

Targeted Digital Advertising: Challenges and Promises

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Wannamaker's challenge

“Half the money I spend on advertising is wasted; the trouble is I don't know which half.” John Wannamaker (1838-1922)

- But targeted digital advertising was supposed to change all that.
 - **Display Ads:** The “new” newspaper/billboard ads, better targeted to interests
 - **Video Ads:** The “new” TV ads, better targeted to interests
 - **Paid Search:** Signal of intent + some demographic data + possible interests
 - **Social Networks:** More demographic information + possible interests
- Was Wannamaker's challenge solved by targeted digital ads?
- Do businesses, especially SMBs, benefit from targeting?
- How should we consider privacy and its impact on welfare?

Paid Search Advertising

- **-80% ROAS!** (**-100%** for own-brand KW)
- Heterogeneous responses consistent with informative view of advertising:
 - **Less informed consumers** are well worth advertising to (> 100% ROAS)
 - **But informed consumers** make it cost-ineffective for a well-known brand
- Likely much better for SMBs but very hard (impossible?) to measure

Econometrica, Vol. 83, No. 1 (January, 2015), 155–174

CONSUMER HETEROGENEITY AND PAID SEARCH EFFECTIVENESS: A LARGE-SCALE FIELD EXPERIMENT

BY THOMAS BLAKE, CHRIS NOSKO, AND STEVEN TADELIS¹

Internet advertising has been the fastest growing advertising channel in recent years, with paid search ads comprising the bulk of this revenue. We present results from a series of large-scale field experiments done at eBay that were designed to measure the causal effectiveness of paid search ads. Because search clicks and purchase intent are correlated, we show that returns from paid search are a fraction of non-experimental estimates. As an extreme case, we show that brand keyword ads have no measurable short-term benefits. For non-brand keywords, we find that new and infrequent users are positively influenced by ads but that more frequent users whose purchasing behavior is not influenced by ads account for most of the advertising expenses, resulting in average returns that are negative.

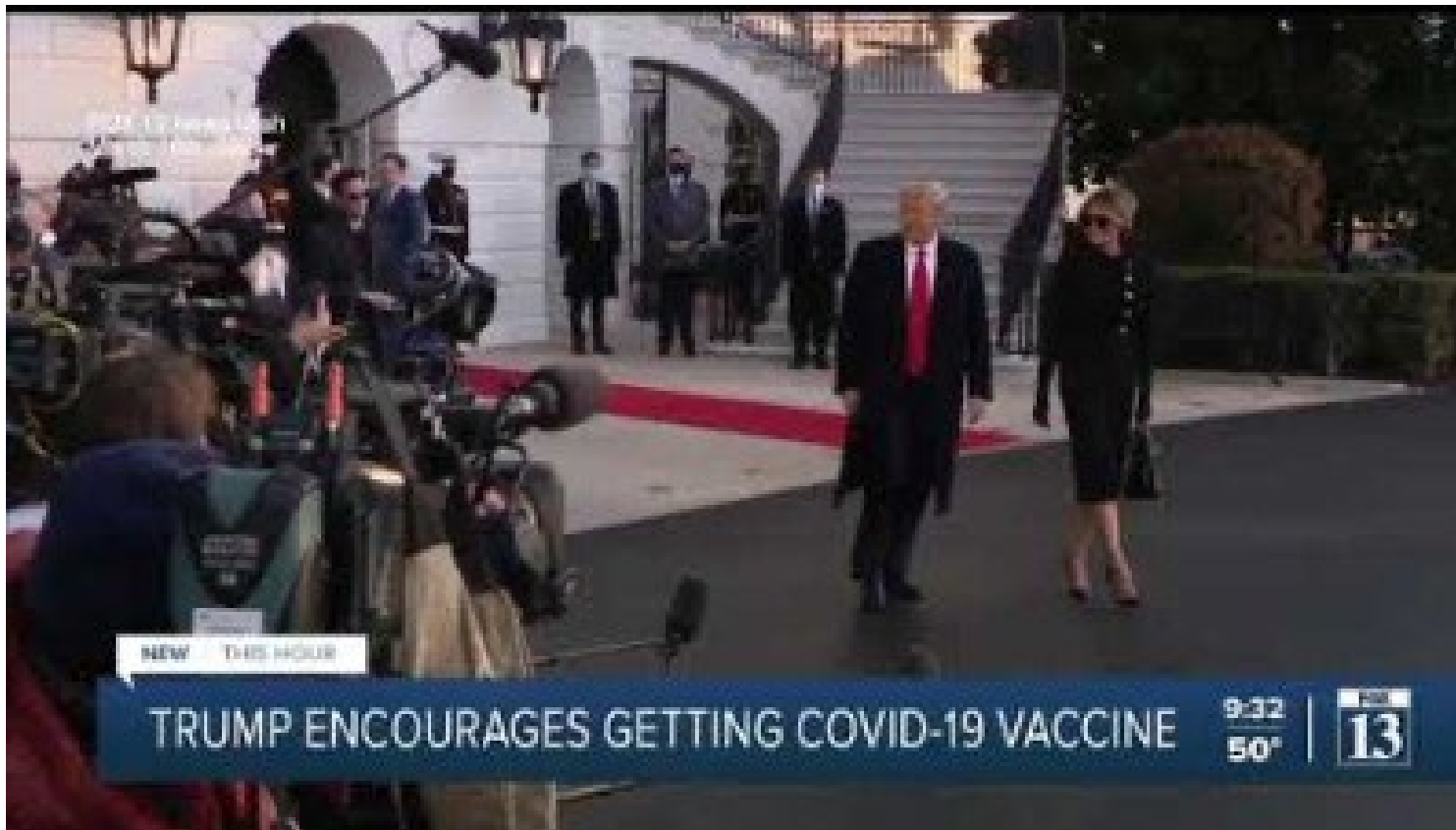
KEYWORDS: Advertising, field experiments, causal inference, electronic commerce, return on investment, information.

1. INTRODUCTION

ADVERTISING EXPENSES ACCOUNT for a sizable portion of costs for many com

Targeted Video Ads: An Attempt to Increase Vaccines

Using Politics to Solve a Problem Caused By Politics



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RESEARCH ARTICLE | SOCIAL SCIENCES



Counter-stereotypical messaging and partisan cues: Moving the needle on vaccines in a polarized United States

BRADLEY J. LARSEN, TIMOTHY J. RYAN, STEVEN GREENE, MARC J. HETHERINGTON, RAHSAAN MAXWELL, AND STEVEN TADELIS [Authors Info & Affiliations](#)

Ad Campaign Details

- Selected about 2,000 low-vaccine (<50%), small (<1M resident) counties
- Randomly assigned half to *treatment* (i.e., **eligible to** get this ad on YouTube) and half to *control* (not eligible to see ads)
- Spent close to **\$100,000** on YouTube from Oct 14 to Oct 31, 2021
 - Got **11.6 million ads**, costing **\$8.55 per 1,000** ad impressions on avg
- Hit over **6 million unique viewers** (some saw it more than once)
 - 52% on phones, 30% on TV, 13% tablets, 4% computers
- Ad played on **150,284 distinct YouTube channels**
- **Primary targeting was by location (later excluded age 18-24)**
 - possible by age, gender, income, parental status, location

Cost Effectiveness was very high!

- The average treatment county had an increase of **102.6 vaccines**
- 1,014 counties were treated
 - Implies a total increase of 104,036 vaccines
- We spent \$96,408.56 (less than \$100 per county on average)
 - **Implies a cost of \$0.93 in ad spending per vaccine!!**
 - Much cheaper than other attempts to increase vaccination rates!! (\$24-\$82)

Analyzing the effect of **treatment intensity**

- Can't just replace $Treat_i$ dummy with the number of ads!
 - **Possible endogeneity:** Google may be sending more ads to counties that are more receptive (more likely to get the vaccine)
- We follow Angrist and Imbens (1995), using instrumental variables to estimate the effect of increased treatment intensity

$$y_{it} = \alpha + \lambda_t + \gamma_i + \delta(Ads_i \times Post_t) + \eta(Population_i \times Post_t) + \varepsilon_{it}$$

where we instrument for $Ads_i \times Post_t$ using $Treat_i \times Post_t$

- $\hat{\delta}$ is the coefficient of interest, the average causal response (ACR) to an increase of 1,000 ads per county

Measures of treatment intensity (Persuasion?)

Treatment Intensity Measure	Engagement Rate (1)	View Rate (2)	Click Rate (3)	Ads per 100 Residents (4)	CPM (5)
A. Controlling for Population × Post Dummy					
Average Causal Response	8.255* (6.333)	12.34* (9.467)	94.12* (72.11)	48.37* (37.10)	4.877* (3.742)
Pop. × Post	275.5*** (18.70)	275.4*** (18.70)	275.0*** (18.74)	274.8*** (18.77)	275.4*** (18.71)
B. Controlling for Population × Date Dummies					
Average Causal Response	8.153* (6.335)	12.19* (9.469)	92.96* (72.12)	47.77* (37.10)	4.817* (3.742)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	151945	151945	151945	151945	151945

Engagement rate = fraction of users watching at least 10 sec.

- a 1σ increase in engagement rate results in 8.255 vacs

View rate = fraction of users watching the full ad

- a 1σ increase in view rate results in 12.34 vacs

Click rate = fraction of users clicking on the link to the original Fox News story

- a 1σ increase in click rate results in 94.12 vacs

- a 1σ increase in **ads per 100 residents** results in 48.37 vacs

- a 1σ increase in **CPM** results in 4.887 vacs

Social Media Ads: Do they help businesses?

- How easy is it for businesses to understand how well their ads are doing?

“some producers seem to have figured out their business (or at least are on their way), while others are woefully lacking.”

(Syverson, 2011 p. 327)

?? $\text{Max } \pi$??

- **Questions:**

1. Can variation in marketing effectiveness explain some of the huge variation in revenue generation and profitability per unit of input?
2. Can this shed light on “levels of sophistication” and “learning”?

- **Answers:** Yes and yes!

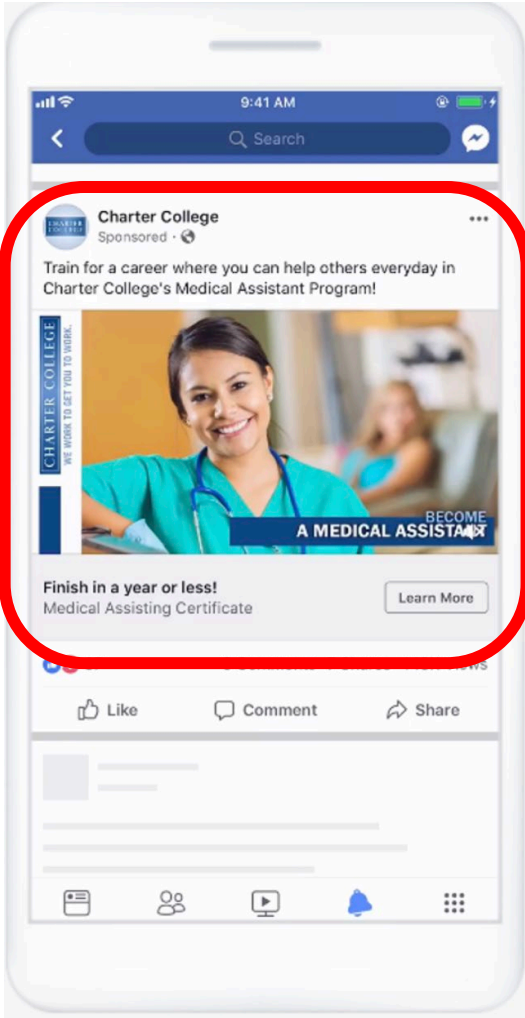
Learning, Sophistication, and the Returns to Advertising:
Implications for Differences in Firm Performance*

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Nils Wernerfelt[‡] Nick Dadson[§] and Lindsay Greenbaum[§]

April 2023

Ad Campaigns on Meta: Creative, Objective, Targets, and Budget



Budget & schedule

Budget ⓘ

Daily Budget ▼ \$250.00 USD

You'll spend up to \$312.50 on some days, and less on others. You'll spend an average of \$250.00 per day and no more than \$1,750.00 per calendar week. [Learn more](#)

Schedule ⓘ

Start date


Oct 27, 2022 10:00 PM
Pacific Time

End - Optional

Set an end date

Choose a campaign objective

- Awareness
- Traffic
- Engagement
- Leads
- App promotion
- Sales



Sales
Find people likely to purchase your product or service.

Good for:

- Conversions ⓘ
- Catalog sales ⓘ
- Messenger and WhatsApp ⓘ
- Calls ⓘ

Audience

Define who you want to see your ads. [Learn more](#)

Create new audience Use saved audience ▼

Custom audiences Create new ▼

Search existing audiences

Exclude

Locations

Location:

- United States

Age

20 - 30

Gender

All genders

Detailed targeting

Include people who match ⓘ

Interests > Business and industry

Marketing

Delivering Ads and Recording Sales

- Auctions, Bidding, and Budgets

- Advertisers determine campaign budget and bidding strategies to target users likely to engage
- Meta's ad algorithm uses ML to estimate user “action rate” and ad “quality score” and optimizes ad delivery by scaling up bids for users predicted to convert.
- Winner: Total Value = Advertiser Bid × Action Rate + Quality Score

- Pixels and Outcomes

- “Pixels” are used by advertisers to track website visitors' actions (purchase, add-to-cart, etc.)
- Pixels send information about what happens on the advertiser’s site to Meta (Google, Twitter...)
- Meta Pixels can monitor/record 17 standard events, and advertisers can customize further.

Experimental Design



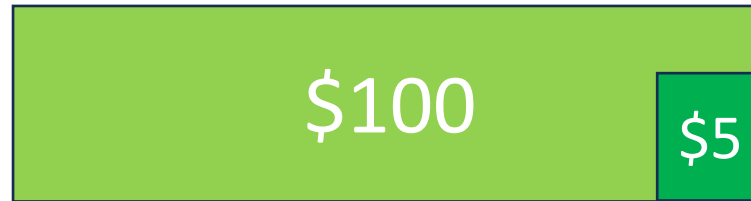
AEA RCT Registry

The American Economic Association's registry for randomized controlled trials

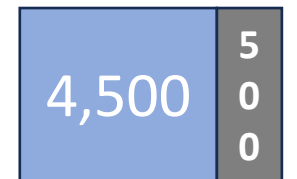
Experiment eligibility (advertiser):

- Meta Pixel for tracking sales
- Ad campaign: Sales
- Advertiser had spent > \$0 in the preceding 90 days;

Advertiser's Daily Budget



Target users



Measure total revenue on advertiser's website!

Compliance is perfect for Holdout users, but only one-sided for Ad Eligible users

Data

- Sample Size:
 - 700,000 ad campaigns from 210,000 advertisers across 25 industries
 - 3.94 billion unique user-ad opportunity pairs
 - > 8.9 million purchases and many other “conversion events” (e.g., “add to cart”; “signup” ...)
- Data collected
 - 17 standard events that Pixels report (purchases, key page views, completed registration forms...)
 - Data is gathered on the total number of user conversion events recorded by the Pixels
 - Purchase data: Revenue generated; Number of purchases (in each experimental group)
 - Total number of conversions (aggregation of all recorded Pixel events)
 - Ad budget spent by the advertising campaign serves as the key independent variable

Benchmark Results: Average ITT effects

Dependent Var:	(1) Revenues	(2) Purchases	(3) Purchasers	(4) Conversions
Budget Spend	3.3098*** (0.1233)	0.1029*** (0.0132)	0.0179*** (0.0021)	0.3980*** (0.1096)
Group Size	-0.0063*** (0.0010)	0.0002 (0.0001)	0.0000 (0.0000)	0.0066*** (0.0021)
Constant	62.3880*** (1.7389)	0.3350 (0.1993)	0.0350 (0.0333)	-1.1422 (3.0721)
<i>N</i>	1,323,760	1,323,760	1,323,760	1,323,760
<i>R</i> ²	0.696	0.613	0.618	0.604

Table 4 reports the results of estimating equation (1) for revenues, our primary outcome variable, as well as purchases, purchasers, and conversions, which are our secondary outcome variables of interest. In each regression, the dependent variable is the outcome variable corresponding to each column header. Each regression includes ad campaign fixed effects. Standard errors are in parenthesis. We cluster standard errors at the advertiser level. Statistical significance: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Experience matters – Historical Ad Spend

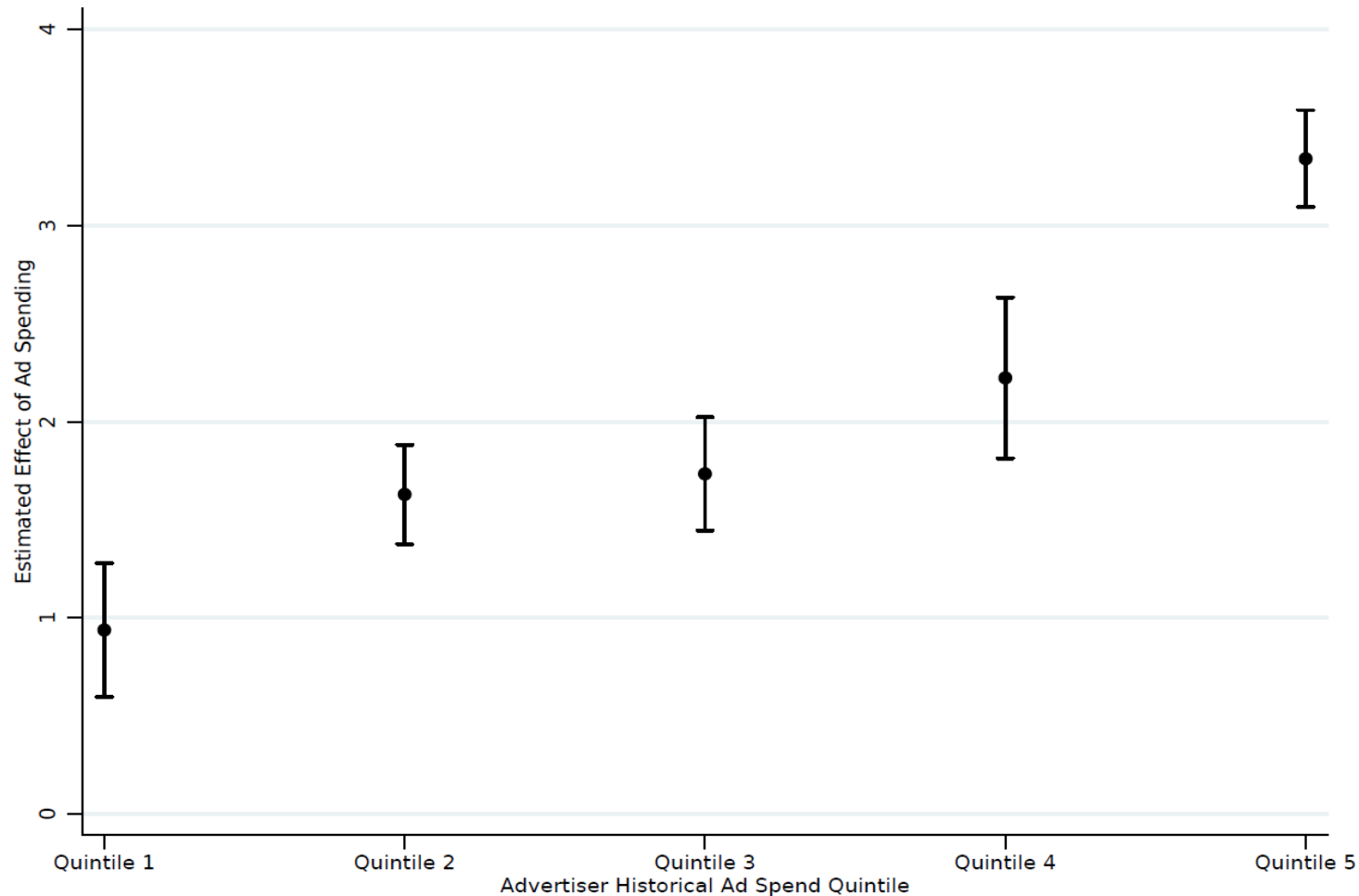


Figure 4 presents the results of splitting the sample by quintiles of historical ad spending and estimating equation (1) for the observations that fall within each quintile (95% conf. intervals).

Establishing Advertiser Learning

“Learning can only take place through the attempt to solve a problem and therefore only takes place during activity.”

(Arrow, 1962)

- **Idea**: advertisers who are more engaged in updates are taking on the necessary “activity” that Arrow refers to for LBD to occur
- **Simple approach**: We divide our campaigns into 2 groups:
 - a) no updates to campaign;
 - b) updates to campaign;

The Economic Implications of Learning by Doing

It is by now incontrovertible that increases in per capita income cannot be explained simply by increases in the capital-labor ratio. Though doubtless no economist would ever have denied the role of technological change in economic growth, its overwhelming importance relative to capital formation has perhaps only been fully realized with the important empirical studies of Abramovitz [1] and Solow [11]. These results do not directly contradict the neo-classical view of the production function as an expression of technological knowledge. All that has to be added is the obvious fact that knowledge is growing in time. Nevertheless a view of economic growth that depends so heavily on an exogenous variable, let alone one so difficult to measure as the quantity of knowledge, is hardly intellectually satisfactory. From a quantitative, empirical point of view, we are left with time as an explanatory variable. Now trend projections, however necessary they may be in practice, are basically a confession of ignorance, and, what is worse from a practical viewpoint, are not policy variables.

Further, the concept of knowledge which underlies the production function at any moment needs analysis. Knowledge has to be acquired. We are not surprised, as educators, that even students subject to the same educational experiences have different bodies of knowledge, and we may therefore be prepared to grant, as has been shown empirically (see [2], Part III), that different countries, at the same moment of time, have different production functions even apart from differences in natural resource endowment.

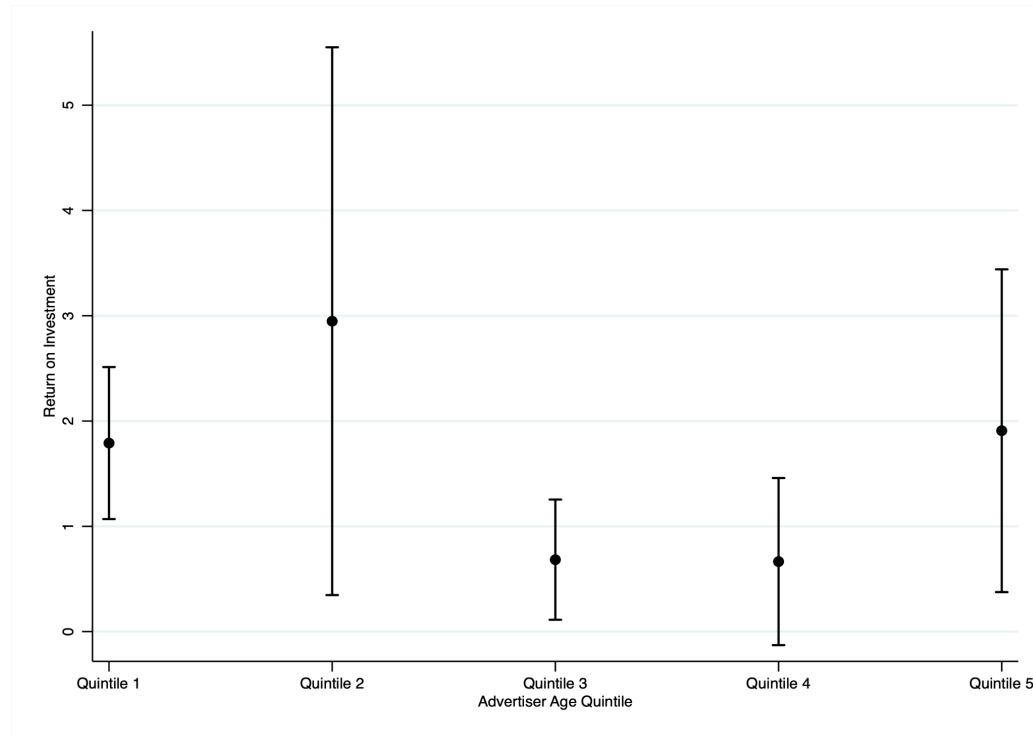
I would like to suggest here an endogenous theory of the changes in knowledge which underlie intertemporal and international shifts in production functions. The acquisition of knowledge is what is usually termed “learning,” and we might perhaps pick up some clues from the many psychologists who have studied this phenomenon (for a convenient survey, see Hilgard [5]). I do not think that the picture of technical change as a vast and prolonged process of learning about the environment in which we operate is in any way a far-fetched analogy: exactly the same phenomenon of improvement in performance over time is involved.

Of course, psychologists are no more in agreement than economists, and there are sharp differences of opinion about the processes of learning. But one empirical generalization is so clear that all schools of thought must accept it, although they interpret it in different fashions: Learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity. Even the Gestalt and other field theorists, who stress the role of insight in the solution of problems (Köhler’s famous apes), have to assign a significant role to previous experiences in modifying the individual’s perception.

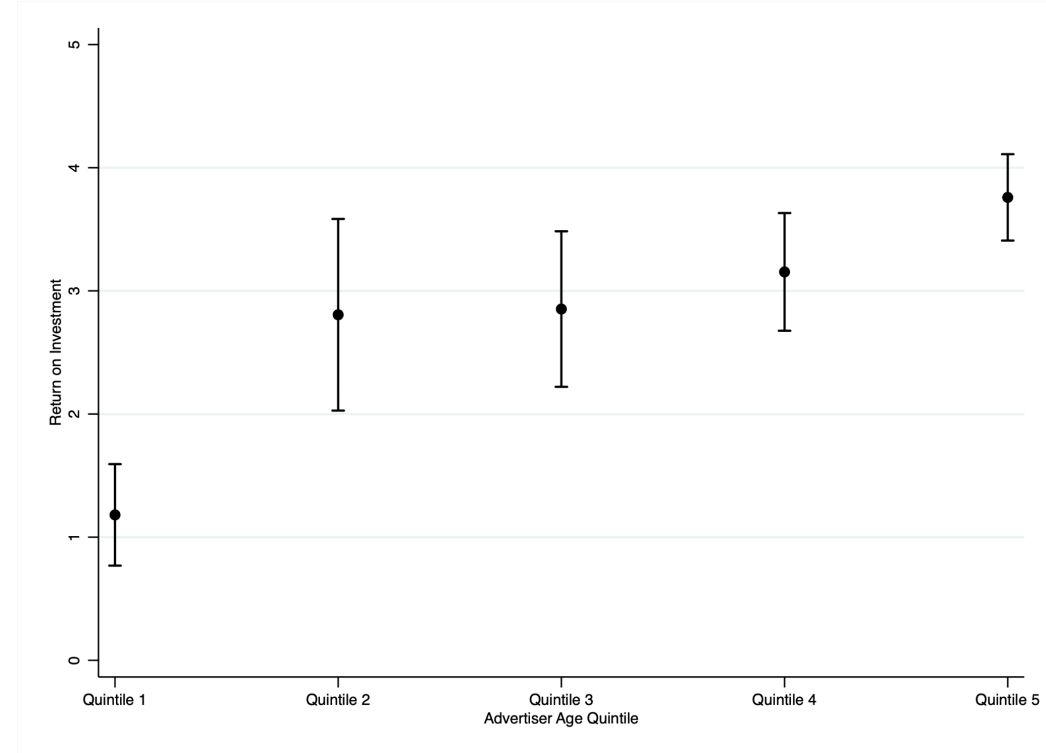
A second generalization that can be gleaned from many of the classic learning experiments is that learning associated with repetition of essentially the same problem is subject to sharply diminishing returns. There is an equilibrium response pattern for any given

Learning activities and age: Advertisers

Figure 6: The Effect of Ad Spending on Revenues by Advertiser Age Quintiles and Advertiser Update Behavior



Never updated campaigns

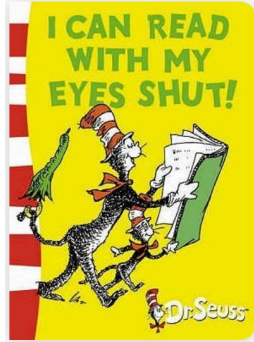


Updated campaign at least once

These figures present the results of first splitting the sample into advertisers that have never updated any of their ad campaigns, and those that have made at least one update across their campaigns. For each sample separately, we split the data by quintiles of advertiser age and estimate equation (1) for observations that fall within each quintile. Each bar shows the regression point estimate on Budget Spend and the corresponding 95% confidence interval.

Establishing Advertiser Sophistication

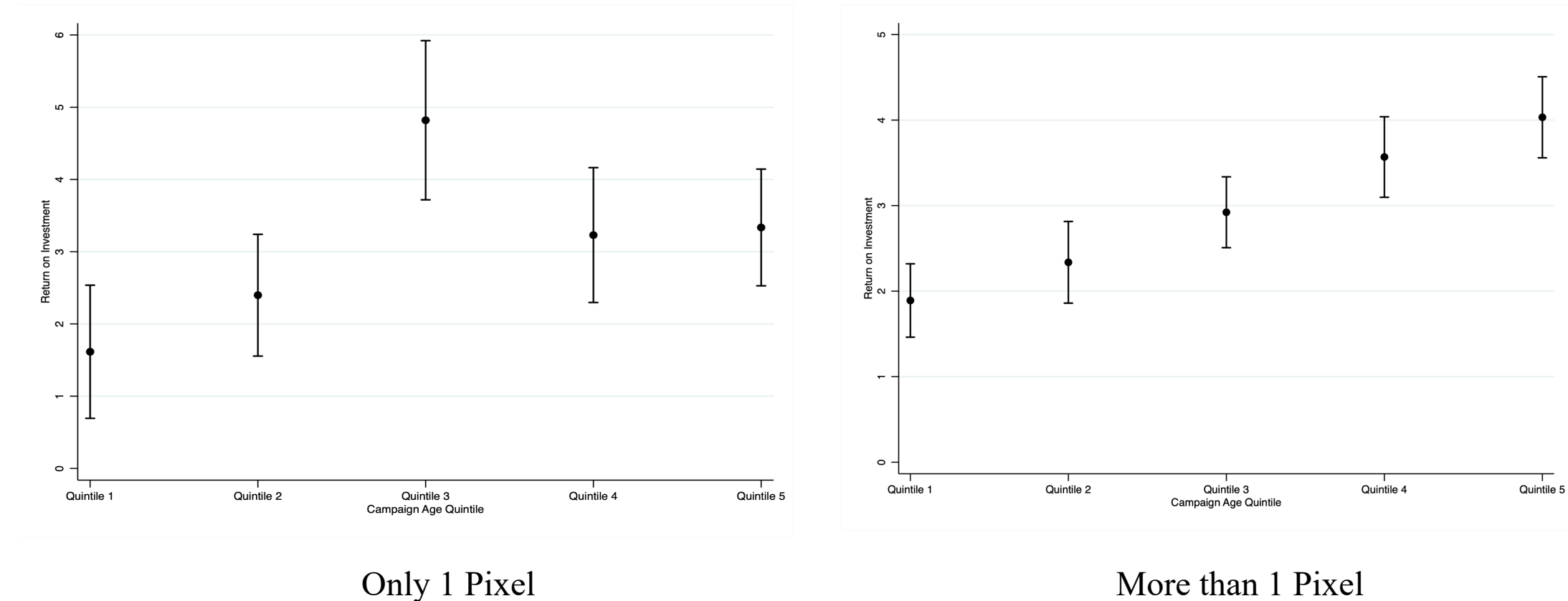
“The more that you read, the more things you will know. The more that you learn, the more places you'll go.” (Dr. Seuss, 1978)



- **Idea**: advertisers who “read” more data should learn better
- **Approach**: We divide our campaigns into 2 groups in two ways:
 - a) Track only 1 pixel (the median – must have at least 1);
 - b) Track more than 1 pixel;
 - c) **Adopts CAPI integration (“Conversion API” – guarantees better quality data to Meta);**
- **Note**: Sophistication is correlated with learning:
 - Advertisers who track > 1 Pixel make, on average, 23% more campaign updates
 - Advertisers with CAPI integrations make, on average, 28% more campaign updates

Sophistication (Pixels) and campaign age

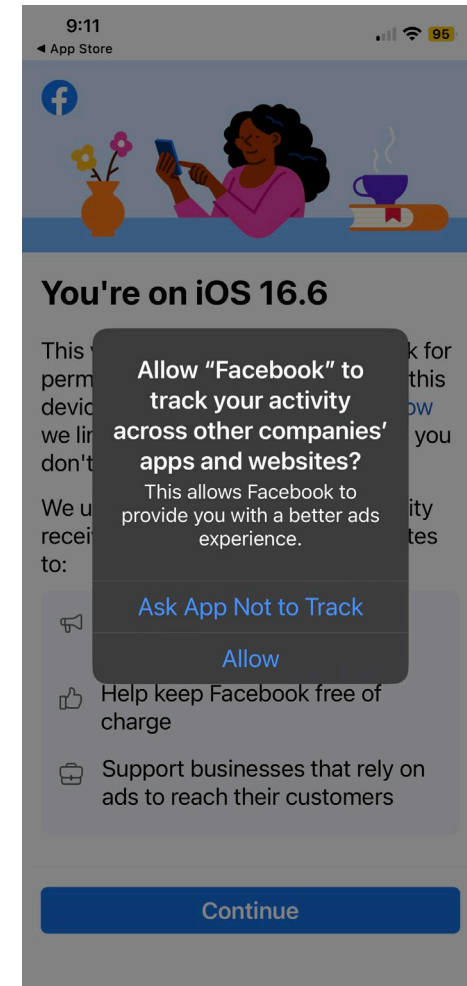
Figure 7: The Effect of Ad Spending on Revenues by Campaign Age Quintiles and Pixel Event Tracking Behavior



These figures present the results of first splitting the sample into campaigns run by advertisers that track below and above the median number of Pixel events through their Meta Pixels. For each sample separately, we split the data by quintiles of campaign age and estimate equation (1) for observations that fall within each quintile. Each bar shows the regression point estimate on Budget Spend and the corresponding 95% confidence interval.

Introducing Privacy Considerations

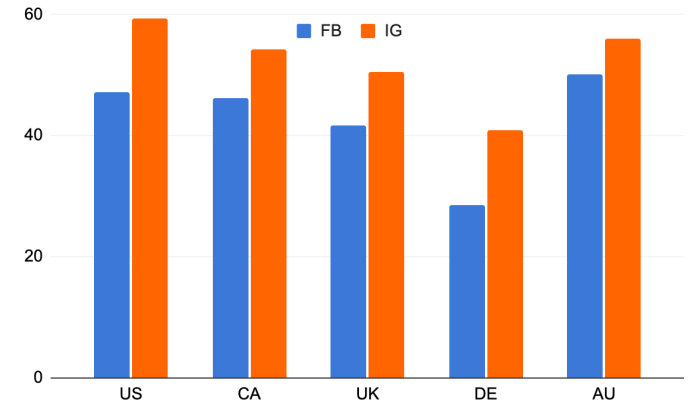
- Testing ad effectiveness requires identifying users who were exposed to ads vs. those who were not.
 - *The identifier for advertisers (IDFA) is a random device identifier assigned by Apple to a user's iOS device. The IDFA is used for tracking and identifying a user (without revealing personal information) and linking user actions and events to campaigns and channels. (The Android equivalent to the IDFA is the Google Advertising ID or GAID.)*
- Many are concerned with privacy and tracking (**Caveat: privacy paradox...**)
- In 2021 Apple implemented App Tracking Transparency (ATT)
 - Pop-up with the “default” being “no 3rd party app tracking”
 - Google has yet to implement this (pushed from late 2023 to 2024)
- What will ATT do for advertising effectiveness and business success?



Natural Experiment: iOS vs. Android

- Different countries have different exposure to ATT
- Meta classifies business into 25 “industry verticals” (Retail, Ecommerce, Technology, Automotive, Non-Profit...)
- Divide the users to whom Meta shows ads into 2 categories:
 - Users who do not allow data linking (iOS users who “opted out”);
 - Users who do allow data linking: (iOS who opt in + other devices)
- ATT impacted different industries in different ways!

ATT Opt-Out Rates (%) on FB and IG as of Aug 2023



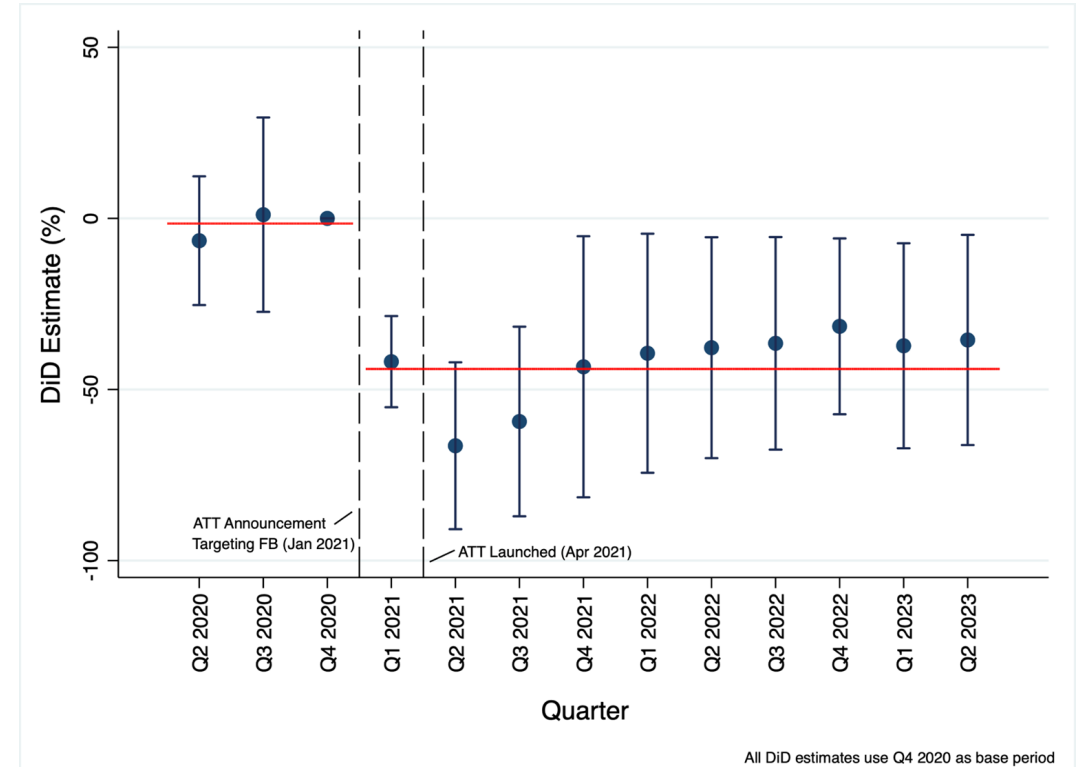
Most Affected U.S. Verticals	
Vertical	“Opt-Out” %
Retail	60.2
Consumer Packaged Goods	59.0
Restaurants	55.2
Ecommerce	54.4
Entertainment and Media	50.9



Least Affected U.S. Verticals	
Vertical	“Opt-Out” %
Gaming	41.3
Energy, Natural Resources, and Utilities	44.1
Advertising and Marketing	44.3
Agriculture	44.7
Politics	45.8

Diff-in-Diff: Exit from Meta Ads

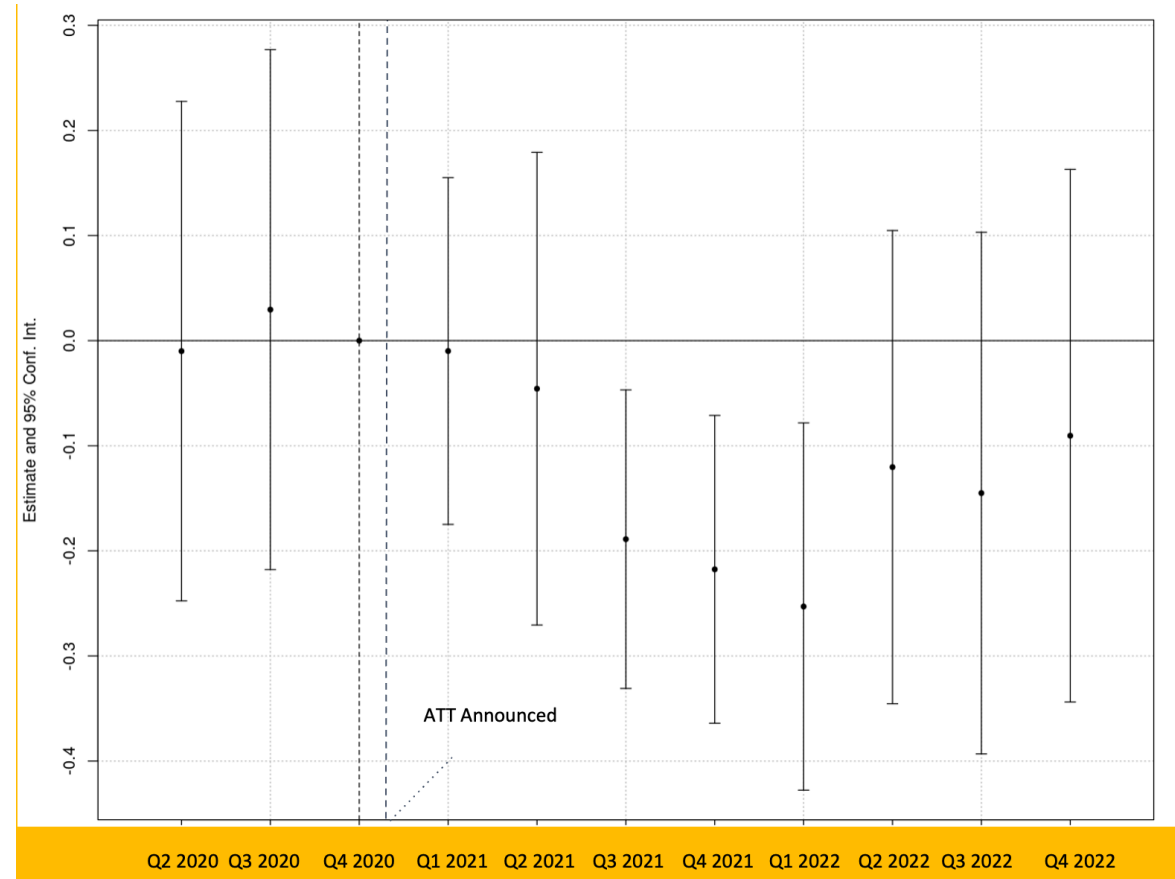
- U.S. industries more impacted by ATT have 43% higher rates of advertiser Net Exit.
- The effect is primarily driven by small businesses who are more reliant on offsite signal



- ***But this is advertising on Meta. What about “real” business outcomes like registration and survival?***

Diff-in-Diff: External Data (in progress)

- ATT created at least a 14.9 percent reduction in new business registrations.
 - This compares the outcomes between the top/bottom 5 impacted industries, based on the **Business Formation Statistics (BFS)** data.
- **Preliminary analysis** identifies similar results for other key macroeconomic outcomes:
 - Decreased employment: -3%
 - Decreased wages: -2%
 - Decreased total output: -6%



Conclusion


- Ads work well when they are targeted well
- Targeting requires data savviness in measurement and analysis
- Privacy concerns may make consumers feel better (WTP?) but seem to come at the expense of ad effectiveness and business success.
- We have SO MUCH more to learn about this industry and its welfare implications.

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COMMENTARY · MEDIA

What the well-meaning critics of online advertising are missing—and how they could hurt the communities they're trying to protect

BY **ANDREA BREANNA**
February 28, 2023 at 3:59 AM PST



Small publishers that serve diverse communities rely on targeted advertising for a considerable part of their revenue.
GETTY IMAGES