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Competing for time: A study of mobile applications ☆

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ABSTRACT

Mobile applications compete for scarce user time-a mechanism I term “budget competition”-regardless of functional similarity. Complementary apps are gross substitutes when budget competition dominates functional competition. I estimate a discrete-continuous demand model to quantify the two types of competition using overlapping user data from China in 2017. Exploiting app updates to identify complementarity, I find significant substitution between functionally independent apps, demonstrating that categories are often poor proxies for competition. While budget competition can be large in absolute terms, it is often small relative to functional competition. I discuss when budget competition may play a larger role.

1. Introduction

In November 2025, the U.S. District Court rejected the Federal Trade Commission’s narrow “Personal Social Networking” market definition, ruling instead that Facebook and Instagram compete for user time in a broader market that includes TikTok and YouTube. For economists, this ruling underscores a critical methodological gap: tools for quantifying competition among apps are underdeveloped. Traditional SSNIP (small but significant and non-transitory increase in price) tests are inapplicable in zero-price environments, and qualitative reliance on functional categories proves inadequate. While the Apple App Store classifies TikTok as “Entertainment” and Facebook as “Social Networking,” the court found that users actively substitute between them, noting that such “artificial categories do not make sense.”[1] This highlights an urgent need for new quantitative frameworks to analyze competition where prices are zero.

The binding time constraint complicates competition among apps even more. Users have at most 24 h per day. A minute spent on TikTok is a minute not spent on Facebook. In this paper, I refer to this as “budget competition” to distinguish it from “functional competition” captured by complementarity or substitutability. Similarly, expenditure on housing and food would crowd out discretionary spending. Budget competition is salient in the mobile Internet industry because of the scarcity of time and its concentration

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[1] See Mem. Op. at 51, Fed. Trade Comm’n v. Meta Platforms, Inc., No. 1:20-cv-03590-JEB (D.D.C. Nov. 18, 2025), ECF No. 693.

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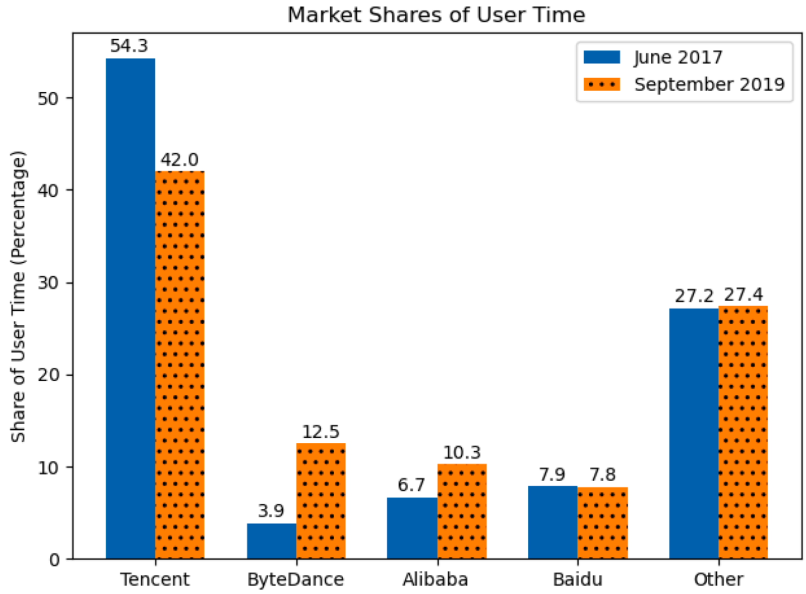

Fig. 1. Market Shares of Tech Giants in China. Note: Market shares are calculated based on time spent on apps developed by each tech giant in China. Data Source: Quest Mobile.

(see Fig. 1). Budget competition has been invoked in the landmark antitrust cases *Qihu v. Tencent* in 2013[2] and *FTC v. Meta* in 2025[3] to expand the relevant market. Tencent contended that its instant-messaging software QQ competes with all other Internet companies for user attention.[4] Meta argued that it competes with TikTok and YouTube for “users’ time and attention”.[5] Both claims are trivially true, as all apps compete for time regardless of their functions. However, the key is the quantitative impact of budget competition. If time constraints outweigh functional interactions, complementary apps are gross substitutes. To accurately estimate competition among apps, we must consider both functional competition and budget competition, which necessitates a structural model of demand with a binding time constraint, in addition to allowing for complementarity/substitutability. In this paper, I develop such a model to estimate substitution between apps from observational data and decompose the substitution into functional competition and budget competition.

To distinguish between budget and functional competition, consider a thought experiment in which an app is shut down. There are two reasons the exit of an app could affect other apps. First, because of substitutability (complementarity), users find the remaining apps more (less) appealing. Hence users will spend more (less) time on the remaining apps. This is the functional competition effect. Second, the exit of an app means time that used to be spent on that app is now “free”, and users can allocate it to the remaining apps. This is the budget competition effect. I propose a model of time allocation to apps. The model features a quadratic utility function (Thomassen et al., 2017)[6] to capture important features of apps: the discrete-continuous nature of app usage, zero prices, complementarity/substitutability, and a binding time constraint. I derive analytical conditions under which budget competition dominates functional competition and a pair of complementary apps become gross substitutes.

I estimate the model using a weekly panel of app usage of top apps in China, covering the first quarter of 2017. For each pair of apps, I observe not only their usage but also the number of overlapping users who use both apps in a week. I use updates of apps to identify complementarity/substitutability. Updates of an app should affect the utility of that app but not the *utilities* of other apps. However, updates of an app could change the *usage* of other apps through complementarity/substitutability. This model is estimated using a GMM strategy *a la* Berry et al. (1995). In all specifications, I include an outside option consisting of offline activities and a generic app that accounts for any other application usage. I apply this model to a pair of substitutes *a priori* (Baidu Map and Amap) and a pair of complements *a priori* (Baidu and Baidu Map) to validate the model. My model can correctly identify complements and substitutes. I apply the model to WeChat and iQIYI, the two apps that command the highest share of user time and budget competition are expected to be large between them. WeChat and Kwai are also analyzed because they are a pair of independent apps *a priori* and Kwai experienced spectacular growth after 2017.

2 For a brief introduction of this case, see https://www.pymnts.com/cpi_posts/qihoo-360-v-tencent-first-antitrust-decision-by-the-supreme-court/ and https://enipc.court.gov.cn/en-us/news/view-22.html.

3 See the relevant documents at https://www.courtlistener.com/docket/18735353/federal-trade-commission-v-meta-platforms-inc/

4 The Supreme People’s Court rejected this argument with qualitative analysis in the final adjudication in 2013.

5 The District Court accepted this definition based on observational and experimental evidence.

6 Lewbel and Nesheim (2019) also use a quadratic utility model.

I find significant diversion between WeChat and Kwai (6% from WeChat to Kwai and 30% from Kwai to WeChat), two apps in different categories. This shows that categories can be a poor proxy for competition. Budget competition explains only a small fraction of the substitution patterns. For pairs with relatively low usage, like Baidu Map and Amap or Baidu and Baidu Map, the impact of budget competition is negligible, accounting for a time shift of less than 0.02 h per 1000 smartphone users. Budget competition effects are orders of magnitude larger (12 h when WeChat exits and 7 h when iQIYI exits for 1000 smartphone users in a week) for WeChat and iQIYI because a large number of users spend a substantial amount of time on both of them. However, budget competition explains only 2% of the overall effects. We get similar results for WeChat and Kwai. Budget competition explains less than 1.5% of the overall effects. In summary, for the top apps in China in 2017, budget competition is substantial in magnitude but minor when compared to functional competition. The analysis of more recent data from 2024 suggests that despite the significant growth in the mobile app market since 2017, the relative role of budget competition remains small. Budget competition will play a larger role if functional interactions between apps are minimal, which is more likely if the time budget under consideration is small.

This paper contributes to the emerging literature on mobile applications. Due to data limitations, researchers have mostly focused on the supply side of apps (Bresnahan, Orsini, Yin and Pai-Ling, 2014a; Bresnahan, Davis, Yin and Pai-Ling, 2014b; Ershov, 2018; Jin, Liu, and Wagman, 2024; Leyden, 2022; Li and Agarwal, 2017; Liu, Nekipelov, and Park, 2014; Liu, 2017; Wen and Zhu, 2017; Yin, Davis, and Muzyrya, 2014). The demand side for apps is either absent or described with aggregate ranking or downloads data from app stores (Carare, 2012; Deng, Lambrecht and Liu, 2022; Ghose, Han and Pil, 2014; Cecere, Le Gue and Lefrere, 2020; Li, Bresnahan, and Yin, 2016; Li and Tsai, 2022; Yi, Lee, and Kim, 2019).[7] An immediate predecessor of this paper is Han et al. (2016). They employ a multi-nominal discrete-continuous extreme value (MDCEV) model developed by Bhat (2005). However, in their paper, joint usage is explained purely by correlated preferences. In contrast, this study explicitly disentangles substitutability/complementarity from correlated preferences using overlapping user data and instrumental variables.

A concurrent paper by Kawaguchi et al. (2022) simulates mergers of apps. They estimate demand and supply for apps in two categories with usage and advertising data from Japan. Their paper imposes more restrictive conditions on demand. Aridor (2025) addresses the market definition problem in the mobile Internet industry through experimental methods. Aridor (2025) finds significant cross-category substitution, which is consistent with the theoretical prediction and empirical findings in my paper. Allcott et al. (2020) and Allcott et al. (2022) study the welfare implications and addiction of social media apps using experimental results.

Methodologically, this paper extends the framework proposed by Berry et al. (1995). This model represents the first attempt to integrate four key components into a consumer demand framework: discrete-continuous decisions, interactions between products, budget constraints, and estimation with instruments. This paper contributes to the literature on the demand for differentiated goods in economics and marketing, particularly focusing on cases where complementarity is of interest (Ershov, Laliberté, Jean-William and Orr, 2018; Gentzkow, 2007; Kim, Allenby, and Rossi, 2002; Lewbel and Nesheim, 2019; Mehta, 2007; Nair, Dubé, and Chintagunta, 2005; Song and Chintagunta, 2006, 2007; Thomassen, Smith, Seiler, and Schiraldi, 2017; Vélez-Velásquez, 2019; Wang, 2024). Unlike Gentzkow (2007), this paper accounts for both the extensive margin (selection of products) and the intensive margin (quantities of selected products) in consumer decisions. This distinction is crucial for estimating complementarity. Consumers purchase two boxes of cereal with different flavors due to their preference for variety (which exhibits decreasing marginal utility) rather than complementarity. A discrete choice model employing bundles of various products cannot distinguish between complementarity and taste for variety. Taste for variety is captured through satiation parameters and can be estimated with usage data in this study. Additionally, this paper contributes to the investigation of time allocation within transportation research (Bhat, 2005, 2018; Kitamura, 1984; Pawlak, Polak, and Sivakumar, 2015, 2017) by directly estimating relationships between activities. Moreover, this model offers a flexible second-order approximation to consumer decisions, allowing for adaptation to explore other research topics.

This paper contributes to the ongoing policy discourse on regulating the digital economy (European Commission. Directorate General for Competition, 2019; Furman et al., 2019; Scott-Morton et al., 2019). A key challenge in analyzing the digital economy is that the digital economy is characterized by free services, whereas conventional economic tools necessitate pricing data.[8] Complements and substitutes are defined with compensated cross-price elasticities and market power is defined with prices as well. This study employs time variations rather than price variations to model the demand for apps. The concept of budget competition resonates with the “curse of bigness” central to the New Brandeis movement (Khan, 2018; Wu and Cashman, 2018). Budget competition suggests that the concentration of user time and attention harms consumers, transcending traditional functional boundaries. However, the empirical results of this study indicate that the magnitude of the budget competition effect is likely modest within the mobile Internet industry.

The empirical results have direct policy implications. First, they demonstrate that categories can be a poor proxy for competitive relationships, suggesting that a more nuanced approach is needed for market definition. Second, the decomposition of competition I propose introduces a novel "theory of harm" for consumers. The framework reveals that the merger of complementary/independent

[7] Both Wu et al. (2022) and Lee (2018) use a panel of individual usage of smartphone. However, both observe usage of categories rather than apps. Lee (2018) estimates the demand for smartphone. Wu et al. (2022) uses a hidden Markov model to analyze what motivates mobile app usage.

[8] In his opinion piece in the Washington Post, Wu (2018) argues:

> “Our standards for assessing mergers, fixated on consumer prices, were a poor match for the tech economy and are effectively obsolete.”

In the report commissioned by the Stigler Committee on Digital Platforms, Scott-Morton et al. (2019) proposes

> “The law needs better analytical tools to take into account the impact of potential and nascent competitors and competition. Market definition will vary according to what consumers are substituting between[......].”

apps, which might seem benign, could harm users if budget competition dominates functional competition. Ultimately, this paper offers a rigorous structural model to empirically evaluate the significance of budget competition, providing a new tool for policymakers and regulators to better understand and address the unique competitive dynamics of the digital economy.

2. A theory of budget competition

This section formally defines and distinguishes budget competition from functional competition. I then provide an analytical characterization of budget competition and functional competition within a quadratic utility framework. This characterization reveals that budget competition can dominate functional competition and a pair of complementary apps can be gross substitutes.

2.1. Definition

To quantitatively define budget competition, we focus on the exit of an app.[9] There are two reasons the exit of an app could affect other apps. First, because of substitutability (complementarity), users find the remaining apps more (less) appealing. Hence users will spend more (less) time on the remaining apps. This is the functional competition effect. Second, the exit of an app means time that used to be spent on that app is now "free", and users can allocate it to the remaining apps. This is the budget competition effect.

Consider the original time allocation bundle, $\mathbf{t}^o = \arg\max U(\mathbf{t})$, and the new bundle, $\mathbf{t}^n = \arg\max U(\mathbf{t}|t_j = 0)$, subject to the same time constraint $\sum_{k=0}^{J} t_k = T$. $\mathbf{t}^n - \mathbf{t}^o$ summarizes the effects of the exit of app j. To formally separate budget competition and functional competition, I introduce an intermediate step. In the intermediate step, the user chooses an intermediate bundle, $\mathbf{t}^i$, such that the marginal utilities of $\mathbf{t}^i$ are equal to the marginal utilities of $\mathbf{t}^o$ except for app j. That is, $\mathbf{t}^i_{-j}$ is the solution to the following system of equations:

$$\frac{\partial U(\mathbf{t}^i_{-j}|t^i_j = 0)}{\partial t^i_k} = \frac{\partial U(\mathbf{t}^o)}{\partial t^o_k} \quad \forall k \neq j \& t^i_k \geq 0 \tag{1}$$

Note that the time constraint is irrelevant in this step. $\mathbf{t}^i - \mathbf{t}^o$ is the functional competition effect because the difference is entirely due to complementarity or substitutability among apps. $\mathbf{t}^n - \mathbf{t}^i$ is therefore the budget competition effect. We can extend the definition to an entry as well.

Price changes and a wealth budget can also be incorporated. Consider pay-per-use by adding $g(W - \mathbf{p} \cdot \mathbf{t})$ into $U(t)$ where $\mathbf{p}$ is the vector of hourly prices of apps, W is the total wealth, and $g(\cdot)$ is the utility of wealth. When p_j changes from p^o_j to p^n_j, the intermediate bundle is given by

$$\frac{\partial U(\mathbf{t}^i|\mathbf{p}^o_{-j}, p_j = p^n)}{\partial t^i_k} = \frac{\partial U(\mathbf{t}^o|\mathbf{p}^o)}{\partial t^o_k}$$

where $\mathbf{t}^o = \arg\max U(\mathbf{t}, \mathbf{p})$, subject to both the time constraint and the monetary constraint. Budget competition extends to even more complicated constraints. The intermediate bundle $\mathbf{t}^i$ in (1) is not the outcome of an optimization and can always be calculated regardless of the number of constraints. For most products, monetary constraint is the only relevant constraint. Housing and food expenditure would crowd out discretionary expenses. Purchasing a new car would likely reduce vacation expenditures. Nevertheless, previous literature has not formally explored budget competition. The reason is that the budget shares of traditional products like cereals and yogurt are generally small. Consumers would not become poorer because they buy an expensive cup of yogurt. In contrast, time shares of leading apps can be large. A user may spend two hours on Instagram and two hours on TikTok within a single day. Users would find other apps to "kill time" if TikTok is blocked.

2.2. Relationship with Slutsky/Hicksian decomposition

The concepts of budget competition and functional competition relate to the substitution effect and the wealth effect in the classical demand theory. With Slutsky/Hicksian decomposition, we isolate the wealth effect of a price change through wealth compensation, ensuring that the original bundle is just affordable or the original level of utility is just attainable (Mas-Colell et al., 1995). In this paper, I isolate the budget competition effect of a price change by restoring the marginal utilities to the original level. In Table 1, I compare the two ways of decomposition and the two sets of definitions of complements and substitutes considering the effects of an increase in $p_{j'}$ on product j. Whereas the wealth effect can be negative (for normal goods) or positive (for inferior goods), the budget competition effect is always positive. A notable implication from Slutsky/Hicksian decomposition is that when the wealth effect dominates the substitution effect, the Walrasian demand for an inferior good increases after an increase in its own price. A similar surprise arises from my decomposition: when budget competition dominates functional competition, complementary goods are gross substitutes. This idea will be formally elucidated when we set up the utility model.

[9] The analysis applies to entry and price changes as well.

Table 1
The Effects of an Increase in $p_{j'}$ on Product j.

Product Relationship	Definition	Decomposition	
		Substitution Effect	Wealth Effect
Substitutes	$\frac{\partial h_j(\mathbf{p},u)}{\partial p_{j'}} > 0$	+	− (normal); + (inferior)
Complements	$\frac{\partial h_j(\mathbf{p},u)}{\partial p_{j'}} < 0$	−	
		Functional Competition	Budget Competition
Substitutes	$\frac{\partial^2 U(\mathbf{x})}{\partial x_j \partial x_{j'}} < 0$	+	+
Complements	$\frac{\partial^2 U(\mathbf{x})}{\partial x_j \partial x_{j'}} > 0$	−	+

Note:
1. $h_j(\mathbf{p}, u)$ is the Hicksian demand of product j given prices $\mathbf{p}$ and a utility level u. $U(\mathbf{x})$ is the utility of consuming $\mathbf{x}$.
2. The upper panel presents Slutsky decomposition and the lower panel my decomposition.

2.3. A utility framework

To study budget competition between a pair of apps, we consider a smartphone user who allocates her time to four options $j = 0, 1, 2, 3$. $j = 1, 2$ are the two apps of interest. $j = 0$ is the option of not using a smartphone and $j = 3$ is a generic app capturing the use of any other apps. Her time allocation can be described by $\mathbf{t} = [t_0, t_1, t_2, t_3]'$ where t_j is the amount of time allocated to option $j = 0, 1, 2, 3$. The utility maximization problem of consumer i is

$$\max_{\mathbf{t}} \boldsymbol{\mu}'\mathbf{t} + 0.5\mathbf{t}'\boldsymbol{\Gamma}\mathbf{t} \tag{2}$$

$$s.t. \mathbf{1} \cdot \mathbf{t} \le T \tag{3}$$

where $\boldsymbol{\mu} = [\mu_0, \mu_1, \mu_2, \mu_3]'$ and

$$\boldsymbol{\Gamma} = \begin{bmatrix} \gamma_0 & 0 & 0 & 0 \\ 0 & \gamma_1 & \gamma_{12} & 0 \\ 0 & \gamma_{12} & \gamma_2 & 0 \\ 0 & 0 & 0 & \gamma_3 \end{bmatrix}.$$

The quadratic utility function in (2) can be seen as a second order approximation of any reasonable utility function. Intuitively, the first order parameter μ_j (taste parameter) determines if j is used. I assume $\mu_0 = 1$ to normalize the utility. The second order parameter γ_j (satiation parameter) determines how much time is spent on app j. The interaction parameter γ_{12} is negative if the two apps are substitutes and positive if they are complements. γ_{12} determines if the two apps are likely to be used together. We assume other interaction parameters in $\boldsymbol{\Gamma}$ like γ_{01} or γ_{23} to be 0 because a user of app 1 or app 2 should always have a positive t_0 and t_3.

The conventional definition of complements and substitutes[10] hinges on the **cross-derivatives of compensated demand functions**, aligning closely with the substitution effect in the classical demand theory (Mas-Colell, Whinston, and Green, 1995). For a pair of apps with $\gamma_{12} = 0$, their compensated cross derivatives would be positive, making them substitutes by the conventional definition. In other words, any two unrelated products are substitutes because they can substitute each other in providing utility. This may be at odds with how firms think about competition and substitution. Firms usually think about competition in terms of functions and features. In contrast, my approach defines complements and substitutes based on the **cross-derivatives of utility functions**, and hence does not rely on utility maximization or expenditure minimization. This distinction is compatible with our definition of budget competition in Section 2.1.

2.4. Analytical characterization

Within the quadratic utility framework, we consider the budget competition effect of the exit of app 2 on app 1. Eq. (1) can now be simplified when app 2 exits the market[11]:

$$\mu_1 + \gamma_1 t_1^o + \gamma_{12} t_2^o = \mu_1 + \gamma_1 t_1^i.$$

In Table 2, I provide analytical solutions for functional competition and budget competition depending on whether t_1^o and t_1^i are strictly positive. Note that for app 2 to have any competitive effect, be it budget competition or functional competition, t_2^o must be strictly positive, which is implicitly assumed in Table 2.

[10] Samuelson (1974) discusses various definitions of complements and substitutes. Berry et al. (2017) discuss seven categories of complements.
[11] The marginal utilities of app 3 and the offline option would not change with the exit of app 2 because I assume $\gamma_{20} = \gamma_{23} = 0$.

Table 2
Analytical Decomposition.

t_1^o	t_1^i	Functional Competition ($t_1^i - t_1^o$)	Budget Competition ($t_1^n - t_1^i$)
$t_1^o > 0$	$t_1^i > 0$	$\frac{\gamma_{12}}{\gamma_1} t_2^o$	$(1 - \frac{\gamma_{12}}{\gamma_1}) t_2^o \frac{1}{\gamma_1(\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3})}$
$t_1^o > 0$	$t_1^i = 0$	$-t_1^0$	$\max\{0, \frac{T - \frac{\mu_1 - \mu_0}{\gamma_0} - \frac{\mu_1 - \mu_3}{\gamma_3}}{\gamma_1(\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3})}\}$
$t_1^o = 0$	$t_1^i > 0$	$\frac{\mu_2 - \mu_1}{\gamma_1} + \frac{\gamma_2}{\gamma_1} t_2^o$	$[(1 - \frac{\gamma_2}{\gamma_1}) t_2^o - \frac{\mu_2 - \mu_1}{\gamma_1}] \frac{1}{\gamma_1(\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3})}$
$t_1^o = 0$	$t_1^i = 0$	0	$\max\{0, \frac{T - \frac{\mu_1 - \mu 0}{\gamma_0} - \frac{\mu_1 - \mu_3}{\gamma_3}}{\gamma_1(\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3})}\}$

Note: This table presents analytical characterizations of functional competition and budget competition. The calculations are in Appendix D.

The results in Table 2 are intuitive. Let us focus on the first row and assume $\gamma_{12} \leq 0$, $t_1^o > 0$ and $t_1^i > 0$. In the intermediate step, $\frac{\gamma_{12}}{\gamma_1} t_2^o$ is diverted to app 1 due to functional competition. That leaves the user with $(1 - \frac{\gamma_{12}}{\gamma_1}) t_2^o$ of free time, which is allocated to the remaining options *proportional to the inverse of their satiation parameters*. The intuition is similar for complements. When $\gamma_{12} > 0$, t_1^i decreases by $|\frac{\gamma_{12}}{\gamma_1}| t_2^o$. Therefore, the free time is $(1 + |\frac{\gamma_{12}}{\gamma_1}|) t_2^o$ and larger than t_2^o. For users with $t_1^o > 0$ and $t_1^i > 0$, the gross diversion ratio consists of two parts: diversion because of functional competition ($\frac{\gamma_{12}}{\gamma_1}$) and diversion because of budget competition ($(1 - \frac{\gamma_{12}}{\gamma_1}) \frac{\frac{1}{\gamma_1}}{\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3}}$):

$$\text{Diversion Ratio}(DR) \equiv \frac{t_1^n - t_1^o}{t_2^o} = \frac{\gamma_{12}}{\gamma_1} + (1 - \frac{\gamma_{12}}{\gamma_1}) \frac{\frac{1}{\gamma_1}}{\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3}} \tag{4}$$

When $\gamma_{12} = 0$, we have $DR = \frac{\frac{1}{\gamma_1}}{\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3}} > 0$ despite the fact that the two apps are functionally independent. However, for budget competition to change the relevant market definition, budget competition has to be large enough. Note that within the quadratic utility framework, we have $t_j^o \propto \frac{1}{\gamma_j}$. Therefore, for budget competition ($\frac{\frac{1}{\gamma_1}}{\frac{1}{\gamma_0} + \frac{1}{\gamma_1} + \frac{1}{\gamma_3}} t_2^o$) to be large for a user, we need t_1^o and t_2^o to be large. When we consider usage of many users i, we need t_{i1}^o and t_{i2}^o to be positively correlated across i. For antitrust authorities, mergers involving apps with significant shares of user time or apps targeting the same niche market should trigger scrutiny from antitrust authorities, irrespective of their functional aspects. Candidates are superapps or social apps with many functions (WeChat, Alipay, Baidu, Facebook, Snapchat), gaming apps (PUBG, Honor of Kings), and video and streaming apps (YouTube, TikTok, Twitch, Netflix).

Consider the case when $\gamma_{12} > 0$ and the two apps are complements. The diversion ratio in (4) can be positive or negative. This means complementary apps can become gross substitutes because of budget competition. The threshold for the diversion ratio in (4) to be positive is given by

$$DR \geq 0 \Leftrightarrow \gamma_{12} \leq -\frac{1}{\frac{1}{\gamma_0} + \frac{1}{\gamma_3}}.$$

In other words, γ_{12} has to be sufficiently small for a pair of complements to be gross substitutes. When $\gamma_{12} < 0$, the two apps are substitutes. Budget competition leads to a diversion ratio larger than the one predicted by functional relationship.

2.5. *Budget competition in the* FTC v. Meta *case*

In the *FTC v. Meta* case, John List calculated gross diversion ratios from Facebook and Instagram to other apps based on an experiment. However, the court has doubts about those gross diversion ratios:

> "Those numbers might not represent substitution if they merely reflected where users were spending time anyway. Suppose that someone was already spending 10% of his day on YouTube. If, when he was paid to spend less time on Instagram, he devoted 10% of his newfound free time to YouTube, then he would not be using that app to substitute for Instagram but simply spending additional time as he normally would have."[12]

Implicitly, the court draws a distinction between budget competition and functional competition, suggesting that the former does not constitute genuine competitive constraint. To address this concern, List calculated an indexed ratio of "(1) the share of erstwhile Instagram time that a user allocated to an app to (2) the share of pre-treatment time that this user was spending on the app".[13] The competitive patterns implied by these indexed ratios were described as "even more striking" than the gross ratios by the court.

[12] Mem. Op. at 46, Fed. Trade Comm'n v. Meta Platforms, Inc., No. 1:20-cv-03590-JEB (D.D.C. Nov. 18, 2025), ECF No. 693.
[13] Ibid.

From the perspective of my model (see (4)), what List did is to use $\frac{t_1^o}{T-t_1^o}$ to approximate $\frac{\frac{1}{\gamma_1}}{\frac{1}{\gamma_0}+\frac{1}{\gamma_1}+\frac{1}{\gamma_3}}$ and his indexed ratio is $\frac{DR}{\frac{t_1^o}{T-t_1^o}} \approx \frac{\frac{\gamma_{12}}{\gamma_1}}{\frac{t_1^o}{T-t_1^o}} + (1-\frac{\gamma_{12}}{\gamma_1})$, which is an increasing function of $\frac{\gamma_{12}}{\gamma_1}$.[14] Drawing on the theoretical characterization in Section 2.4, we derive two implications. First, budget competition is competition. The assertion that diversion driven by budget constraints "might not represent substitution" is unfounded. To define a relevant market , we do not need to distinguish between budget competition and functional competition if we have credible gross diversion ratios.[15] Second, budget competition is not large enough to change the market definition of major apps like Facebook and Instagram in the United States in 2025. This is consistent with the results I find for Chinese apps in 2017.

3. Data and estimation

In this section, I first introduce the data used for estimation. I then add more details to our model so that the model in Section 2.3 is estimable. Lastly, I discuss how we can separately identify complementarity and correlated preferences.

3.1. Data

I utilize a proprietary weekly panel dataset from iResearch, a prominent Chinese consulting firm specializing in the mobile internet industry. The data span the first quarter of 2017 and consists of three parts: app usage, total smartphone usage, and overlapping user data.

The app usage data covers the top 300 Android apps in China across 290 demographic groups for 13 weeks. A demographic group is defined by gender, age (below 24, 25–30, 31–35, 36–40, and above 40), and province (29 provinces). To ensure reliability, the sample is restricted to apps with at least 50,000 estimated active users, resulting in an average of 82 apps per week-market pair. For each app, we observe the number of weekly active users (per 10,000 devices) and the average time spent on the app per device. I also have similar usage metrics for all Android smartphones, which allows us to calculate each app's market share in terms of active users within its respective demographic group.

Most importantly, I have overlapping user data. For each pair of apps, I observe the number of Android users who used both apps at least once during the week. Intuitively, this variable is crucial for the identification of complementarity.

3.2. Additional assumptions

To estimate the model in Section 2.3, I add simplifying assumptions. To normalize the level of the utility function, I assume $\mu_0 = 1$. I assume $\mu_3 = 2$ so that all users spend a positive amount of time on the generic app.[16] μ_3 can be any number greater than μ_0. Because time spent on $j = 0$ is a residual term ($t_0 = T - t_1 - t_2 - t_3$) in the model, I set γ_0 to a small negative constant, -0.001 ($\frac{1}{2} \times 0.001 = 0.0005$). With these assumptions, the utility maximization problem of consumer i in market $m = 1, 2, \dots, M$ is

$$\max_{t_{i0m},t_{i1m},t_{i2m},t_{i3m}\geq 0} t_{i0m} - 0.0005t_{i0m}^2 + \sum_{j=1}^{2} \mu_{ijm}t_{ijm} + 2t_{i3m} + \frac{1}{2}\sum_{j=1}^{3}\gamma_{ijm}t_{ijm}^2 + \gamma_{12}t_{i1m}t_{i2m} \tag{5}$$
$$s.t. \quad t_{i0m} + t_{i1m} + t_{i2m} + t_{i3m} = 168$$

T becomes 168 in (5). The number 168 is the total number of hours in a week and the time scope of this utility function. This choice is imposed by the data structure; I happen to observe weekly usage. One can certainly consider utility functions defined over various time periods like a month, a day, an hour, or even a second if the data allows. Estimated demand models will be different but valid within their respective time scopes. For example, when modeling usage for every second, all apps are gross substitutes because of budget competition. Depending on the question of interest, we might opt for different time scopes. For instance, if we want to study the effects of marketing campaigns, we want to set T to be a day or a week rather than a year. If possible, we should choose T spanned by the observed usage of all options of interest. If users never use smartphones between 11 pm and 7 am and we are interested in app usage, then we should consider $T = 16$ for daily data or $T = 16 \times 7 = 112$ for weekly data.

3.3. Consumer heterogeneity

Consumers have different preferences for apps. Consider the case where we can only observe aggregate outcomes for a set of markets (denoted with m). μ_{ijm} and γ_{ijm} are parameterized as

$$\mu_{i1m} = \mathbf{x}_m \boldsymbol{\beta}_1^{\mu} + \xi_{1m}^{\mu} + \varepsilon_{i1m} = \delta_{1m}^{\mu} + \varepsilon_{i1m} \tag{6}$$

[14] When $\gamma_{12} = 0$, $\frac{t_1^o}{T-t_1^o} = \frac{\frac{1}{\gamma_1}}{\frac{1}{\gamma_0}+\frac{1}{\gamma_1}+\frac{1}{\gamma_3}}$. In an earlier version of this paper, I derive an index of budget competition when $\gamma_{12} = 0$.

[15] In the *Qihu v. Tencent* case, we do not have such gross diversion ratios.

[16] All users in my dataset spend a positive amount of time on Android smartphones. Otherwise they are not observed.

$$\mu_{i2m} = \mathbf{x}_m \boldsymbol{\beta}_2^{\mu} + \xi_{2m}^{\mu} + \varepsilon_{i2m} = \delta_{2m}^{\mu} + \varepsilon_{i2m} \tag{7}$$
$$\gamma_{i1m} = \mathbf{x}_m \boldsymbol{\beta}_1^{\gamma} + \xi_{1m}^{\gamma} = \delta_{1m}^{\gamma} \tag{8}$$
$$\gamma_{i2m} = \mathbf{x}_m \boldsymbol{\beta}_2^{\gamma} + \xi_{2m}^{\gamma} = \delta_{2m}^{\gamma} \tag{9}$$
$$\gamma_{i3m} = \mathbf{x}_m \boldsymbol{\beta}_3^{\gamma} + \xi_{3m}^{\gamma} = \delta_{3m}^{\gamma} \tag{10}$$

where $\mathbf{x}_m$ is a set of exogenous market level variables including fixed effects.[17] I follow Berry et al. (1995) and Nevo (2000) in denoting market-level parameters with $\boldsymbol{\delta} = (\delta_{1m}^{\mu}, \delta_{2m}^{\mu}, \delta_{1m}^{\gamma}, \delta_{2m}^{\gamma}, \delta_{3m}^{\gamma})$. ξ^{μ} and ξ^{γ} capture app-market specific idiosyncratic error terms. For example, a weather shock to market m may increase the marginal utility of Uber but not that of Google Docs. ε_{i1m} and ε_{i2m} are individual error terms that are iid across individuals but can be correlated across apps. ε_{i1m} and ε_{i2m} capture unobserved individual characteristics that influence utilities derived from apps. For example, users with cars, compared to those without cars, derive higher utilities from Google Maps and lower utilities from Uber. Therefore, the preference for Uber and the preference for Google Maps can be negatively correlated. As discussed in Train (2009), the variance of μ_{ijm} cannot be separately identified from the mean of μ_{ijm}. Hence, the variance of ε_{ijm} is assumed to be 1 for all j. I assume $(\varepsilon_{i1m}, \varepsilon_{i2m})$ follows a normal distribution $N(\mathbf{0}, \boldsymbol{\Sigma})$[18], where

$$\boldsymbol{\Sigma} = \begin{bmatrix} 1 & \rho \\ & 1 \end{bmatrix}.$$

$\rho_{jj'}$ captures correlated preferences between app j and app j'. We can certainly add individual error terms in γ_{ijm} as well and allow them to be correlated. Correlated preferences and individual error terms are introduced to account for overlapping users, which occur at the extensive margin (i.e., the decision to use another app conditional on already using one). Consequently, overlapping users are best explained through error terms in the taste parameters rather than the satiation parameters. It is difficult to come up with additional variations to identify correlation between γ_{ijm} and $\gamma_{ij'm}$.

γ_{12} and ρ together explain the overlapping users of app 1 and app 2. An econometric challenge is to disentangle γ_{12} from ρ, which will be discussed in the next section.

3.4. Identification

Intuitively, both γ_{12} and ρ can explain the observed share of overlapping users, s_{12}^*. If one observes that many users use both NYTimes and WSJ, it could be the case that NYTimes and WSJ are complements as they offer different perspectives on the same events, or that users have strong demand for news in general. In the first case, $\gamma_{12} > 0$. In the second case, $\rho > 0$. In economic textbooks, complements and substitutes are defined with compensated cross-price elasticities of demand: if an exogenous increase in the price of product A leads to a decrease in the compensated demand of product B, then they are complements; otherwise, they are substitutes. When there is no price, one can extend the definition: if users spend more time on an app due to an exogenous increase in its utility, the (marginal) utility of its complements (substitutes) would increase (decrease). This definition, based on cross-derivatives of the utility functions, forms the foundation of my identification strategy, which utilizes app updates as instrumental variables. Updates of app 1 should change the *utility* of app 1 but not that of app 2. However, updates of app 1 can change the *usage* of app 2 through γ_{12}. Therefore, I use the following moments to identify nonlinear parameters γ_{12} and ρ

$$E(s_{12m}^* - s_{12m}) = 0 \tag{11}$$
$$E(update_{1m} \cdot \xi_{2m}^{\mu}) = 0 \tag{12}$$
$$E(update_{2m} \cdot \xi_{1m}^{\mu}) = 0 \tag{13}$$

There are two unique parameters to be estimated, γ_{12} and ρ. Correspondingly, we have three moments in Eqs. (11)–(13). This model is overidentified. The moment in (11) matches the observed overlapping user and the predicted overlapping user given γ_{12} and ρ. The moments in Eqs. (12) and (13) are based on the assumption that the update history of app j (app j') should not enter the utility of app j' (app j) directly. As Android update data is unreliable,[19] I utilize the update history of the corresponding iOS app, which cannot affect the utility of any other Android app. Specifically, update history is described by three variables: the cumulative numbers of small updates, medium updates, and major updates.[20] Using cumulative values allows my IVs to capture update effects even if adoption is not immediate. A limitation of update history is that it varies over time but remains constant across geographic markets. In Section 3, I have a weekly panel of demographic groups and update history will be collinear with week fixed effects in $\mathbf{x}_m'$. To address this problem, I construct market-specific update history variables, enabling each market to respond to updates differently. In Section A, I provide reduced form evidence that the overlapping user data and the update history contain new information about the relationship between apps beyond the correlation of active users.

[17] In an earlier version of this paper, I add network effects in $\mathbf{x}_m$ and estimate the network coefficients with extra instruments. The results are similar to the results presented here.

[18] Any distribution would be compatible with my model. I choose the normal distribution because it is the "natural" choice in the sense of the central limit theorem.

[19] One reason is that developers can release Android apps outside mainstream app stores.

[20] "Small", "medium", and "major" are defined by the digits of version numbers.

Table 3
Identifying Variations.

Parameters	Variables	Data
β_1^μ	$s_{1mw} = \frac{1}{N_{mw}} \sum_i \mathbb{I}(t_{i1mw} > 0)$	Active users of app 1
β_2^μ	$s_{2mw} = \frac{1}{N_{mw}} \sum_i \mathbb{I}(t_{i2mw} > 0)$	Active users of app 2
β_1^γ	$t_{1mw} = \frac{1}{N_{mw}} \sum_i t_{i1mw}$	Average time spent on app 1
β_2^γ	$t_{2mw} = \frac{1}{N_{mw}} \sum_i t_{i2mw}$	Average time spent on app 2
β_3^γ	$t_{3mw} = \frac{1}{N_{mw}} \sum_i t_{i3mw}$	Average time spent on smartphone
γ_{12}, ρ	$s_{12w} = \frac{1}{N_w} \sum_i \mathbb{I}(t_{i1mw} t_{i2mw} > 0)$, $update_{1w}$, $update_{2w}$	Overlapping users and updates

Note: w denotes the index for weeks, while m represents the index for markets. N_{mw} stands for the number of Android smartphone users in market m during week w.

The identification of linear parameters $\boldsymbol{\beta}$ is straightforward and relies on the following moment conditions:

$$E(\mathbf{x}_m' \xi_{1m}^\mu) = 0 \tag{14}$$

$$E(\mathbf{x}_m' \xi_{2m}^\mu) = 0 \tag{15}$$

$$E(\mathbf{x}_m' \xi_{1m}^\gamma) = 0 \tag{16}$$

$$E(\mathbf{x}_m' \xi_{2m}^\gamma) = 0 \tag{17}$$

$$E(\mathbf{x}_m' \xi_{3m}^\gamma) = 0 \tag{18}$$

The identifying variations for each parameter are listed in Table 3.

3.5. Estimation methods

I use GMM to match moments predicted by the model with moments calculated from the data. The full set of parameters to be estimated is $\boldsymbol{\theta} = (\beta_1^\mu, \beta_2^\mu, \beta_1^\gamma, \beta_2^\gamma, \beta_3^\gamma, \gamma_{12}, \rho)$. As in Nevo (2000), denote the linear parameters with $\theta_1 = (\beta_1^\mu, \beta_2^\mu, \beta_1^\gamma, \beta_2^\gamma, \beta_3^\gamma)$ as they will enter the GMM function linearly and the nonlinear parameters with $\boldsymbol{\theta}_2 = (\gamma_{12}, \rho)$. Consider the data structure in Section 3. I observe a set of markets, which are defined to be demographic groups, for 13 weeks. Denote weeks with w. For each market-week unit, I observe s_{jmw}^*, the share of consumers who spends time on app j, and t_{jmw}^*, the average time spent on app j in hours. For each week, I also observe the total number of overlapping users between app 1 and app 2, c_{12w}^*. The asterisks indicate that they are observed variables. Hence the endogenous variables to be explained are $\mathbf{y}_{mw}^* = (s_{1mw}^*, s_{2mw}^*, t_{1mw}^*, t_{2mw}^*, t_{3mw}^*)$ and c_{12w}^*. The exogenous variables include $\mathbf{x}_{mw}$, a set of week and market fixed effects. Note that $\boldsymbol{\delta} = \mathbf{x}_{mw}\boldsymbol{\beta} + \boldsymbol{\xi}$.

With those notations, the model can be summarized as

$$(\mathbf{y}_{mw}^*, c_{12w}^*) = f(\boldsymbol{\delta}, \gamma_{12}, \rho) = f(\mathbf{x}_{mw}\boldsymbol{\theta}_1 + \boldsymbol{\xi}, \gamma_{12}, \rho)$$

where $f(\cdot)$ is the nonlinear model described in Section 2.3 and ξ is the stack of all market level error terms.

Based on the above eight sets of moments from (11) to (16), the GMM estimation is to minimize

$$\min_{\theta} n \cdot (\frac{1}{n}(\sum_{mw} \mathbf{z}_{mw} \cdot \xi_{mw})\hat{\mathbf{W}}(\frac{1}{n}(\sum_{mw} \mathbf{z}_{mw} \cdot \xi_{mw}))') \tag{19}$$

where $\xi_{mw} = (\xi_{1mw}^\mu, \xi_{2mw}^\mu, \xi_{1mw}^\gamma, \xi_{2mw}^\gamma, \xi_{3mw}^\gamma, \xi_{2mw}^\mu, \xi_{1mw}^\mu, \mathbf{c}_{12'w}^* - \mathbf{c}_{12'w})$, $\mathbf{z}_{mw} = (\mathbf{x}_{mw}, \mathbf{x}_{mw}, \mathbf{x}_{mw}, \mathbf{x}_{mw}, \mathbf{x}_{mw}, update_{1mw}, update_{2mw}, \mathbf{1})$, and $n =$ 143 is the number of markets. Note that θ_1 does not enter $\frac{1}{N_{nw}} \sum_{mw}(s_{12'w}^* - s_{12w})$ given $\boldsymbol{\delta}$. Therefore, we can limit the global search to $\boldsymbol{\theta}_2 = (\gamma_{12}, \rho)$ as θ_1 is a linear function of $\boldsymbol{\delta}$.

This estimation follows Berry et al. (1995) with an inversion step and a global search step. I need to find the values of $\boldsymbol{\delta}$ that match the five observed market outcomes $\mathbf{y}_{mw}^* = (s_{1mw}^*, s_{2mw}^*, t_{1mw}^*, t_{2mw}^*, t_{3mw}^*)$ given (γ_{12}, ρ). This is to solve the following system of nonlinear equations,

$$\mathbf{y}_{mw}^* = \mathbf{y}_{mw}(\boldsymbol{\delta}, \gamma_{12}, \rho) \tag{20}$$

Note that each component in $\mathbf{y}_{mw}$ is monotonically increasing in the corresponding component in $\boldsymbol{\delta}$. I solve (20) by iterating on $\boldsymbol{\delta}$ analogous to the contraction mapping used by Berry et al. (1995) and Gowrisankaran and Rysman (2012):

$$\boldsymbol{\delta}^{new} = \boldsymbol{\delta}^{old} + \boldsymbol{\phi} \cdot \{ln(\mathbf{y}_{mw}^*) - ln(\mathbf{y}_{mw}(\boldsymbol{\delta}^{old}, \gamma_{12}, \rho))\} \tag{21}$$

where $\boldsymbol{\phi}$ are five positive tuning parameters used in the iterations.

Despite the appealing features of quadratic utility functions, there is no analytical solution to quadratic optimization problems. Therefore, I use numerical integration to form expectations of $\mathbf{y}_{mw}$. Let N_s be the number of simulations used for integration. We have

$$\mathbf{y}_{mw}(\boldsymbol{\delta}, \gamma_{12}, \rho) = \frac{1}{N_s} \sum_{n=1}^{N_s} \mathbf{y}_{nmw}(\boldsymbol{\delta}, \gamma_{12}, \rho) \tag{22}$$

where $\mathbf{y}_{nmw}$ are the individual outcomes for the nth draw of $(\varepsilon_0, \dots, \varepsilon_J)$. In practice, I use 1000 Halton draws in the integration.

To summarize, the estimation consists of the following steps:

1. For a pair of (γ_{12}, ρ), invert out $\boldsymbol{\delta}(\gamma_{12}, \rho)$ with the mapping described in (21).
2. Calculate $c_{jj'w}(\boldsymbol{\delta}(\gamma_{12}, \rho), \gamma_{12}, \rho)$ and the value of GMM function in (19).
3. Find (γ_{12}, ρ) that minimizes the GMM value calculated in step 2.

Empirically, the weighting matrix $\hat{\mathbf{W}}$ is obtained through a two-step iterative process, starting with $W_0 = I$. The minimum GMM value is found using a grid search over the parameters (γ_{12}, ρ).

4. Estimation results

I estimate the model on four pairs of apps. The first two pairs are a pair of substitutes (Baidu Map and Amap)[21] and a pair of complements (Baidu and Baidu Map).[22] I choose the two pairs to test if the model can infer complementarity/substitutability from data. I analyze two additional pairs to investigate competition among major apps. WeChat and iQIYI were chosen because they were the top two apps in terms of user time share in 2017. WeChat is a superapp with many functions: instant messaging, social media ("Moments"), mobile payment ("WeChat Pay"), content distribution ("Subscriptions"), and app store ("mini programs"). WeChat achieved near-universal adoption and accounted for more than 25% of user time spent on smartphones in 2017. iQIYI is a leading video streaming platform. According to the results in Section 3.3, I expect budget competition between WeChat and iQIYI to be the largest among the top apps. I also study WeChat and Kwai, a pair of apps that were *a priori* considered independent, as Kwai is a short-video app with no obvious functional overlap with WeChat in 2017. This pair is particularly relevant due to Kwai's spectacular growth following 2017.

To reduce computational burden, I aggregate market outcomes over provinces.[23] Therefore, for each pair of apps, I have a panel of 11 markets[24] for 13 weeks. The summary statistics are in Table 4. Note that for all t^* and s^*, the denominators are the number of smartphone users in the same market. App usage exhibits significant heterogeneity across demographic groups. For example, the average time spent on iQIYI ranges from less than 0.1 h to over 2 h, while the share of overlapping users for WeChat and iQIYI varies from 0.8% to 24%. In Section B, I present the "first stage" results. While the results are weak for some apps, updates of iOS apps are positively correlated with active users of the corresponding Android apps.

In Table 5, I present the estimates of (γ_{12}, ρ) for each pair of apps. The model correctly identifies Baidu Map and Amap as substitutes. A negative γ_{12} and a large ρ are characteristic of direct competitors. Instruments are necessary to credibly estimate the relationship between apps. In column (2) of Table 5, I also estimate γ_{12} with the assumption $\rho = 0$ and no instruments are used[25] In this specification, Baidu Map and Amap are estimated to be almost independent apps. Baidu and Baidu Map are correctly estimated to be complements. WeChat and Kwai are estimated to be substitutes ($\hat{\gamma}_{12} = -0.08$). In the first quarter of 2017, the two apps have no obvious overlapping functions. On the Google Play Store, WeChat is classified as "Communication" and Kwai "Video Play and Editing". Therefore, categories are a poor proxy of competitive relationships. $\hat{\gamma}_{12}$ in columns (4) and (5) are close to 0. However, because γ_{12} enters the utility function as $\gamma_{12} t_1 t_2$, its economic significance depends on $t_1 t_2$.

To understand the economic significance of γ_{12}, I quantify the value of substitutability/complementarity with compensating variation (CV). I calculate the compensating variations (CVs) of individual apps and pairs of apps. Specifically, the total time a user has is increased to compensate for the loss of an app (or the pair), ensuring that their maximized utilities remain identical before and after the hypothetical app (pair) shutdown. The difference between the sum of individual app CVs and the CV of the app pair captures the value of substitutability/complementarity. This utility specification aligns with the discrete model outlined in Gentzkow (2007), establishing that such discrete choice models are a specific case within the framework of this study. The results are in Table 6. As we will see later, the budget competition effects can be large despite a small γ_{12}. As expected, the complementarity/substitutability term has the same sign as γ_{12}. This term is much larger in columns (3) and (4) despite the small $\hat{\gamma}_{12}$.

5. Budget competition and functional competition

In this section, I use the estimated structural model to simulate and decompose the competitive effects of a hypothetical app exit. For each app pair, I choose a market-week unit from the data. Given the estimated $(\hat{\gamma}_{12}, \hat{\rho})$ in Section 4, I solve for $\boldsymbol{\delta}(\gamma_{12}, \rho)$ to match the observed s_j^* and t_j^*. With the model calibrated to the observed data, I then simulate the market outcome for 1,000 users after one of the two apps is hypothetically shut down. I calculate diversion ratios based on the simulations. I then decompose the competitive effects of one app on another into functional competition and budget competition according to the definition in Section 2. Table 7 presents the decomposition of one app's competitive effects on another for 1000 simulated users.

[21] Baidu Map and Amap are the two dominant players in China's mobile map market.

[22] Baidu and Baidu Map are both developed by Baidu, Inc. The core functions of Baidu app are searching and news stream.

[23] In an earlier version of this paper, I estimate the model without such aggregation. The estimated competition patterns are similar to the results reported here.

[24] Gender and five age groups define 10 markets; and an "other" market to account for the difference between national usage and the total usage of the balanced market panel.

[25] Without instruments, we do not have variations to estimate both γ_{12} and ρ.

Table 4
Summary Statistics.

	Variables	Mean	StdDev	Min	Max	Unit
Baidu Map and Amap	$s^*_{BaiduMap}$	0.1463	0.032	0.0877	0.2414	–
	s^*_{Amap}	0.1277	0.0286	0.0832	0.2164	–
	s^*_{12}	0.022	0.0038	0.0138	0.0285	–
	$t^*_{BaiduMap}$	0.0367	0.0085	0.0195	0.0652	hour
	t^*_{Amap}	0.0746	0.0192	0.0421	0.1564	hour
	t^*_{3mw}	16.6915	3.1601	10.5834	21.8704	hour
Baidu and Baidu Map	s^*_{Baidu}	0.2494	0.0464	0.1555	0.3321	–
	$s^*_{BaiduMap}$	0.146	0.0323	0.0876	0.2414	–
	s^*_{12}	0.0495	0.0031	0.0439	0.0557	–
	t^*_{Baidu}	0.3086	0.0524	0.1475	0.4001	hour
	$t^*_{BaiduMap}$	0.0366	0.0085	0.0195	0.0652	hour
	t^*_{3mw}	16.4493	3.1086	10.4568	21.5881	hour
WeChat and iQIYI	s^*_{WeChat}	0.8354	0.0527	0.7311	0.9345	–
	s^*_{iQiyi}	0.2609	0.1134	0.0831	0.4704	–
	s^*_{12}	0.2605	0.008	0.2468	0.2749	–
	t^*_{WeChat}	4.2076	0.6946	2.5212	5.5897	hour
	t^*_{iQiyi}	1.0767	0.5255	0.0932	2.0335	hour
	t^*_{3mw}	11.0409	2.3751	6.5253	14.7386	hour
WeChat and Kwai	s^*_{WeChat}	0.8352	0.0532	0.731	0.9346	–
	s^*_{Kwai}	0.1154	0.0148	0.0864	0.1451	–
	s^*_{12}	0.1072	0.002	0.104	0.109	–
	t^*_{WeChat}	4.3685	0.5473	3.2078	5.5869	hour
	t^*_{Kwai}	0.1896	0.017	0.1519	0.2246	hour
	t^*_{3mw}	12.2633	2.6741	6.7176	16.3154	hour

Note:
1. s^* is the number of active users of the corresponding app (pair) divided by the number of active users of Android smartphones. $t^*$is the total number of hours spent on the corresponding app divided by the number of active users of Android smartphones.
2. The statistics are based on 13 observations for s^*_{12} and 143 observations for other variables.
3. $t^*_{BaiduMap}$ in the first panel and $t^*_{BaiduMap}$ in the second panel are different because the balanced panels are different for the two pairs. The same applies to s^*_{WeChat} in the third and fourth panels.
Data Source: iResearch.

Table 5
Structural Estimates for the Four Pairs of Apps.

	Baidu Map and Amap		Baidu and Baidu Map	WeChat and iQIYI	WeChat and Kwai
	(1)	(2)	(3)	(4)	(5)
γ_{12}	−1.15	−0.02	0.1467	0.0587	−0.08
	(0.0136)	(0.0042)	(0.0174)	(0.0064)	(0.0054)
ρ	0.7711	0	−0.0448	−0.264	0.42
	(0.0106)	–	(0.0085)	(0.0065)	(0.0208)
IV	Yes	No	Yes	Yes	Yes

Note:
1, Standard errors are in parentheses.
2, There are 143 market-week observations.
Data Source: The author's calculations.

Conventional categorizations of apps often fail to accurately capture the true competitive dynamics within the digital market. I find significant substitution between WeChat and Kwai, two apps from different categories. Specifically, when WeChat exits the market, 6% of its time diverts to Kwai. Conversely, when Kwai exits, about 30% of its time is reallocated to WeChat. The diversion ratio is large for a pair of apps with no obvious overlapping functions. This suggests that these categories are a poor proxy for genuine competitive relationships. In an antitrust case involving Kwai, WeChat should be included in the relevant market. This cross-category substitution pattern is similar to the experimental results in Aridor (2025). In this paper, we can further explain this substitution pattern with budget competition and functional competition.

Columns (1) and (2) of Table 7 show that budget competition is negligible (less than $0.02 \times 60 = 1.2$ min for 1000 smartphone users in a week) for apps with limited usage. As expected, the largest budget competition effect is observed between WeChat and iQIYI. When WeChat exits the market, time spent on iQIYI would increase by 12 h for 1000 smartphone users because of budget competition. This

Table 6
Compensating Variations of the Four Pairs of Apps.

	Baidu Map and Amap	Baidu and Baidu Map	WeChat and iQIYI	WeChat and Kwai
	(1)	(2)	(3)	(4)
CV of App 1	9.3945	194.2896	6688.65	3567.6392
CV of App 2	16.8407	11.1509	1216.88	94.9661
CV of Both	33.4262	204.2014	7431.99	3817.5046
Complementarity (Substitutability)	−7.1911	1.239	473.55	−154.8994
Estimates $(\hat{\gamma}_{12}, \hat{\rho})$	(−1.15, 0.7711)	(0.1467, −0.0448)	(0.0587, −0.264)	(−0.08, 0.42)

Note:
1, All numeric cells are the sum of CV in hours for all 1000 simulated smartphone users in one week.
2, The calculations are based actual data from different markets in the data. This is why CVs of WeChat are different in columns (3) and (4).
Data Source: The author's calculations.

Table 7
Functional Competition and Budget Competition.

	Baidu Map and Amap (1)	Baidu and Baidu Map (2)	WeChat and iQIYI (3)	WeChat and Kwai (4)
The Exit of App 1				
Budget Competition	0.0027	0.0126	12.04	3.3248
Functional Competition	7.875	−2.4075	−664.98	220.1286
Total Effects on App 2	7.8777	−2.3949	−652.95	223.4533
Diversion Ratio	35.04%	−0.74%	−11.85%	5.98%
The Exit of App 2				
Budget Competition	0.0091	0.0191	7.12	0.5007
Functional Competition	8.8863	−2.2601	−358.27	58.2947
Total Effects on App 1	8.8954	−2.2409	−351.16	58.7954
Diversion Ratio	21.28%	−10%	−19.56%	29.08%
$s_1^* \times 1000$	105.6	259.4	930.1	772.5
$s_2^* \times 1000$	83.2	105.6	431.5	122.1
$t_1^* \times 1000$	22.4	322.2	5511.7	3739.1
$t_2^* \times 1000$	42.1	22.5	1795.7	202.5
estimates $(\hat{\gamma}_{12}, \hat{\rho})$	(−1.15, 0.7711)	(0.1467, −0.0448)	(0.0587, −0.264)	(−0.08, 0.42)

Notes:
1, This table is based on data from anonymous markets in the data set.
2, All competition effect cells are the sum of changes in usage in hours for all 1000 simulated smartphone users in one week.
Source: iResearch and the author's calculations.

effect is notable, even surpassing the functional competition between two leading mapping apps, Baidu Map and Amap. However, the budget competition effect is less than 2% of the functional competition effect ($12.04 \div 664.98 = 1.81\%$, $7.12 \div 358.27 = 1.99\%$) despite a modest $\hat{\gamma}_{12} = 0.0587$.[26] Another pattern revealed in Table 7 is that budget competition increases quadratically with t_1 and t_2. For example, comparing column (2) to column (4), we have $\frac{3.3248+0.5007}{0.0126+0.0191} = 120.8$ and $\frac{3739.1}{322.2} \times \frac{202.5}{22.5} = 11.6 \times 9 = 104.4$.

Budget competition may be much larger because of the significant increase of usage of apps like WeChat and Kwai. To analyze the evolution of competition, I obtain a snapshot of **aggregate** app usage in China during the final week of March 2024. I use the same $(\hat{\gamma}_{12}, \hat{\rho})$ in Table 5 and match $\delta(\gamma_{12}, \rho)$ to the new data in 2024. The budget competition results are in Table 8. Among the six unique apps in the four pairs (Baidu Map, Amap, Baidu, WeChat, iQIYI, and Kwai), Kwai experienced the most significant increase in usage.[27] Comparing the last columns in Tables 7 and 8, the time spent on Kwai increased by a factor of 12, and the budget competition exerted by Kwai on WeChat increased by more than 13 times. However, functional competition also increases by more than 12 times. Therefore, budget competition is still small relative to functional competition. For the pair of WeChat and iQIYI, budget competition "decreased" because the usage in 2017 is observed for a group of power users of WeChat and iQIYI and the usage in 2024 is the aggregate usage of all Android users. This finding highlights that the magnitude of budget competition can vary significantly across different user segments. A cautionary note is that for each pair of apps, (γ_{12}, ρ) may have changed in 2024. In 2022, WeChat added

[26] To put $\hat{\gamma}_{12} = 0.0587$ into perspective, note that the market level mean of γ_1 from inversion is 0.2714. According to (4), the diversion ratio implied by functional competition is approximately $\frac{\hat{\gamma}_{12}}{\hat{\gamma}_1} = -21.63\%$, which is close to the gross diversion ratio of -19.56% in Table 7.

[27] This comparison is not precise as the usage in 2017 is observed for a demographic group and the usage in 2024 is the aggregate usage of all Android users.

Table 8
Functional Competition and Budget Competition in 2024.

	Baidu Map and Amap (1)	Baidu and Baidu Map (2)	WeChat and iQIYI (3)	WeChat and Kwai (4)
The Exit of App 1				
Budget Competition	0.0146	0.1418	3.8864	13.25
Functional Competition	67.625	−26.24	−270.508	1926.45
Total Effects on App 2	67.64	−26.098	−266.622	1939.70
Diversion Ratio	61.66%	−2.94%	−4.67%	34%
The Exit of App 2				
Budget Competition	0.0962	0.2618	2.9845	6.779
Functional Competition	109.164	−27.67	−146.424	729.36
Total Effects on App 1	109.26	−27.408	−143.44	736.14
Diversion Ratio	33.34%	−24.98%	−23.1%	30.17%
$s_1^* \times 1000$	265	383.1	886.7	886.7
$s_2^* \times 1000$	359	265	234.7	305.3
$t_1^* \times 1000$	109.7	887.7	5706.3	5706.3
$t_2^* \times 1000$	327.7	109.7	621.6	2439.6
$t_3^* \times 1000$	30625.4	30065.4	24734.9	22916.9
Estimates $(\hat{\gamma}_{12}, \hat{\rho})$	(−1.15, 0.7711)	(0.1467, −0.0448)	(0.0587, −0.264)	(−0.08, 0.42)

Notes:
1, This table is based on aggregate app usage in China during the final week of March 2024.
2, All competition effect cells are the sum of changes in usage in hours for all 1000 simulated smartphone users in one week.
Source: iResearch and the author's calculations.

short video functions to directly compete with Kwai and TikTok. The budget competition we get from this extrapolation exercise is likely an upper bound for WeChat and Kwai.

While budget competition can be substantial in absolute terms, it is often dominated by functional competition. It is highly improbable that budget competition would transform a pair of complementary apps into gross substitutes. However, if we strongly believe that $\gamma_{12} = 0$, then budget competition becomes a crucial factor for top apps with significant time shares. Such a scenario might arise when observing app usage over a sufficiently short time interval, T. Over such a brief period, meaningful interactions between apps are minimal, and we can confidently assume $\gamma_{12} = 0$. Consequently, all "interactions" between apps are instead captured by correlated preferences (ρ), and competition is then fully explained by budget competition.

6. Conclusion

This paper introduces a novel framework for studying competition in the mobile internet industry by formally defining and quantitatively evaluating budget competition and functional competition. I develop a discrete-continuous consumer demand model that accounts for complementarity, substitutability, and a binding time constraint.

I estimate the model with a weekly panel of app usage in the first quarter of 2017 in China. I find significant cross-category substitution. Categorizations are not a reliable tool to analyze competition. Most of the diversions are explained by functional competition rather than budget competition. Budget competition would likely change the relevant market definition if we believe functional interactions are minimal.

The demand model presented here incorporates several key features: discrete-continuous decisions, product interactions, budget constraints, and estimation using instrumental variables. It can be extended to include other industry features, such as network effects, advertising, and two-sided markets, or adapted to analyze demand for other goods. A limitation of this study is the absence of dynamics. The high concentration of user time on a few apps suggests that addiction, as noted by Allcott et al. (2022), may play a significant role. Future research could provide important insights by evaluating budget competition within a model that accounts for user addiction.

CRediT authorship contribution statement

Han Yuan: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

The authors do not have permission to share data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

From December 2020 to June 2021, I was a resident scholar at Luohan Academy, which is an affiliate of Alibaba. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Reduced form evidence of identification

Identification of complementarity ($\gamma_{jj'}$) and correlated preferences (ρ) comes from two sources: the overlapping user data and updates of apps as IV. In this section, I provide reduced-form evidence of their usefulness. Consider the following simple regression equation:

$$ln(q_{jt}) = a + b^{ols}_{jj'} ln(q_{j't}) + \varepsilon_{1jt} \tag{A.1}$$

where q_{jt} is the number of active users of app j in week t nationwide. $b^{ols}_{jj'}$ summarizes the co-movement between j and j' and is increasing in both $\gamma_{jj'}$ and $\rho_{jj'}$. When we have overlapping user data and updates, we can use the following two regressions:

$$ln(q_{jt} - c_{jj't}) = a + b^{c}_{jj'} ln(q_{j't} - c_{jj't}) + \varepsilon_{2jt} \tag{A.2}$$

$$ln(q_{jt}) = a + b^{iv}_{jj'} ln(q_{j't}) + \varepsilon_{3jt} \tag{A.3}$$

where $c_{jj't}$ is the number of overlapping user between j and j'. In (A.3), I use the update history of the iOS version of j' as instruments for $q_{j't}$. Specifically, I use the cumulative numbers of small, medium, and major updates of j'. Therefore, $b^{diff}_{jj'} = b^{ols}_{jj'} - b^{c}_{jj'}$ is the information we can get from the overlapping user data and $b^{bias}_{jj'} = b^{ols}_{jj'} - b^{iv}_{jj'}$ is the information we can get from the instruments. I then regress estimates of $(b^{ols}_{jj'}, b^{c}_{jj'}, b^{iv}_{jj'}, b^{diff}_{jj'}, b^{bias}_{jj'})$ on a category dummy which equals one if j and j' are in the same category defined by iResearch and zero otherwise. The categorization is based on functions and conforms to traditional definitions of a market (map, browser, music, etc.). Despite the criticism of categorizations in the introduction, they are still informative. A pair of apps in the same category should have a negative γ and a large ρ. If the estimates of $(b^{ols}_{jj'}, b^{c}_{jj'}, b^{iv}_{jj'}, b^{diff}_{jj'}, b^{bias}_{jj'})$ are correlated with this category dummy meaningfully, then we may conclude that the overlapping user data and the IV are useful.

I have the update histories of 84 apps and I run regressions on $83 \times 84 = 6972$ pairs of apps. Note that I have only 13 observations for each pair of apps because both overlapping user and update history are observed at the national level. I simulate 1000 samples of $(b^{ols}_{jj'}, b^{c}_{jj'}, b^{iv}_{jj'})$ for all pairs using the mean and variances from estimated equations (Eq. (A.1)), (Eq. (A.2)), and (Eq. (A.3)). Then I regress 1000 such samples of $(b^{ols}_{jj'}, b^{c}_{jj'}, b^{iv}_{jj'}, b^{diff}_{jj'}, b^{bias}_{jj'})$ on the category dummy. The mean and the 95% confidence interval of the coefficients from the 1000 regressions are in Table A.9.

The coefficient in column (1) of Table A.9 is significant and positive. This is because preferences for apps in the same category are often highly correlated. Instruments should remove at least some of the bias because of correlated preferences (ρ). This is what we see in column (2): a smaller and insignificant coefficient. A cautionary note is that the coefficient in column (4) is not significant. One might be concerned about the weak IV problem given that the confidence interval in column (2) is much larger than that in column (1). The results in Table A.10 are conditional on an F statistic above 10. There are 50 apps with an F statistics above 10 and hence $50 \times 84 - 50 = 4150$ observations. The confidence intervals are smaller in column (2) in Table A.10 and the coefficient is still insignificant. Therefore the insignificance of the coefficient in column (2) in Table A.9 is not driven by weak instruments. The relationship between $b^{c}_{jj'}$ and the structural parameters $\gamma_{jj'}$ and $\rho_{jj'}$ is complicated. The co-movement of *the exclusive users* for apps in the same category is much larger than the co-movement of their *total active users*. One explanation is that the growth of competing apps mostly comes from exclusive users rather than overlapping users. In other words, users who did not use either A or B started

Table A.9
Reduced Form Evidence of Identification.

	$b^{ols}_{jj'}$ (1)	$b^{iv}_{jj'}$ (2)	$b^{c}_{jj'}$ (3)	$b^{bias}_{jj'}$ (4)	$b^{diff}_{jj'}$ (5)
Same-Category	0.1636 [0.087, 0.239]	0.0246 [−0.269, 0.337]	0.3784 [0.298, 0.456]	0.139 [−0.183, 0.45]	−0.2148 [−0.325, −0.103]
N	6972	6972	6972	6972	6972
R^2	0.0004	0.0000	0.0012	0.0001	0.0005

Note: The coefficients and the 95% confidence interval are based on 1000 simulations.
Data Source: iResearch and the author's calculations.

Table A.10
Identification with Strong Instruments.

	$b^{ols}_{jj'}$ (1)	$b^{iv}_{jj'}$ (2)	$b^{bias}_{jj'}$ (3)
Same-Category	0.1163	0.0375	0.0788
	[0.044, 0.186]	[−0.056, 0.129]	[−0.041, 0.197]
N	4150	4150	4150
R^2	0.0004	0.0000	0.0001

Note: The coefficients and the 95% confidence interval are based on 1000 simulations. The regressions are based on the group of apps with a first stage F statistic larger than 10.
Data Source: iResearch and the author's calculations.

using A or B but not both. Overall, the reduced form results indicate that the overlapping user data and updates are useful for our identification.

Appendix B. Update histories of apps and their relationship with active users

In Table B.11, I list the most recent iOS version for each app in the 13 weeks of the first quarter of 2017. We observe only one major update, which happened in the third week for Amap. For WeChat, there are only minor updates. For the other four apps, we observe a mix of minor and medium updates.

To understand how updates may affect active users, I regress weekly active users on update variables for each of the 11 markets and for each app. This approach, consistent with the IV strategy in the structural model, allows for market-specific responses to updates. For each app, I obtain 11 sets of coefficients and their standard errors. I then simulate 1000 realizations for each coefficient and calculate the mean and 90% confidence interval for each app based on these simulations. The results, shown in Table B.12, indicate that all coefficients are positive, with only two insignificant exceptions. This suggests that updates of iOS apps are positively correlated with active users of the corresponding Android Apps.

Table B.11
Updates of Apps.

Week	Baidu	Baidu Map	Amap	WeChat	iQIYI	Kwai
1	8.2	9.6	7.8.8	6.5.3	8	4.1.3
2	8.2.5	9.6	7.8.8	6.5.3	8	4.1.6
3	8.2.5	9.7	8	6.5.3	8.0.1	4.2.0
4	8.2.5	9.7.3	8	6.5.4	8.1	4.2.1
5	8.2.5	9.7.3	8	6.5.4	8.1	4.2.1
6	8.2.5	9.7.3	8	6.5.4	8.1	4.2.1
7	8.2.5	9.7.3	8	6.5.5	8.1	4.2.1
8	8.2.5	9.7.3	8	6.5.5	8.2	4.2.2
9	8.2.5	9.7.3	8	6.5.5	8.2.1	4.2.2
10	8.2.5	9.7.3	8	6.5.5	8.2.1	4.2.2
11	8.2.5	9.7.3	8.0.2	6.5.5	8.2.1	4.3
12	8.3.1	9.7.5	8.0.2	6.5.5	8.2.1	4.3.1
13	8.3.1	9.7.5	8.0.4	6.5.6	8.2.1	4.3.1

Note: This table lists the most recent iOS version for each app in the corresponding week in the first quarter of 2017.
Data Source: Apple App Store.

Table B.12
Updates and Active Users.

Updates	Baidu	Baidu Map	Amap	WeChat	iQIYI	Kwai
Minor	−73.76	60.70	58.95	19.59	8.34	9.01
	[−240.7,42.5]	[−1.9,192.6]	[0.52,176.8]	[−121.87,166.5]	[−56.29,80]	[−16.8,40.7]
Medium	35.28	48.98	–	–	4.09	−1.46
	[−120.8,218.1]	[−32,161.1]	–	–	[−173.9,140.1]	[−69.5,67.8]
Major	–	–	83.49	–	–	–
	–	–	[9.5,187.6]	–	–	–

Note: The coefficients and the 90% confidence intervals are based on 1000 simulations.
Data Source: iResearch, Apple App Store, and the author's calculations.

Table C.13
Covariates of Baidu Map and Amap in Taste Parameters.

Covariates	Baidu Map	Standard Error	Amap	Standard Error
Week (02)	−0.0078	0.0083	−0.0452	0.0052
Week (03)	0.0275	0.0074	0.0026	0.0053
Week (04)	−0.0349	0.0084	−0.0466	0.0067
Week (05)	0.0276	0.0098	−0.0466	0.0097
Week (06)	0.0649	0.0069	−0.0466	0.0069
Week (07)	0.0631	0.0074	0.0053	0.0071
Week (08)	0.0657	0.0119	−0.0016	0.0113
Week (09)	0.0465	0.0271	−0.0138	0.0166
Week (10)	−0.0838	0.0094	−0.0138	0.0053
Week (11)	0.0944	0.0073	−0.0138	0.0071
Week (12)	0.107	0.0081	−0.0066	0.0062
Week (13)	0.1295	0.0085	−0.0138	0.0059
Female	0.265	–	0.4661	–
Male	0.3792	–	0.543	–
Age (< = 24)	0.2557	–	0.5019	–
Age (25∼30)	0.4124	–	0.6479	–
Age (31∼35)	0.552	–	0.7084	–
Age (36∼40)	0.2724	–	0.4142	–
Age (> = 40)	0.1185	–	0.2504	–

Notes:
1, This table provides parameters of covariates in μ_1 and μ_2 corresponding to the column (1) of Table 5.
2, The coefficients of gender and age groups are the simple average of market fixed effects with corresponding characteristics.
Data Source: The author's calculations.

Appendix C. Covariates in μ_1 and μ_2

The covariates in μ_1 and μ_2 are market fixed effects and week fixed effects. In Table C.13, I provide covariates from the estimated model of Baidu Map and Amap (Column (1) in Table 5). In the following table, I report week fixed effects and aggregate market fixed effects by gender and age groups. The results are reasonable: users between 31 and 35 and male users derive higher utility from map apps because they are more likely to own and drive a car in China.

Appendix D. Budget competition

The intermediate bundle (t_0^i, t_1^i, t_3^i) defined by (1) is easy to calculate. The functional competition in Table 2 is $t_1^i - t_1^o$. After this step, we can calculate how much time is left to be allocated as $\Delta T = T - t_0^i - t_1^i - t_3^i$. The intermediate bundle can be seen as the result of utility maximization over t_0, t_1, and t_3 subject to a time budget of $t_0^i + t_1^i + t_3^i$. Note that apps 0, 1, and 3 are independent. We can solve for the new bundle as the same utility maximization problem subject to a time budget of $t_0^i + t_1^i + t_3^i + \Delta T$. The following two lemmas are useful when calculating the final bundle. The budget competition effect of app 2 on app 1 is $t_1^n - t_1^i$.

Lemma 1. *For J independent apps that are used, when there is extra time ΔT, the increase in time spent on app j is $\Delta t_j = \Delta T \frac{1}{\gamma_j} \frac{1}{\sum_{k=1}^J \frac{1}{\gamma_k}}$.*

Proof. From the FOCs of the old bundle, we have

$$\mu_j + \gamma_j t_j^0 = \mu_k + \gamma_k t_k^0 \Rightarrow t_k^0 = \frac{\mu_j - \mu_k}{\gamma_k} + \frac{\gamma_j}{\gamma_k} t_j^0.$$

Similarly, we have $t_k^1 = \frac{\mu_j - \mu_k}{\gamma_k} + \frac{\gamma_j}{\gamma_k} t_j^1$. Because of the time constraint, we have

$$\sum_{l=1}^J t_l^0 = T \Rightarrow \sum_{k=1}^J \left(\frac{\mu_j - \mu_k}{\gamma_k} + \frac{\gamma_j}{\gamma_k} t_j^0\right) = T \Rightarrow t_j^0 = \frac{T - \sum_k \frac{\mu_j - \mu_k}{\gamma_k}}{\gamma_j \left(\sum_{k=1}^J \frac{1}{\gamma_k}\right)}$$

The budget constraint with extra time ΔT is

$$\sum_{l=1}^J t_l^1 = T + \Delta T \Rightarrow \sum_{k=1}^J \left(\frac{\mu_j - \mu_k}{\gamma_k} + \frac{\gamma_j}{\gamma_k} t_j^1\right) = T + \Delta T \Rightarrow t_j^1 = \frac{T + \Delta T - \sum \frac{\mu_j - \mu_k}{\gamma_k}}{\gamma_j \left(\sum_{k=1}^J \frac{1}{\gamma_k}\right)}$$

Therefore we have

$$\Delta t_j = t_j^1 - t_j^0 = \Delta T \frac{1}{\gamma_j} \frac{1}{\sum_{k=1}^{J} \frac{1}{\gamma_k}}$$

□

Lemma 2. *When an app q is used because of the extra time ΔT,* $t_q^1 = \frac{T+\Delta T - \sum_k \frac{\mu_q - \mu_k}{\gamma_k}}{\gamma_q(\sum_k \frac{1}{\gamma_k})} \le \frac{\Delta T}{\gamma_q(\sum_k \frac{1}{\gamma_k})}$

Proof. Because q was not used ($t_q^0 = 0$), we have

$$\mu_q \le \mu_k + \gamma_k t_k^0 \Rightarrow \frac{\mu_q - \mu_k}{\gamma_k} \ge t_k^0 \Rightarrow T \le \sum_k \frac{\mu_q - \mu_k}{\gamma_k}$$

The FOCs of the new bundle are

$$\mu_q + \gamma_q t_q^1 = \mu_k + \gamma_k t_k^1 \Rightarrow t_k^1 = \frac{\mu_q - \mu_k}{\gamma_k} + \frac{\gamma_q}{\gamma_k} t_q^1$$

Combined with the new time constraint, we have

$$T + \Delta T = \sum_k \frac{\mu_q - \mu_k}{\gamma_k} + \frac{\gamma_q}{\gamma_k} t_q^1 \Rightarrow t_q^1 = \frac{T + \Delta T - \sum_{k \neq q} \frac{\mu_q - \mu_k}{\gamma_k}}{\gamma_q(\sum_k \frac{1}{\gamma_k})}$$

Because $T \le \sum_k \frac{\mu_j - \mu_k}{\gamma_k}$, we have

$$\frac{T + \Delta T - \sum_k \frac{\mu_q - \mu_k}{\gamma_k}}{\gamma_q(\sum_k \frac{1}{\gamma_k})} \le \frac{\Delta T}{\gamma_q(\sum_k \frac{1}{\gamma_k})}.$$

□

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