

# Competition and Privacy

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# Research Question

Does More Competition Lead to More or Less Privacy Intrusion?

# Motivation

Privacy has become increasingly important in the mobile economy

- On average,<sup>1</sup> a mobile phone is located by apps 3691 times/day
- Photos and files data are accessed 2432 times/day

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<sup>1</sup>Statistics published by Xiaomi privacy team, January 2021

# Policy Debate Worldwide

- Regulators are concerned that insufficient competition leads to privacy abuse
  - ▶ US: DOJ vs. Google, 2020; FTC vs. Meta, 2021
  - ▶ EU: German antitrust regulators vs. Facebook, 2020



# Policy Debate Worldwide

## Regulators' Hypothesis

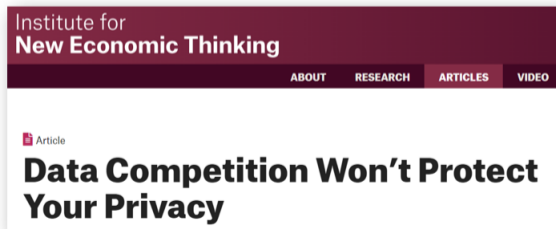
“ Emboldened by [the decline of market threats](#), Facebook revoked its users' ability to vote on changes to its privacy policies and then (almost simultaneously with Google's exit from the social media market) [changed its privacy pact with users.](#)”

(The New York Times, 2019)

# But Competition Might Not be the Cure

## The Alternative Hypothesis

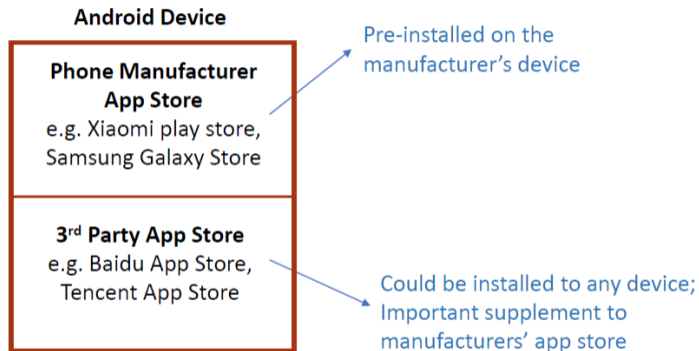
- “But as Breaking Away explores, **more competition will not help when the competition itself is toxic**. Here rivals compete to exploit us by discovering better ways to addict us, **degrade our privacy**, manipulate our behavior, and capture the surplus.” (Stucke, 2022)
- Large firms collect less sensitive data & invest more on privacy protection (Kummer and Schulte, 2019; Dulberg, 2021)



# Outline

- 1 Introduction
- 2 Context**
- 3 Identification
- 4 Data and Model
- 5 Results

# Chinese Android App Markets



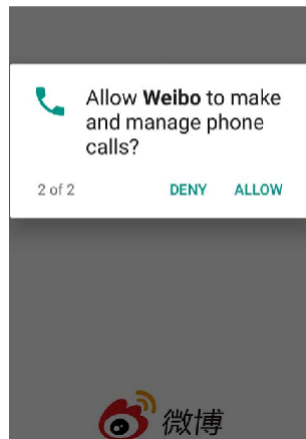
- App data from a major 3rd party Android app store (top 5)



# Measuring Privacy

- Privacy intrusion: the number of permissions requested (Krafft et al., 2017; Kesler et al., 2017; Kummer and Schulte, 2019)
  - ▶ Apps need to request permissions to **Android** if they want to access users' data or control device functions
  - ▶ The number of permissions: the level of data access and device control of an app
  - ▶ Particularly 'dangerous' permissions defined by Android

- Permission  $\neq$  user consent



# Measuring Competition

- Focus on a policy shock to competition which
  - ▶ Reduced the number of available products in treated markets
  - ▶ Increased market concentration in treated markets

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# Identification Challenge

- Competition in a market is endogenous
  - ▶ Confounds affect both competition and firms' privacy intrusion
  - ▶ E.g. market size, product features

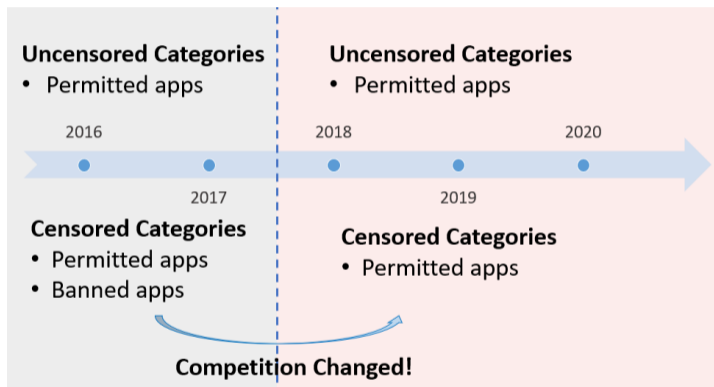
# Identification Strategy

## Internet Censorship and Censorship Circumvention

- In 2003, China launched the Golden Shield Project
  - ▶ Some of the most popular global websites and their apps are banned (Facebook, YouTube, NYT...)
- People can still use the banned apps with censorship circumvention tools (e.g. VPNs)
- In 2017, new regulation prohibits such tools not authorized by the government

# Policy Change Affects Competition

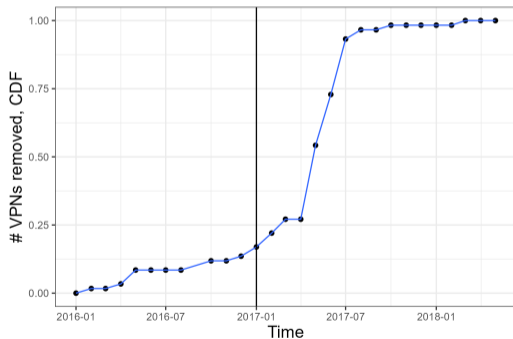
## Defining Treated and Control



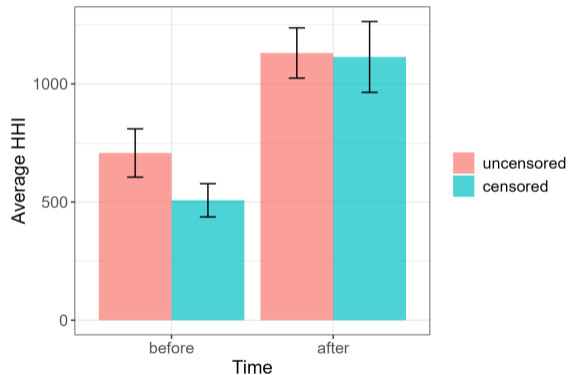
- Treated: **permitted** apps in censored categories
- Control: **permitted** apps in uncensored categories

# Evidence of Policy Change

## ● Removal of popular VPNs



## ● Change in market concentration



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# Data

## App Data

- A list of 17,001 apps available on the 3rd party Android app store
- Downloaded all historical versions 2014 - 2022 for apps in sample (327,734 App Installation packages)
- Permissions, app functions, and revenue model data from the App Installation Kit (APK) packages

## Censorship Data

- Censorship status and blocking time data from greatfire.org
- A category is censored if  $\geq 1$  top non-Chinese apps were banned before 2017 (20 out of 87 categories)

## Model: SynthDID

- Used the synthetic differences-in-differences design (SDID) (Arkhangelsky et al., 2021)
- SDID combines desirable features of DID and synthetic control

# Variable Definition

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau, \mu, \alpha, \beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^N \sum_{t=1}^T (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\}$$

- **Unit of analysis:** a version of a *permitted* app (monthly)
- **Outcome** ( $Y_{it}$ ): the number of permissions by app  $i$  at month  $t$
- **Treatment** ( $W_{it}$ ): 1 if an app is in a censored category *and* the observation was after the policy shock
- Controlled for app and month fixed effects ( $\alpha_i, \beta_t$ ), and unit and time weights ( $\hat{\omega}_i, \hat{\lambda}_t$ )

▶ Summary statistics

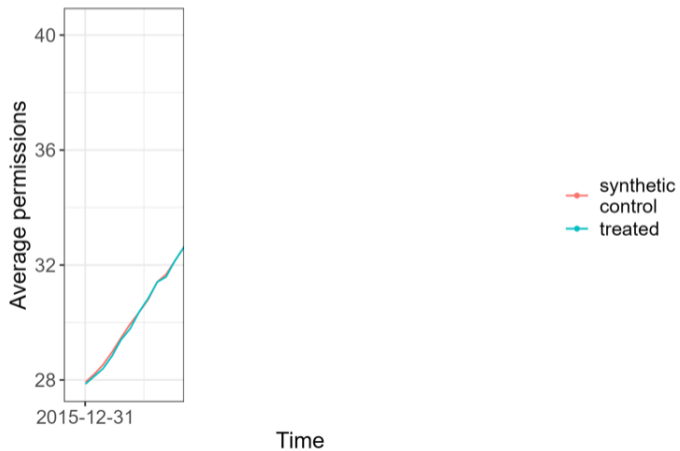
▶ SDID weights

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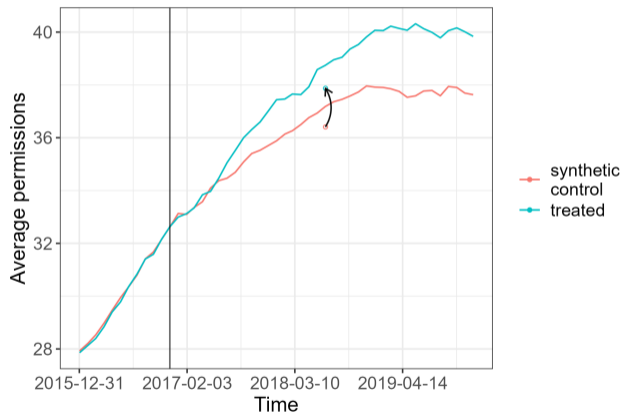
# SynthDID Results

All Permissions, Before



# SynthDID Results

Lower Competition Leads to More Intrusion



# Numerical Estimates

Table: Estimated Treatment Effects

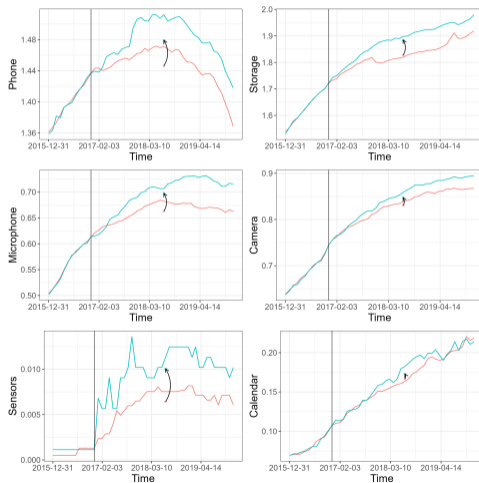
	<i>DID</i>	<i>Synth. DID</i>	<i>Synth. DID</i>
	(1)	(2)	(3)
	All Permissions	All Permissions	Dangerous Permissions
Treated	1.927***	1.463***	0.310***
Std. Error	(0.503)	(0.482)	(0.078)

Notes: Clustered standard error by market and by month is reported for the DID estimate. Jackknife standard errors are reported for synthetic DID estimates. The number of observations is 137,788. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

- Robustness on (a) dangerous permissions & (b) effect is due to competition

# Examples of Affected Permissions

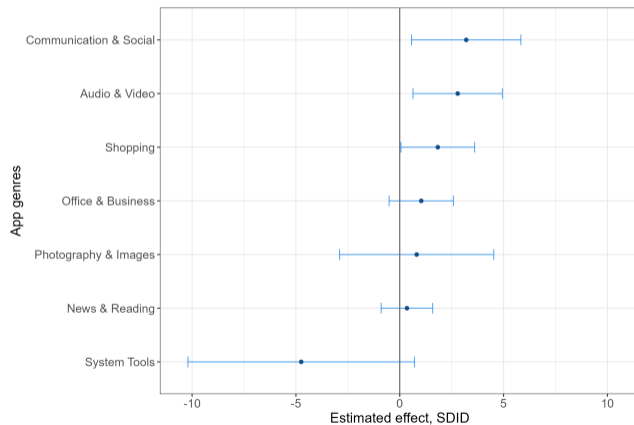
Effect Comes from Various Permissions...





# Heterogeneity by App Genre

- Genres are defined by the app store



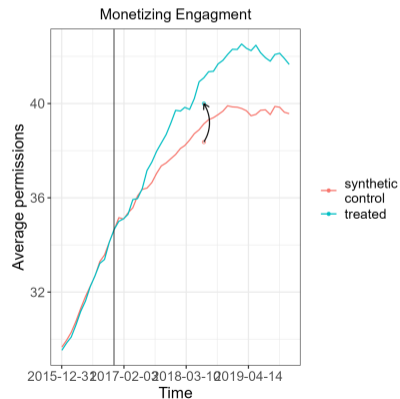
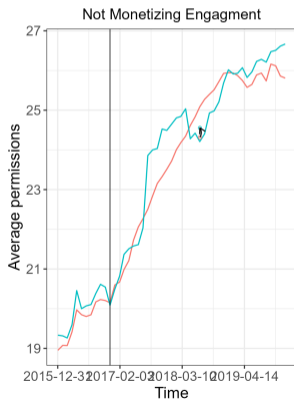
# Mechanism: What Are the Increased Permissions for?

## Intrusion for Engagement

- Analyzed each of the 150 most commonly used permissions
  - ▶ Treated apps increased requests in 114 of the 150 permissions
  - ▶ But some of the most affected permissions are specifically designed to engage users, especially through direct marketing
- This suggests treated apps substantially increased their effort to engage consumers

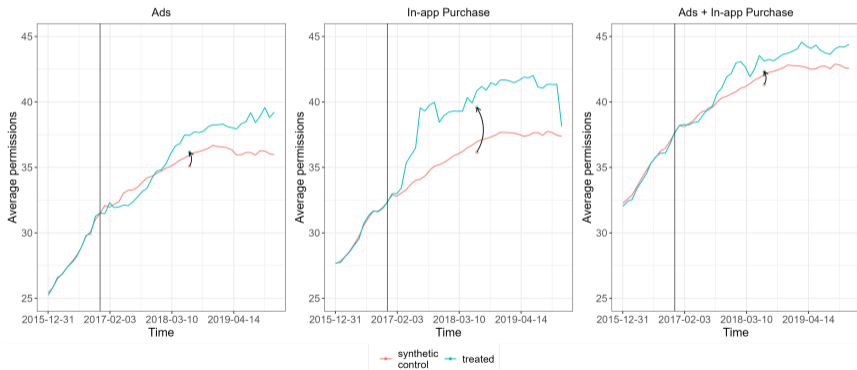
# Does Increased Engagement Effort Explain the Effect?

- If yes, effect should be larger when firms have stronger incentives to maximize engagement
- In particular, when engagement is profitable



# Stratifying by Pre-treatment Monetization Model

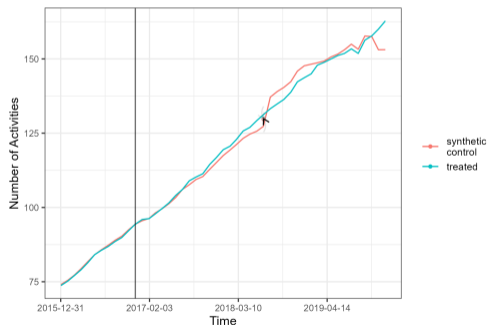
- The largest effect comes from the subsample with an in-app purchase model



# What Does Not Explain the Effect?

## Alternative Explanations

- Treated apps increased permissions to develop more functions? No.
- ... because they are facing more or different entrants? No. ▶ Alt.explanation: entrants
- ... because they use data to improve ad targeting? No. ▶ Alt.explanation: ads



(Est. effect = 0.19, p = 0.93)

## To Summarize

- I study a policy shock that reduced competition in some app categories but not others
- I find that reducing competition leads to more privacy intrusion from treated apps
- This is one of the first empirical study on the relationship between market competition and firms' privacy invasion
- For regulators, this research suggests an important way to protect privacy is by restricting market power and encouraging competition

## Thank you. Questions?

- Email: [yiw386@pitt.edu](mailto:yiw386@pitt.edu)
- Paper link: <https://shorturl.at/FDC9g>
- Paper QR code:



# This Research in One Page

## Does More Competition Lead to More or Less Privacy Intrusion?

- Context: Chinese Android app markets, 2016 - 2020
  - ▶ Privacy: permissions requested by apps
  - ▶ Market: a group of similar-functioned apps (e.g. news apps)
  - ▶ Competition: degree of concentration in a market
- Challenge: Competition is endogenous
- Solution:
  - ▶ Exogenous policy shock that reduced the competition in censored markets
  - ▶ Synthetic diff-in-diff: censored vs. uncensored markets over time
- Findings:
  - ▶ Decrease in market competition  $\Rightarrow$  more privacy-intrusive behavior



# Summary Statistics

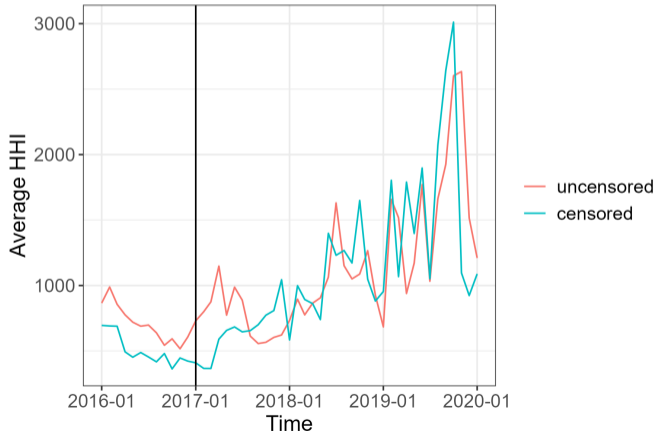
Table: Distribution of Top 10 App Categories by Treatment Status

Group	Category	Observations	% within group
Treated	Productivity	41203	17.24%
Treated	E-shopping	38409	16.07%
Treated	Communities	25381	10.62%
Treated	Information	20932	8.76%
Treated	Videos	16271	6.81%
Treated	Chat	16209	6.78%
Treated	News	15905	6.65%
Treated	Novel	9315	3.90%
Treated	Music	8083	3.38%
Treated	Livestream	7976	3.34%
Control	Tools	41552	7.60%
Control	Learning	40112	7.34%
Control	Office software	29741	5.44%
Control	Examination	25918	4.74%
Control	Discounts	23353	4.27%
Control	Medical	23055	4.22%
Control	Early childhood education	22868	4.18%
Control	Games (children)	20829	3.81%
Control	Cars	17425	3.19%
Control	Car renting	16052	2.94%

# Backup Slide 1: Competition

## Policy Change Affects Competition

- The average HHI of censored markets increased by 183.36 compared to the uncensored markets [▶ HHI bar chart](#)



## Backup Slide 2: SynthDID Weights

- Larger weights on control units that are 'similar' to treated units, and pre-treatment periods that are 'similar' to post-treatment periods

$$(\hat{\omega}_0, \hat{\omega}^{sdid}) = \underset{\omega_0 \in \mathbb{R}, \omega \in \Omega}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T_{pre}} (\omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{it}) - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^N Y_{it} \right)^2 + \zeta^2 T_{pre} \|\omega\|_2^2 \right\}, \quad (1)$$

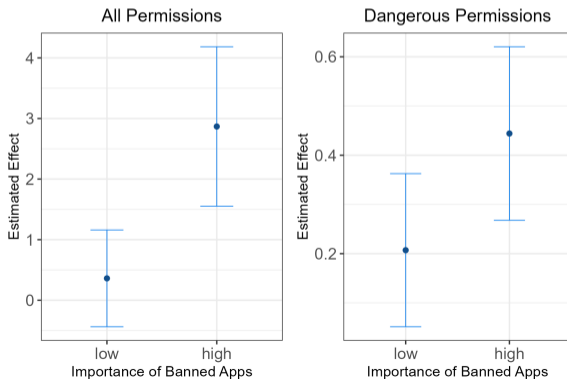
$$(\hat{\lambda}_0, \hat{\lambda}^{sdid}) = \underset{\lambda_0 \in \mathbb{R}, \lambda \in \Lambda}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N_{co}} (\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{it}) - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^T Y_{it} \right)^2 \right\},$$

▶ Variable Definition

# Backup Slide 3: Competition

If this is really about competition, then...

- Categories where banned apps have larger market shares should be more affected by the shock ▶ Robustness checks
  - ▶  $\geq 2$  banned apps in the top 1000 app rank in China in 2016
  - ▶ Video, communication, news... vs. emails, browsers, storage...



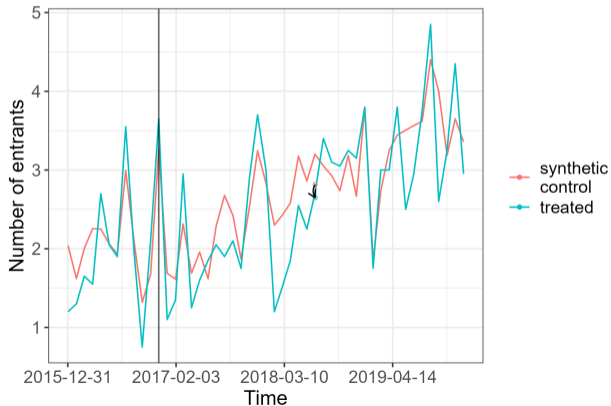
## Backup Slide 4: Dangerous Permission Types

- Phone (7 permissions)
  - ▶ phone status, number, identifier
  - ▶ directly call phone numbers
- Storage (6 permissions)
  - ▶ access stored images and files from *other* apps
- Microphone (1 permission)
- Camera (1 permission)
- Body sensors (2 permissions)
- Calendar (2 permissions)
- Call log (3 permissions)
- SMS (6 permissions)
- Location (3 permissions)
- Contacts (3 permissions)

# Backup Slide 5: Entry

Can the Effect of the Incumbents Affected by Entrants?

- The number of entrants is not significantly different
- The behavior of entrants is not significantly different



## Backup Slide 6: Advertising

### Is It Really Not about Advertising?

- The treatment does not affect whether an app uses an ad model, or the number of in-app ads.
- So treated apps did not increase how many ads they display.

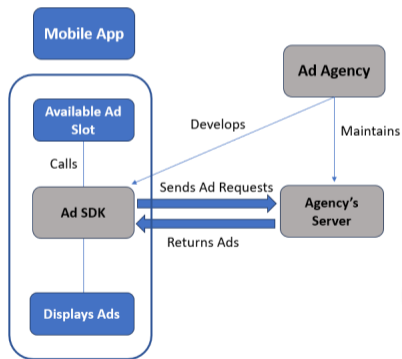
	(1)	(2)	(3)
	Has Ad	Number of Ad Activities	Permissions (Apps w/o Ads)
Treated	-0.008	-0.059	2.672**
Std. Error	(0.013)	(0.543)	(1.268)

Notes: N. Obs. is 137,788; 137,788; 101,577, respectively

# Backup Slide 6: Advertising (Continued)

## Is It Really Not about Advertising?

- But could they collect data to delivery better-targeted ads? No.
- The effect survives for treated apps that had no ads throughout.



▶ Alternative Explanations



# Why Does Competition Affect Firms' Incentives for Engagement?

## A Theoretical Explanation

- An engaged consumer is more profitable with less competition
  - ▶ Intuitively: apps need to capture and monetize engagement
  - ▶ Apps have a stronger incentive to capture user engagement when it is more monetizable
  - ▶ Consistent with empirical findings on monetization

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