5	passing 217:22	162:10,20 168:10	215:1,7,23 216:13	270:12 277:14
105:6 117:22,22	passionate 230:25	Pedro's 156:20	216:21 217:8,20	278:25 300:4,6
133:10 134:7,15	passive 192:14	peeking 133:14	218:15,16,20	304:5 305:7,13,15
135:19 143:8	paste 325:8	peers 300:14 353:17	220:3,20,23	305:25 306:1,10
144:17 146:16,18	patent 299:16	penalize 12:13,17	221:12 228:22	306:10,12,15,20
148:8,24 152:1	path 289:3	38:16 361:20	229:2 231:17	307:10,19 308:21
154:5 157:17	pathetic 190:14,16	penalized 137:4	233:16 235:5	308:22,24 329:18
187:11 207:7	190:18	penalizing 361:18	242:25 245:4	329:20 330:4,16
211:11 226:24	patient 10:8 14:5	penetration 252:9	246:25 247:10	330:22,24 333:20
240:5 247:19	299:22,23 306:18	people 11:17 24:7	249:2,4,14 252:2	333:20 338:16,23
249:8 252:18	306:23	27:4 28:13,16 29:6	253:8,8 259:24,25	338:25 343:13
322:18 324:25	patient's 307:7	32:7,17,18,19	261:21,23 269:3,8	349:15,16,17
325:23 326:18	pattern 226:11	35:25 36:1,22	269:18,20 270:25	366:21,22,22
327:5,9 329:12,16	233:14 269:25	39:16 41:8,8,25	273:5 274:9	369:16,23 370:4,6
330:1,6 333:7,23	371:19 372:23	42:24 43:2 44:19	277:22 278:19	370:7,11,14,20,23
335:9 337:24	patterns 93:22	46:2,24 47:23	295:5 307:25	371:8,20,21,22
339:8,17 340:5	233:18 374:6	49:22 50:12 51:10	314:17,23 315:11	372:3,4 373:3,7,8
345:6 347:3	Patti 358:12 362:25	51:22 52:6 56:8	315:12 318:7	373:10,17,21,22
349:15 352:22	paucity 57:17	58:4 61:1 64:9	319:7 321:7,8	374:19,19,21
355:4,14,16	Pauline 175:13	72:4,5 75:12,18,19	326:2,16 327:3	375:10,12,25
356:24 363:14	pay 13:14 15:11	75:25 78:5 79:8	329:8,10,18	376:7
372:11,16,22	107:15 111:4	82:21,21 90:12,13	330:25 331:6	percentage 59:23
383:6 391:6	116:9,12 163:8,18	92:21 93:3,19 94:4	333:9 334:16,17	370:16 371:7
particularly 46:4,20	179:20 190:21	94:10,11 100:22	341:2 342:20	374:22,23 375:4
96:3 181:16 233:7	219:22 221:4	109:9 112:20	343:17 345:9,10	375:21 376:12
233:21 234:14	236:4 239:24	139:15 141:3	353:3,9,16 356:8	381:18
238:22 240:9	240:15 242:13	146:15,21 153:13	358:10 359:21	perfect 140:7
242:12 248:22	260:18,24 325:20	158:13,14,14	361:18,20,24	340:22
309:12 391:7,9	326:2	159:8,23 161:3,6	364:3 367:20,23	perfectly 79:25
particulars 380:18	payday 367:19,21	161:10 165:7	374:20 377:19,23	121:1 281:12
parties 54:7,13	368:1,2 370:3,8	167:13 169:6	379:19 382:12	318:2
131:4 132:2,16	383:7 385:9,10	173:1,11 175:20	383:6,9,11 384:4,8	perform 266:10

performing 360:18	persuasion 132:25	353:14 364:22	65:18 189:5,13	262:18 271:25
period 106:17	134:22 135:15,20	373:14 375:3	190:6 202:11,13	290:14 292:7,17
107:11 108:1,6	135:23 147:5	377:19	237:24,25 239:25	292:17 296:10
112:1,4 120:12	148:18 151:10	pictures 203:8,9	253:13 279:1	305:19 330:5
322:19,19 328:16	persuasive 134:25	346:5	292:20	331:9 337:1
357:11	142:25 322:16	pie 46:5 304:1	Platinum 367:25	339:17 340:12,17
periodically 377:6	pertains 22:14	piece 174:9 236:2	play 38:9,12 66:23	343:10,11,15,22
periods 106:25	pertinent 325:10,10	351:20	68:18 86:23	347:7,22 349:17
108:12,20 120:14	329:23 346:24	pieces 44:7 139:20	118:10 189:15	352:21 361:11
120:15,16	perverse 187:5	140:12	192:13 269:25	372:18 392:17
perks 330:15	pesky 358:14	piloting 245:5	played 54:4	pointed 54:23
persist 64:7	Petrie 22:25	pin 33:3 35:10 36:3	player 262:1,11	185:24 315:3
persistent 68:21	Petroleum 9:22	96:7 340:9,11	players 18:8 190:23	365:22
264:15,16	Pew 300:3	pin- 96:7	260:14 261:19	pointing 80:9
persistently 281:11	Pfizer.com 304:7	pinning 341:23,23	plays 87:13 355:19	points 133:20 295:9
person 39:8 44:23	Ph.D 5:11 182:21	pipes 28:25	Playstation 15:1	police 8:15 12:9
50:14 51:17 77:14	258:23 269:18	pitch 352:1	pleasant 5:16	policewoman 8:14
132:20,22 141:11	pharmacies 304:18	place 20:2 86:11	please 19:15 20:4,6	policies 17:20 47:3,5
141:12 183:18	305:4	262:1 278:2	43:19,21 70:12	47:8 180:10
190:4 271:9,14	phenomenon 73:2	292:23 331:7,24	163:3 170:24	283:11
273:13 368:17	118:23 197:1	334:4 378:9	215:13 288:10	policing 14:22
personal 14:11	phone 59:16 68:3	placebo 341:24	379:7 393:24	policy 2:9 9:8 10:17
personalized 41:1	264:21 265:2	placed 68:2	pleasure 118:15	17:12 20:23 22:2
215:2	271:14	places 205:8 304:4	130:6 171:25	24:10 25:11,25
personally 85:3	phones 260:4	364:10	379:2	26:11 42:10,12,15
perspective 31:1	photographed 20:9	placing 318:23	plot 342:15	45:23 47:12,13,17
41:16 42:5 49:4	phrasing 292:8	plagiarism 325:5	plotting 317:25	48:8 50:3,8 55:19
58:1 94:16 104:17	physics 95:24	plan 20:16 143:12	plug 188:12	77:20 92:3 141:5
105:17 113:15	Pi 107:5,6,8,24,25	316:7	plus 37:19 105:16	142:3 173:9
145:2 160:8	109:24 137:16,22	plane 258:3	125:22,22,23,24	175:11 179:11
170:14 172:9,16	138:15 143:15,17	planner 302:8	126:20 215:4	180:11 201:23
181:6 189:16	pick 48:17 70:2	planning 6:17 251:4	pocket 306:21	202:4 209:13
214:17 264:5,6	141:17 150:9	251:5 389:2,20	podium 324:15	211:25 212:1,2
265:14,16 266:8,9	232:4 236:11,22	platform 53:19	390:3	229:4 241:20
268:6 278:24	275:10 294:15	54:21 56:6 58:8	point 39:10 48:11	243:18 244:1
290:20 292:5	355:18 359:15	63:22 64:1,10	50:15 63:25 68:3	290:22 294:5
314:25 330:18	picked 70:1,3 320:5	65:13,14,16,21	90:24 98:20	295:9 299:1,19
361:8 391:15	picking 70:8 89:18	66:10,15 119:7,9	109:11 110:22	300:21 314:25
perspectives 41:14	237:5,17 238:24	197:11 248:16	125:9 130:13	315:8 331:4
persuade 130:18	240:17 242:8	253:12 255:7	142:5 148:14	332:17,18,19,21
132:6 133:6	293:21,22 317:7	256:20 262:3	156:24 159:20	332:21 344:17
142:22 149:10	318:3 319:14	264:10 266:20,25	160:17 171:22	346:14 363:22
164:1 355:21	320:14	267:1,4 269:16	186:8 187:14	364:9 377:3 388:4
persuaded 138:25	picks 89:15 306:7	270:2,3 277:5	188:7 200:23	388:8,11 391:5
194:11	picture 30:3 46:1	278:2,3 282:6	202:5,5 207:15	policy-oriented
persuadee 132:16	47:2 51:17 59:6	291:3 296:10	213:17 214:18	17:17
persuader 131:5,6,8	189:7 203:22	359:13	232:18 246:19	policymaker 332:15
132:7,9,16 156:6	205:7 240:8	platforms 58:12	247:2 249:23	policymakers

179:12,13 253:19 329:23 346:24 policymaking 18:5 polite 215:10 political 54:13 191:24 201:8 poll 329:8,15 Pollet 185:2,14 polling 253:9 polynomial 285:9 287:21 pool 81:4 281:2 385:19,21 pooled 81:7 pooling 278:21 poor 35:25 255:25 poorly 76:20 295:4 pop 198:18 Pops 58:17 popular 11:24 196:10 202:13 203:5 217:12,17 244:23,25 245:13 250:12 261:2 population 31:22 44:23 252:7,8,13 252:14,14 364:19 369:4,23,25 371:5 372:13 374:16,18 populations 63:18 253:10 312:25 portion 46:11 pose 244:18 posed 329:15 position 18:5 27:9 58:17 61:20 69:6 69:14 87:10 88:15 92:25 157:7 159:11 160:11 165:4 331:18 394:13 positioning 292:7 positive 95:13 190:17 207:5,11 309:19 311:10 365:12 positively 5:17 positives 125:19	Poss 358:12 possibilities 135:2 167:21 335:2 possibility 237:19 342:4 386:23 possible 39:20 42:22 47:12 48:17 126:4 146:9 178:24 180:12 268:3 272:9 317:13 318:12,15 332:14 334:12,23 336:16 340:19 343:20 351:18 386:13 possibly 23:18 120:11 136:20 332:11 352:25 353:4 post 132:11 197:15 197:19 204:12 353:7 356:4 389:3 post- 342:17 post-expiry 341:7 post-powertrain 346:20 post-purchase 353:1 posted 163:14,15 posting 20:12 potential 5:18 16:15 16:23 17:19 20:12 44:12 48:3 77:23 109:5 132:6 133:7 179:14 211:10,15 212:18 225:24 228:15 235:23 237:16 285:15 376:25 potentially 33:14 45:18 63:22 84:13 97:2 126:11 219:22 225:22 226:1,7 229:19 234:15 244:4 250:17 255:6,8 264:7 274:13 285:6,17 287:2 380:15 387:18 power 73:19,22,23	74:6,11 81:5 101:25 154:3 378:18,19 powertrain 327:17 327:25 328:1 339:1,2,12,12,13 339:14 344:15 346:11 347:24 348:24,25 practical 157:2 practice 8:9 9:4,18 14:3 55:24,25 65:5 159:5,12 378:10 practices 8:18 9:6 9:22 16:13 17:22 18:3 24:2 pre 342:17 356:3 357:19 pre- 71:9 341:6 346:6 352:12 pre-expiry 340:25 341:2 345:10 346:8,15 pre-filled 67:7 pre-manufacturer 340:7 pre-mobile 66:18 pre-owned 356:13 preachy 337:22 precise 55:24 79:2 92:2,15 337:19 precisely 159:24 160:3 preclassified 272:4 precludes 338:10 predetermined 335:25 predict 229:13 266:14 271:23 284:19 285:7 predicting 284:2 prediction 267:22 268:3,12 271:23 273:12 275:9,21 276:13 277:13 283:19 284:2 290:7 predictions 115:22	267:21 345:16 predictive 267:11 268:5 277:14 284:4 285:6,11,23 predicts 47:11 predominantly 27:18 prefer 151:9 preference 41:19 58:5 60:19 63:7 78:4 136:23 143:14 148:13 184:2 213:18 220:22 preferences 46:14 131:9 137:7 147:4 147:25 149:9 157:9 181:18,22 182:5 184:10 213:3,20 217:2,24 287:1,8 prefers 151:13 prejudice 238:16 242:8,9 255:22 premise 207:23 premium 256:12 260:23 premiums 326:1 331:2,3,12,14 prescription 298:12 301:9 302:9 303:12,23 307:18 311:15 316:19 321:13,13 prescriptions 306:17,23 prescriptive 57:15 preselect 352:14 presence 73:3 212:3 324:17 present 6:7 58:3 100:9 141:23 171:15 224:16 225:8,8 241:1 282:5 308:5 324:10 present-bias 183:19 183:21 184:15	185:16,23 presentation 20:18 24:16 39:22 100:21 103:6 124:7 155:9,10 326:13 331:18 366:21 379:5 381:7 382:21 presented 20:21 44:1 130:2 224:11 240:25 258:4 298:3 324:5 350:18,25 351:6,8 353:1 382:2,11 presenter 19:2 53:7 presenters 43:23 378:25 388:19 389:4 presenting 224:18 251:16 presents 295:25 350:22 preserving 7:20 279:23 presidential 286:22 press 22:24 57:3 182:19 184:23 244:23,25 245:13 250:13 pressure 351:24 pressures 203:15 presumably 92:21 318:15 383:8 presumption 214:22 pretend 193:9 pretended 193:21 pretty 30:16 39:14 39:15,25 42:2 50:18 51:14 52:3 65:23 76:13 91:14 103:1 146:22 167:1 170:16 185:19 199:17 200:5 204:21 207:14 216:6 258:16 277:13 282:8 283:5 288:5 289:6,17 298:14
---	--	---	--	---

307:1 347:5	prior 93:25 114:6	probabilistic 293:1	217:11,16,20	56:11 92:18
368:24 369:11,17	286:10 298:18	probabilities 340:10	244:24 253:7,8	103:16 104:24
373:16 374:21	299:12	343:1	267:19,23 268:8	106:1 107:5,8,13
388:3	pristine 334:2	probability 31:14	268:19,22 271:22	107:18,18,23
prevailing 24:2	privacy 2:9 10:2	31:22 72:13 107:2	271:22 273:22	109:19 110:8
prevent 361:17	13:24 14:2,2,12,15	107:4,5,6,8,22	285:3,19 286:14	111:4,25 112:2,8
preventing 79:21	17:24 20:14,23	111:24 112:3	288:3,15,16	115:5 133:7 136:9
Prevention 10:1,4	22:2,14 23:25 24:1	114:7 116:10	289:11,12 290:3	157:16,21 158:10
preview 330:12	24:10,24 25:2,6,10	123:1 135:7	290:19,20,22	165:18,21 176:23
previous 54:23	26:11 41:9 42:15	139:14,16,18	322:9,11,12	176:23 192:25
108:12 165:12	42:20 46:14 47:3	140:2 142:4,7	359:20 362:13	194:21 211:3
308:11 327:11	131:1 145:4	150:5,6 293:3,5,14	373:1 378:2	321:9 326:5,6
328:22 336:4	151:13 161:4	293:17 339:21	problematic 9:6	327:14 328:6
price 27:25 30:22	170:18 179:22	347:18,21,24	187:13	329:12 345:4,7,14
38:9,11,12,15,17	186:7,10 205:1,1,5	349:18	problems 105:16	345:15 359:11
38:20,21,23 39:7	205:5,12,16,17	probably 5:5 6:13	268:24 285:5	377:16 386:5
45:5,13 46:12	206:2,4,9,10,21,23	7:14 9:1,11 10:11	288:22 364:2,5,8	production 103:16
112:14 162:4	207:5,6,10,13,15	16:18 17:17 18:2,4	377:12	products 12:4 15:24
163:6,7,8,14,15	208:3,17,18,21	18:20,23 23:17	proceed 20:1 57:25	15:25 110:7
164:2 167:4,5,11	209:6,13,21 210:5	34:22 45:12 46:21	70:10	117:17 186:14
168:1 220:14	214:15,18,19	83:24,25 126:12	proceedings 396:4,8	218:15 321:8
237:14 248:15	215:8,17,18,20,23	131:24 141:2	process 13:4 46:16	325:24 326:2,4
249:25 255:13,22	216:10 220:4,19	166:8 186:10	57:11 103:16	328:24 331:10
326:15 338:6,7	220:24 222:25	196:24 203:24	130:16,23 134:12	345:1,3 346:21
344:4 355:19,21	225:12,19 226:3	220:12 241:16	188:9 215:1 300:7	347:3 350:1,22,24
391:18	228:9,10,12,14,15	251:25 252:1	316:3 337:8 383:3	353:21 359:14,18
priced 30:19 256:2	230:7 254:4	259:21 261:1	processing 181:25	360:12 362:23
prices 46:21 49:5	259:17 266:18	262:2 272:8	182:14 187:15,16	386:1
163:22 167:24	278:1 279:23	294:15 302:6	188:12	professionally 54:9
179:21 184:19	280:8 281:23	322:13 352:18	proclivity 357:18	professor 130:8
206:12 249:3	290:22 294:23	353:24 385:18,21	procurement 133:4	171:5,8 224:25
251:18 252:16	295:7 391:14,14	389:20 393:12	produce 109:19,21	241:14
253:5 262:9 344:3	392:11	problem 29:10	109:23 110:6	professors 225:14
344:7,7 356:2	privacy-intrusive	30:14 32:15 44:4	114:13,22 115:5	242:22
pricing 128:16	207:25	51:7 64:3 102:10	137:8 226:13	profile 23:13 132:20
237:10 249:24	privacy-preserving	105:21,22 108:15	351:16 386:10	132:23 216:25
primarily 188:24	279:21	109:7,13 110:24	produced 54:21	profiling 295:20
211:18	PrivacyCon 225:13	110:25 111:1	104:24 105:2	profit 211:19 243:21
primary 236:25	private 7:24 50:24	112:11,13,15	114:10,23	profitable 240:2,13
287:18,18 304:22	174:15 205:6,8,9	116:6,7,8 117:20	producer 105:7	242:12 350:1
304:23	210:17 219:25	117:21 127:19	304:6	profits 24:11 128:14
prime 60:10 144:13	222:7 291:16	140:6 144:25	producers 109:9	318:24 330:16,19
principal 183:9	363:10	146:24 148:3	304:18	338:7
204:6 359:20	privy 329:5	151:3 162:9,15,16	produces 107:7	profound 234:13
principle 54:22	prize 12:5	162:17 164:8	112:2	program 16:1 100:8
principles 178:8	prized 255:24	167:7 168:4 169:3	producing 107:4,23	168:12 186:1
print 189:10 303:16	prizes 231:6	177:13 183:9	111:25	245:5 394:20
309:16,19 312:13	proactive 170:5	202:18 213:19	product 35:13 56:3	programming

112:12	proportion 51:7	public 14:14 159:25	250:14,21 335:20	345:14,14 349:4
programs 12:6	proposal 390:15	160:5 173:9	purpose 44:10	359:11 360:12
260:6	proposals 166:23	174:10 175:11	333:22 338:13	361:13 379:20
progress 103:2	216:13	176:24 202:3	purposes 23:9,11	quantify 24:18
progression 339:22	propose 198:23	205:6,6,9 210:19	218:6	26:22 32:5 341:25
Progressive 58:24	proposed 337:5	229:10 290:22	push 42:23 96:9	quantile 36:22
58:25	propositions 124:4	publicized 357:8	157:1 206:14	quantitative 100:14
prohibition 47:18	proprietary 41:4	publicly 174:22	pushed 42:21	173:15 177:19
project 25:15 39:18	prosaic 237:8	published 10:17	193:21	178:18
42:3,8 167:23	prospect 184:12	173:9 175:10	pushing 43:7	quarter 305:16
projects 180:5,8	protect 7:20 8:7	186:17 195:4	put 12:24 39:8 59:17	306:21
386:11,20	14:2 116:24	209:18 238:3	66:15 75:22 77:6	quasi-hyperbolic
proliferating 55:11	124:16 148:16	publisher 24:11	79:7 101:23,24	181:17
prominence 55:15	protection 1:7 7:11	30:9	102:1 122:8	queries 310:16
89:19	7:18 10:2,8,15	publishers 27:14	124:12 166:19	query 310:15
prominent 29:6	11:11 13:24	39:25 42:6 48:25	181:23 186:1	question 12:18
56:23 61:5,7,10	170:11 171:2	54:16 261:21	218:20 220:23	16:25 17:12,18
62:12 64:16,20	172:7,16 176:13	262:4	221:5 229:10	18:11 19:4 24:14
69:2 77:1	180:22 207:13	publishes 45:25	236:19 278:2	25:4,21 33:6 37:3
prominently 101:23	208:19 209:14	publishing 51:1	305:21 318:12	41:6 42:16 43:20
promising 291:24	363:9 380:15	puffery 134:25	330:18 357:16	45:23 46:4 47:2
promote 146:12	390:25	pull 80:23 149:11	372:12 380:2	50:1 53:9 59:3,10
193:1 194:25	prototype 177:22	219:8	389:5 390:16	60:9 63:10,11,21
195:1 347:2	178:5,15	pulled 122:8 287:3,4	393:19	72:1 74:9 78:9,19
promotes 226:16	proud 225:1	pulling 43:17 309:9	puts 66:16	78:23,23 79:1,5
promotion 194:19	provide 45:12 87:1	punchline 72:20,23	putting 6:5 43:3	83:8,17 84:23
304:23	91:4 152:14	74:14 76:5,17	48:25 49:1 67:6	85:24 88:22,23
promotional 193:15	179:19 209:23	85:13 151:6	79:5 100:7 282:14	90:2,8 93:11
304:19,20,21	212:7 298:19,23	152:21 241:19,19	289:20 372:19	102:21,24 106:14
305:16 306:2	299:3,5,6 332:11	347:16	394:18	109:4 112:24
307:20 308:2,16	336:15 358:13	purchase 27:23	puzzle 178:25	119:24 150:17
310:2,5,7,8,10	361:12 363:1	91:23 249:14	puzzling 172:11	159:14,15,21
311:23,25 312:13	365:16 369:7	250:14,22 255:17		160:19 163:2,6,12
313:12 315:12	provided 19:16 20:8	329:19 330:5	Q	163:22 176:4
promotions 12:5	61:20 74:19 88:3	332:5,6,8 338:6	QJE 319:6	179:9 180:2
prompts 301:1	290:8,9 311:20	343:7,13,14,19	qualify 131:14	186:16 207:20
pronounced 233:7	providers 174:11	345:2,8,11,15	qualitative 100:15	209:11 210:24
234:14 238:16	provides 48:2 92:15	346:1 347:2,21	177:23	214:13,16,21
propagate 201:16	125:20 193:12	349:18 350:7	quality 86:3,12	215:2 225:7,20,21
propensity 227:6	204:11 212:17,20	351:14,23 355:5	101:12,13 103:19	227:3 232:3 234:2
242:7 360:20	303:1 314:19	357:9 391:21	105:25 107:8,16	239:8 241:14
362:17 365:1	providing 158:3	purchased 362:22	107:18,18,23	243:10 247:21
380:7	provisioning 344:22	purchasing 135:5,6	109:19 110:5,7	250:18 252:19
properly 55:22	344:23	239:20 329:7	112:2 114:13	253:11 254:3,15
381:5	provoke 151:7	332:1 347:18	115:3 117:1,12	254:24 255:10
property 221:10,12	proxy 29:11 355:11	pure 95:9 147:17	119:15,20,21	262:20 265:7,16
221:24 271:24	prudent 347:4	274:16 276:19,22	120:1 121:1 122:6	277:19,24,25
272:9	psychologists 71:13	purely 128:20	131:13 187:23	278:9 280:21

295:13 296:5,23 314:3 315:1,1 326:16,18 329:10 329:11,22 331:6 332:10 333:5,8 335:4,9 347:17 353:22 354:24 360:2 363:22 364:9 380:21 387:3,21	quite 12:17 13:21 41:6 49:16 63:4 67:22 85:15 88:23 92:5 106:22 149:14 172:21 173:18 174:16,19 203:23,25 224:18 228:1 230:6,18 232:23 233:8,10 238:9,21 241:19 243:4,7 260:3 261:12,18 270:7,8 273:3 370:12,22 386:19	248:22 269:24 ranging 239:21 rank 84:5 365:14 ranking 292:21 365:16,17 rapidly 54:8 rare 172:12 rarely 179:1 rate 65:7 87:25 95:15,16 183:2,3,5 185:17 265:21 274:8 279:8 343:14,14 366:24 368:21,22 369:2,8 369:10,15,15 370:15 371:1 373:17 374:15,23 375:11	388:15 raw 235:3,14 248:7 249:18 253:21 271:5 371:9,16 Razzino 396:3,16 RD 347:14 348:3 re-highlight 85:5 re-randomization 68:22 reach 13:12 14:16 16:4 113:4 115:15 237:18 238:25 246:16 249:2 250:3 252:2 253:2 253:9 254:16 reached 5:15 15:9 33:1 83:13 211:13 234:20 246:22 reaching 255:15 react 47:3 90:13 123:10 207:24 215:12 229:14 reacting 227:7 235:15 reaction 93:24 324:14 reactions 58:10 94:1 94:3 reactivity 96:1 read 11:20 75:16 126:1 184:22 187:22,24 189:25 244:15 282:18 284:25 296:14 315:14 321:20 382:18 reader 315:16 320:23 reading 126:13 157:14 190:6 250:18 282:21 317:14 ready 211:3 real 17:6 18:19 34:6 56:14 58:5 59:10 60:19 63:7 68:12 95:21 130:6 141:3 166:14 180:13	194:4,22 195:14 230:2 351:22 368:4 386:16 real-life 39:14 41:17 reality 33:17,20,24 185:21 285:21 realizations 107:12 realize 29:19 41:13 48:9 59:18,20 153:10 202:20 213:4 324:13 realized 140:4 239:13 330:16 338:7 realizes 330:19 realizing 34:22 really 5:20 6:2,2,3 7:25 8:5 12:9,17 12:24,25 16:20 17:10 18:7,9,15,15 22:6,10 23:5,12,24 24:13,17 25:5 26:1 26:4,4,20 27:1,7 28:4,7,12 29:4 30:21,25 31:16 34:24 36:10 37:10 38:8 42:4,21 43:5 44:10 45:4,9,10 48:1,6,10 49:15 51:8 53:14 55:7,7 57:17 60:2,4,6 63:3 76:23 77:17 79:4,5 82:6 84:17 86:9 91:9 93:16 94:4,11 96:19 101:23 102:7,13 102:16,21 106:6 106:16 109:15,20 110:1 111:23 112:25 114:10 116:8 117:5 119:24 120:6,9,20 121:2,4 125:12 128:14,20 146:14 151:21 152:12 156:8,9,13 159:8 161:15,24 162:18 165:2,3 172:17,25
questionable 213:22 questions 26:1 34:21 41:20 42:17 42:21 43:8,9 46:22 48:17,19 70:17 73:22 85:22 86:14 101:6 103:25 118:6 126:21 127:13 129:3 162:20,24 171:17 171:18,20 179:18 180:11 184:2,11 184:12 210:15 241:7,17 254:13 266:18 267:6 277:18 283:7,23 283:25 294:16,25 296:25 314:6 322:13 324:21,23 332:2,3 347:6 352:5 357:4 358:14 380:25 381:4 393:4	quo 47:8 quote 186:25 249:2 quoted 205:20	rated 73:7 76:20 86:4 87:3 rates 86:22 88:1,5 262:6 303:23 343:13 362:15 364:15,19,25 366:6 368:20,20 369:5,12,12,21 370:5,10,19,21 371:1,21 373:20 374:9 375:21 376:20 381:8,17 rating 67:13 82:23 86:6 168:19 362:7 362:8,11 ratings 76:20 86:1,3 86:15,17,19,21 87:1,1,4,6,7,8,10 93:4,5 183:13 359:16 rational 240:17 rationale 291:15 349:7 rationalization 240:14 rationalize 332:13 346:5 rationally 242:10 Raval 4:11 174:11 358:4,6 387:4	reached 5:15 15:9 33:1 83:13 211:13 234:20 246:22 reaching 255:15 react 47:3 90:13 123:10 207:24 215:12 229:14 reacting 227:7 235:15 reaction 93:24 324:14 reactions 58:10 94:1 94:3 reactivity 96:1 read 11:20 75:16 126:1 184:22 187:22,24 189:25 244:15 282:18 284:25 296:14 315:14 321:20 382:18 reader 315:16 320:23 reading 126:13 157:14 190:6 250:18 282:21 317:14 ready 211:3 real 17:6 18:19 34:6 56:14 58:5 59:10 60:19 63:7 68:12 95:21 130:6 141:3 166:14 180:13	R R 137:23 138:16 race 226:9 243:13 286:22 287:7,18 287:19 racial 192:1 radically 52:3 raffle 377:24 raise 43:21 243:10 raised 295:13,14 raises 47:21 187:15 Raluca 88:12 Ramey 150:25 random 59:16 70:8 120:18 293:6,19 336:13,13 randomization 68:21 70:20 71:21 292:18 randomize 61:1,4 61:18 70:3 87:7,9 randomized 68:24 69:20 72:3 176:14 177:19 randomizing 72:2 randomly 29:17 32:7 70:2 337:25 randomness 291:4 range 145:17 147:15 170:16 174:20

173:3,5 174:19	realm 173:19	142:9,22,23 143:1	reduces 345:15	285:9 305:20
178:4,22 180:6	realtime 24:21 28:5	143:15 144:8	reducing 288:21,21	309:13 310:11
192:17 197:1	28:21,23 29:22	145:3,4,24 146:4	Redwood 58:17	366:14
200:24 206:13	35:9,12 38:11 40:7	146:10 147:9	refer 291:20 329:11	regret 217:9
207:17 208:4	48:22 133:20	149:20 151:13	347:6	regular 328:11,13
209:1 213:25	322:1	153:24 156:7	referees 322:10	328:17
219:25 220:1,25	reason 23:17 31:17	receiver's 131:9	references 180:14	regulate 17:21
225:17 227:23	63:24 71:7 113:25	139:13 140:1	180:14	74:16 103:7
230:17,25 232:20	152:24 182:5	receivers 131:23,24	referred 286:11	104:15,15 117:14
235:18 236:5,17	196:23 200:18	131:25 135:12	289:23 291:18	125:17 207:22
237:10,13 238:25	203:14 228:19	137:3 151:11	325:17	208:22
241:8 244:14	234:22 236:14	receives 140:13	referring 210:19	regulated 190:12
245:17 247:6	237:7 245:19	146:9 353:10	282:25	regulates 161:8
248:3 253:22	246:16 249:11	363:11	refers 30:4	regulating 23:18
254:25 255:24	250:11 286:12	recess 99:2 323:6	refinance 186:1,3	110:22
256:9,13 258:23	290:12 305:19	recipe 127:2	refinanced 186:4	regulation 100:15
259:18 260:12,15	327:8 330:14	recipients 300:4	reflect 172:4 242:9	116:18,23 117:23
261:9,12 262:2,20	356:19 362:6	331:23	382:9	117:24 118:10
263:1,3,24 265:17	363:25	recognition 147:14	refrain 337:20	160:8,10,13,16
265:18,20 266:6,7	reasonable 77:22	recognize 40:21	refreshed 284:25	175:1 181:5
266:9 267:10,10	92:17 199:15	179:12	regard 25:13 30:21	188:22 190:11,13
267:23,25 268:8	reasonably 10:19,25	recommend 173:8	regardless 80:11	206:3,5 208:17,18
268:12 277:19	56:1 77:24 280:6,9	recommended 60:7	regenerate 217:4	208:21 209:6,21
279:17 280:4	281:7	reconcile 206:22	regime 62:6	212:11 215:6
281:22 292:8,11	reasoning 128:4	record 14:4 19:7	region 118:24	275:6,17 283:11
294:10 295:5,9	182:2	43:19 96:17	119:13 149:5,14	regulations 25:7
296:18,22 298:20	reasons 80:6 116:21	recorded 18:25 20:7	336:11 337:19,21	56:20 57:4 126:17
298:21,24 300:21	116:25 117:4	20:10 68:10 396:4	337:22 338:24	179:5 180:11
300:21,22 302:13	128:6,6 158:13	recording 396:5	340:6 346:8,11,15	207:2,15 211:17
306:7 307:21	190:18,22 217:17	records 220:13	346:20	266:19 278:2
309:18 310:15	222:15 249:20	221:4 222:17,19	regional 124:17	regulator 55:19
311:8 312:8	250:8 276:5	recouping 331:14	regions 342:1	63:3 110:14
314:10 315:19	296:17 366:7	recover 341:25	registered 390:22	159:20
316:10 317:6	reassuring 369:17	354:10	395:3	regulators 23:18
318:24 319:1,1,7	recall 59:15 60:8	recovering 217:15	registration 389:12	35:2 43:1 100:19
319:13 320:7,23	357:14,19 390:6	recruit 15:24	Registry 10:5	101:20 102:23
321:17,21 322:7	recalls 357:7,12	rectangle 316:25	regress 308:9	105:23 391:5
322:17 334:4,4	receive 13:20 353:2	recursively 285:25	regressing 317:6	regulatory 22:12
354:12 355:6	353:4,6,11 360:22	red 31:11 140:14,14	regression 82:1	41:15 42:5 126:18
358:19 359:24	received 6:1 14:13	141:9,11,13,20	234:2,4 248:8	148:14 179:4,7
364:17 366:4,5,13	136:4 177:10	144:5 157:9 158:1	308:5 310:19	206:17 209:7
367:5 370:21	331:24	158:2 164:6 168:1	335:7,10 336:4,9	reject 337:11
374:22,23 379:8	receiver 131:5,7,11	287:13 306:6	339:4,18,19,23	related 5:10 17:18
379:20 382:13,15	131:12,15,16,18	375:8	341:17 342:14	20:13 60:23 71:25
383:15,20 385:1	131:22 136:18,21	redness 167:11	355:25 374:17	88:23 93:11 118:9
387:15 388:12,21	137:5,14,15	redress 8:2 9:1 16:7	375:18	156:2 206:20
389:15 390:13,18	138:18,24 139:19	reduce 275:21	regressions 81:2	210:22 269:2
391:5 393:5 394:1	140:3,9,10 141:8	reduced 396:5	249:19 275:3	296:5 340:17

365:3 376:14,17 390:24 396:7 relates 274:3 292:7 292:17 relations 133:2,3 relationship 285:11 287:20 relationships 9:23 285:22 286:21 relative 72:14 172:18 198:19 208:11 273:15 309:23 312:12,13 312:13 371:6 373:4,11,23 375:12 382:2 396:9 relatively 110:12 113:10 130:15 150:15 163:12 172:17 284:11 286:6 288:17 349:22 relaxed 285:15 relevance 125:16 315:8 relevant 43:12 62:24 69:23 79:3,5 80:5 100:15,19 104:7 132:11 157:3,3 170:17 180:12 264:8 287:25 294:5,5 332:23 344:18 391:5,9 reliability 348:25 354:2 reliable 179:19 354:15,16 reliably 31:22 39:20 187:8 relied 173:23 reluctant 208:7 rely 130:14 277:23 REM 381:13 remain 19:15 20:3 remaining 318:18 318:20	remains 69:7,15 remarked 41:8 remarks 4:15 118:20 388:23 390:1 remedies 161:21,23 172:13 remember 114:25 157:6 196:4,7 237:15 240:6 256:18 337:2 354:16 357:15,19 384:5,6 remembers 196:5 remind 31:9 43:18 187:3 reminded 391:10,16 reminder 353:14,15 reminds 379:17 remove 368:10 392:6 removing 245:6 rent 184:25 rental 185:7 repair 12:7 354:18 repaired 13:18 repeat 89:4 repeated 32:23 33:3 repeatedly 48:10 rephrase 78:23 replicate 136:13 148:25 report 59:23 64:4,7 68:10 91:10 93:21 reported 74:5 384:8 reporter 384:16 396:1 reporting 208:20 209:9 210:3 218:6 338:11 343:3 reports 11:14 30:12 31:7 36:7 repositories 218:19 repository 208:24 represent 252:13 315:17 representation 248:6	representative 184:3 193:20 Representatives 23:22 represented 246:13 246:21,24 247:20 251:25 254:7 358:4 representing 34:19 represents 72:16 repugnant 206:14 reputation 2:20 100:2,5 101:4,18 102:4,8 104:2,19 104:20,21,22 105:3,21 106:4,7,8 106:9,11,13 108:4 108:13,24,25 109:2,5 110:1,2,10 110:12,18 112:19 113:9,13,18,19 114:2,3,4,8,9,15 114:20 115:3,17 115:20,20 116:1 117:21 118:20 119:4,10,14,17,25 120:21 121:2,3,22 122:1,15,19 123:19 125:7,14 126:11,24 127:23 128:14 165:13 reputational 112:9 112:10 113:1 117:4 121:13 128:6 reputations 101:6 119:1 121:8 125:10 request 53:8 166:23 169:14 require 19:1 30:18 92:9 required 177:11 requirement 164:3 requires 19:14,17 206:2 335:11 research 5:12,13,19 9:8,8 14:19 17:11	18:15 22:11 41:14 43:7,12 48:3 78:23 103:25 118:22 120:4 125:20 171:16 172:8,12 172:22,23,24 173:13,22 174:19 175:8,10 176:2,24 177:7,24 178:10 178:18 179:1,8,10 179:14,18 180:8 182:20 186:17 191:1,17,18 210:23 213:24 225:4,6 235:6 262:23 283:7 299:20,22 300:3 301:1 324:20 326:19 330:2,21 332:2 339:8 384:2 385:7 386:8,10 researcher 59:22 191:20 researcher's 22:12 214:17 researchers 35:2 59:11 170:16 171:15 172:15 173:6,14,22,23 196:25 316:11 researching 329:5 reservation 45:5,13 reserve 30:22 38:11 reserved 30:19 reset 264:19,20,25 271:10 278:15 resets 271:8 resides 218:11 338:23,25 residual 338:19 345:3 resolutions 316:23 resolve 119:22 resolved 145:2 resource 333:19 resources 7:23 17:17 respect 56:10 92:17	92:18 322:15 respond 73:9 90:22 responded 5:17 90:2 responding 5:25 241:10 329:13 351:21 364:7 responds 351:6 response 16:1 57:14 64:2 85:13 95:13 129:4 216:11 262:6,10,12 265:21 387:4,6 Responsibility 10:7 responsible 174:12 179:7 327:21 328:2,2 responsive 265:25 312:5,23 responsiveness 35:21 72:7 94:1 rest 34:6 83:1 114:18 305:14 restatement 137:12 restaurant 53:19 58:8,15,16 59:8 60:7 61:20 65:15 67:6,15,20,25 68:1 68:3,5 69:11,22 73:3 82:3,4,9 83:13,24 89:11,13 95:14,15,16,19 96:20 157:15 359:12,19 394:23 restaurant's 81:10 restaurants 59:9 66:6 67:14 73:7,10 76:19 82:13,14,14 82:18,19,21,22 83:1 86:4 87:15 93:4,5 restaurants' 81:24 Restore 10:9 restrict 207:2 restricted 382:19 restricting 206:4,5 restroom 19:12 restrooms 19:9 restructure 16:7
---	--	---	---	--

result 75:17 81:11 82:25 84:17 124:11,13,22 142:11,12 143:3 149:19 153:25 161:5 188:2 199:15,20 227:1 227:16 228:4,16 233:21 235:7 236:25 237:7 238:15 239:1 242:5,13 243:1 250:2,2 289:17 312:3,3 344:16,19 350:15 357:2	returns 266:10 reveal 58:25 142:6 148:16,17 193:10 218:17 revealed 41:18 69:1 78:4 187:1 220:22 revealing 143:21 206:25 reveals 58:19 revelation 167:17 revenue 40:4 revenues 40:10 reverse 185:11 review 7:10 187:20 187:22 191:4 197:15,19 198:7 198:24 316:3 337:8 347:16 360:7 361:6,15 362:5 377:20 reviewed 360:12 reviewer 365:19 reviewers 197:16 360:4 365:14,19 reviewing 200:6 reviews 14:8,9,12,14 67:19 195:11,21 195:22 198:10,12 198:13,19 199:11 199:13,20 200:2,3 200:12 358:22 359:1,3,15 360:9 360:21 361:11 362:10 365:4,7,11 365:12,14 revisiting 286:10 rewarding 50:17 rewritten 22:13 rich 23:12 35:9,24 36:2 67:22 82:6 112:12 173:5 232:17 238:16,17 246:8 290:25 333:24 richer 256:1 richness 35:7 rid 265:11 266:19 277:20 278:23	ride 120:11 127:20 ridiculous 48:24 riding 105:12 riff 228:7 right 11:13 22:4 23:16 26:2,8,24 28:12,19 30:2 31:8 31:18 34:16,21 35:4 36:9 37:20 39:21 40:14 43:15 49:5,8 50:14 51:9 52:5 55:1 58:23 60:7 61:15,24 69:3 69:18 71:3 73:16 74:14 77:12 78:10 78:15 79:4,8 84:22 85:10 88:20 95:2 96:20 97:2 98:3,3 98:3,15 99:1 111:18 118:4 119:15,17 121:3 122:1 123:7,11 128:17 130:5 133:7,8,13,16 134:12,12,19 135:17 136:10 137:21 139:5 141:5 142:11,17 143:10 144:17,23 145:16 146:13,13 147:9,19 148:2,21 149:15 152:10 153:1,2 154:17,18 154:23 155:2,5,12 156:15 157:11 158:8,12,21,22,23 159:25 160:4,20 161:12,22 164:16 165:9,15 167:8,13 167:19,19 168:17 169:9 171:21 174:15 183:16 191:8 193:13,23 196:1,8,8 197:3,23 199:16 200:9 201:2 203:20 205:1,2 209:25 210:7,18 211:25	212:1 217:19,23 221:2,10,12,24 222:6,8,15 224:9 228:23 230:3 232:14 233:10 235:10 238:4 240:21,24 241:17 244:20 245:18,22 245:24 247:1,2,12 248:5 249:16,19 251:25 253:24 254:10 255:1,17 255:18 256:3,5,15 258:5 266:1,7 267:13,24 268:3,8 268:20 270:23 272:1,5,7,16,22 273:1,12,14 274:5 274:14 275:12 277:21,23 279:16 279:18 282:24 283:20,22 284:12 285:12 287:19 288:5 289:5,10 291:21 292:9 294:22 295:1,12 296:5 303:4 304:8 309:10 312:8 316:23 317:11 320:20 322:5 326:24 327:7,12 331:10,11 334:11 335:13 337:9,12 337:13,15,18 338:1 340:21 341:20 344:23 348:7 350:19,20 351:6 352:9,23 353:10 354:2,5 355:23 363:2 373:6,6 379:19,21 381:14,21,22 382:14 383:10,15 383:22,22,23 384:25 393:7 395:1 right-hand 19:12 342:17	rights 211:13 Ringold 175:7 RIO 174:10 ripe 22:10 rise 111:22 rising 369:16 risk 181:21 314:13 348:19 352:10 risk-averse 345:1,5 345:7,22,23,25 348:20,23 risks 298:23 299:5 301:6 risky 345:4 robust 66:10 128:2 robustness 81:8 306:18 Rochester 20:22 role 5:8 8:12 53:21 85:6 86:23 87:13 118:10 130:22 172:7 189:14 201:20 334:13 336:7 355:19 391:1 roles 192:13,24 room 6:13 19:4,10 56:15 173:2 224:6 228:23 241:16 269:4 299:24 322:10 324:15 325:11 326:24 329:16 331:22 336:10 Rooms 1:19 Rotman 171:9 roughly 62:19 64:5 66:4 68:11 71:22 round 6:25 11:12 12:3 204:18 389:21 rounds 11:12 routine 179:11 row 134:21 276:11 rows 276:8 rule 158:11,16 241:1 288:12 293:14 296:7 335:19
--	--	--	---	--

342:4 356:4	270:14 302:11,13	scale 31:24 71:23	203:22	276:17 277:25
rulemaking 9:3	303:13,14 306:15	137:23 149:2	se 93:8 386:9	278:8 292:7
rules 9:3 29:12	306:25 338:17	scaling 32:4	seamless 319:13	294:23 295:23
38:12,15	366:9 380:6	scam 363:14	search 2:16 3:20	308:15 322:3
run 36:5,14 82:1	samples 366:8	scammers 12:14	53:2,6,19 56:15	334:14 335:24
120:15,16 202:3	sampling 270:10,15	scams 12:5,13	58:7,15,18 59:8,17	340:17 346:4
243:4 251:21	Samuelson 104:19	scandal 51:12	64:1,2 65:16,17	361:14 365:13,20
268:24 273:22	105:20 117:10	scenario 279:4,12	66:3,16,16 67:3,6	367:17
302:6 339:15,20	satisfaction 162:1	279:24 280:7	67:11 69:12 75:1,7	second- 314:5
341:17,24 355:25	365:5,21,22	scenarios 26:6	75:8,10,15,22 82:8	secondary 295:8
366:14 384:5	satisfied 366:4	279:25 284:18	83:14,21,22 84:1,2	seconds 23:1 29:3
391:7 392:15,24	satisfy 133:8	scenes 174:17,23	93:24 96:17 268:5	37:10 203:20
393:12	satisfying 366:4	358:11	298:1,7 300:6,6,16	section 195:7
running 6:14,24	save 211:21 239:5	schedule 98:25	300:19 301:15	sector 226:16,24
204:17 268:9	savings 331:3	scheduled 294:15	302:8,12,15,17	sectoral 206:17
339:18,20 377:15	saw 72:2,5 193:16	schedules 352:13	303:5,8,25 307:4,6	security 18:24 20:5
389:15	193:17,25 194:25	Schelling 150:4	308:9,13,23 314:5	155:2,2 179:22
runs 37:10	201:1 225:12	Schneider 187:18	315:11,18 316:20	205:13 214:4,5,12
rushing 19:20	228:11 230:9	scholar 180:21	317:6 319:22,23	215:18,20 216:20
rusty 154:16	234:10 235:14	Scholarship 10:4	searched 307:14	220:11,12 222:25
Rwanda 256:10	238:22 246:21	school 132:25 171:5	searcher 301:25	see 12:8 16:11 22:7
	247:6 256:6	171:7,10 172:11	302:5 303:1	22:22 27:11,12,21
S	259:22 289:21	185:8 203:4 204:4	307:23,24 310:22	27:22 29:22,24
S 146:7	327:10 374:24	204:5 242:22	311:17,19,19	31:3 32:24 39:12
S.W 1:20	375:5 380:9 382:1	313:20	searchers 311:21,22	40:23 43:6 48:12
sabbaticals 180:6	385:25 390:8	schools 192:8,9	312:5,22	57:25 58:19 63:12
sad 130:10	saying 8:14 92:14	science 6:11 22:8	searches 66:11 67:8	63:18 64:15 67:19
sadly 391:25	98:13 147:7	53:12 226:18	67:8 88:12 302:18	82:1 84:14 88:4,10
Safe 10:6	160:15 197:2	231:3 258:14	308:13 312:9	90:16,18,18 91:11
safer 126:16	203:3,5 211:8	268:21 275:11	317:16,25 320:3,4	95:18 98:6 102:2
Sahni 2:16 53:17	215:15,16 216:3	390:7 394:5	320:16,19 321:5,6	106:1 107:12
sake 79:12	218:5 219:10	sciences 95:25	searching 75:21	112:16 118:18
sale 27:13 30:5	239:11 249:5	scientific 6:3	307:8,16 311:14	120:4 123:4,5,5
330:19 338:8,8	250:14 254:8	scope 40:2 64:14	318:8	125:9 140:14
348:10	256:10 267:25	121:23	season 201:3	141:18 157:2
sales 68:5 133:5	282:19 325:3	score 292:22,22	Seattle 245:14	172:25 174:15
160:21 330:4	337:15 362:4	293:2,4,16	second 12:19 28:4	194:25 198:14,18
333:18,20 338:17	376:18 390:10,15	scotch 124:18	28:21 32:10 35:16	199:1,1,10 201:2,4
351:24 352:1,22	391:4	Scotland 124:18	38:9,10,15,20	204:19 208:15
352:25 356:9	says 41:9 59:19	scrapable 192:21	67:25 70:22 72:23	209:23 210:14
salesperson 135:8	135:23 138:22	scrape 230:15	77:23 86:8 100:3	213:19 227:23
saliency 88:25 91:1	142:13 150:10	scraped 192:19	134:5 181:6	232:24,25 233:2
97:17,23 98:11,12	184:14 205:23	screen 58:24 59:7	184:17 187:14	233:13,19,20
98:12,18	210:11 220:22	325:14 327:11	191:16 192:2	234:13,17,24,25
salient 23:4,5 89:7	236:2 326:14	328:22 329:18	202:5 208:6	235:17,19 237:13
94:7	351:3 353:18	331:20	215:19 221:22	237:13 238:15
salvage 355:9	369:17 374:2	screening 6:3	251:11 253:11	239:19,22,25
sample 184:3 268:5	375:1	screenshot 203:20	260:20 272:19	243:14 247:8,10

247:17 248:3,7,9	261:10 274:9	137:1,14,16 138:7	302:18 362:24	285:6,15 286:6
255:25 256:5,7,10	322:21 353:14	138:9 139:6,8,24	382:22	287:23 288:10
256:13 259:11	378:10 380:10	140:1,11,14,23	separated 54:18	291:4 292:16
261:11 264:7	386:19	141:5 142:19	separately 308:13	308:15,19 310:20
266:13 268:25	sees 88:14 112:2	143:17,20,25	separates 185:20	315:23 316:4,4
270:13 276:12	segment 242:12	144:3,5,8,11 145:6	separating 183:16	317:5 327:13
277:14 279:25	segmentation 263:2	145:14,19,19,25	separation 54:17,20	334:9 336:3
280:15 281:19	segments 158:12	146:8 147:7	September 1:13	337:23 343:17
298:14 304:2,3	select 339:15	149:21,25 156:6	66:22	354:21 360:14
305:2 306:6 307:6	selected 302:11	sender's 142:15	sequence 286:17	362:25 363:13,13
307:13,21,24	352:17	147:13	series 173:8 228:4	367:14 368:5
308:21 309:8,12	selection 110:24	senders 151:9	232:21 350:22	372:6,7,10,11,15
309:17 310:3,4	116:7,8 117:20,21	168:24,25 169:2	serious 74:3	372:15 375:9
311:20 312:11	168:12 275:24	sending 45:7 131:6	seriously 221:15	379:14 391:2,15
313:3,10,11	276:1 341:15	131:10 139:9	254:8	sets 96:24 152:7
316:21 318:1	361:23 364:13	187:7 244:14	serve 170:12 212:8	161:11 174:7
320:18 322:11	368:16 376:25	senior 180:21	227:24	185:15 249:22
323:4 325:13	self-diagnose 314:20	sense 7:12 10:12	served 168:16 226:8	272:14 273:7
326:13 331:19	self-regulate 156:23	11:4,23 16:16	242:1,2 361:1	314:9 363:3,19
336:9 341:6,8	self-regulation	22:12,12 41:24	serves 86:18 255:14	372:8
342:19,20 343:6	40:20 57:12	45:11 50:2 53:23	service 133:8 206:12	setting 24:20 34:11
343:12,13 344:12	self-selection 360:5	53:25 54:4 56:7	325:23 329:12	38:22 85:25 86:1,5
344:12,13 345:9	360:10 372:25	59:6 60:15 62:13	360:18 386:3	86:5 89:3 90:16
351:21 356:1,4,18	374:3 378:12	65:7 66:2 78:14	services 12:6 177:4	94:6,8 133:9 150:4
359:12 361:12	sell 13:16 29:7 127:5	83:12,23 92:14,15	218:14 253:17	150:22 152:14,17
362:15 369:21	160:21 186:15	106:16 110:25	servicing 3:11 158:11	161:1 187:6
370:4,18 371:4,18	216:20 220:9,12	113:2,8 122:10	224:3 225:9	208:12 262:25
373:13 374:10,21	220:13,14 221:13	133:13 147:18	230:11 361:1,2,3	264:14 288:10
375:13,23 376:4	222:8 253:14,16	150:5 164:4 167:2	session 2:8,19 3:9	325:23 329:4
377:17,17 379:7	270:3 368:2,9	168:2 174:23	4:5 22:1 67:3	333:4,5 352:24
379:18 380:23	seller 152:2,18	190:19 203:18	68:22 75:22 100:1	settings 86:13
382:4,5 388:3	156:5 158:22	205:12 213:13	100:4,10 224:1,10	133:11 151:1
389:12 391:13	161:20,25 163:7	219:19 227:13	324:1	178:23 231:25
394:21 395:2	163:17,20 164:1,8	237:9 243:11	sessions 169:12	264:16
seeing 42:3 45:15	362:7	290:16 353:18	set 25:5 28:5,11 29:7	settlement 13:13
71:3 94:5 114:9,9	seller's 145:2	373:14 382:11	33:2 41:5 42:16	14:16 15:9 16:4,5
127:9 134:15	sellers 362:5	383:19 390:23	58:11 72:4,5 83:7	24:8
148:1 227:14	selling 27:2 37:14	392:16	88:8 98:19 134:8	setup 108:16,24
229:19 262:12	141:9 270:1,2,2	sensitive 14:11	139:17 140:5	117:9 139:5 197:4
307:4 346:6	330:17	82:23 123:21	141:17,18 167:10	318:17
seek 7:24 301:2	sells 104:22 270:5	sensors 32:13	171:14 220:25	setups 113:25
314:22,24	Senate 23:21	sent 228:19 230:9,10	226:20,24 231:19	seven 199:11 306:15
seeking 301:22	send 127:2 139:6	282:20 390:10	231:19 236:13	328:18,20
315:2 385:1	140:2 228:17	392:21	239:16,18 245:20	Seventh 1:20
seen 100:22,24	389:10	sentinel 363:4,6,17	248:14,14 249:10	several-fold 330:23
173:8 183:23	sender 131:13,17	363:24,25,25	262:18 264:23	severe 319:12
206:16 208:2	134:23 135:2	374:12 379:16	272:4,19,22 280:4	sexism 227:11
211:17 228:8	136:18,20,21	separate 72:25 89:7	283:23 284:4	sexting 203:5 204:8

shade 38:21 145:8	124:7 195:6	320:12	162:12,16 167:23	singer 193:19
shadow 122:20,21	378:20	shows 22:20 25:23	200:5 276:14	single 27:8,8,9 30:24
122:24 123:16	shorter 339:13	37:23 90:12 98:12	281:23 284:8	63:25 166:25
124:25	342:11	213:25 227:19	309:25 349:20,23	236:2 331:1
shallow 288:6	shortest 188:23	276:8,8,10 289:15	350:3 369:11	sit 160:23 170:3
shape 16:9 334:2	shot 59:7	300:3 320:11,19	373:8,15	site 204:11 270:8
370:18	shout-out 257:6	341:12 371:16	significantly 278:13	304:6,7
shaped 96:8	show 26:3,5 59:9	shut 36:5 166:13	281:13	sites 30:9 200:19
share 40:7,11	61:12 67:12 69:23	sic 343:18	silly 393:7	304:10,12,13,19
145:11 146:11	73:1 83:19 84:21	sick 221:6	similar 45:17 48:13	304:20,22,23,24
200:20 208:7,10	93:1 141:10 155:4	side 19:12 24:17,18	58:13,20 62:5,14	305:3,6 307:20
208:12 212:20	162:3 187:4	27:13,15,20 35:9	62:15 76:13 80:20	310:5
213:2 219:6 278:7	200:17,18,25	50:9 54:18,18,19	85:14 89:5 133:1	sitting 167:7 224:15
279:2 280:22,24	201:17,18 203:3	55:20 58:23 61:15	141:24 144:10	353:2 379:21
282:6 283:10	227:5,9,13,16,25	69:18,20 126:17	150:10 165:7	situate 134:19
285:1 290:15,17	232:13,16,20,22	132:3,13,14	233:10,23 248:20	situation 54:15
290:21 333:18	233:10 235:25	138:15,18 140:9	249:25 250:1	96:21 125:7
369:23 370:14,16	236:16 240:8	151:3 251:2 301:4	253:7 280:1 281:9	134:13 152:1,7
371:7 374:18	241:24 242:4,4,6,6	304:1 305:5	312:16 355:3,12	166:6 185:23
376:8	246:3,14 262:19	314:11,16 317:16	355:13,13 370:18	227:19
shared 8:3 43:1,2	262:20 278:20	330:7,21 335:1	373:13 385:11	situations 60:22
214:8 218:2	280:7 286:2	342:17 345:20	391:17	79:19 133:5 135:7
sharing 119:7	305:20,21 310:25	348:15 350:25	similarity 327:10	151:25 155:19
200:19 208:8,11	312:17 320:17	351:13	similarly 101:12	162:8 163:19
208:13,16 259:17	321:25 326:1	sides 300:12,24	115:2	206:24 212:5
267:1,3 278:4,6	337:10 340:24	301:12 314:11	simple 38:18 39:5	216:14 316:7
280:25 281:7,10	359:16,17 368:19	sign 81:1 351:4	62:10 107:20	six 29:8 34:25 80:2
281:12,15 283:13	374:17 376:4	sign-in 217:18	131:3,7,18 139:5	200:2
290:5 296:24	380:12 389:16	signal 53:21 86:19	140:5 183:20	sixth 203:5
sharp 335:7,10	showcasing 326:20	86:23 87:3 105:9	224:19 230:21	size 31:16,25 32:4
shed 301:11	showed 185:16	114:9 149:3	231:5 232:23	33:4 263:19
shift 52:3 186:6	208:1 310:3	150:11 162:5	234:3 240:21,21	280:13 366:24
shining 124:2	368:23 375:18	199:18 319:9	244:15 245:23,24	381:9
ship 127:4	showing 11:25 70:9	362:9	268:18 275:19	skeptical 319:1,1
shirk 102:3 106:9	72:13 213:12	signaling 70:6 73:1	286:1 290:11	skepticism 57:6
110:7 119:21	239:6 242:16	73:1,13 77:5 84:22	339:22	skills 172:23
123:8	359:1,3 365:6	84:22,23 86:20	simplification	skip 65:11 76:17
shirking 102:11	370:24	89:2,7,15,18,24	107:16	106:23 113:5
106:12 108:17	shown 59:19 65:2	93:6 95:21 155:24	simplify 80:8	144:23,23
shock 184:18,19	66:16 89:11,14,17	345:12,12,17	simplifying 34:12	skipped 116:22
shocked 258:25	89:21,22,25 94:9	346:12 349:2	simplistic 122:13	212:15
shocking 11:20	226:6,19,21 227:3	signals 105:11,16	176:19	sleep 381:13
249:3	231:17 233:1,6	109:7 115:14	simply 235:21	slice 391:12,12
shocks 331:16,17	234:19 261:5	150:13 195:16	237:13 241:9	393:12
shopped 82:19	264:12 271:12	significance 234:12	242:9,19 274:16	slicing 391:8 393:6
Shoppers 10:9	276:3 277:7	349:10,12	343:4	slide 116:22 275:5
shopping 178:9	279:10 286:13	significant 13:7,20	simulate 38:5	312:8 336:4 387:7
short 98:6 120:15	295:24 296:24	47:23 55:19 59:14	simulations 294:24	slides 43:18 204:22

246:14 324:22	202:6,12 203:17	144:9 174:6	251:12,16 252:13	64:8,10 76:23
334:21 343:3	204:9 208:14	sorry 31:7 32:21	252:15,17,18,21	130:9 156:21
347:11 389:3,6	214:4,5,12 216:20	33:20 34:15 46:18	254:1,4,6 257:5	255:21 258:11
slightly 45:19	217:25 220:12	64:13 69:3 86:21	262:8 288:13	326:17 383:2,4
189:16 307:6	224:3 227:9	104:10 113:17	294:3 295:8	393:1
310:9 353:5	235:25 236:3,7	144:15 217:15	298:13 301:11	speaker 188:23
354:15	237:24 239:16,25	249:12 272:13	306:7,8 307:4	speakers 170:24
slippery 165:25	250:19 251:1	307:1 317:12	314:5,10 315:6,16	speaking 116:7
slogan 229:7	256:20 322:19,22	349:14	315:20 316:14	155:18
slope 165:25 340:6,8	388:13	sort 7:24 10:15	318:4 319:25	speaks 43:4 85:18
slots 30:9	socially 104:10,16	11:25 12:15 13:3	320:4,19,22	89:18 154:14
small 11:19 39:14	111:11,12 112:21	16:15 17:12 18:17	321:11,16,18	special 277:22
41:13 74:12 91:3	113:12 117:25	25:6 27:20 28:8	356:14 360:21	390:16,18,19
197:22,24 198:17	society 364:8	30:15 33:18 34:17	361:11 362:9	392:22,24 393:9
199:9 213:17	socioeconomic	36:23,23 41:11	363:13 365:3,25	393:16,24 394:2
233:15 261:12	182:15	44:21,22,25 45:5	370:18,19 371:18	specialized 175:8
277:9 280:15,19	socks 34:5,7	45:13,14,20,22	372:3 374:8 377:3	specific 34:3 44:6
288:8 293:21	soften 296:23	46:3,15,24 47:1,5	378:7 382:7	46:14 78:22 85:25
307:1 342:21	softens 290:13	47:7,10,15,25 48:8	383:13,15 391:18	146:14 162:4
350:3 366:8	software 13:2,2	49:3 97:20 121:8	sorting 334:14	264:13 277:2
368:24 386:12	368:10	126:18 132:20	337:4 340:16	279:7 291:17,20
smaller 280:12	sold 27:5 28:10 30:8	144:20,25 147:16	345:22 346:7	296:11 330:14
293:12 368:15	42:20 71:20	149:5 150:11	348:19 352:10,18	391:6
smallest 138:1 368:5	222:21 338:4	151:7 152:17,19	353:23	specifically 154:14
smartphone 259:20	solution 146:3 204:2	156:14 161:1	sorts 378:11	157:24 262:15
259:23	204:2 229:5,17,18	162:8 163:9 166:6	sound 19:18	282:15,25 283:17
smartphones 202:15	243:7 286:15,19	166:9 168:5 169:2	sounds 183:16	283:18 284:14,23
204:5	solutions 188:10	180:21 189:3,9	388:15	288:1,23 334:1
Smith 2:12 43:13,15	229:4 286:17	191:22 192:12,15	source 307:17	specification 167:15
43:25 64:13	solve 29:10 32:15	193:2 196:14,25	311:15 316:16	374:13 375:7
smoking 316:19,19	140:6 168:7 243:3	197:1,8,25 198:24	359:8	specifications
316:20 317:25	285:4,5,19 288:4	199:8,14 202:23	sources 47:10 264:3	315:24 357:13
smooth 350:7	364:3	203:15 209:1	290:24 300:13	specifics 136:16
smoothly 6:14,24	somebody 34:18	216:15 217:10	303:20	291:2 326:9
Snapchat 202:10	44:24 77:13 83:20	218:12 227:1,23	south 20:1 343:25	specify 29:11,12
Snapchats 203:19	108:7 115:4,5,6	229:7 230:13,25	Southern 118:12	214:15,19,23
Snyder 6:21	293:16,18 365:10	231:22 232:3	171:7	specifying 31:10
so-called 54:20	someone's 214:1,12	233:8 234:11	soy 158:12,15	spectrum 135:11
168:11	somewhat 229:2	235:4,10 236:6,7	space 31:11,12	338:22
social 3:12 20:12	313:6 338:12	236:10,20 237:13	35:10,12 193:12	speculating 38:16
22:13 95:25	368:12 375:21	238:19,20 239:9	197:12 261:16	speculative 200:24
110:17 113:14	somking 316:22	239:14,21 241:5	268:5 285:25	221:14
170:19 182:9,9	Sony 14:24,25 15:10	241:17 242:3	286:22 329:7	speed 29:10
188:22 189:4,5,7	193:23	244:21,23 245:12	336:10	spend 12:16 23:7
189:15,22,23	soon 170:3 188:8	245:21 246:10,11	spaces 158:10	24:15 35:22
191:10,12,20,21	203:12,21 243:2,6	248:1,9 249:7,21	spammed 196:2,7	232:11 236:2,6
192:2,9,14 193:3	333:2,3 388:25	249:22,23 250:6	spanning 338:3	251:8 289:9
201:13,15,25	sophisticated 141:2	250:18,25 251:2,4	speak 19:2,2,5,7	331:11

spending 180:20 303:12,14	stakes 39:14	329:5 365:25	Stephanie 6:22 245:16	237:9 240:22 288:18 289:17 347:13
spends 317:5	stamp 229:9	starter 162:8	Stephen 245:18,20	strategic 131:16,22 131:24 135:13 148:19 153:22 156:22 160:25 334:14 340:15 348:4,9 349:21 365:9
spent 257:2 329:6	stance 92:10 93:7	starting 26:20 42:23 130:13 202:14 209:22	steps 288:7,25	strategically 353:4
spikes 320:19	standard 13:7 73:1 112:15 136:23 140:24 149:19 161:21 181:15 184:22 186:24 266:8,12 267:11 272:20 273:3 283:24 316:4 369:9,15	starts 37:14 142:23	Steve 182:20 362:3	strategies 260:16
spillover 309:11	standardized 369:7	state 48:18 54:17 287:14,14,17 338:2 367:15 374:16 384:20	stick 76:9 123:13	strategy 38:19 39:7 168:5 335:6
spillovers 309:8 312:11	standards 10:16 77:3 339:8	statements 128:23 165:7 337:19,20	stickily 62:14	stream 150:8 191:1
spin 202:23	standing 103:24	statement 10:18 56:14 57:14 77:20 92:7,24 94:18 96:9 98:14 299:3,4 315:5	stifle 209:16,24	Street 1:20 19:24 20:1 394:25
spinning 201:5	standpoint 125:12 331:5 332:22 333:16 346:14	states 27:24 50:13 54:6 65:22,24 66:4 175:19 181:1 319:22 337:25 338:2	stipulates 56:21	streets 384:3
split 248:1,8,12	stands 146:3	stating 48:25	Stivers 3:7 6:4 170:7 170:9,10 180:16 188:18 204:15 210:7,10,12 213:14 217:14 219:12 222:3,16 222:23	strength 124:14
splitting 34:17	Stanford 53:4,17 130:3 282:11	stations 9:24	stock 355:8,12 359:14	strengthen 157:4 315:20,25 321:19
spoke 162:9,10	star 42:23 97:24 176:8,16,21 359:16 362:11 365:17	statistical 234:12 349:10 371:13 377:25	stood 216:17	strengthened 311:5
spoken 353:9	stars 176:20 362:5	statistics 309:24 331:5	stop 95:24,25 109:3 118:5 127:7 162:20 181:11 208:5 214:25 288:8,9 387:1	stress 302:1
sponge 126:23	start 9:15 21:1 22:17 23:16 31:8 46:24 48:8 54:3 67:5 86:10 100:3 114:2 126:6 131:11 138:7 146:21 166:20 169:16 170:2 171:11 181:10 198:17 204:20 207:22 213:5 224:5 225:8 259:19 278:5,6 287:15 300:6 313:21,25 358:16 390:4 392:18	status 47:8 69:19 182:15 263:22	stoppage 392:1,5,15	strict 209:15 304:16 315:5
sponsor 59:1 70:22 74:20	started 14:5 22:17 26:7 54:10 193:17 193:25 194:1 209:17 239:10 296:18 302:9	statistically 309:24	store 66:23 68:19 101:9 133:23,24 269:16 392:2	strictly 204:3
sponsored 58:23,25 62:20 70:16,19,20 71:4 80:9,12 81:6 90:14,24 91:8 302:19 305:6,9		staying 324:3 358:7	stores 219:6	strikes 241:13 322:18
sponsorship 2:14 53:1,5 57:1 58:22 69:19 72:11		steadfast 54:22	stories 308:4 362:20 362:24	striking 321:12
Spoon 65:22		Steak 394:23	storing 156:18 259:17	string 382:25
spread 22:25 29:17 71:22		STEM 226:16,24 231:7 235:12 240:7 241:23,23 244:23 245:1,7,25 247:7,8	story 37:9,10 84:22 84:22,23 86:9 88:9 89:7,8 126:25 183:22 186:5,24 230:7 305:23 307:15 308:6,7 311:13 321:16,19 330:7 384:11,18	stringent 164:4
spreading 393:21		stems 113:19	Stouffer 173:20	strong 5:9 74:16 98:14 115:14,24 287:9 303:10 371:14
spur 57:20		stenographer 41:22	straight 172:10	stronger 234:22,23 309:22 310:4 311:3 312:18,24 319:18 349:12
spurious 386:15		step 45:22 103:22 168:7 170:13 249:6 284:12 339:4 344:12,12 344:13,13	straightforward 78:7 117:8 138:3 152:20 153:20 230:21 235:2	strongly 114:5 123:10
spyware 368:8,9,10 370:13 385:9,12				struck 225:17
squint 234:8				structural 24:23 25:4,12 26:21 37:24 42:15 78:11
Sri 348:18 352:6				structure 31:5 197:21 198:2
Sridhar 3:17 88:24 98:13 282:11				
Sridhar's 88:23 90:2				
Sriram 4:7 324:5				
stack 317:15,16				
stacked 372:8				
Stacy 6:15				
staff 6:19 176:25 180:7 359:21 394:17				
stage 171:14				
stages 258:16				

372:20,23	151:17,18 214:13	suggestions 18:13	103:22 114:22	Switzerland 115:25
structures 218:22	subscripts 340:1	156:25 238:1	115:6 128:1	116:2 246:9
struggle 322:9	subsequent 92:20	283:6 291:11	140:22 144:20,21	symbol 98:2
struggled 226:24	312:10	315:23 322:8	147:12 150:12	symptoms 314:21
stuck 83:18 166:7	subset 10:10 32:9	347:15 349:9	155:16 164:17,24	314:21
student 101:2	substandard 324:23	389:7	180:9,12 197:17	system 19:16 51:24
182:21 258:23	333:16	suggestive 224:23	204:1 217:24	264:24 266:17
269:18 324:20	substantial 10:24,25	238:5,7 249:25	231:12,16 243:23	269:24 280:5
students 218:1	13:17 15:21 93:25	251:4	256:6 259:20	281:16
232:9 259:1	178:14 364:13	suggests 119:16	261:9 329:15	systematic 307:21
studied 327:8	substantially 178:7	185:10 207:12	335:13 352:7	347:18
studies 47:15 57:17	178:19	229:15 328:1	364:4 382:22	systematically 356:3
57:20 71:14 388:2	substantive 75:10	sum 386:18	384:1 389:5,16,17	
study 3:10 41:19	265:16 266:2	summarize 199:3	389:17 393:21	T
42:9 56:6 57:19	290:5	312:7 315:9 320:7	surge 162:12,15	T 125:22,22,23,24
121:2 175:15	substitute 96:12,13	376:5	surplus 25:23 38:22	340:2
176:14,15 177:16	186:12	summarizing	46:11 111:7 112:7	T-Mobile 174:12
178:25 197:1,7	substitutes 346:21	313:25	128:20 167:12	table 68:13 121:25
224:2 229:11,12	346:23	summary 115:18	surprise 5:16 6:2	233:11,12 234:10
243:19 244:2	succeeding 300:22	291:10 298:20,20	11:20 331:20	276:7 307:1
252:22 300:3	success 173:25	sundry 179:5	surprised 312:2	tables 232:21,22
321:24 324:25	successfully 367:15	super 114:12 115:8	surprising 48:22	234:11 307:25
357:6	succumb 74:13	380:11	259:22 356:6	taboo 222:9
studying 152:11	suck 158:2	superintendent	surveillance 205:15	tackle 24:14 241:7
326:15 333:9	suddenly 75:9	204:7	survey 11:23 12:3	241:18 283:8
335:10	Sudhir 4:15 5:15 6:4	superiority 291:17	59:15,16 60:15	290:4 334:19
stuff 34:24 40:7	6:16 388:22 390:3	supervised 272:25	71:11 184:5,7	tackling 352:21
189:25 193:2	390:4	supervision 396:6	208:9 300:4	Tadelis 362:3
200:15 203:11,19	sued 13:9 362:2	supplemental 328:7	366:10 377:15	tag 28:1 101:22
322:18 386:22	367:15	supply 307:17	378:8	tail 232:15,16
392:6	suffer 102:4 164:7	311:15 336:19,21	surveys 11:11,14	302:15 361:23
style 55:5 94:13	suffice 326:24	336:22 354:25	17:24 18:1 26:19	tailor 162:3,4
stylus 59:6	329:25	355:3,7	173:24 175:15,18	tailor-made 335:8
sub 109:24	sufficient 57:13	support 76:10	186:21,24 253:8	tailored 2:24 130:1
sub-populations	120:14	121:15 241:2	377:14 388:9	130:4,12 139:7
313:9 382:9	sufficiently 56:23	246:24 320:6	survive 158:7	142:24 151:12
sub-sample 9:13	208:14 221:17	329:14	susceptible 327:21	tailoring 130:16
sub-spaces 285:21	suggest 76:16,25	supported 54:13	suspect 171:19	Taiwan 256:11
subject 20:11 93:19	94:10 200:9	supportive 313:6,14	331:22 376:16	take 7:9 8:12 12:9
177:6	239:23 248:25	suppose 147:23	suspicious 20:4	25:3 26:21 40:6,25
submissions 6:1	250:6 346:4,6,7,15	167:2 340:22	187:10,11	41:5,11 42:15
393:18,18 394:2	suggested 26:16	supposed 12:9 19:20	sustain 121:19	43:16 46:10 67:23
submit 29:14,15,17	95:20 176:8 226:5	123:12 203:19	sweet 388:21	72:9 74:6 83:4
393:15	248:19,19,21	259:8 342:6	Swiss 101:22 115:23	94:21 95:23 98:25
submitted 20:11	251:7 252:23	sure 6:14 17:13	Swiss-made 101:23	118:7 127:12
submitting 31:13	suggesting 254:2	37:20 52:4 53:7	switch 26:15 50:25	162:23 168:6
32:8	suggestion 90:8,11	54:15 57:8 70:5	220:4 258:2	170:15,21 171:16
Subramanian 2:25	295:14 353:21	74:11 90:20 91:21	switched 258:10	181:6 183:14

203:20,22 221:13	193:6,17 200:15	targeted 245:25	114:25 117:12	tends 124:10 205:21
228:6 237:2	200:16,23 215:19	247:23 249:8	122:5 134:5,13	242:14 304:10
251:19 254:8,12	217:25 221:6,7	293:4 296:13	139:12 203:25	314:14
254:15,16 256:19	228:7,21 245:8	391:2	226:18 231:4	tension 106:20
270:17 273:4	250:10 254:6	targeting 3:16 23:15	tedious 126:1	112:21 119:19,22
277:17 280:25	261:7 269:13	35:8 44:17,25 45:8	Tel 101:1	tentatively 5:16
284:13 292:12	270:9 271:17,21	46:10 47:9 250:10	Telemarketing 10:1	term 35:14,14,16,16
324:14 331:17	274:23 276:7	258:1,7 259:13,14	television 298:22	35:18 36:8 55:24
337:3 347:6 352:4	277:6 283:5 284:5	262:14,15,16	299:3 306:6,9	186:12 226:17
374:11 380:18	291:1 292:1	263:2,3,8,9,14,16	309:20	310:18 316:20
383:16 386:24	295:14 301:1	264:1,4,7,9 265:18	tell 36:19,25 37:22	terms 10:15 35:14
391:12 393:14	302:5 313:22	265:22,23,24	40:15 41:1,22 65:5	50:6,6 51:4 57:16
take-it-or-leave-it	320:8 324:7 365:2	267:24 268:2	65:12 73:22 79:8	62:24 86:25
112:5	376:23 377:7,8	276:19,20,22	93:9 118:16	100:13 121:19
takeaway 42:18	388:14	278:24 279:22	127:14 141:3,8,14	133:17 134:16
117:5 164:14	talked 35:4 80:6	280:9 281:21,25	149:3 152:13	150:16 158:16
253:20	110:17 125:18	282:1 289:24	153:8 159:3	165:12 166:7
takeaways 364:11	133:1 149:17	293:14,17 295:15	164:21 175:4	178:2 196:11
taken 175:17 205:8	155:21 177:18	296:6,7,19,21	181:3 182:23	205:25 207:18
takes 27:18 261:13	181:9 185:2	332:24,25 343:17	183:22 187:9	220:1 232:15
263:10 272:4	192:16 193:22	343:21 349:21	194:3 197:2 198:9	240:18 252:21
274:1,2 275:17	204:6 210:16	391:19	199:5 204:6	255:3 267:2
276:10 328:17,19	218:5 231:3	taste 26:25 146:16	212:22 218:2	279:22 283:19
340:3	271:19 362:2	158:15,17	225:13 230:4,5	287:1 291:6
takeways 252:21	373:25 387:20	tastes 146:7	232:9 235:6,7,13	293:12 294:9
taliban 316:2	392:22	Taylor 213:10	235:25 236:1	303:2 305:22
talk 2:24 23:5 30:2	talking 24:16 97:10	teach 41:15	239:3 255:7 271:7	310:17,22 328:24
40:17 42:7 46:2	116:6 119:18	teaching 130:9	271:20 272:16	334:24 335:15
51:15 58:14 64:25	148:23 153:4	team 7:4,4,4 230:9	280:4 295:2,6	349:17,20,25
70:13 81:23 82:2	159:21 184:18	230:16 232:9	305:23 308:6	354:2 392:13
97:3 100:5,22,24	186:6,7 189:10	237:20 324:11	326:18 353:8	terrible 144:14
101:4 111:20	218:8 220:3	tear 327:22	359:13 367:10,14	183:3
113:16 118:18,24	222:13 242:25	tease 353:24	370:9 377:10	terrific 379:22
122:14 124:6,16	284:23 295:22	tech 225:2 229:7,9	telling 45:10 75:4	territory 50:22
130:1,4,13,22	296:12 298:13	technical 342:8	148:2 153:7 257:4	terrorism 192:1
131:1 134:22	310:15 324:18	technically 149:11	276:24 319:6	test 13:3 66:18 70:6
135:5 150:19	352:25 365:8	157:7	320:18 368:16	93:12 156:10
152:1,7 154:12,15	381:10 393:1	technician 19:1	391:11	173:16 176:11,17
154:17 155:13	talks 45:3 91:7	technique 184:7	tells 39:3,12 45:23	178:23 187:7
156:5,8,10 159:16	119:6 124:7	techniques 96:8	63:2 238:4 280:16	224:22 226:15
161:15,17,23	157:21 393:3	121:9 173:13,16	ten 111:17 171:15	230:4,6,18 231:12
162:8,17 170:22	tamper 348:7	179:23 388:13	323:4	240:21,22 241:22
172:11,14 176:2	target 29:13 31:10	technologies 109:18	tend 223:2 234:24	241:22 245:23
180:7,19 181:20	31:17 32:5 231:14	114:3	241:23 247:19	272:9 341:10,11
182:4 188:14,14	231:20 250:15	technologists 221:20	304:11,11 307:14	341:11,12 348:12
188:15,22,24	263:17 265:21	228:25	321:4,5 324:14	355:17 371:14
189:1,14,14,23	266:23 267:5	technology 15:2	384:5	tested 13:1 351:25
191:10,15 192:25	270:24	103:21 107:2	tended 233:16	testing 13:5 71:10

177:20 178:6	thanking 313:22	202:25 205:10	295:22 296:20	118:5,21 119:13
179:24 270:17,21	390:5	207:22 215:17,22	302:1,23 303:24	120:8,13,17 121:6
270:23	thanks 7:3 13:10	216:22 221:8	304:14 307:3,5	121:9,25 122:5,13
tests 337:2,5,9,10	53:11 89:9 151:19	225:17 228:6,13	312:6 319:2,17,19	123:15 125:14,23
341:24 342:12	151:20,20 210:5	230:20 231:18,24	321:3 322:20	126:5,9,10,16,21
350:13	257:1 282:13	234:16,23 241:24	328:6 337:5,15	127:7,22 128:3
Texas 127:1	298:4 324:12	243:12,25 248:3	340:19 342:9,25	131:19 132:5,5,15
text 387:15,17	340:18 347:11	250:17 251:11	350:12,12 354:6	133:2,12,17
text-finding 387:11	357:20 358:6	253:18 254:24	355:2 358:8,22	134:12,25 135:1,5
texting 203:8	378:17,23,25	266:24 275:23	359:15 362:1,4	135:6,11,16
thank 5:3,24 6:8,10	379:1	276:16,17 277:5	363:23 370:17	139:14 140:15,18
6:12,20 20:15 22:6	theft 10:3 374:13	278:10 282:20	376:3,13,21 377:5	140:21 143:22
43:3,8,11,24 48:14	theme 376:15	305:21 315:3,12	378:11 379:8	145:5 147:11
48:16,19 52:6 53:3	themselves 268:8	318:11 320:25	381:6 382:24	148:10 151:25
53:9,12 77:6,9,12	365:12	321:10 341:16	383:7 385:14	153:9,13 156:23
77:15,15 85:19,21	theoretical 79:17	349:2 350:5,16	388:24 391:13	158:5 159:5,13,15
88:21 98:8,23 99:1	104:17 150:3	353:12 354:9	392:19,23 393:6	159:17 160:14
100:6,6 118:9,14	159:13,14	355:20 367:14	394:4	161:5,14 162:11
127:12 129:5,6	theoretically 85:8	368:13,19 369:21	think 6:15 7:21	162:17 163:11
130:5 151:14,16	theories 201:5,11	374:8 380:19	11:18 14:14 15:3,8	164:23 166:10,11
162:21,23 165:15	theorist 100:11,12	385:5 386:17	16:22 18:7 22:10	166:12,19,22
166:15 168:8	theory 37:22 38:18	387:5 392:21	24:25 25:5,10,12	167:14,22 170:15
169:9,16 170:4,5,9	39:3,12 94:2 96:1	things 17:5,10 18:18	26:2,6 30:16 31:20	173:1 175:16
171:24 180:13,16	100:10 106:21	22:17 26:10 28:7	35:19 36:2 39:18	176:21 178:21
180:18 188:15,18	166:12 184:12	35:22 36:4 40:24	40:16 41:7,14,17	179:14,19 180:1,6
188:21 204:15	365:25	42:24 46:3 48:11	42:4,11,16 43:4	181:12,16,19
210:13 222:16,24	theta 136:22 137:15	48:21 50:7 51:16	45:5,9,22 46:19,23	182:1,5,13 183:8
223:5,7 224:6,13	140:16,17 141:18	52:3 77:21 81:1	47:1,4 48:1,6 49:8	184:13 185:3,5,21
244:6,9,12,13,14	thing 24:12,25 28:2	84:4 85:4 97:1	50:5,10,16 51:3,3	186:9 189:3,5,7,12
254:10,12 256:14	29:19 32:3 33:10	102:4 118:21	51:16 56:12 60:22	189:21 190:12
256:25 257:6	34:22 44:12,15	135:3 144:9 146:3	61:9,13,22 63:13	191:17,18 192:7,8
258:2,8,10,13	46:18 47:4,20	148:2,22 154:17	68:14 71:3,12,13	192:12,15,23
282:8,10 294:12	49:17 55:3 60:11	155:13,17 158:25	73:17 76:3 78:25	194:1,6,8,12 195:3
294:14 295:10	81:22 84:13 89:1	166:10 168:20	79:19 80:23 81:7	195:4,19,24
296:25 297:2	98:13 106:5	170:22 174:20	81:22 83:2 84:7	196:10,10,11,12
298:2 313:14	108:11,21 110:16	181:5 184:15	85:3,7,18,24 87:12	196:14,25 199:9
322:5,7,25,25	113:7 137:5 140:8	186:13,20 189:1	88:5,19 90:7 92:6	199:15,19 200:21
323:5 324:3,3,8,9	140:22 146:17,18	190:5,9 191:22	93:9,18 95:11	201:1,17,19,20,22
324:11 347:7	146:20 147:20	196:2,9 202:23	96:23 97:5,9,12,15	201:23 202:25
352:4 357:20	149:1,18 150:2,19	205:25 209:5	97:16 98:18	203:14 206:3,23
358:2,7,9,12	153:1 157:6	214:6 218:25	100:23 101:3,8	207:4,7 208:17,18
378:15,21 384:22	165:23 174:14	220:23 221:10	102:1,7 103:2,5,12	209:5,6,12,13,13
384:22 387:1,3	180:20 181:7	231:10 233:4	103:13 104:7,18	209:14 210:2,2,22
388:18,18 389:14	184:6 186:8	239:12,23 241:1	105:13 107:14	211:2,5,9,23
394:16,17,20	187:14 191:16,18	255:8,19 262:8	110:2,12,25	214:16,22 215:5
395:4	194:7,20 195:19	264:4 265:6	112:25 113:7	215:25 216:16
thankfully 81:13	196:1 197:7	267:19 268:9,24	114:6 116:23	217:9,11 219:12
191:4	200:16 201:17	281:11 289:24	117:1,1,8 118:2,4	219:14,22 220:20

220:20 221:2,7,10 221:15,21 222:12 222:15 225:8 226:22 227:4 228:1,13,14 229:1 229:7,21,25,25 236:7 237:8,9 238:23 239:1,7,14 241:1,2,11,15,23 242:17 243:18 244:2 245:25 246:15 247:4,12 251:12 252:22 253:19,20 254:5 254:24 255:2,5,20 264:22 269:9,9,25 270:4 272:14 277:18 279:12 281:18,20 285:18 286:24 289:6 292:2,5,14,14 293:24 294:5,7,18 294:19 295:7,14 302:23 304:22 305:18 306:11 312:3,4 313:5,13 314:9 315:19 318:5,22 319:15 319:17 320:8 321:17,19 326:23 326:24 331:10 335:15 344:25 345:12 347:13 348:2,17 349:7,11 349:23 350:4,10 350:17,19 351:15 351:19,24 360:13 360:16 361:16,19 366:11 368:13 371:13,15 374:1 376:1,15,25 377:1 377:15 378:1,9,24 379:8 382:11 383:13 384:7 385:20 387:8,10 387:21 388:2 390:5,6,19,20 392:1,17 393:3,5	394:9,11 thinking 18:10 46:24 48:8 49:3 64:19 79:22 90:14 91:19 92:6 108:18 118:25 119:7 126:14 132:19 145:1 148:6 166:20 205:21 207:15 210:17,21 216:5,6 218:4 221:16 229:2 254:1 255:2 314:7 318:25 319:20 353:24 355:6 359:11 383:19 385:14 386:7 390:14,17 392:13 394:4 thinks 43:5 205:22 third 15:18 47:17 219:3 249:10 260:25 292:17 295:25 298:2 343:24 367:25 third-party 218:10 218:18 219:3 Thirty-five 306:15 thought 36:14 81:11 85:12 89:2 106:12 126:13 128:11 138:5 151:7 157:13 160:18 166:17 168:9 178:3 182:12 228:8 243:2,3,5 277:8 285:1 295:11 352:8 380:20,20 381:16 382:24 383:25 385:5 thoughtful 75:14 120:7 thoughts 18:10 86:7 91:18 126:3 128:8 244:21 250:8 383:1 thousand 369:24	371:2 374:20 thousand-person 366:10 thousands 36:16 66:14 383:17 threatening 361:21 361:21 threats 204:9,10 206:10 335:5 336:6 337:3 340:14 three 3:9 11:12 40:3 47:7 49:24 59:9 72:9 77:21 80:25 81:4 85:4 140:12 154:17 155:13,17 181:4 184:4,15 189:23 192:13 204:10 224:1,10 233:4,18 235:1 246:9 251:18 260:15 270:5 272:14 274:2 285:16 295:22 302:8 327:23 328:18 365:7 373:15 three-day 270:16 three-prong 10:23 threshold 39:10 146:24 147:1 306:16 352:15 throw 88:25 216:9 276:20 throwaway 391:3 thrown 186:15 throws 159:21 Thumbnail 251:5,7 ticket 377:24 tied 266:18 338:12 388:12 Tim 330:8 333:5 344:2 time 5:6 12:16 14:12 23:7 25:9 26:9 27:10,22 29:12,16 29:17,18 30:22,23 30:24 37:21 38:15	39:9 40:15 43:24 44:2 48:16 49:12 52:5 63:13,14,17 65:12 68:21 70:10 73:14 77:17 80:3 81:2,23 106:23 108:17 121:16 127:7 134:8 136:15 137:25 148:1 151:23 162:19 169:10 170:21 173:11 176:7,9 181:17 182:5 184:2,9 185:24 189:17 193:14 195:18 199:17 204:17,19 208:6,9 209:19,21 210:8 211:16 212:10 213:12 216:15 217:5 221:6 223:5 224:8 224:17 236:3,6,14 239:16 261:4 262:18 263:13 268:22 269:5 271:9,15,25 274:4 277:6 280:8 281:18 286:1 289:9 295:17,25 296:15 299:25 300:8 302:6 306:6 307:8 311:18 316:9 317:20,20 318:5 324:16 332:21 340:3 342:8 344:4,17 357:7 359:4 360:7 374:16 381:1,12 381:13,20 389:18 time-specific 318:4 times 13:6 27:15 36:16,16 138:15 233:1,2 234:18 245:14 246:9 309:2 321:14 365:23 384:16 timing 139:23 316:8	tiny 51:10 tip 174:15 title 20:24 130:12 241:4 to-bumper 346:16 349:15 today 6:15 7:5 11:7 24:9 40:10 104:8 106:23 112:17 117:5 124:6 125:18 133:13 171:25 172:3 173:4 175:17 180:1 206:9 224:16 299:14 302:2 326:20,20 331:9 378:24 380:16 389:21 392:8 393:15 today's 5:20 6:11 326:13 331:18 told 35:6 62:20 135:8 145:15 251:16 256:20 258:9 266:20 279:7 325:2 329:9 337:7 353:13 356:8 363:1 393:7 tomorrow 108:3 353:19 ton 167:20 386:22 tons 327:3,3 334:22 tool 302:8 toolkit 24:23 25:12 tools 25:5 42:15,16 294:4 top 12:1 16:8 40:3 40:22 63:15 73:23 74:7 84:1 87:21,24 110:23 117:20 134:21 135:17 163:25 164:7 270:5,10,11 276:11 281:1 308:20 319:11 338:15 342:22 357:15 topic 23:23,24 53:24
--	---	--	---	---

79:3 188:25 193:7 196:21 228:24 325:10 329:6 387:22 topics 223:3 393:22 Toronto 171:9 total 11:21 246:15 246:16 310:7 totally 177:9 305:23 387:24 totals 235:22 Toubia 184:8 Tough 214:21 town 157:15,17 180:22 toy 38:5 106:18 182:24,24 184:14 Toyota 357:19 track 62:2 266:21 273:24 277:21 295:1 trackability 128:7 tracked 43:24 47:14 47:14 tracking 23:5,6,9,10 26:17 28:12 29:20 30:12 31:7 36:7,18 39:24 46:5 161:3 192:17 264:14 295:19 trackings 33:8 tracks 22:24 161:2 161:11 trade 1:1,18 2:1 3:1 4:1 8:6 9:15 171:3 172:4,8,19 173:7 177:8 180:9 221:18 347:10 358:4 363:8 traded 346:19 tradeoff 112:16 142:20 143:4 147:21 151:8 164:10 207:13 268:10 tradeoffs 222:9 traditional 65:17 172:24 179:24	285:19 325:16,17 326:3,5 traffic 23:11 trained 318:22 training 236:13 263:19 270:17,20 270:22 272:11,24 transacted 356:1 transaction 221:16 transactions 46:20 338:14 transcribed 396:8 transcript 20:7 388:24 389:2 transfer 147:17 transform 38:1 transformation 339:21 translate 88:8,15,16 90:5 92:7,23 93:6 179:23 translates 268:11 270:19 translating 87:14 90:4 translation 95:12 transmit 150:1 transparency 49:14 229:6,16 243:23 transparent 26:3 138:8 145:16 154:8 TransUnion 174:1 treat 32:22 302:3 312:19 treated 346:18,21 treatment 301:3 314:22 324:16,17 335:12,16,16,19 335:22 336:11,13 354:11 393:13 tree 182:1 288:17 trees 275:3,6,18 288:2,3,4,6,14,20 289:1 Trek 42:23 tremendously 134:1 350:1	trend 130:15 134:3 134:5,14 trends 133:15 316:17,21 317:24 322:1 374:16 triangle 40:21 Tribune 22:19,21 23:3 27:14 trick 142:1 tricked 72:12 76:8 83:9 tricking 75:2 tricky 268:8 273:7 tried 40:19 41:24 70:19 92:25 103:11,25 117:9 246:2 255:11 256:18 285:13 339:6 354:4,11 357:13 368:2 tries 275:20 301:11 trigger 13:4 trim 141:24 Tripadvisor 197:12 197:14 198:12,19 199:12,13 200:2,4 triple 251:23 tripled 251:17 trivial 139:4 troubling 203:1 true 49:11 131:21 135:9 140:19 152:23,23 165:16 222:5 245:16 250:12 251:10 272:9 341:5 384:12 truly 247:9 trust 333:19 367:25 truth 9:20 141:8,15 202:1 truth-telling 194:23 truthful 160:12 truthfully 160:10 try 16:12,21 25:8 26:22 28:16 31:6 42:10,12 43:21 50:23 53:25 56:4	60:18 126:23 139:6 149:9 152:9 152:18 153:13 173:16 175:18 178:11 180:3 186:2 192:24 193:1,8,9 209:7 221:25 224:18 229:23 230:8 231:22 234:1 241:17 242:6 250:15 267:17 268:14 277:17 283:3 284:6 285:8 315:22,24 316:3,4 318:11 327:7 334:12 336:15,16 355:2 356:1 364:1 364:2 367:2 369:7 376:5 377:7,9,17 386:14 387:8,23 392:3 trying 23:12 28:13 38:16 41:21 47:25 51:20 65:5 95:11 95:17 96:10 130:18 132:3,17 133:6 135:2 140:10 152:3,4 156:16 157:1,2 160:21 168:22 174:25 175:23 177:5 203:16 224:7 227:18 235:5 241:25 243:21 244:18 256:17,20 267:21 267:23 268:2 272:2 275:18 281:22,24 282:2 283:8,18,24,24 285:4,5 288:4 290:4 300:15,17 318:23 327:7 331:25 339:19,20 361:17 364:1 366:15 372:9,14 380:22 393:21	Tucker 3:12 90:7,10 224:11,13 254:23 255:18 256:9,17 256:23,25 294:17 294:22 322:14 391:11 turn 19:25 54:8 118:11 166:13 204:17 390:2 turned 15:16 268:25 355:9 turns 12:25 15:2 42:5 65:15 72:1 73:6 140:6 141:1 147:13 166:8 168:25 184:3 202:9 206:1,7 275:12 309:3 TV 189:10 251:3 262:23 298:15 320:13 Twelve 251:6 twice 309:4 twist 152:8 twisted 202:1 Twitter 15:6 190:4,8 two 2:19 10:16 27:18 28:20 30:1 30:25 32:12 33:15 35:14 36:4 39:6 46:3 53:14,19 58:12,12 61:13,22 63:18 67:24 79:5,6 79:17,22 80:23 81:5,15,16 85:8 86:14 100:1 103:17,18 104:14 113:17,24 115:12 117:8,11 119:6 120:14,15 121:20 121:25 122:4,14 122:20 124:4 125:22,25 126:20 126:20 131:4,10 134:14 135:21 136:17 137:18,19 137:22 138:2 139:20 142:5
--	---	--	--	--

143:16 160:13	160:13 174:11	uncheck 217:22	265:23 317:14	universities 304:11
182:11,22,25	175:2 176:6	uncomfortable	332:12 393:2	University 20:22
183:1,2,13,25	243:12 301:25,25	226:14	understands 131:16	53:4 77:10 100:4
185:15 187:2	302:1 327:15	unconsciously	153:24 164:5	101:1 118:12
188:25 191:22	338:20 354:1	229:25	understood 32:17	130:3,8 171:6,7,9
193:7 207:11	382:8,10 385:19	uncovering 143:4	undertaken 340:24	196:20 258:6
222:9 226:4	385:24 386:2	under- 247:19	undertaking 326:20	313:18,21 324:6
230:12 232:22	typewriting 396:5	251:24 254:6	underwriters	unlawful 10:5
243:4 258:3 263:2	typical 12:23 68:24	under-representa...	330:24 331:20	134:24
265:3 266:17,17	72:14,15,17 73:25	244:25	334:21 353:9	unobservable
270:17,20 286:25	74:18 87:19 88:3	under-represented	unemployment	149:20 197:9
287:9 294:19	300:10 306:14	248:23	366:24	unobservables
298:11 300:24	316:2	underdeveloped	unequal 243:14	334:13 336:7,12
304:9 305:11	typically 33:25	255:16	unethical 191:13	unobserved 25:18
314:11 324:4	119:13 125:6	underestimated	unfair 7:22 8:8,19	25:20 30:4,11,15
327:15 328:10	157:15 183:4	98:24	unfairness 8:8 9:17	35:11,16,18 36:6
332:3 334:10	291:20 292:19	undergrads 29:4	10:22 16:2	36:18 37:1 316:9
338:20 339:6	377:4	undergraduates	unfortunately 18:23	unpleasant 30:21
341:15 342:23		230:10,12	57:7 204:16	unquote 187:1
346:5,20 356:11		underlying 153:5	222:23 269:5	unravel 108:11
361:17 362:20,24		158:4,5 207:4	282:4	213:12 321:16
366:7 370:12		227:11 285:9	unharmed 92:13	unraveling 212:25
376:25 384:4		332:12 365:1	uniform 8:15,17	unreliable 354:12
385:8,10,11 388:7		underpin 179:4	uniformly 39:6	untracked 47:24
two-by-two 83:17		underserved 65:17	uninformative	unusual 38:8
two-line 299:4		understand 13:3	362:6	unverifiable 152:6
two-part 177:16		45:20 46:1 51:20	uninformed 141:7	unwilling 209:23
two-sided 262:3		61:17 64:10 65:9	142:4 143:20	213:1
two-star 200:2,3		66:8 71:12 77:19	149:11 273:16	up-sales 348:14
two-way 268:18		90:25 91:3 92:21	unintentional	update 66:22,25
285:16		94:25 140:11	227:14 242:19	68:17
two-year 16:5		151:10,12 156:16	unintentionally	updates 389:5
tying 31:1		159:17 161:15	229:25 232:4	Upende 2:25 135:5
type 11:24 35:4		162:7 168:24	236:11 245:11	135:9 151:17,19
81:24 82:20 97:22		173:16 175:1,23	uninterested 235:12	154:23
108:1 109:17,22		177:25 179:13	unique 234:20	upward 372:22
116:10 121:12,23		180:10 203:24,25	250:19 251:14	Urban 65:22
142:6 145:8		213:19 214:17	300:9	urbanization 366:23
149:21 160:9		229:24 253:23	uniquely 32:20,21	urge 82:8 386:21
167:18 176:5		265:17 266:9	unit 27:6 71:19	urgency 353:18
220:10 302:2		267:7,23 337:8	United 27:24 50:13	urging 15:4
307:4,5,22 314:8		360:13 380:12	54:6 65:22,24 66:3	Ursu 88:12
314:18 355:13,15		385:2	175:19 181:1	USA 118:11
378:6 380:8		understanding	255:12 319:22	usage 260:4,5,12
types 12:1 32:17		16:21 17:19 94:4	uniting 135:16	use 10:16 17:5 24:20
42:6 101:5 103:18		132:24 142:23	univariate 381:22	24:23 25:6 28:5
103:18 115:22		163:6 176:20	universal 235:10	42:22 56:2 67:6,23
117:11,14 149:12		178:23 212:10	universeness 210:22	78:11 91:20 117:9

130:19 132:19,21 135:2 136:7 142:21 159:18,24 160:4 161:6 163:5 164:2 172:12 173:13 174:2 176:5 177:3 179:1 180:24 187:17 189:21 190:17 192:9 197:20 198:22,23 202:5 204:3,5 206:1,4,11 211:10 212:2 215:3 217:19 224:22 225:25 241:8 260:19 261:4,4 263:3 266:21 270:13,14 271:3 273:3,18,19 275:3 276:5,6 282:12 284:3 285:8 286:15 300:1,4,6 306:16 359:7 363:2,24 365:16 387:21	user-level 295:16 user-resettable 271:7 user-specific 276:25 users 24:1 25:17 27:3 30:10,13 31:4 31:11,12 32:9,14 32:17 33:16 35:8 42:7 67:13 68:24 71:11 234:20 259:23 264:14 270:16,18 278:11 278:22 295:19 uses 38:8,14 190:7 usual 93:19 298:7 usually 22:17 25:6 160:22 189:13,22 191:10 192:4,5,12 203:10,10 269:18 299:10 369:2 UT 151:17,19 utilities 137:24 177:5 utility 92:11 93:7 137:1,2,2,6 138:23 147:17 151:4 186:9 214:15,19 214:23 215:7,15 215:24 216:8,10 217:8 utilization 137:25 utilize 161:16	valuations 35:13 38:4,7 value 3:15 44:11,16 44:17,22,24 45:4,7 49:10 50:24 74:1,4 74:12 83:25 86:20 87:2,6 103:14 105:10 107:17 108:4 109:1,2,5,10 110:4,9 112:14 114:16 116:11,15 116:18 128:1 186:11,12 220:19 222:5,12 238:14 258:1,6 259:12,15 266:5,6 278:10 282:1 283:16 284:11 292:8,10 293:13 340:4 356:1 values 44:8 45:1 74:5 132:18 207:5 207:11 246:10 van 150:9 variability 274:8 variable 275:24 276:1 286:1 321:11 340:3,8,11 342:16 355:18 371:25,25 variables 263:15 272:22 275:25 276:2 284:5 285:6 285:11,23,24 286:25 289:24 355:12 357:14 variance 36:5,20 365:15 variants 274:8 variation 197:11,20 248:9,11 255:11 280:14,19 293:7 320:5 322:4 333:13,24,24 334:6 338:18 339:2 340:9 347:18 348:4 354:15 355:18	370:22 varies 35:15 314:7 variety 212:23 239:20 various 35:22 47:10 47:15 55:12 57:9 229:4 322:21 vary 26:5 36:8 231:11,13 336:19 360:20 365:14 366:6 369:22 372:10,16 374:10 vase 240:8 vases 239:21 vast 289:7 vector 317:17 vehicle 9:20 327:15 327:20,23 328:3 330:6 333:7,11,15 333:17,21,23 334:24 335:17 338:3,8 340:2,4,12 342:18 345:24 348:6,21 349:1,3,5 351:10,13 353:2 355:14,15 356:1,3 356:22,24 vehicles 334:2,8,9 334:11,16,18 336:21,22 345:10 346:1 348:10 354:13,16,17,18 354:21 355:3,7,7,8 355:10 356:20 vendor 244:18 Venkataraman 4:7 324:6,9 330:11 336:21,23 344:6 344:11 352:7,20 353:8 354:4,9 355:1,23 356:7,15 356:17,19 357:11 verifiable 155:6,6 155:15 verification 209:3 verified 244:17 verifies 197:15 verify 155:22	version 38:18 124:12 127:10 180:25 185:25 202:1 260:22,23 275:5 versions 177:21 versus 51:5 62:8,20 64:16 80:9 81:6 83:10 90:24 91:5,8 117:12,17 121:17 121:23 126:17 128:25 178:15 199:25 205:6 222:7 245:4 251:8 278:11 293:24 308:1,2,16 319:23 320:3 322:16 325:16 356:4 372:7 vertical 122:15 150:21 157:19,22 vested 160:2 victim 363:2,19 368:20,22 369:4,8 369:14,21 370:5 370:15,19,21,25 372:7,10,15 373:5 375:5 380:8 victimization 375:2 376:20 382:3,10 382:15 victimized 364:3,24 victims 11:18 12:2 175:21 363:14 367:8,12,24 368:6 368:11,15 369:6 369:12,18,24 370:3,10 371:2,6 373:11,23 375:1 380:5,14 victory 13:21 video 7:5 200:17,22 view 54:2 59:13 156:24 159:20 160:17 181:24 207:15 290:14 353:17 361:11 viewable 49:18
useful 45:12 60:22 65:6 77:18 81:21 83:2 85:9,10 89:3 108:6 110:1 117:23 127:23 209:5 214:11 229:2 274:12 290:2 294:1 386:14 user 27:9,23 29:20 32:25 35:19 36:15 36:16 44:17 45:8 56:25 68:19,21 262:17,19 263:4 263:11 264:11 267:2 271:8,24 274:4,16,17 279:23 280:5 289:21,25 358:22 359:1,3 user's 35:20 user-generated 322:20	V v 173:19,20,25 174:1 vague 282:23 valid 285:10 validity 249:24 337:2,18 Valley 127:1 valuable 81:23 97:1 227:15 276:25 277:3 281:10 283:21 289:23 290:1 385:18 valuation 38:1,20 145:14,18			

viewed 245:4	walk 184:23 286:1	220:16,16 221:4	325:7,15,16,18,19	24:19 26:20 28:21
views 172:2,4	340:1 342:8	222:16,24 228:6	325:19,22 326:3,4	29:6,15 31:15
vigorously 281:19	378:22,22 394:22	230:5,23 231:11	326:16 327:14,16	32:15 39:19 42:20
Villofler 6:22	walking 19:3 185:5	232:8 233:4	328:8,11,11,12,14	44:7 45:6 50:10,16
vineyard 101:10	185:5,17	238:25 240:3	328:25 329:3,7,17	51:19 58:3 59:13
vintage 355:13	want 6:10,12,20 7:9	243:10,17,25	329:19 330:5,10	60:9,18 61:8,10,11
violate 208:3	8:12 15:14 16:20	246:3,4,6 247:1	330:17,25 331:6	64:18 65:7 68:5
violated 14:15	17:11,14 18:9 19:4	248:18 249:2,4	331:21 332:1,5	70:15 74:4 75:3
violators 16:15,17	19:5 20:15 22:6	253:1,15 254:13	333:1 334:4,22	76:4 79:2 80:15,18
16:23 17:6	26:24 28:15 32:5	257:5 260:17,22	338:9,19,20	80:21 82:13 88:18
violent 384:3	37:14,25 38:21,25	262:10 265:17,20	340:13 341:21	92:11 93:17 95:13
virtual 193:12	43:18,18 45:22	265:20,24 266:5,9	342:19 343:8,10	96:23,25 97:2,14
visibility 107:7	46:18 51:23 61:3	266:10,11,16,24	343:23 344:4	97:16 98:11,16,17
visible 262:2	70:7 76:22 80:8	267:6,8 268:12,15	345:8,11,16 346:9	103:11 104:18
vision 71:14	82:16 84:5,9 85:5	272:12 273:10	346:11,16,17,17	120:8,13 121:5,7
visit 75:12 83:21	85:16 95:1,23 96:1	277:21 278:3	355:5 356:9	122:14 123:3,6
84:19 141:12	96:9 102:22	279:17,18 285:7	warranty 4:7 324:2	128:22 133:11
162:13 164:8	104:12,13,15	286:5 301:14	325:17 326:6	139:12 145:5
217:5,6 391:20	105:15 106:8,18	307:2 328:7	327:16,17,25,25	147:11 150:2
visited 22:21 23:2	108:3,12,25,25	329:10 350:23,24	328:1,13,15,17,23	163:17 182:1,10
28:13 85:1	109:2 110:3,15,20	351:5,11 352:6	332:4,7,8 333:1,2	184:13 190:16,17
visiting 75:11 81:10	113:16 114:17	358:9 360:17	333:11,12 335:1	196:6,25 205:25
162:14 180:21	116:3,11,12,13,19	364:4 368:19	335:17,18 338:24	207:18 208:3
visitors 66:5,6	116:21 117:14	369:20 371:9	340:7 341:9 343:9	210:3 211:22
visits 27:24 299:22	120:19 121:7	373:25 377:8	343:12 344:9,9,15	213:6,7 215:25
visual 88:25 89:5	124:21,23 126:18	379:12 382:22	344:20,22 346:10	216:21 217:3,9
visualize 31:11 39:5	127:8,20,24	383:13 386:9,24	347:19,19 348:4	218:24 219:22
Vita 15:1	128:20,23 130:24	387:6 388:23	348:11,22 349:3,6	221:24 226:1
voice 358:18,19,23	134:19 135:21	389:5,14 392:2	349:8 350:8,18	227:25 228:3,8
359:9,24 360:2	138:11,12,16	wanted 40:15 44:3	351:1,4,7,10,13,14	229:14 233:11
365:24 381:5	140:8 145:7,8,20	44:12 70:4,6,11	355:22 356:23,25	241:25 244:19
voiced 361:24	146:4,5 151:6	84:7 86:7 96:14	357:10	247:11 253:14
Volkswagen 12:23	153:9,14 154:1,1,4	100:20 110:21	Washington 1:21	255:2,9 261:2
12:24 13:10,14,17	155:10,11,15	128:1 136:16	258:6	264:25 274:10
24:8 101:25 106:1	159:22 160:4	143:24 163:12	wasn't 88:23 195:5	275:19 276:2
106:10 114:10,23	161:22 162:7	172:6 200:17	256:6 282:19,22	284:8 289:13
114:24	165:2 168:4	232:3 234:16	315:3 329:5	294:7 298:24
volume 284:7	170:21 176:8	246:20 271:21	357:17 381:6	303:6 305:11
302:12	178:8 180:14	277:25 294:17	382:18	311:24 315:14
voters 153:14	181:5,7,10 185:19	296:18 382:7	watch 9:5	318:7 319:21
VPNs 278:20	186:8,13,14 187:3	392:25 393:11	watches 115:23	322:23 325:6
vs 137:2 138:13	187:14 188:7	wants 32:18,18	watching 14:22	326:17 329:9
vulnerable 182:10	195:20,21 200:9	104:14 106:16	watchmakers	334:18 335:1
	200:15,16 207:6,6	132:6 196:2 238:5	101:22	336:5,24 341:4
	210:2 214:11	239:4 282:6	water 184:21	343:23 350:25
W	215:9 216:13,19	289:12	wave 239:23	351:2,7,8 352:1
wait 19:6 43:19	218:14,15,16,17	warrant 331:5	waving 239:10	353:24 355:17
217:14	219:25,25 220:5,8	warranties 324:8,24	way 17:25 19:21	371:3 377:22
waiters 359:22				

382:2 390:11	234:3 235:3 236:9	299:11 303:7	91:12	women 226:6,22,25
ways 28:20 71:15	236:17 237:5,14	325:8,9 377:21	whatsoever 108:16	227:3,6,9,15,20
93:18 183:25	237:17 239:19	388:25 389:3,12	345:20	231:20,21 233:2,3
207:11 226:8	240:17 252:1,15	389:13	whichever 327:24	233:6,8,20 234:13
234:19 263:2	259:13 260:25	websites 40:3 217:5	328:5,20	234:14 235:9,11
363:23 391:8	265:16 282:2	217:5 248:25	white 23:20 144:15	235:16,17,19,24
we'll 18:18 19:23,25	294:14 300:15,17	251:5 301:21	157:10 250:1,6	236:2,6,14,23,24
20:2,3,7,15,17,19	301:12 303:4,5,5	302:24 304:3	287:17 361:1	237:1,14,18,22
43:21 52:5 53:3	303:15,18 308:9	306:1 308:16	who've 185:2	238:11,14,17,19
98:25 100:3	309:16 310:1,15	313:12 315:11,12	wi-fi 18:21	238:19 239:2,6,9
132:19 134:21	313:2 324:21	week 59:17 257:3	wide 239:20 269:24	239:11,19,24,25
138:16 141:18	326:9 331:13	361:16	widely 357:8 369:22	240:4,5,12 241:25
162:23 169:7,16	333:24 334:6	weeks 103:1 391:22	393:22	242:2,11,16 243:5
170:6 171:17	336:1,2 354:19	391:23,24 392:4	widespread 12:9	246:6,13,21,21,24
191:15 204:19	358:17 364:1	392:11	wife 60:5	247:6,6,19 248:21
215:19 221:20	376:7 380:15	weight 12:3 94:22	wild 49:21	249:7,11 250:3,7
223:7 224:8	389:2,4 394:1	95:8	willful 142:13	250:10,11,14,16
254:12 258:2	we've 53:25 74:10	weighting 377:25	148:13	250:22,24 253:2,4
301:23,24 302:2	174:4,24 175:15	378:9	Williams 245:16,18	254:18,25 255:16
308:5,11,13,15	175:22,24 179:5	weights 378:4	245:20	255:22,25 256:1
310:19 322:11	180:4,5 192:16	weird 221:8	willing 13:14 47:14	256:12
323:3,4 358:2	206:8,16 208:2	welcome 2:5 5:1,6	207:18 212:7	women's 245:17
389:13 394:21	211:17 218:7	213:15 389:10,13	218:20 220:9	wonder 168:15
395:2	225:15 227:1	395:4	240:15 242:13	194:1 293:20
we're 8:16 9:13 16:4	228:8,22 238:2	welfare 24:12,13	252:1,20 361:5	315:17 322:16
34:17 38:3,3 50:13	241:3 242:24	49:2 76:23 77:2	willingness 6:7	355:19
50:22 56:4 58:6	255:2 303:11	92:10,12,25 93:8	98:24 107:15	wondered 238:13
60:18,25 61:4 62:2	306:18 308:17	105:17 131:2	111:4 116:9 163:8	291:13 292:8
62:3 81:1 87:9	322:21 340:23	144:24 147:10,12	179:20 220:15	wonderful 90:15
95:17 98:25 121:4	368:5,11 369:5	147:15 160:17	win 39:1 231:6	172:1 180:23
130:25 131:3,21	375:11 378:24	182:9,9 188:5,22	334:25	225:15 230:6,14
133:13 134:12,14	393:6	189:19,21 191:14	win/win 209:1	230:19 232:9
134:23 135:19	weak 319:10	195:4,5,6,7,8,13	windows 77:13	237:20 241:13
136:2,10,11	weaken 278:1	196:11 313:2,2	358:13	282:14 295:7
137:22 138:18	weaker 105:9	well-known 60:10	wine 101:9,9,10,12	313:22 322:24
139:1,4 140:7,22	wealth 386:10	well-meaning	122:2	378:24 392:12
142:13 148:6,21	wealthier 188:1	178:20 179:12	WinFixer 368:7	394:18
148:22 149:15	wear 8:15 327:22	Wellesley 230:14,16	370:13	wonderfully 379:24
150:22 159:15	web 10:6 23:8	230:20,25 232:9	winning 293:3	wondering 33:18
170:2,15 173:2	webcast 20:10	237:21 244:10	wire-tapped 205:13	98:4 177:12
189:19,20 196:14	WebMD 304:3	went 83:23 87:23	wish 174:20	317:18 354:24
207:12 209:22	305:5	204:13 217:1	wishes 214:9	357:5
215:17 216:1	webpages 28:16	238:18 248:25	withdrew 367:20	word 59:1,2 70:16
223:4 224:4,7,16	102:18	weren't 95:5 237:15	within-restaurant	70:16 71:4,5 90:13
224:17,21 225:11	website 14:7 20:8,13	301:3 368:3	82:5	90:24,25 91:21
227:4,4,14,22	40:25 51:14	west 49:22	woman 234:24	190:1,17 193:8
231:9,13,16,20	216:15,25 231:3	whatnot 55:17	240:16 247:7	194:4,22 206:8
232:1,6 233:25	252:10 261:14	59:18,24 75:1	woman's 251:8	241:8 251:19

321:21 335:14	84:24 127:15	151:5 184:5	49:8,21 59:21	yesterday 13:25
worded 292:15	274:1	251:10 254:1	63:10 64:9,13	37:18 57:8 159:22
words 20:25 78:24	Workshop 14:1	326:15 383:5	71:15,16 87:1 89:9	162:10 180:1
92:2 240:11,16,23	world 15:19 17:10	worthwhile 50:8	91:12 97:8 98:15	206:10
286:14 385:6	24:23 25:9 32:16	143:10,23	100:6 102:25	yesterday's 159:6
work 6:3 9:2 24:15	35:24 38:5 39:6	wouldn't 6:6,23	106:22 110:4,14	yield 52:5
26:6 39:13 40:15	49:25 61:14,16,16	220:12 229:13	112:13 127:21	Yik 204:11
57:23 76:14 84:23	61:19 62:5,19,21	237:13 262:7	128:15 150:24	Yoganarasimhan
100:10,25 103:1	64:21 69:17,19	392:12 393:23	168:5 187:24	3:16 258:5,8 259:6
105:19 117:7	76:13,18 78:15,16	wow 50:9 140:15	196:9 200:7 211:1	259:11 294:20
125:11 131:24	86:19,21,21 87:1	243:2 269:11	211:7 219:11	295:10,21 296:9
139:13 155:1	90:17 91:2,3 93:2	275:1	254:23 256:23	297:2
159:23 160:16	95:14 132:5 167:3	wrapped 224:15	259:6 308:17	York 27:15 384:16
174:15,17 180:5	167:15 169:7	wrestle 51:21	310:14 322:14	young 172:18
180:12 181:9	179:21 180:13	write 196:22 245:15	344:13 349:14	202:13 203:24
187:3 194:11	181:19 182:23	272:12 360:8	353:8 354:4,9	227:15 233:8
209:17 224:14	207:7 217:2	365:10,12	355:1,23 357:5	240:4
230:10 253:13	221:20 228:21	writing 41:22	378:21 384:17	younger 233:21,22
258:22,24 267:13	231:15 236:20	188:11 379:7	387:25	238:20 242:11,11
271:2 284:6	237:3,10 240:11	391:17	year 11:22 13:9 14:7	311:3 312:18
289:23 291:8,16	241:9 244:1	written 24:6 236:2	14:16 15:17 41:6	334:16 345:10,24
294:18 296:1	251:21 252:7,8,14	249:21 295:8	183:8 191:23	Yu 101:1
298:5 324:19	259:23 262:24,24	360:7 392:10	204:4,11 263:23	
336:25 346:3,13	276:4 298:11	wrong 17:13 182:8	269:11 306:18,24	Z
358:19,25 365:6	worlds 61:14,23	194:17 195:23	315:5 331:13	zero 37:17 45:4,8
365:19 379:19	201:7	208:3 209:4	363:11	73:14 107:19
387:16 389:20	worried 189:19,20	352:24 388:11	year's 316:23	109:25 137:9
390:24 391:4	191:2 228:20	wrongdoing 17:3	year/month 310:14	222:9,10 293:19
393:10,25	267:19 316:17	wrote 391:24	years 7:6 8:10,12	369:2,3 371:11
work-at-home 12:6	317:10 318:21		29:8 34:25 172:10	Zettelmeyer 76:15
worked 11:10	385:17	X	172:22 173:15	zillions 274:25
173:21 174:10	worries 191:19	X 2:2 3:2 4:2 35:14	174:25 178:22	zip 215:3 216:22
175:12,23 176:12	192:5,5	36:20 145:13	180:21 183:1,2,13	217:22 363:21
189:2,2 209:19	worry 142:16	369:22 374:18	193:24 205:5	366:17 367:2
225:1 230:19	190:10 205:10		208:2 209:18,18	368:22,25 369:24
231:19 269:8	215:20 241:25	Y	216:11 251:6,7	371:11 380:2
273:21 275:7,12	243:3,13 264:2	Y 36:17 145:22	264:24 302:9	Zomato 65:14,15
299:24 319:3	348:5,5	369:24 371:25	306:15 327:5,23	66:5,10 67:13
336:10 389:17,17	worrying 316:14	374:19 375:10	328:4,18,19,20	Zomato.com 66:12
389:18,18	worse 131:25 178:1	Yahoo 27:23,24	336:2	71:20
workers 287:1	255:23 264:25	28:15	yell 37:21	zone 71:18
working 40:16 94:9	266:22 278:13,14	Yahoos 49:24	yellow 58:20 69:1,3	zoom 67:16
136:10 180:8	327:4 362:18	Yak 204:11	69:4 89:1	Zvika 2:21 100:25
209:17 268:12	worse-off 290:14	Yakov 130:7	Yelp 58:13,19 59:18	
275:25 293:18	worst 168:16 194:20	Yale 6:16 100:4	66:2,6 359:12,14	0
295:3 296:18	195:1	101:2 196:19	359:21 360:6	0 139:11 142:18
workings 230:20	worth 47:4 112:8	Yaniv 196:20	Yesim 2:17 77:10	305:7 370:7
works 75:2,3 76:1	126:2 143:24	yeah 33:6 37:4,15	85:21 87:19	371:21 375:12

002 74:2	210:10,11 338:15	2012 14:6 15:13	35,000 343:25	372:4,4 373:22
01 29:3 37:10	394:22	374:12	35,200 343:18	377:16 384:8
05 74:4	15.2 277:14	2013 14:8 24:5 40:5	350 50:12	50-plus 393:17
09 184:23	16 1:13 306:1	2014 14:23 65:15	358 4:10	500 368:6 370:6
<hr/>	17 369:16	66:9,20 67:2	36 338:25	53 2:14
1	17.7 270:19	173:10 329:6	36,000 327:23	55 333:20
<hr/>	170 3:6	338:3 339:10	328:18 343:18	55-year- 247:20
1 31:21 139:11	18 202:8 260:2	2015 56:20,21 65:21	347:20 349:15	<hr/>
142:18 340:4	18- 230:24 245:25	66:5 374:12 390:6	352:9	6
349:16,17	19-year 230:24	2016 1:13	37 199:13	6 67:14 306:11
1-800 299:7	190 226:19 232:1	2018 51:20	37.8 11:21	6.8 40:6
1,000 36:24 368:11	236:10	20K-odd 338:17	373 302:9	6:00 394:21
1,500 367:24	191 231:14 248:5	22 2:9	38 268:18	60 26:18 75:12
1,500-way 285:17	1914 9:15	224 3:10	390 4:15	306:9 373:21
1,600 268:20 275:25	1968 9:20	25 15:11 20:17 39:9	<hr/>	60,000- 347:23
1.01 39:1	1970s 172:20	53:7 234:15	4	60,000-mile 348:24
1.5 40:12	1972 9:21	248:22 260:8	4 51:17 260:18	613,000 14:9
1.7 24:4	1978 9:24	370:20 372:4,4	279:25 299:14	622 71:22
1:50 223:7	1980 10:22	373:10,22	4,000 367:13 369:1	64 391:22,24 392:3
10 8:12 13:13,15	1983 10:16	25- 247:20 368:24	4.5 299:14	392:11
20:18 22:22 30:24	1997 298:18 306:7	25,000 270:7	4:05 323:5	64-week 392:10
47:11 202:14	19th 54:5	25.6 11:17	4:30 167:9,10	65-year-olds 246:1
308:21 309:2	1st 394:25	250 270:8	40 13:6 20:16 25:24	660 299:13
321:14	<hr/>	258 3:15	39:23 40:11 48:24	<hr/>
10.8 11:16	2	27,000 270:18	178:22 329:18,19	7
10:45 99:1	<hr/>	298 3:19	371:8 373:17	<hr/>
100 2:20 7:6 8:10	2 40:12 186:4	<hr/>	400 1:20	7 186:2,2 259:25
23:1 47:19 52:1	259:23,24 308:22	3	44 247:16 248:22	7.9 24:5
66:4 136:1 370:4	330:22 367:23	3 51:17 308:22	47 338:23	7:30 6:20
370:11 371:20	2,000 351:5,12	330:22 343:13	48 186:22	70 8:17 9:10 300:4
372:4 373:7	2.8 260:2	349:15	48,000-odd-miles	70,000 368:6
375:25 390:21	2/28 183:1,15,17,21	3,000 68:9	343:24	72,000 328:4,18
100-plus 391:22	184:16 185:20	30 50:13,20 172:10	<hr/>	75 68:11 372:4,4
100,000 221:5	2:00 167:8	178:22 200:4	5	373:7
328:20	20 12:1 40:6 97:13	217:5 306:10	5 2:6 260:18 278:25	76 306:20
101 273:12 394:24	227:2 242:3 246:7	351:3 373:17	279:25 372:3	78 300:6
11 24:6 40:10 50:11	294:14 330:15	384:8	375:12	79 333:20
202:8,14	20-year 14:16	30- 183:7	5,000 231:17	7Pi 137:17
11-year-old 203:3	200 16:6	30-year 183:11	5:00 167:8	7th 19:24
11-year-olds 203:7	2000 194:1 216:18	30,000 344:13	5:37 395:7	<hr/>
12 251:6 367:12	2000s 306:8	368:25	50 6:1 15:11 32:1	8
369:16	2001 191:2	300 139:15 370:6	48:24 75:12 217:5	8 308:24
12:30 169:16	2002 24:4 222:14	300,000 368:11	246:13,20,22,24	8:30 1:14
120 66:4	2008 184:23	31st 393:9	260:10 270:6,10	8:37 5:2
13 261:16	2008-2012 366:18	32 305:25	270:11 281:1	80 5:11 30:22 66:5
130 2:24	2009 338:3	321 71:17,22	304:5 307:10	270:11 370:11
135 271:2	2010 299:13	324 4:6	330:24 337:25	371:8 373:10
14 329:6	2011 11:16,22	34 234:15	370:20 371:20	85 75:6 338:16
15 12:1 111:16	306:11			86 330:4

9

9 270:20

90 47:16 371:20

91 305:13

96 299:12 305:15

97 299:1

98 186:23

99 38:25 96:7 135:7

194:1