Selling Subscriptions

Liran Einav, Stanford and NBER
Ben Klopack, Texas A&M
Neale Mahoney, Stanford and NBER

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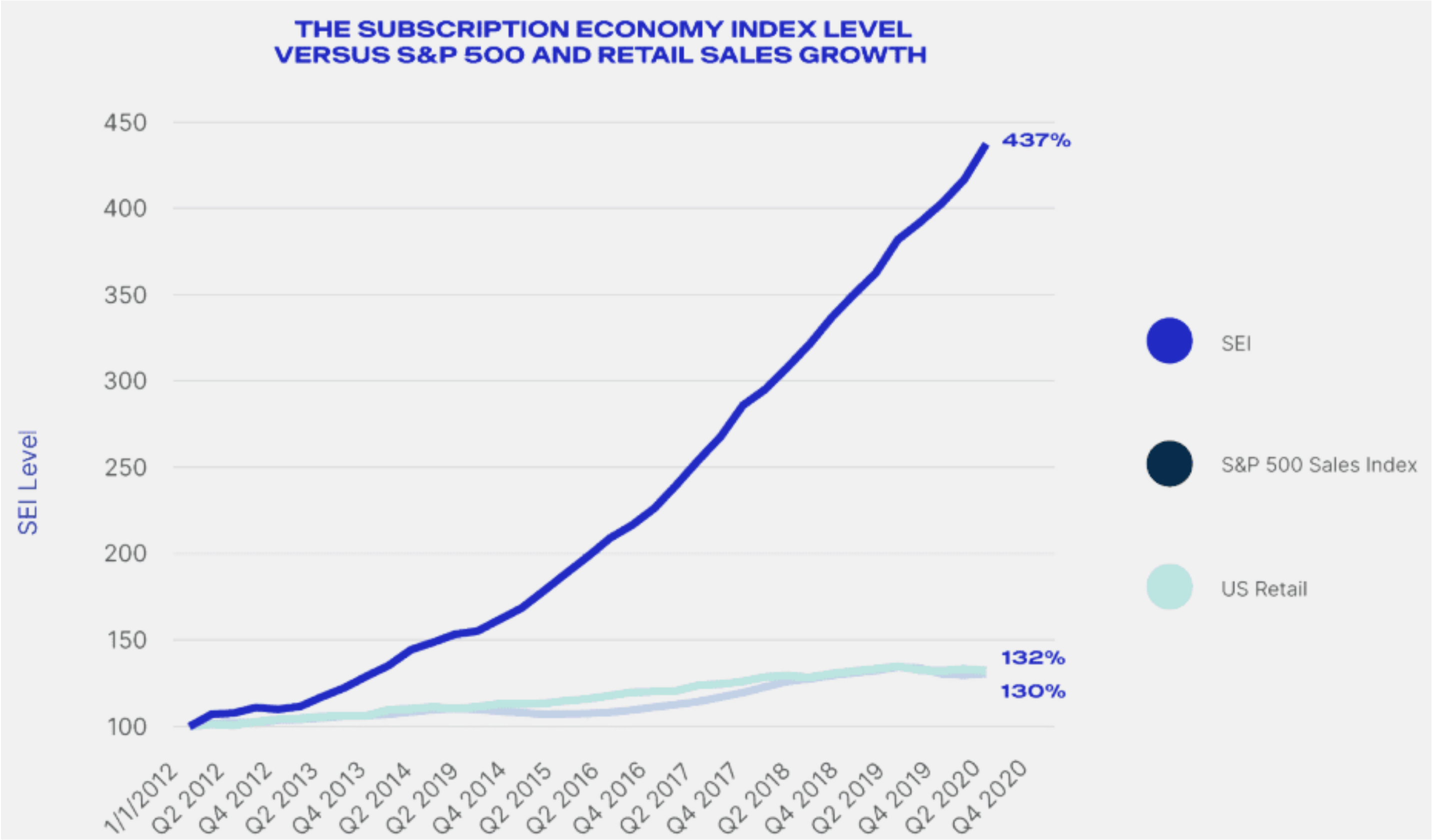
Fixing ideas: top “subscription” services in the US

SUBSCRIPTION CATEGORY	EXAMPLES
Amazon Prime	
Beauty subscription boxes	Ipsy, Dollar Shave Club, etc.
Book services	Kindle, Audible, etc.
Children's subscription boxes	Books, toys, games, etc.
Cloud storage	Dropbox, iCloud, OneDrive etc.
Dating apps	Tinder, Match, eHarmony, etc.
Diet/fitness apps	MyFitnessPal, Lose It!, Fitbit, etc.
Digital newspapers/magazines	New York Times, Washington Post, The Atlantic, etc.
Fashion subscription boxes	Stitch Fix, Trunk Club, etc.
Gaming services	PlayStation Now, Xbox Game Pass, Utomik, etc.
Home security systems	ADT, Nest, Ring, etc.
Identity protection service	LifeLock, Identity Guard, etc.
Lifestyle subscription boxes	FabFitFun, My Geek Box, Mindfulness Box, etc.
Meal services	HelloFresh, Blue Apron, etc.
Mobile phone service	Verizon, Sprint, Boost Mobile, etc.
Music streaming	Spotify, Pandora, XM Radio, etc.
Pet’s subscription boxes	BarkBox, Chewy Goody Box, etc.
TV/movie services	Netflix, Hulu, cable, premium packages, etc.
Web hosting	Wix, GoDaddy, etc.
Wellness apps	Headspace, Happify, etc.
WiFi at home	Comcast, AT&T, CenturyLink, etc.

Source: West Monroe report “State of Subscription Services Spending”, 2021

Motivation

- The “subscription economy” is growing rapidly



Motivation

- The “subscription economy” is growing rapidly

- Two benign reasons:
  - Change in the composition of retail towards more digital products, which perhaps lend themselves more naturally to a subscription model
  - Increased demand for “convenience”; e.g., 32% of US consumers surveyed (by Emarsys) say that “they signed up to the subscription because it feels nice to receive something every month”

- Today’s talk:
  - Explore the supply side incentive that is associated with (and potentially amplifying) this trend
  - Inertial and inattentive consumers could get “exploited” by firms

This paper

- Use transaction-level data from a large credit card network to show the impact of consumer “inattention” on subscription cancellations
- Key idea:
  - Monthly renewal is typically automatic
  - Yet, when a card expires, consumers are often required to actively renew
  - Sharp drop in consumer retention rates during the card expiration/replacement month
- Embed this pattern in a stylized model to generate counterfactual retention rates by “fully attentive” consumers
- Use this model to quantify the exploitation benefit of subscriptions to firms and the impact of possible regulatory remedies

Outline

- Data and sample construction
- Descriptive evidence
- Model and estimation
- Counterfactuals / quantification

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- **Data and sample construction**
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Data

- The universe of transaction-level data from a large credit card network, going back to mid 2017
- Each transaction is associated with the (masked) card number, merchant name, transaction date, and amount
- Multiple cards within the same credit card account are linked, though expiration indicator is incomplete in the earlier years of the data, so we only use card expirations from mid 2018 and after

Selected set of subscription services

- Begin with a list of most popular subscription services (from industry reports), which covers 69 services across 21 categories

- Exclude (in order)
  - 12 of the 69 that we could not identify in the data
  - 31 smaller services (<500k monthly transactions on average)
  - 4 services with long-term contracts (two categories: cell phones, ISPs)
  - 6 services associated with many non-subscription products
  - 2 services with short average subscription length (<6 months)
  - 2 services with recent launches
  - 2 services with non-monthly billing

- Final set of subscription services
  - 10 services with at least 500k monthly transactions
  - Digital and non-digital, including entertainment, security, retail, newspapers

Sample construction

- Separately for each service, construct cohorts of subscribers
  - Follow each cohort for 25 months since initial subscription
- A cohort is defined by an initial subscription month t and a card expiration at month $t + x$
  - t runs from Jan. 2018 through July 2019 (19 cohorts total)
  - x is equal to 6, 12, or 18 (though exact month could be one month off)
  - We require accounts (old or new cards) to be active in each one of the 25 months
- Some data cleaning
  - We fill in “single-month holes” (not common; raises average duration from 16.9 to 17.2)
  - We consider two (or more) non-paying months as “unsubscribed”
  - Very large drop in subscription after first month, so we consider the first month as “trial,” drop first month, and consider cards as subscribed only from second month and on
- We aggregate across t (conditional on x)
  - Weighting by cohort size and adjusting for seasonality (neither is particularly important)
- Final sample includes monthly survival rates (by x) for each service

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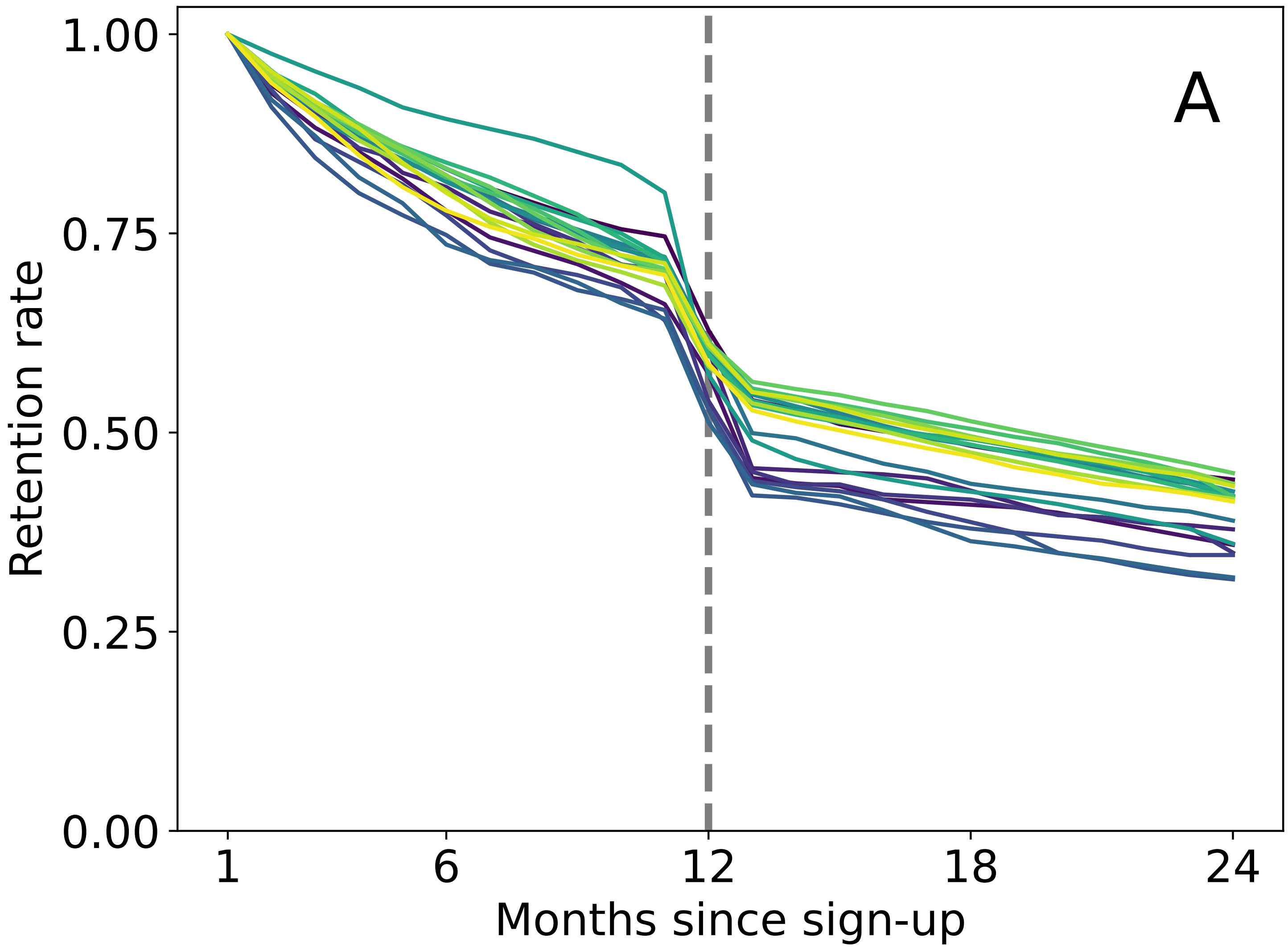
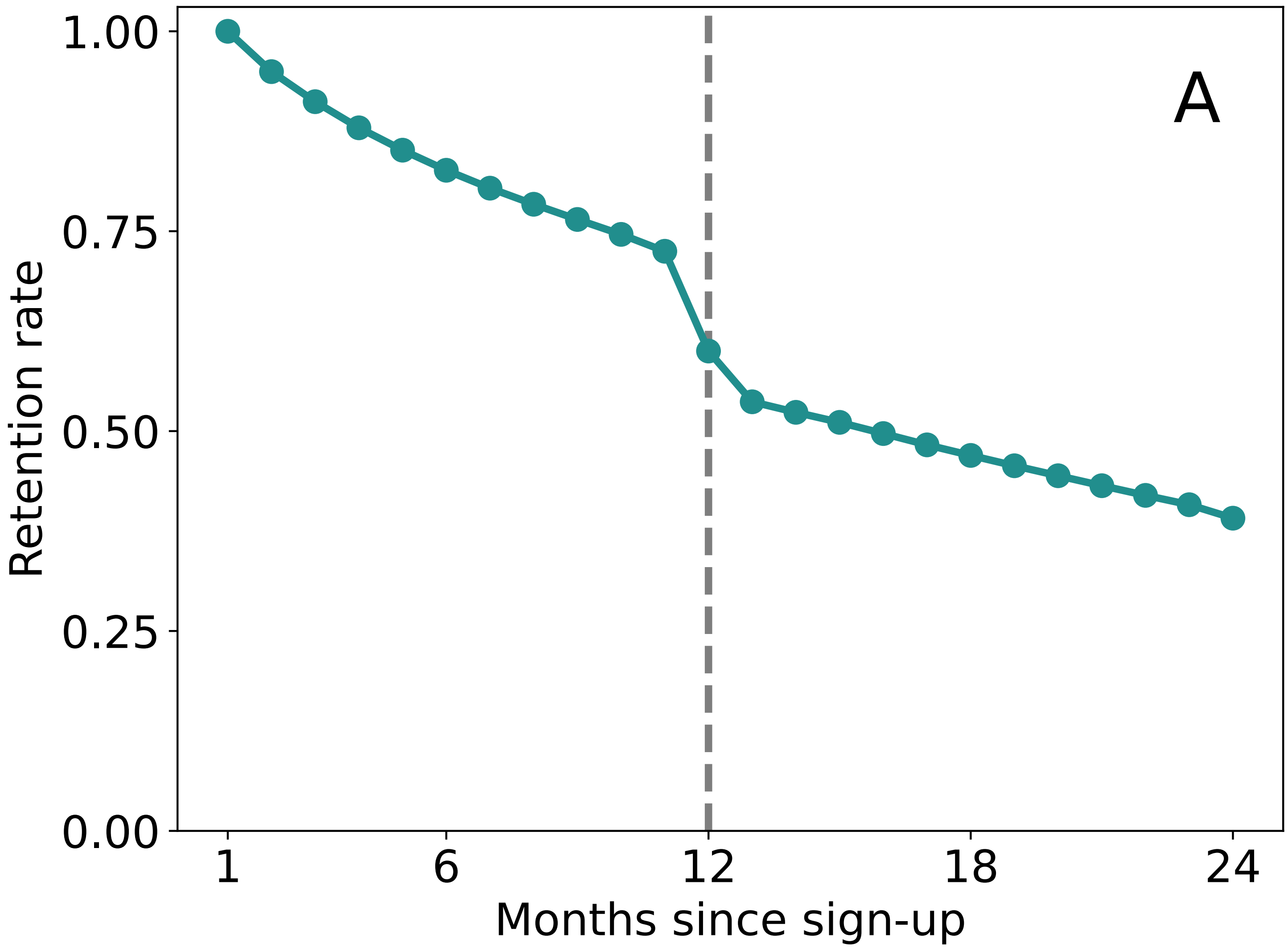
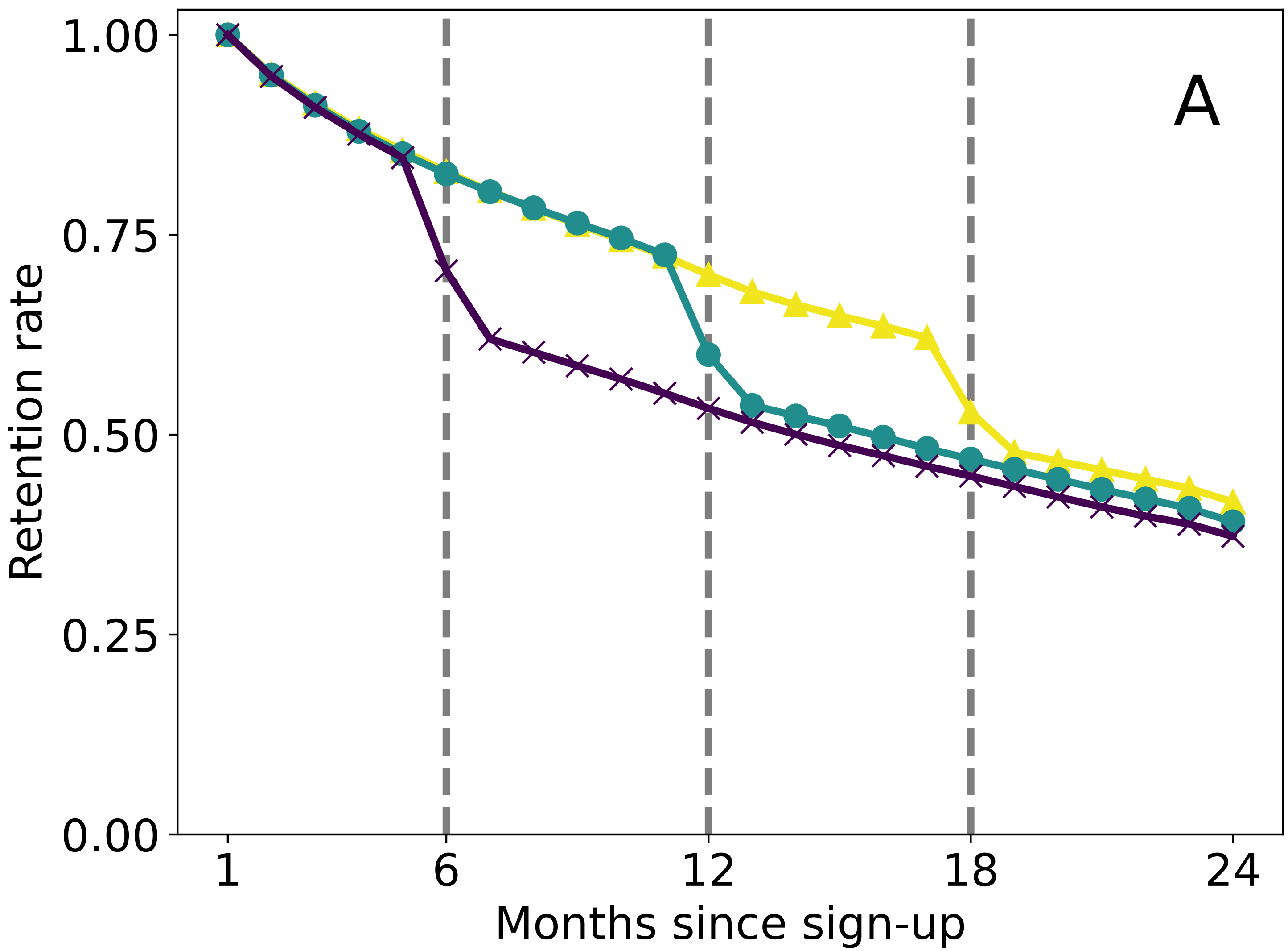
Raw data, service A



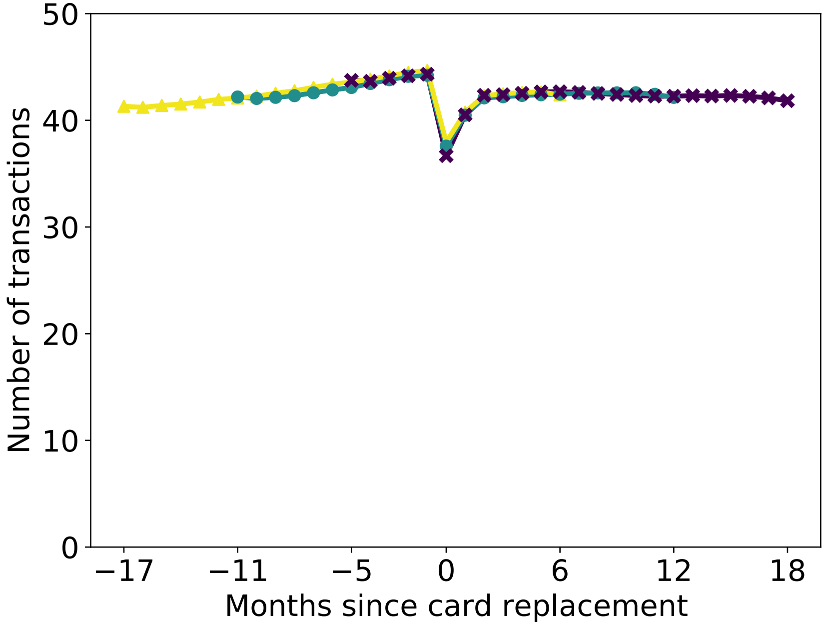
Aggregating cohorts + seasonal adjustment

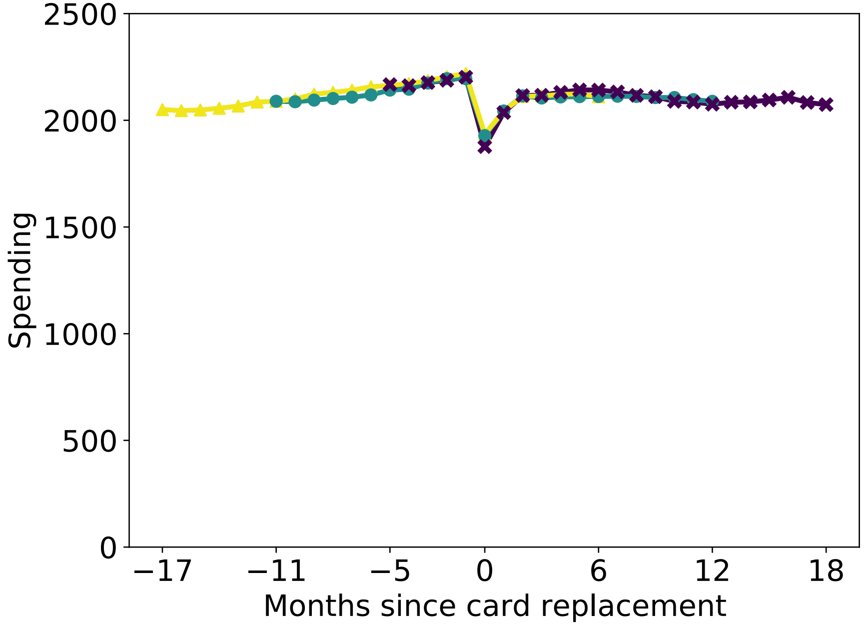


Adding expirations at months 6 and 18

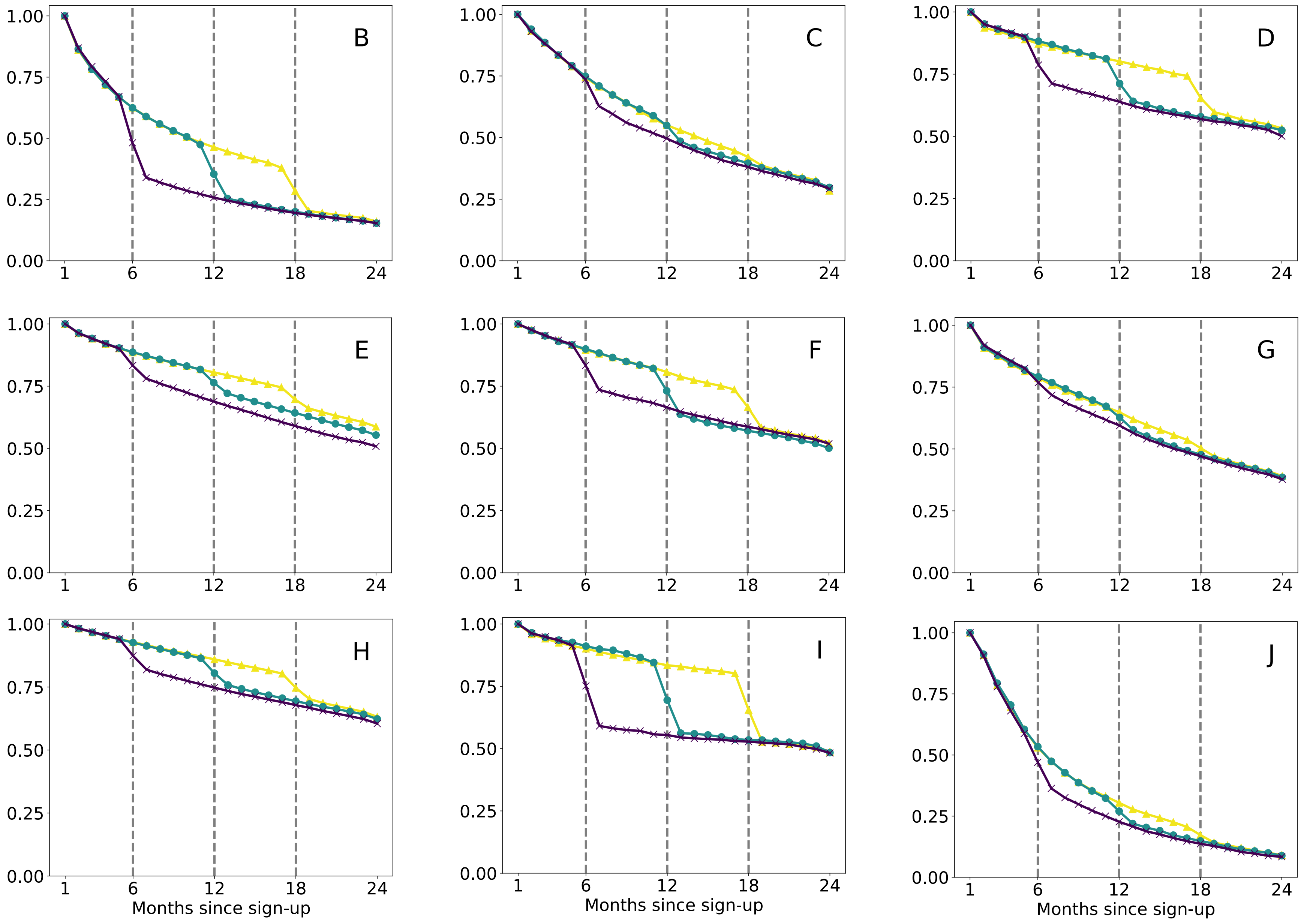


Account activity around card replacement





The other nine services



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Model

- Consider a specific subscription service with monthly price p

- Potential subscriber i has a flow monthly utility from the service, u_{it}, which follows a Markov process, such that $u_{it} \sim F(\cdot\, |u_{i,t-1})$

- A cohort of new subscribers is defined by a distribution of initial utilities $\mathrm{G}(u_{i0}|u_{i0} > p)$, who have been recruited to sign up to the service

- Subscribers are myopic
  - Or equivalently forward-looking but don't anticipate future inattention

- In a given period, a subscriber can be attentive or inattentive:
  - Inattentive subscribers automatically renew
  - Attentive subscribers renew in month t iff $u_{it} > p$
  - Consumers are attentive in a given month with (iid) prob. λ
  - When the card expires, consumers are attentive with prob. 1

Parameterization and estimation

- Denote $v_{it} = u_{it} - p$
- We assume that $F(\cdot)$ is an AR(1) process (but w/o a constant):

$$v_{it} = \rho v_{i,t-1} + \varepsilon_{it}$$

  where $\varepsilon_{it} \sim N(0,1)$, which is a normalization

- Initial distribution is given by an exponential distribution:

$$\mathrm{G}(u_{i0}|u_{i0} > p) \Longrightarrow v_{i0} \sim Exp(\eta)$$

- Estimate service by service using method of simulated moments to recover three model parameters: λ, η, and ρ

Parameter estimates

Service	ρ	λ	η
A	0.990	0.110	0.823
	(0.003)	(0.002)	(0.021)
B	0.856	0.184	0.004
	(0.009)	(0.002)	(0.000)
C	0.946	0.270	1.588
	(0.006)	(0.014)	(0.106)
D	1.019	0.090	1.404
	(0.014)	(0.006)	(0.133)
E	0.999	0.133	2.558
	(0.002)	(0.002)	(0.047)
F	0.978	0.093	1.969
	(0.008)	(0.004)	(0.123)
G	0.946	0.502	3.784
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H	0.995	0.097	3.282
	(0.003)	(0.002)	(0.080)
I	1.053	0.044	0.477
	(0.040)	(0.003)	(0.105)
J	0.819	0.277	0.154
	(0.011)	(0.021)	(0.113)

Lambda			
Mean	St. Dev.	2nd	9th
0.18	0.13	0.09	0.28

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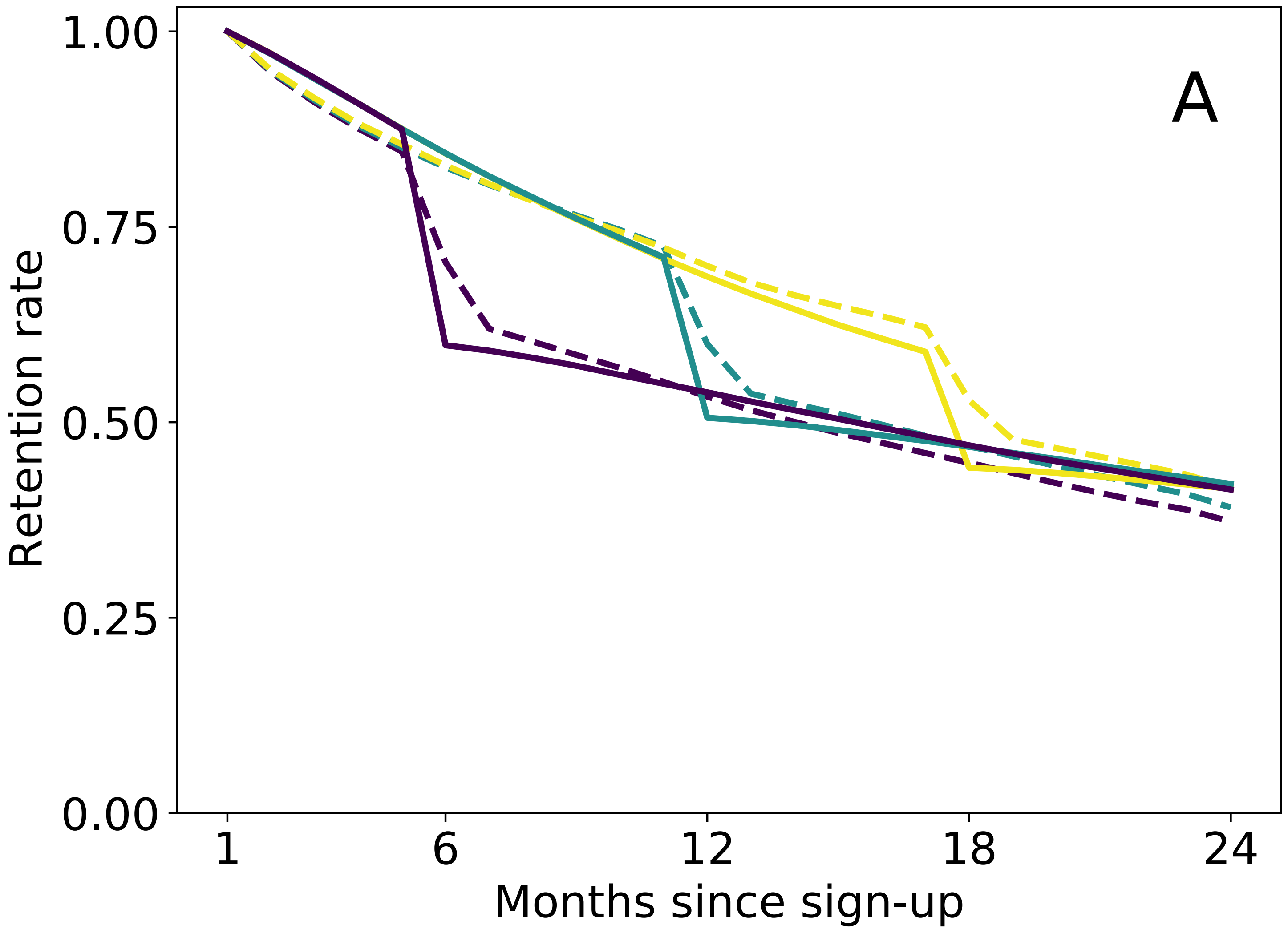
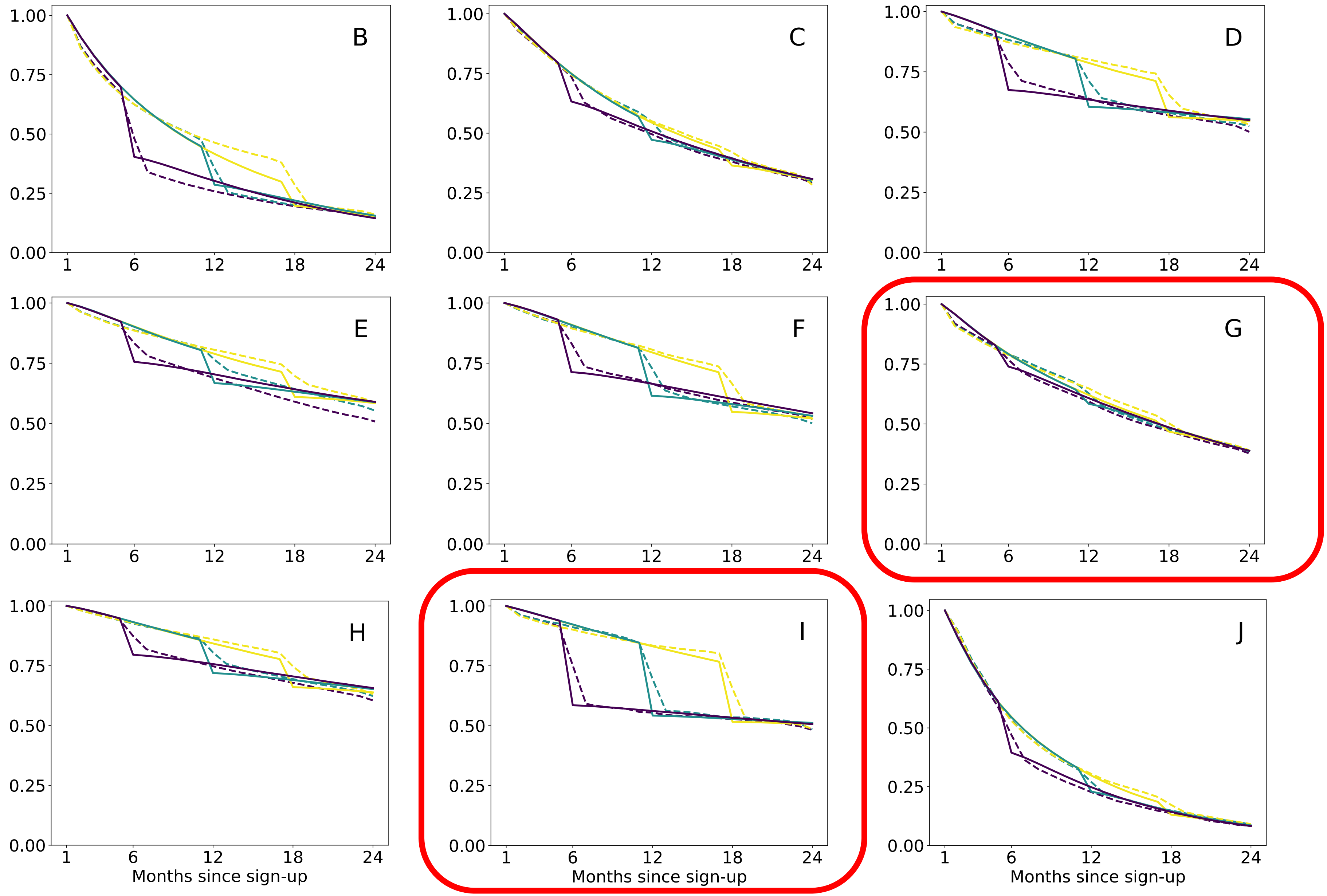
Model fit


A
Retention rate
1.00
0.75
0.50
0.25
0.00
1
6
12
18
24
Months since sign-up

Model fit



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Counterfactuals: revenue impact of inattention

Service	Share unaffected	Avg months subscribed If inattentive	if attentive	Revenue ratio
A	0.05	36.6	13.2	2.08
B	0.00	14.1	4.1	3.18
C	0.00	21.6	13.6	1.52
D	0.27	41.7	9.5	1.60
E	0.21	41.2	20.2	1.39
F	0.04	44.7	19.9	1.87
G	0.00	23.8	20.4	1.14
H	0.20	49.6	24.4	1.43
I	0.25	54.1	4.1	2.19
J	0.00	10.0	4.1	2.35
Mean	**0.10**	**33.7**	**13.4**	**1.87**

- Notes:
  - We run counterfactuals for up to 120 months
  - Discounting makes relatively little difference
  - Impact primarily driven by the more marginal (low v_{i0}) subscribers

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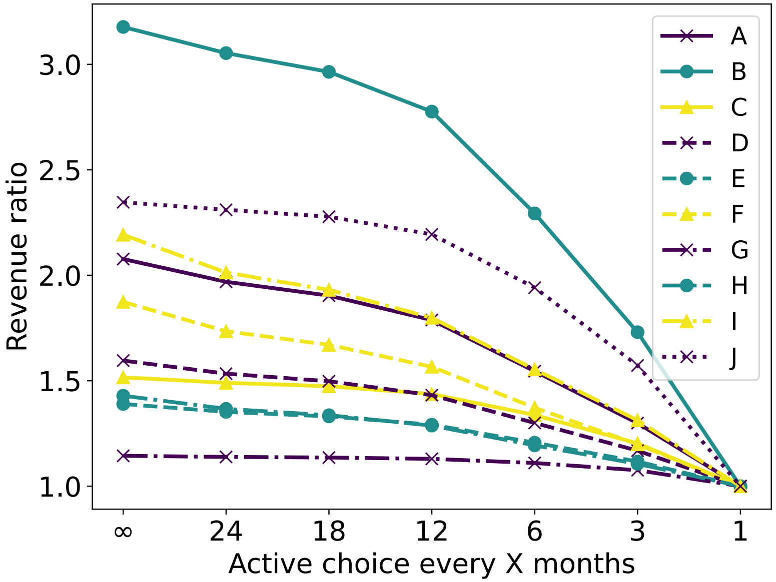
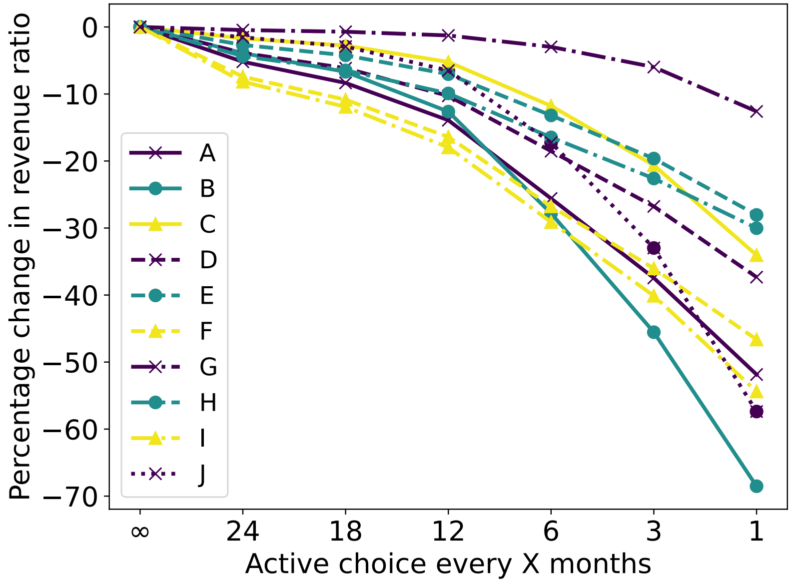
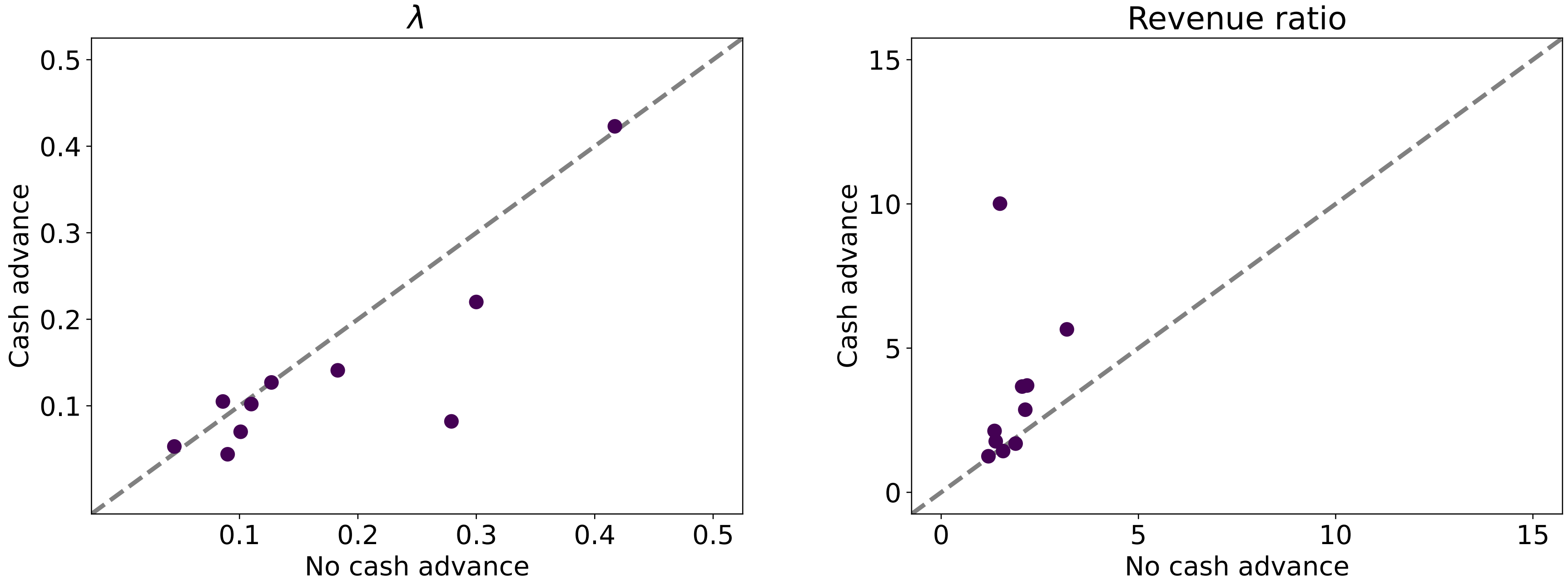
Revenue impact of possible regulatory remedies

- Consider interventions of the form “force active choice every X months”
    - This is in the spirit of a recent FTC policy statement on “negative options” (Oct 2021)
    - This is not “free”; associated with convenience costs





Estimation results by cash advance



Conclusions

- Evidence from 10 subscription services of consumer inattention

- Overall impact of inattention varies a lot across services
  - Estimate the revenue benefit of inattention to be >3x for some services

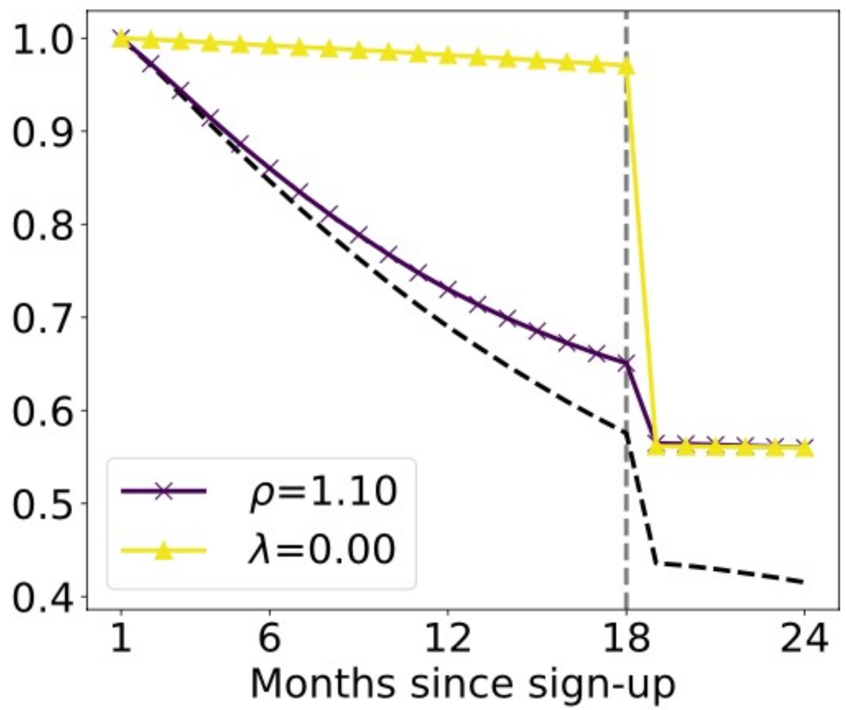
  and across subscribers
  - Everyone seems quite inattentive; but those less financially sophisticated are more so

- These results should be traded off against the (presumably) convenience benefits of subscriptions but suggest that some sort of regulation could be useful, such as:
  - Forced active renewal every X months
  - Make X a choice at the time of subscription
  - Simplifying cancellation (c.f. Chicago Tribune saga)
  - Require “inactive account” notification (but only applicable to a subset of services)

Comparative statics / identification

- Illustrate by starting with estimated pattern with service A (ρ = 0.988, λ = 0.111, and η = 0.855)
- Try to match arbitrary retention rate of 0.56 in the last month by changing one parameter at a time

Holding η = 0.855 fixed:



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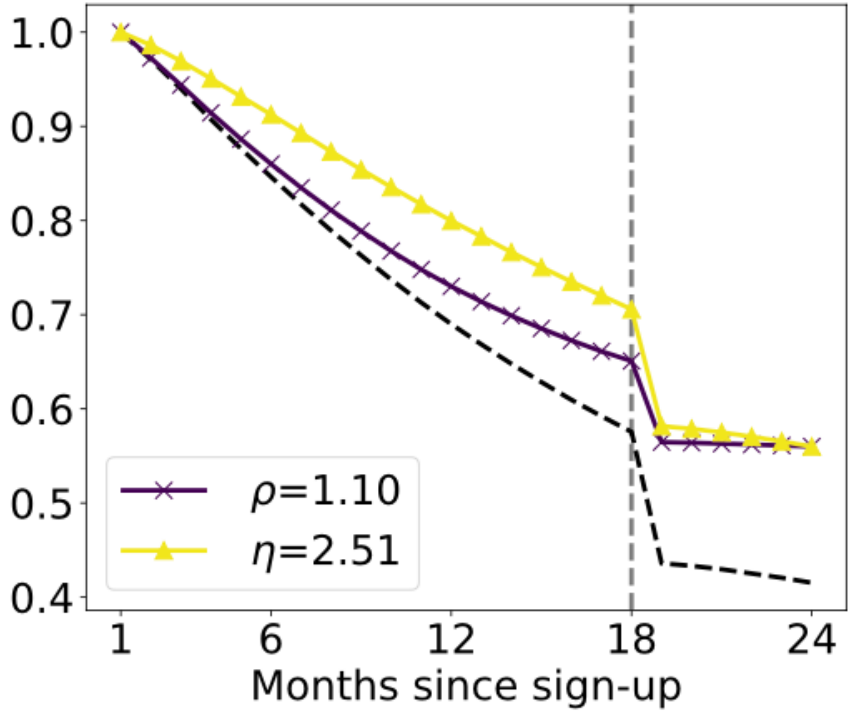
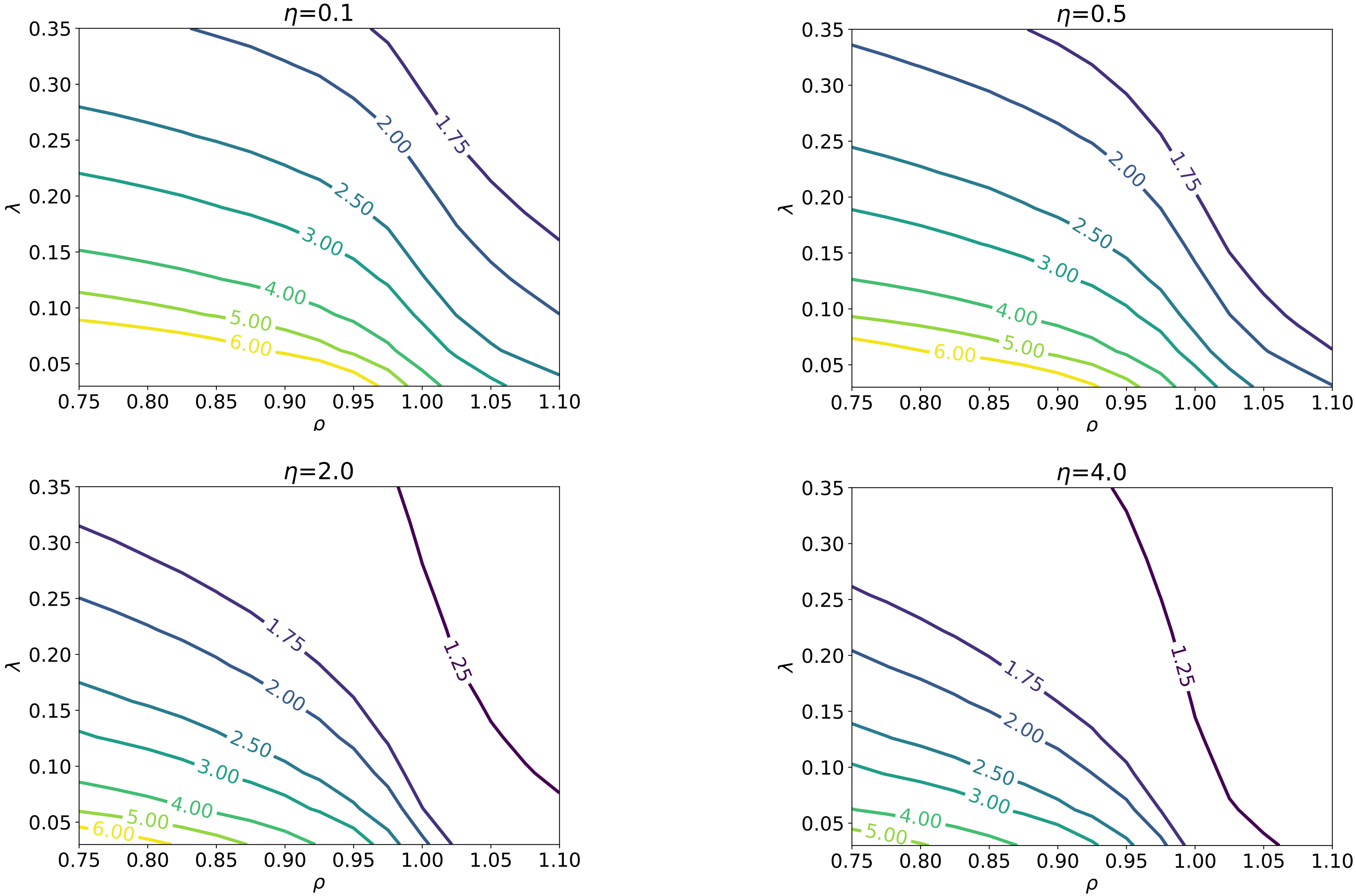


Robustness and heterogeneity

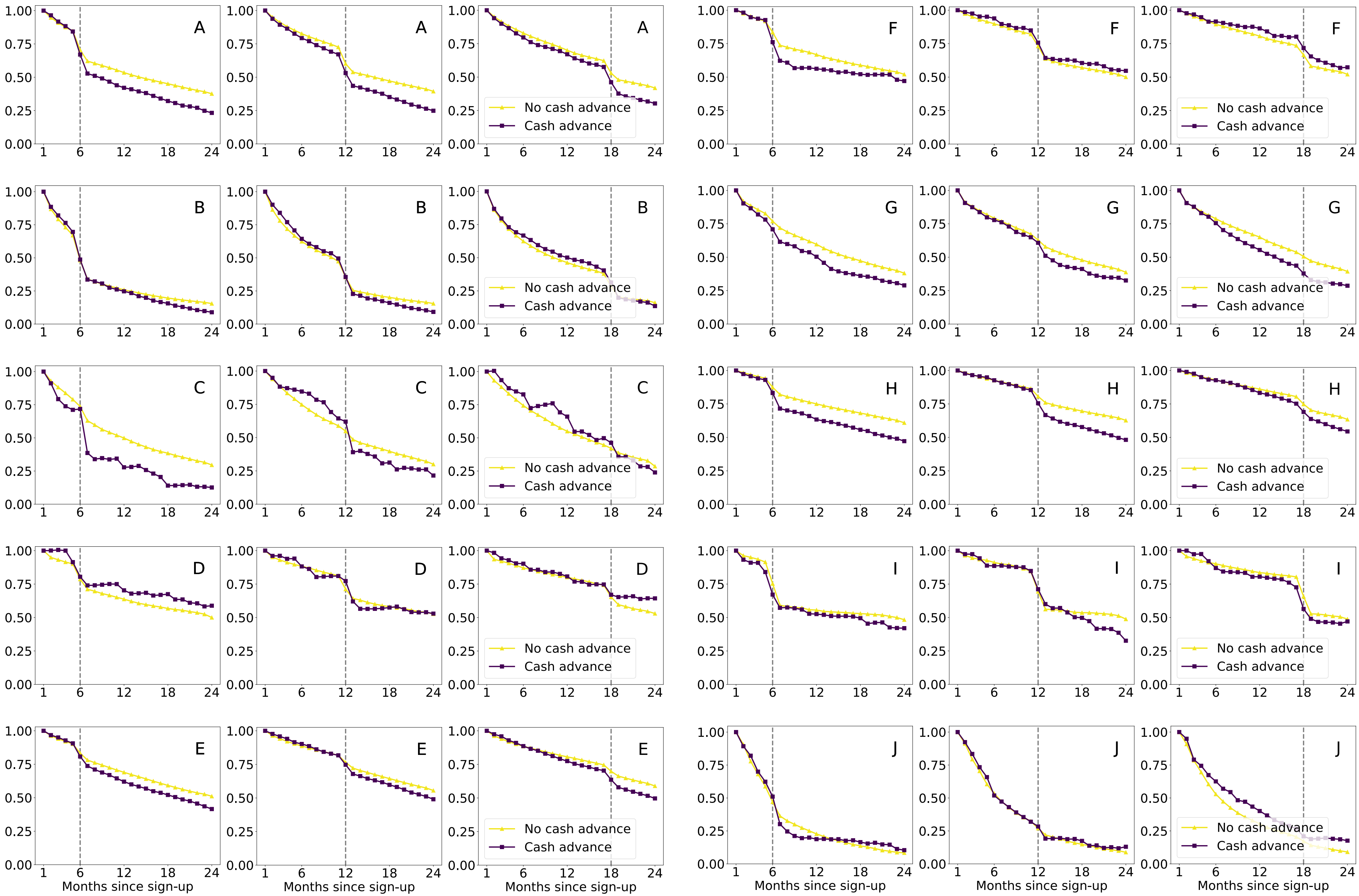
	Lambda					Revenue ratio				
	Mean	St. Dev.	2nd	9th	Corr. w/ baseline	Mean	St. Dev.	2nd	9th	Corr. w/ baseline
Baseline	0.18	0.13	0.09	0.28		1.87	0.57	1.39	2.35	
A. Robustness										
Linear decay of lambda	0.16	0.09	0.09	0.28	0.93	2.88	3.43	1.27	2.67	0.84
Linear decay of lambda with reset	0.17	0.12	0.09	0.28	1.00	2.65	1.88	1.37	2.89	0.86
Lambda at card expiration = 0.75	0.17	0.13	0.07	0.26	0.99	2.55	1.44	1.46	3.57	0.63
Lambda at card expiration = 0.5	0.18	0.15	0.04	0.37	0.97	4.13	4.34	1.53	5.46	0.32
B. Heterogeneity										
Never used cash advance	0.17	0.11	0.09	0.30		1.84	0.56	1.35	2.18	
Used cash advance	0.14	0.11	0.05	0.22		3.42	2.55	1.43	5.65	
Financial sophistication -- Q1	0.20	0.11	0.05	0.36		2.04	1.21	1.27	3.51	
Financial sophistication -- Q2	0.18	0.12	0.08	0.34		1.84	0.67	1.26	2.19	
Financial sophistication -- Q3	0.17	0.12	0.08	0.31		1.89	0.56	1.49	2.28	
Financial sophistication -- Q4	0.18	0.12	0.08	0.30		1.93	0.54	1.41	2.26	

Iso-ratio curves

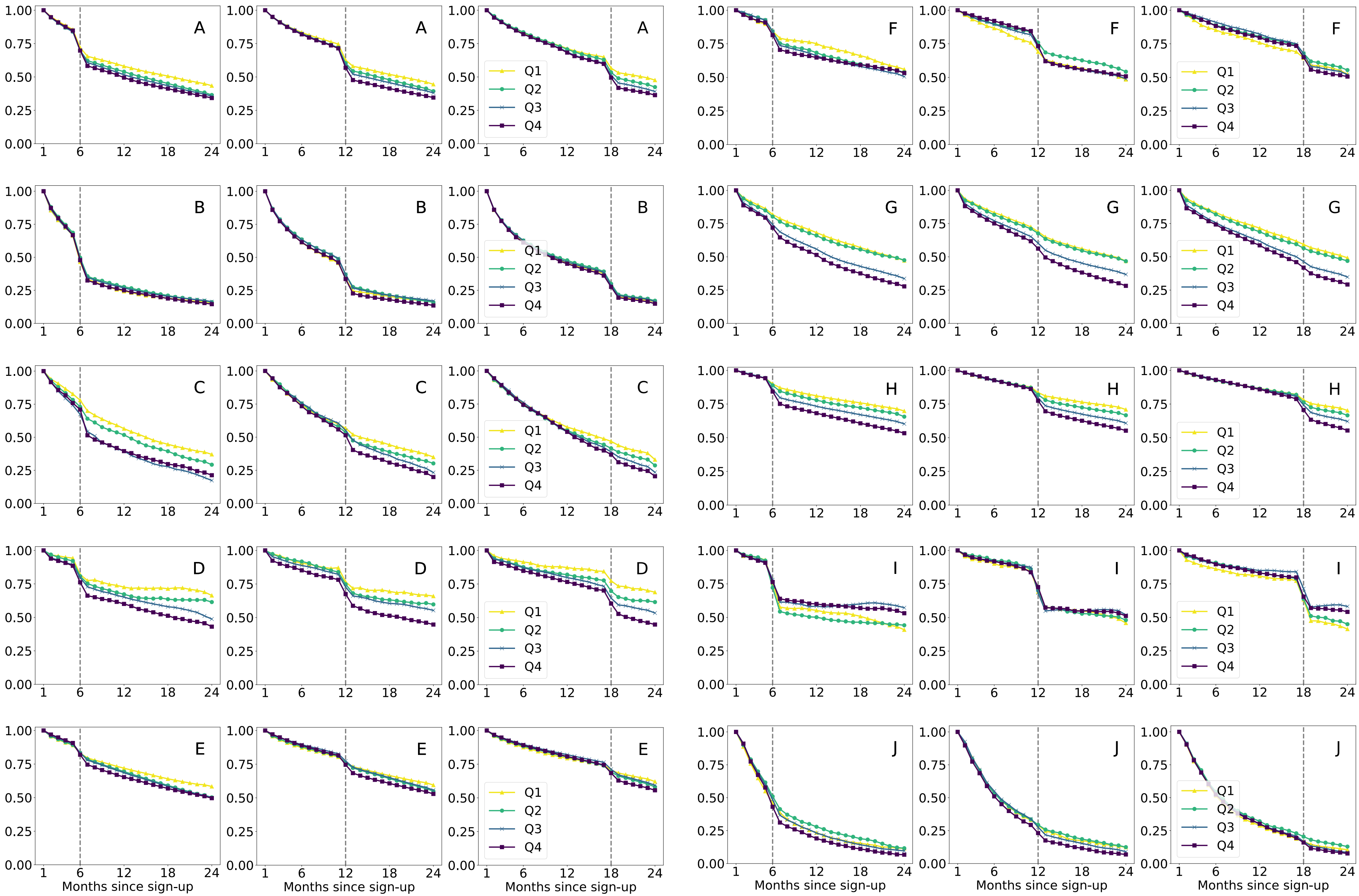
Given η, each line shows all (ρ, λ) combinations that yield the same revenue ratio



Heterogeneity by cash advance



Heterogeneity by financial sophistication



Quartiles of predicted cash advance

Predicted Pr(cash advance)			Mean monthly		
		Share w/	number of	Mean monthly	
Quartile	Mean	cash advance	transactions	spend (USD)	Mean share CNP
Q1	0.129	0.000	76.2	2,722.1	0.402
Q2	0.320	0.001	66.6	3,012.2	0.476
Q3	0.492	0.004	54.2	3,332.3	0.513
Q4	0.672	0.063	45.5	3,056.4	0.416