

Essays on Competition in the Tech Industry and  
Platform Economies

by

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A dissertation accepted and approved in partial fulfillment of the  
requirements for the degree of  
Doctor of Philosophy  
in Economics

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Spring 2024

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## DISSERTATION ABSTRACT

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Doctor of Philosophy in Economics

Title: Essays on Competition in the Tech Industry and Platform Economies

This dissertation examines competition dynamics within technology industries and platform-based economies. It examines three core aspects: acquisition strategies employed by incumbent firms, pricing strategies undertaken by an entrant firm, and the impact of antitrust regulatory interventions.

Chapter 1 gives an overview of each dissertation chapter. In the second chapter, I investigate the acquisition strategies of major tech companies – Google, Amazon, Apple, Meta, and Microsoft, and the interactive dynamics at play. This study separates the underlying motivations that drive these firms to make acquisition decisions, distinguishing between internal motives that seek scale economies and competitive motives that arise to prevent a competitive disadvantage. Using a rich dataset of acquisition records, I quantify the degree to which these firms are responsive to these distinct motivations. By accounting for forward-looking behavior of firms and relying on Markov Perfect Nash Equilibrium concept, I find a set of parameter estimates that make agents' observed actions yield higher expected future returns than their alternatives while also making their observed actions the best response to the moves of other market players. I find that competitive motives can explain a significant share of acquisition decisions, sometimes overshadowing the internal motives.

The third chapter, co-authored with Keaton Miller, studies the commission rate policies of leading app distribution channels. It examines the effect of the regulatory intervention that aimed to change these policies. Specifically we investigate the effect of the legislation

implemented in South Korea that allows developers to opt for mobile payment systems outside the conventionally required billing system of the app stores. We investigate how this regulation affected app performance, particularly among apps which were likely to be most influenced by this change. Using difference-in-differences and triple-difference-in-differences techniques, our finding suggests a potentially positive impact on app revenue, albeit with some degree of noise due to limited data. These results represent a novel finding, as they represent one of the first attempts to empirically measure the effects of this legislation.

The fourth chapter explores whether aggressive pricing strategies can provide a competitive advantage to a smaller app distribution platform with a limited user base. Using proprietary data of one of the minor platforms in South Korea which charges significantly lower commission rate relative to the major players, I use difference-in-differences technique to examine key app performance metrics. I find that the volume of in-app traffic and the number of paid users increase, which implies that the strategy is successful in attracting user traffic on the platform in the short term, while I find these effects to be more significant in the short-run than in the longer-term.

Overall, this dissertation provides comprehensive insights into competition within the tech industry and platform economy. It analyzes the regulatory effects aimed at spurring competition, examines the competition and strategies among incumbent firms, and explores the strategies employed by a new firm to compete against the established incumbents. This dissertation includes unpublished co-authored material.

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## ACKNOWLEDGEMENTS

I would like to thank Professors Keaton Miller, David Evans, Eric Zou, and Jay Wang for their invaluable feedback and insights that have contributed to various parts of my dissertation. I am especially grateful to my advisor, Keaton Miller, for his unwavering support throughout my doctoral studies. I also extend my appreciation to the graduate students at the University of Oregon and participants at the Western Economic Association International Conference, the Midwest Economic Association Conference, the Consumer Protection Symposium hosted by the University of Oregon School of Law, the NABE Tech Economics Conference, and the International Industrial Organization Conference for their valuable comments. Last but not least, I would like to express my deepest gratitude for my friends and family. Your support, encouragement, and belief have been my foundation throughout this journey.

The third chapter of this dissertation was supported by Oregon Consumer Justice Award from the University of Oregon School of Law.

Any errors are on my own.

To Father and Mother

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## CHAPTER I

### INTRODUCTION

My dissertation comprises of papers examining competition dynamics in the technology industry and digital markets. This work is to inform competitive interactions among major technology firms, evaluate effects of regulatory policies and legislation designed to foster competition, and assess the viability of pricing strategies employed by an entrant to effectively compete against established incumbents. Note that this dissertation contains unpublished co-authored material, with Chapter 3 being a joint-work with Keaton Miller.

Chapter 2 demonstrates the economic incentives driving tech giants to pursue acquisitions. Among various motivating factors, I focus specifically on strategic oligopolistic motives that render tech giants observant of rivals' acquisitions when making their own acquisition decisions. I use a dynamic game model and the solution concept of Markov Perfect Nash Equilibrium to estimate parameters that capture the responsiveness to different acquisition drivers. I find that the major tech firms acquire targets with higher probability when observing their rivals making more acquisitions, exhibit sensitivity to interest rates that constrain acquisition financing, and acquire more frequently in areas that they have already acquired targets before. The chapter concludes by suggesting an presence of tech giants competing against one another in increasing number of markets.

In Chapter 3, we examine the short-run effects of opening mobile payment systems in South Korea. Using two sources of variation – differing treatment status across years and countries – we measure whether the legislation impacted key metrics of app downloads and revenue, capturing potential policy effects. While we document no suggestive evidence of likely changes in app downloads, we find an increase in app revenue. We also propose stylized model to simulate the changes in in-app prices, in-app volume, app quality, and app

downloads in response to changes in commission rate. We find lowering commission rate can act as improvement of app quality.

In Chapter 4, I analyze an entrant's pricing strategies and whether efforts to compete against incumbents by offering different commission rate policy is effective. Using novel data provided by the entrant in South Korean market, I use difference-in-differences framework to evaluate whether such price scheme has any effects on apps on the platform. I find suggestive evidence that the policy attracted higher in-app purchase traffic volume, a higher number of paid users, but did not necessarily increase total in-app spending. The chapter concludes by proposing the observed policy effects may be temporary, potentially insufficient for market penetration given incumbents' global reach and network effects.

## CHAPTER II

### WHY FIRMS BUY: DYNAMIC GAMES OF ACQUISITION AMONG TECH GIANTS

#### 2.1 Introduction

Tech markets are often characterized by frequent acquisitions and concentrated market structure, resulting in a distinct oligopoly market structure across various tech sectors. Within these market domains, where a small set of major players exert significant market power, each player meticulously monitors the actions of their counterparts. This scrutiny intensifies, particularly when competitors aggressively pursue the acquisition of startups, seeking an advantageous edge in these competitive areas.

This study analyzes the acquisition records of industry giants, often collectively referred to as the “big five” – Google, Amazon, Microsoft, Meta, and Apple (hereinafter “GAMMA”). They are renowned for their technological innovation and substantial financial resources, enabling them to actively seek out innovative assets and targets. Their pursuit of innovation often leads to an expanding and overlapping competitive landscape, as they encroach on each other’s domains to a greater extent. These firms hold robust market positions within their respective sectors and wield extensive influence across diverse sectors. This not only positions them as direct competitors within specific domains but also hints at the potential for future rivalry across a wide spectrum of markets. Focusing solely on a limited subset of their acquisition activities and neglecting the entirety of their endeavors across multiple sectors risks overlooking essential elements within the broader competitive landscape. This oversight can lead to an incomplete understanding of their acquisition strategies, which holds significant implications for those who rely on these insights to formulate regulatory policies or to devise their own strategic approaches.

Using a rich data set that classifies each acquisition made by the GAMMA firms into specific industry subcategories from 2004 to 2021, I explore motivations driving these dominant players' engagement in acquisition activities across multiple sectors. One of the motivations I explore is their motivations to scale, which revolve around improving a firm's existing technology capabilities or production efficiency by acquiring targets within related businesses – a concept I refer to as “scale economies”. Additionally, I examine their external motivations, where acquisitions are strategically pursued to safeguard and reinforce existing market positions while mitigating the risk of preemptive actions by competitors – a concept defined as the “defensive motive”, “competitive motive” or “preemption motive”. This study explores how increasing rivalries across the GAMMA firms in various sectors make them increasingly adaptive and influential in shaping each other's acquisition strategies. Specifically, I evaluate how the increased acquisition intensity displayed by competitors influences a firm's likelihood of engaging in acquisitions. When an escalation in the acquisition activities of competitors augments the likelihood of a firm's acquisitions, it implies that the firm becomes more inclined to participate in the acquisition race out of concern that rivals might secure targets before itself, thereby placing the firm at a competitive disadvantage.

I answer this question using a dynamic game model, in which each agent's payoff of acquisition is contingent upon macroeconomic factors, scale economies and competitive motive that evolve dynamically over time. Within this model, an agent opts to acquire a target only when the acquisition's current and anticipated future returns surpass the returns from not pursuing such a target. To calibrate the model, I identify a set of parameters that make up an agent's payoff that align with the realized actions observed in the data. I estimate the model using the two-step minimum distance estimator, initially introduced by Bajari, Benkard, and Levin (2007) (hereafter referred to as BBL). This estimator is a

computationally highly effective tool for solving equilibria involving multiple agents. It is worth noting that among the empirical work that builds on the estimator, this research bears close relevance to prior studies conducted by Ryan (2012), Suzuki (2013), and Igami and Yang (2016).

I find that competitive motives and scale economies are statistically significant drivers of acquisition decisions. The influence of these factors grows stronger when a firm has a higher number of past acquisitions, whether conducted by itself or by others. This affirms that scale economies and preemption motives strengthen as the firm and its rivals engage in more acquisitions. This implies that as the historical number of acquisitions increases, each firm is more likely to pursue acquisitions to achieve greater economies of scale. It also suggests that firms feel a greater need and face more competitive pressure to participate in the acquisition race when their rivals have previously acquired more targets, in order to keep up with the competition. The escalating impact of scale economies and preemption motives with an increasing number of acquisitions corroborates the strategic acquisitions becoming more prominent in such contexts.

Furthermore, I find empirical evidence that suggests the significant impact of macroeconomic factors on the overall acquisition strategy of the group under study. Specifically, a high-interest rate environment has been associated with a substantial decrease in acquisition activities for certain firms within the group. This suggests that external economic conditions, such as interest rates, hold considerable sway over the acquisition decisions of these firms, underscoring the highly contingent nature of their strategies in response to macroeconomic variables.

This paper presents three key contributions to the existing literature. First, it advances the literature that investigates the behavioral motives driving firm acquisitions. While numerous reasons have been proposed for firms engaging in acquisitions, some studies

have emphasized the significance of internal motives. These internal drivers include the pursuit of economies of scale (Desyllas & Hughes, 2008; Faulí-Oller, Sandońs, et al., 2018; Granstrand, Håkanson, & Sjölander, 1993; Mermelstein, Nocke, Satterthwaite, & Whinston, 2020; Ruckman, 2005), as well as demand-side scope economies (Gautier & Lamesch, 2021; Mueller, 1997; Teece, 2023).

The former strand of literature suggests that acquisition serve prevalent means to gain access to innovative technology or outsourcing internal research and development efforts, ultimately leading to improved production efficiency post-merger. The latter strand of literature contends that firms may acquire other companies in markets where they do not have overlapping products or services. This is driven by the presence of strong network effects or substantial positive spillover effects, which are particularly prominent in digital markets.

Extending to these literature, I account for competitive aspects of acquisition decision making, especially actions of the others. In oligopolistic markets in platform economies, such factors can greatly influence a firm's strategic decisions. For example, numerous studies emphasize and identifies preemption motives, such that firms acquire another firm or networks to maintain market power, insulate itself from the future rivals, and dominate user attentions (Motta & Peitz, 2021; Norbäck & Persson, 2009; Prat & Valletti, 2022; Stigler, 1950). This study builds on to these existing literature by carefully distinguishing between internal motives and preemption motives that guide the acquisition strategies of the digital platforms.

Second, despite intensified competition among the GAMMA firms across a wider range of markets, there remains a noticeable absence of empirical literature that examine and compare their distinct dynamic multi-market acquisition strategies on an individual basis. Instead, many studies concentrate on assessing the effects of merger policies that

regulate the GAMMA firms as a collective entity or examining the potential pro- or anti-competitive consequences of the GAMMA's collective merger activities on the market (Bryan & Hovenkamp, 2020; Cabral, 2021; Cunningham, Ederer, & Ma, 2021; Katz, 2021). This study addresses a distinct gap in the literature by (1) focusing on ex-ante factors propelling these major players to acquire other companies, diverging from the predominant emphasis on ex-post merger effects, and (2) by comparing and examining the individual merger strategies within the GAMMA group. By analyzing the unique strategies employed by each of the GAMMA firms, this study seeks to provide a more holistic understanding of the dynamics of multi-market competition across the dominant players within the tech industry.

Third, my contribution extends to the literature on the acquisition behaviors of the GAMMA firms. The existing literature has provided limited exploration and comparison of merger activities among the leading tech firms. For example Argentesi et al. (2021) examined the merger activities by Google, Amazon, and Facebook, and found their intense acquisition behaviors in artificial intelligence (AI), data science, and analytic segments. Their study sheds light on specific segments in which the three companies are active in acquisition and offers descriptive insights into the companies' acquisition behaviors. I add dynamic aspects in my study to structurally identify the effect of different behavioral motives.

Similarly Gautier and Lamesch (2021) showed a descriptive and static analysis of whether the GAMMA firms acquire to reinforce their existing businesses or to expand to new markets. Their findings indicate that the GAMMA firms tend to acquire targets that enhance their core operations. While these existing literature explore merger strategies of the technological leading firms, my contribution to this body of literature lies in considering the dynamic evolution of the acquisition landscape.

The decision-making process of an agent today is not solely influenced by present circumstances; it is also shaped by optimal responses that maximise future expected returns. In other words, agents make decision today while considering the ramifications these decisions will have on the competitive landscape in future periods and future returns. The dynamic model allows us to account for such dynamic decision process of an agent, accounting for future expected returns to decide its action today (Gowrisankaran, 1999).

The paper is structured as follows: Section 2 describes the data used for analysis, Section 3 explains the model used for estimation, Section 4 illustrates the estimation processes, Section 5 presents empirical findings. Finally, Section 6 concludes.

## 2.2 Data

**2.2.1 Acquisition Data.** I use Pitchbook as the main source of data for information on targets acquired by the GAMMA firms.<sup>12</sup> The data contains the universe of acquisitions, including date of the deal, the name of the target, and the sector or industry in which the target operates. It also includes information about acquirers, including the date they were found and the sector in which they primarily operate. Several other literature have used this data for analyzing merger and acquisition activities. For example, Tang, Fang, and Jiang (2022) used this database to analyze digital merger and acquisitions in China. Zingales, Kamepalli, and Rajan (2020) used Pitchbook to analyze acquisitions made by Google and Facebook. For my analysis, I use Pitchbook’s classification of target industry sectors to

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<sup>1</sup>Jin, Leccese, and Wagman (2023) used S&P taxonomy, some other literature have used their own self-defined classifications to categorize targets acquired by the GAMMA firms (Argentesi et al., 2021; Gautier & Lamesch, 2021). In this paper, I use Pitchbook’s classification taxonomy, which details conventional industries into more granular sectors. Although a direct comparison between S&P’s taxonomy and Pitchbook’s is not feasible due to limited database access, some sector name such as “Application Software” are present in both database. The total number of acquisition completed by GAMMA, as depicted in Figure 1 of Jin et al. (2023), shows a similar pattern when using Pitchbook data as it does when using the S&P database.

<sup>2</sup>I would like to acknowledge University of Oregon Lundquist College of Business for providing data resources.

Table 1. Number of Targets Acquired

Company	Total Target Acquired
Amazon	93
Apple	134
Google	268
Meta	109
Microsoft	243

*Notes:* The numbers are the cumulative total of targets acquired by the GAMMA firms since they were each founded as of 2021. Multiple targets acquired across different times are treated as multiple entrances.

examine the acquisition behaviors of the GAMMA firms from the second quarter of 2004, when Meta, the youngest member of the GAMMA companies, was founded to the fourth quarter of 2021.<sup>3</sup>

Table 1 summarizes the total acquisition counts by each agent until 2021. The first acquisition by the GAMMA firm dates back to 1987 when Microsoft acquired Forethought, a Multimedia and Design Software company. Since then, Alphabet (Google) emerged as the most prolific acquirer, with a total of 268 acquisitions, while Amazon has been the most conservative, acquiring only 93 targets – Alphabet’s acquisition count is nearly three times greater than that of Amazon. Microsoft closely trails Google, having acquired just 15 fewer companies than the leading acquirer. Apple’s acquisition count stands at half that of Microsoft’s. Meanwhile, Meta can be seen as an acquisitive player, having purchased a comparable number of targets as Apple, despite being youngest in the field.

Since 1987, when the group’s oldest member made the initial acquisition, the GAMMA firms have ventured into a total of 79 different sectors. Figure 1 illustrates the market

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<sup>3</sup>While these tech firms currently hold dominant positions with substantial user-base, their primary industries differ. Founded in 1975, Microsoft has operated primarily in Operating Software Systems, i.e., its Windows PC. Founded in 1976, one year after Microsoft was founded, Apple has specialized in Electronics (B2C), i.e., Mac products. Eighteen years later in 1994, Amazon was founded which primarily operates in Internet Retail. Around the same period in 1998, Google was founded which operates primarily in the IT consulting and outsourcing sector. Six years later in 2004, Meta, Software/Platform Software provider, was founded.

Table 2. Top 10 Popular Sectors for Acquisitions.

Industry	n
Application Software	155
Business/Productivity Software	71
Software Development Applications	40
Social/Platform Software	38
Media and Information Services (B2B)	35
Multimedia and Design Software	35
Entertainment Software	32
Information Services (B2C)	31
Communication Software	30
Network Management Software	28

*Notes:* The classification of sectors and industries follows Pitchbook’s industry categorization. For instance, per Pitchbook’s classification criteria, developers or producers of a software that performs a specific tasks or applications, as well as those not classified else where, fall under the category of Application Software. Business/Productivity software includes producers of enterprise-focused software, primarily designed to manage and automate processes. Software Development Applications encompass softwares that involve planning, coding and debugging, i.e., compilers, debuggers, etc.

expansion and intensity of acquisitions by the group from 1987 to 2021, with the top twenty sectors highlighted in yellow.<sup>4</sup> Among these sectors, Application Software sector is ranked the first as the one where acquisitions have occurred most actively, followed by Business/Productivity Software. Table 2 is a list of the top 10 popular sectors for acquisitions of the GAMMA firms, arranged in descending order.

Using this information, I have constructed a balanced panel dataset consisting of agent-sector tuple ordered quarterly from second quarter of 2004 to the fourth quarter of 2021 to conduct the analysis. Examining each agent’s acquisition behavior across time, Google has made the highest number of acquisitions, with significant fluctuations observed on a quarterly basis. Microsoft, which closely trails Google in terms of the total number of acquisitions since its operation, demonstrates relatively less fluctuation in the overall

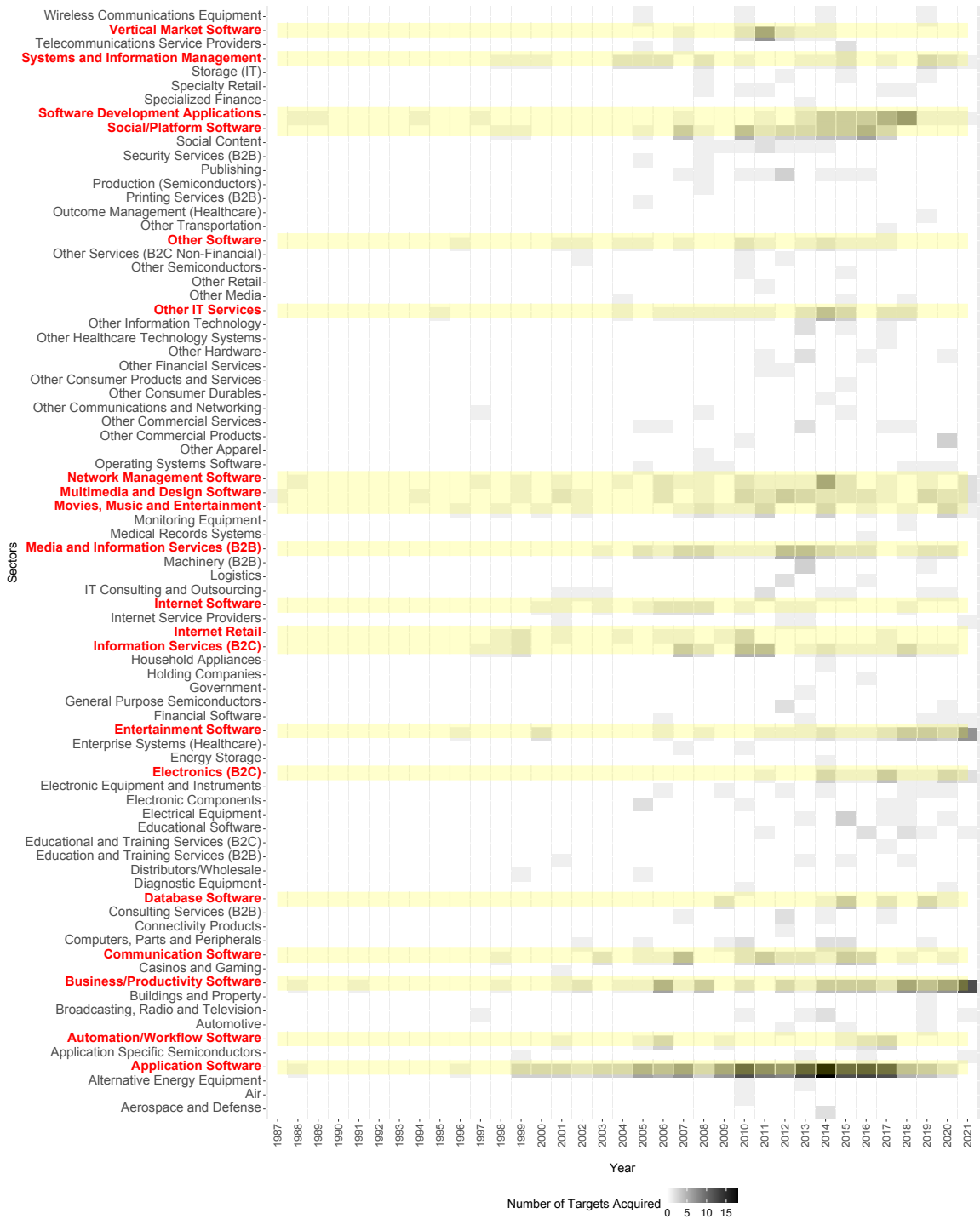
<sup>4</sup>An identification of these 79 sectors can be found in Table A.1. The heat-map illustration that shows the annual intensity of acquisitions by each acquirer across time can be found in Figure 1.

number, although variation intensifies since 2015. This quarterly acquisition trend is graphically demonstrated in Figure 2. Additionally, Figure 3 illustrates the cumulative number of acquisitions made by each player from 2004 to 2021. While Amazon seems to acquire targets at a moderate pace, Google appears to accelerate its acquisition rate starting 2010, prompting Apple and Microsoft to adopt a more aggressive acquisition strategy starting 2014. Meta, which initiated its first acquisition one year after its founding date, shows a rapid increase in the number of acquisition since 2010.

Figure 4 indicates the development stage share of target companies at the time of the acquisition. During the sample period, the majority of the total targets acquired by the tech giants were in the stage of “generating revenue” and “start up” phases, constituting approximately 70% and 15%, respectively, of the total development stage share of target companies at the time of acquisition. The share of targets in the “profitable” stage amounted to only 4% of the total targets acquired by the tech giants. Individually, Microsoft recorded the highest share of targets at the generating revenue stage with 78%, followed by Apple with 73%, Amazon with 70%, Google with 66%, and Meta with 58%. For the startup phase, Meta led with 25%, followed by Google with 16%, Apple with 15%, Amazon with 10%, and Microsoft with 9%. This suggests that the targets acquired by the tech giants are generally in the early stages of their development.

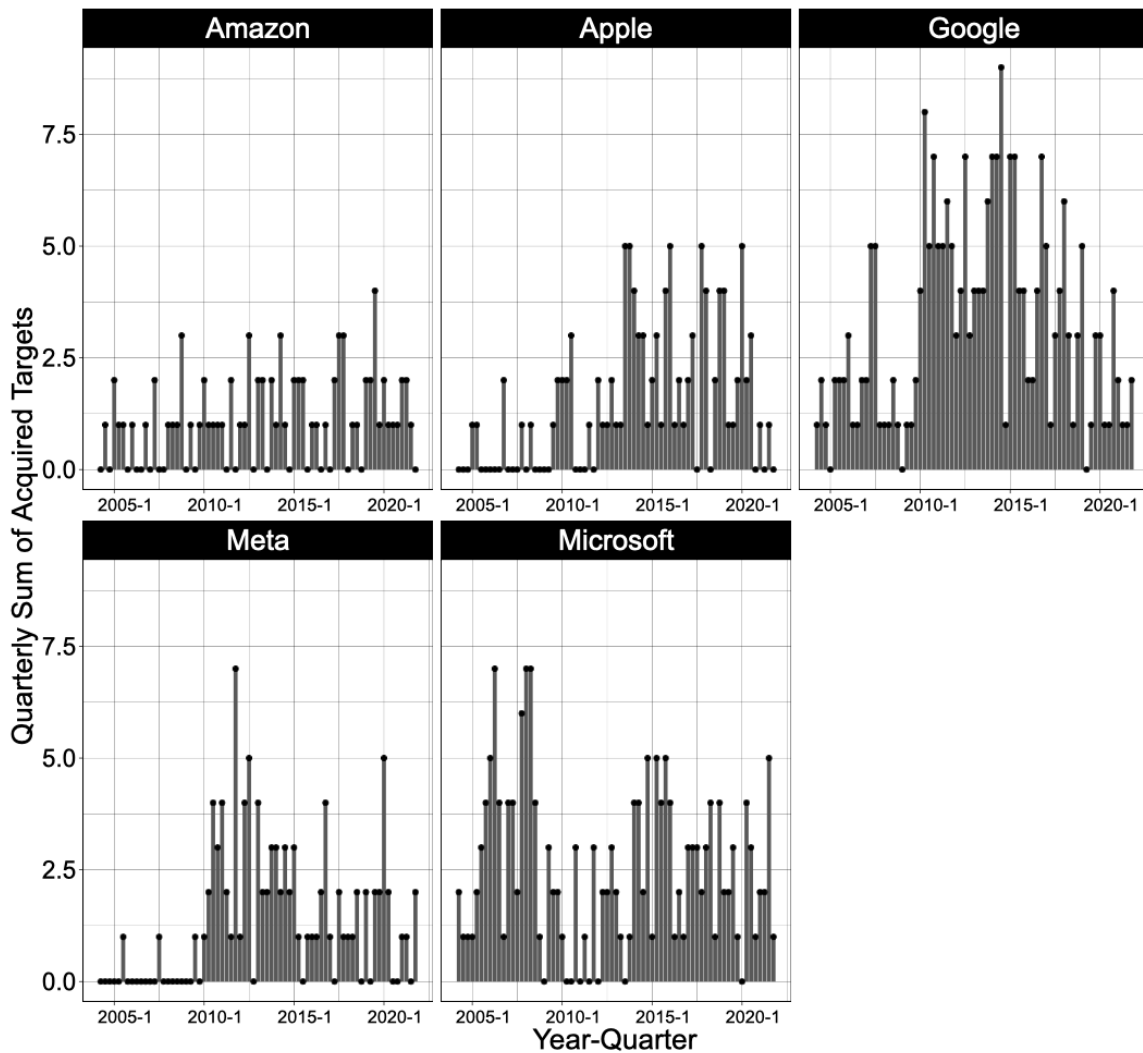
**2.2.2 Macroeconomic Factor.** Some might argue that acquisition herding pattern is likely to be driven by aggregate economic shocks rather than scale economies or competitive motives. To control for any aggregate macroeconomic shocks that may have imposed common shocks to every member of the group, I also use the effective federal funds rate in my analysis. During the analysis period, interest rate has fluctuated from near zero to as high as 5.25%. I used 2.5% (nearing the third quantile of interest rate observed during the period) to separate low interest rate period from the high interest rate period. Using

Figure 1. Annual Acquisition Counts in Each Sector



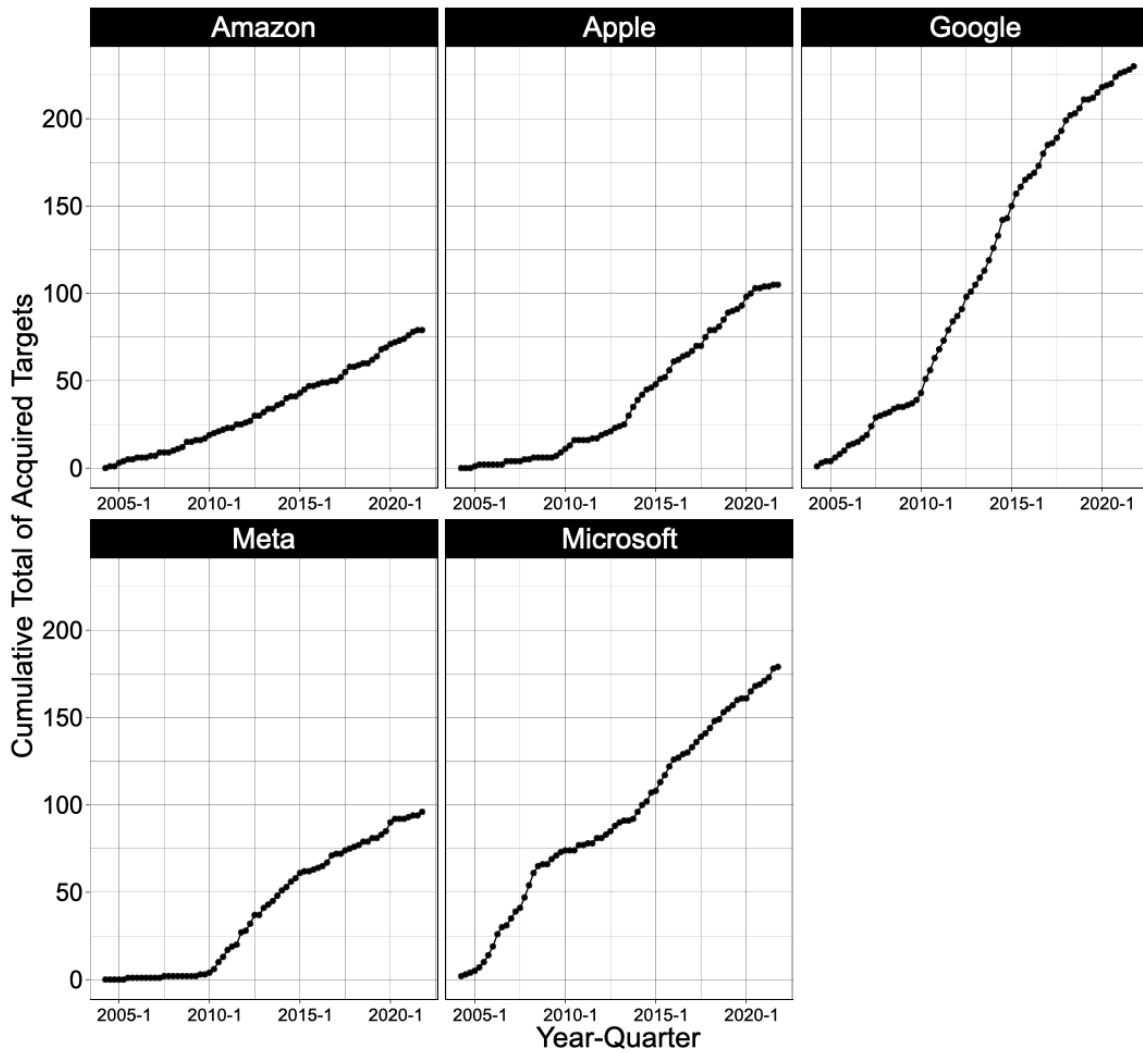
Notes: Sectors highlighted in yellow are the top 20 sectors in which the most acquisitions were made by the GAMMA firms between 1987 to 2021.

Figure 2. Quarterly Sum of Acquisitions



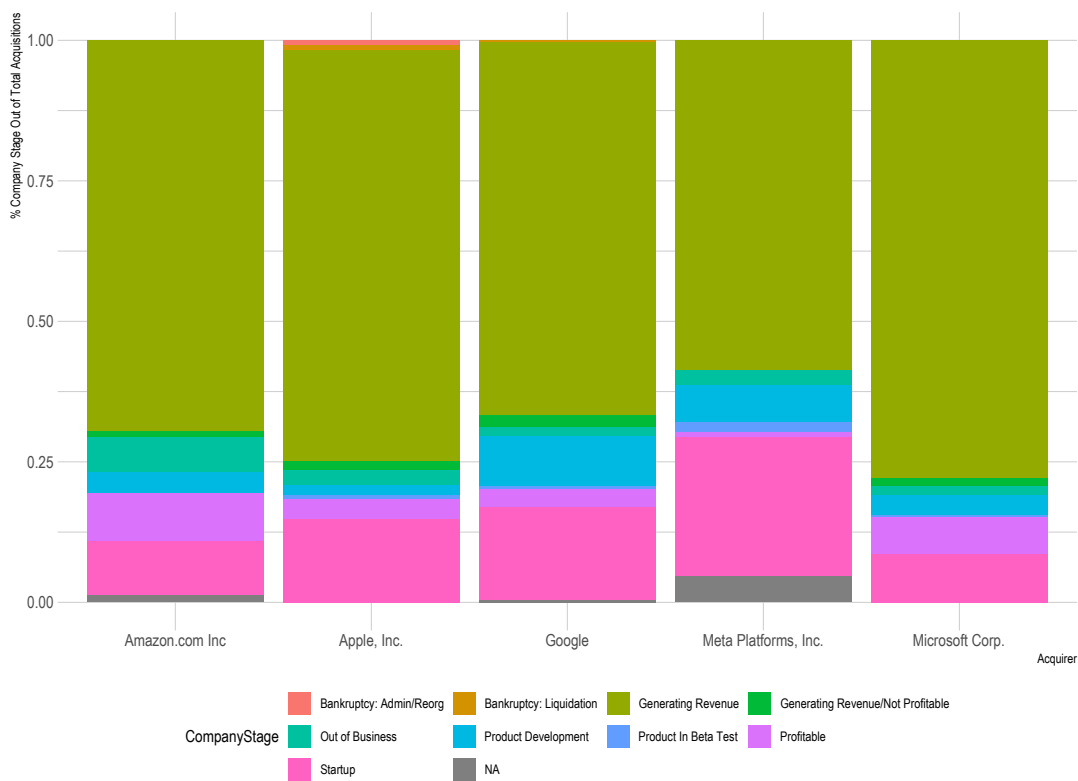
Notes: This figure represents the quarterly sum of acquired targets by each agent, arranged in year and quarter, during the analysis period from 2004Q2 to 2020Q4. Google has been the most active in acquisition during the sample period, acquiring at most 9 targets in a single quarter.

Figure 3. The Cumulative Total Sum of Acquisitions



Notes: This figure represents a rolling totals of quarterly acquisition counts (Figure 2) for each agent.

Figure 4. Development Stage Share of Target Companies at Acquisition



Notes: The classification of the development stage of target companies at the time of acquisition follows Pitchbook’s categorization. The figure represents the distribution of targets by their development stage that were acquired by different tech giants from 2004 to 2021. The majority of the targets acquired by the five acquirers are either in the generating revenue stage or the startup stage.

the classification, the time frame from early 2005 to 2008 is considered a high-interest rate period, while all other periods are categorized as low-interest rate periods.

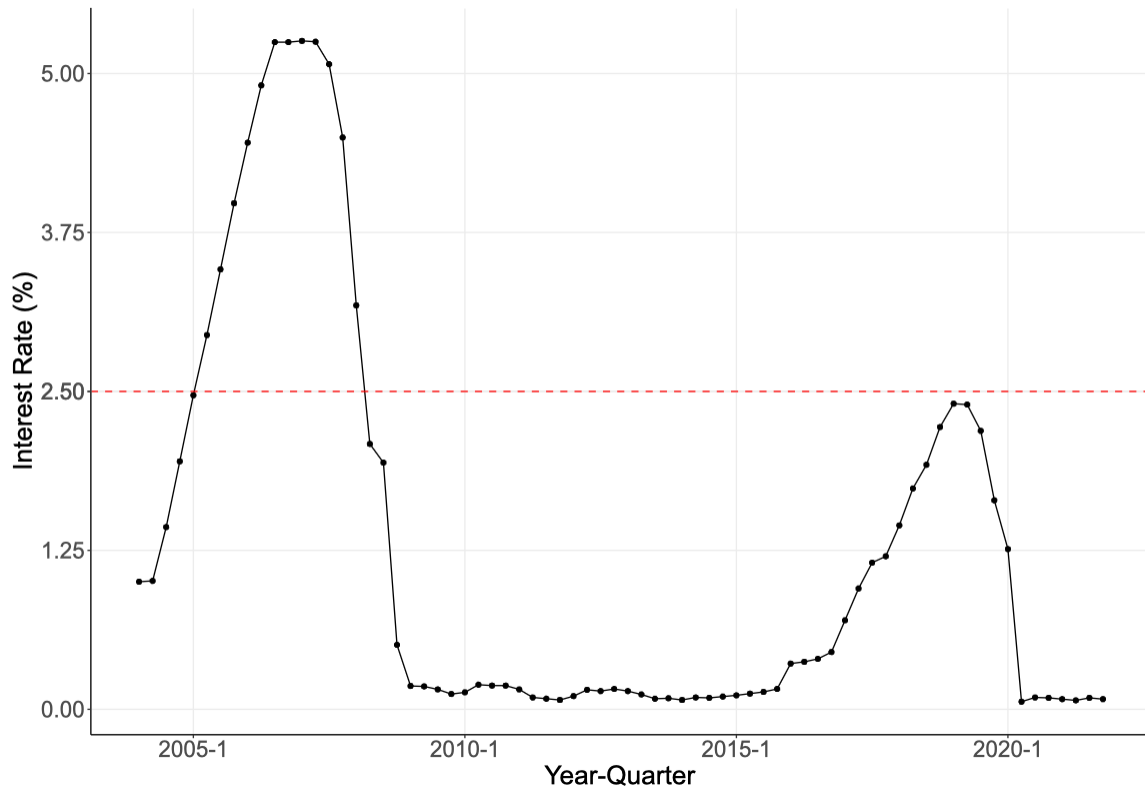
The drop in interest rate may affect the acquirer's behaviors in twofolds: this will enhance financial situation for all acquirers, allowing each of them to borrow funds at a reduced cost of capital, driving more aggressive acquisitions to be observed during the low-interest rate period. On the other hand, low-interest rate may negatively affect acquirer's incentive to acquire a target, as it may also affect the target price to appreciate. Considering that the valuation of most startups relies on the discounted cash flow (DCF) model, a low-interest rates would yield higher present values of future cash flows, driving up startup valuations. Although these conflicting forces will have varying impacts on different acquirers, accounting for them is important to control for aggregate economic shocks that may have otherwise driven the acquisition behaviors.

### **2.3 Model**

My model builds upon the work of Ericson and Pakes (1995), which provides a dynamic framework for examining the discrete choice model of multiple agents. I investigate the behavioral motives of multiple agents in pursuing sector entry through buyouts by constructing a dynamic entry model.

The acquisition game can be framed as a market entry problem with only entries and no exits. Once agents acquire a target in a sector, it implies entry into that sector or market. Throughout this paper, I use the terms 'sector' and 'market' interchangeably, as well as 'enter a market' and 'acquire a target'. In a given quarter, I assume an agent can enter the same market multiple times. This occurs when an agent acquires more than one firm at a given point in time. I count each acquisition as separate market entries. Multiple entries within the same market represent the agent's intent to strengthen its market competitiveness within that sector. In contrast to conventional market entry models, however, I assume that there is no exit. Exit from the market would correspondingly imply selling previously acquired targets or discontinuing the targets' operations. Such post-acquisition activities are

Figure 5. Interest Rate Trend



Notes: Following the 2008 financial crisis, interest rates experienced significant decline. This can be primarily attributed to the deliberate actions of the Federal Reserve, which adjusted interest rates to accommodate economic turmoil triggered by the crisis. Such trend of low-interest rates persisted due to the continued implementation of Quantitative Easing (QE) measures extending through to late 2021.

beyond the scope of this analysis. The model exclusively considers acquisitions without any selling or exits.

**2.3.1 Model Setup.** Time is discrete with each decision period being one quarter. Sector are indexed as  $m = 1, 2, 3, \dots, M$  and are independent of one another.<sup>5</sup> I assume

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<sup>5</sup>I assume that acquisition activities within one sector operate independently of those in other sectors. At this moment, I do not consider scenarios where acquisition activities in one sector influence or deter activities in other markets. Agents' acquisition decisions are influenced solely by events and actions occurring within that specific sector. Acquisition counts are calculated in each market for each period. Rivals' past acquisitions are also calculated in each market for each period.

that all markets and targets are homogeneous, and thus subscript  $m$  is omitted.<sup>6</sup> Acquirers, indexed by  $i = 1, 2, 3, 4, 5$ , enter different sectors, sometimes multiple times in each period.

In this model, I assume that the acquisition activities by the five firms are entirely governed by private shocks that each firm faces in each period and the following three states: the number of targets acquired over the past year by firm  $i$ ,  $e_{it}$  for all  $i$ , the sum of acquired targets over the past year by firms that are not  $i$ ,  $e_{-it}$  for all  $i$ , and the interest rate ( $\text{int}_t$ ). The past number of its own and its rivals' acquisitions help us capture the different responsiveness of each member of the GAMMA firms in response to the intensity of acquisition in a given sector.

To simplify the notation, let

$$s_{it} \equiv \{e_{it}, e_{-it}, \text{int}_t\},$$

where  $s_{it}$  is simply a vector of the three aforementioned states,  $e_{it}$ ,  $e_{-it}$  and  $\text{int}_t$ . The former two states take different values by each firm  $i$  in each period  $t$ . The last state,  $\text{int}_t$  is common across all  $i$  and only varies by  $t$ .

Per-period payoff (utility) of an agent (acquirer) is a function of current states and firm-specific private shocks given by<sup>7</sup>

$$R_i(a_{it}, s_{it}, \nu_{it}; \theta) = \begin{cases} \nu_{0it} & a_{it} = 0 \\ \theta_{1i} + \theta_{2i}\text{int}_t + \theta_{3i}\mathbb{1}(e_{it} = 1) + \theta_{4i}\mathbb{1}(e_{it} > 1) & \\ \quad + \theta_{5i}\mathbb{1}(e_{-it} \in (0, 5]) + \theta_{6i}\mathbb{1}(e_{-it} > 5) + \nu_{1it} & a_{it} = 1, \end{cases} \quad (2.1)$$

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<sup>6</sup>This assumption is based on the similarity of the markets/industries/sectors from which most of the targets that GAMMA has acquired are classified. Considering that the majority the sectors are sub-fields of a bigger sector of information, communication and technology sector, I argue that this assumption is not unreasonable. Relaxing the assumption may require accounting for heterogeneity across distinct markets/sectors.

<sup>7</sup>As shown in Figure 4, it appears that most targets acquired by GAMMA firms are in the early stages of development. This suggests a streamlined acquisition process, sidestepping the intricate decision-making usually tied to merging with fully established entities. Under these conditions, the CEO's influence is likely more pronounced, steering the firm's decision process towards resembling an individual maximizing utility rather than a traditional focus on profit maximization. This characteristic is reflected in the reduced-form model presented in the per-period payoff function.

where  $e_{it}$  is the total number of targets acquired by firm  $i$  discretized into three states,  $e_{-it}$  is the total number of targets acquired by firms other than  $i$  discretized into three states,  $int_t$  is interest rate,  $\nu_{0it}, \nu_{1it}$  is firm  $i$ 's choice-specific private shocks only observable to firm  $i$ .<sup>8</sup> The collection of structural parameters are represented by the letter  $\theta_i = (\theta_{1i}, \theta_{2i}, \theta_{3i}, \theta_{4i}, \theta_{5i}, \theta_{6i})$  for all  $i \in \{1, 2, 3, 4, 5\}$ . Note that a firm will only initiate acquisition when doing so yields greater per-period payoff.

One of the factors affecting a firm's per-period payoff is the interest rate ( $\theta_2$ ). A low-interest rate generally improves the financial situation for all firms, increasing the payoff from acquisitions and incentivizing them to engage more actively in such behaviors. A high-interest rate imposes an opposite economic shock, making all firms less active in acquisition behaviors. However, the effects can also be reversed – the high interest rate may depreciate the future expected cash flow of a target, resulting in lower target valuation, which incentivizes buy-out. Regardless of the direction of these effects, including aggregate economic shocks as one of the controlling variables help mitigate some degree of endogeneity that is generating co-movements in acquisitions across all firms.

The parameter denoted by  $(\theta_3, \theta_4)$  captures the contribution of the scale economies towards the likelihood of a firm making acquisition move. In a typical market entry problem, a firm's own acquisition indicates a degree of cannibalization. In the acquisition game, this indicates a firm's gain derived from scale economies. As a firm acquires increasing number of targets in a given sector, it is more likely to benefit from technological efficiency, thereby achieving scale economies.

An agent's responsiveness to its rivals' acquisition in scale, represented by  $(\theta_5, \theta_6)$ , can be interpreted as an indicator of their defensive motives. Although preemption or defensive motives are challenging to observe directly, they can become evident through how a firm responds to the increasing number of acquisitions made by its rivals. These motives can manifest in two distinct ways: Firstly, the firm's desire to become part of a preemption group, thereby its acquisition likelihood increases as rivals buy more firms and secondly,

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<sup>8</sup>The detailed illustration of discretization can be found in Section 4.1.

its intention to reduce the risk of targets becoming unavailable (sold-out risk). In markets characterized by a limited pool of potential targets available at any given time, there exists a greater risk of targets being rapidly depleted when competitors have previously acquired a substantial number of targets. As a result, the firm is more inclined to make acquisitions to avoid the possibility of targets becoming scarce. In this manner, these acquiring behaviors act as a defense against the risk of being preempted by the other four competitors. If the acquisition likelihood increases in response to the growing sum of the rivals' acquisitions, this can suggest the presence of preemption motives.

**2.3.2 Evolution of the Game.** In each period, every agent participates in acquisition game and the game unfolds as follows:

1. All members of the GAMMA firms observe the quarterly interest rate, the number of acquisitions made by themselves and others in the last four quarters, the firm-specific private shocks, which are identically and independently distributed.
2. Each firm simultaneously makes a discrete choice of whether to enter the market or not (acquire a target in that market or not) based on the given states and private shocks.
3. The number of acquisitions made by each agent in the next state evolves stochastically based on their previous state and current actions.
4. The number of acquisitions made by rivals (varying by each agent) in the next state evolves stochastically based on their previous state and the collective actions of the rivals during the current period.
5. The interest rate in the next state evolves stochastically based on its previous state.
6. This process repeats from step 1 in the subsequent period.<sup>9</sup>

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<sup>9</sup>Appendix ?? provides a detailed development of the game.

All states evolve in stochastic process that follows state transition probabilities that are recovered from the data without the use of predetermined parameters. Endogenous states  $(e_{it}, e_{-it})$  travel through state space probabilistically based on previous states and current actions. Exogenous state  $(int_t)$  evolves according to only its own path.

**2.3.3 Equilibrium.** In each period, each firm make entry decision that maximizes its expected discounted future profit. Let Markov strategy profiles of all firms which maps states and shocks into actions denoted by

$$\sigma^* : (s_{it}, \nu_{it}) \rightarrow a_{it} \in \{0, 1\} \text{ for all } i.$$

With per-period profit, the following bellman equation shows a firm's dynamic programming problem,

$$\begin{aligned} V_i(s_{it}, \nu_{it}, \sigma; \theta) = & \max_{\sigma(s_{it}, \nu_{it})} R_i(s_{it}, \nu_{it}, \sigma; \theta) \\ & + \beta \mathbb{E}[V_i(s_{it+1}, \nu_{it+1}, \sigma; \theta) | s_{it}, \sigma], \end{aligned} \quad (2.2)$$

where the expectation is over the distribution of  $\nu_{it+1}$  and  $s_{it+1}$ ,  $\sigma$  is a vector of Markov strategy profiles of all firms which maps given states and shocks into actions,  $\beta \in \{0, 1\}$  is a discount factor.

In a Markov-perfect equilibrium, it must be true that

$$V_i(s_{it}, \nu_{it}, \sigma^*; \theta) \geq V_i(s_{it}, \nu_{it}, \sigma'_i, \sigma^*_{-i}; \theta)$$

where  $\sigma^*_{-i} = \sigma^*(s, \nu) \setminus \{\sigma^*_i(s, \nu)\}$  is a vector of Markov strategies of players that are not player  $i$ ,  $\sigma'_i$  is alternative strategies that are not Markov strategies. This implies that each player  $i$  acted best response to the other players' strategies and that choosing alternative policy  $(\sigma^*_i)$  yields lower expected future returns.

I assume that the data are generated consistently across all markets, adhering to the same Markov perfect equilibrium. This assumption is a typical requirement for obtaining

consistent parameter estimates, as indicated in prior research (Bajari et al., 2007; Ryan, 2012).

## 2.4 Estimation

The estimation technique that I use (BBL) takes two-steps: (1) estimating the optimal policy function by regressing actions on states in a reduced-form framework, and (2) impose optimality conditions to find a set of parameters that best aligns with the conditions. In other words, it seeks to identify a parameter set that minimizes deviations from the optimality conditions. During the second step, expected future returns under optimal policy and alternative policies are separately computed with some guess about  $\theta$ . With a sufficiently large set of perturbed policies, BBL categorizes optimality-violating cases where alternative policies yield greater expected return than the optimal policy. It then finds a set of parameters that minimizes the overall distance between the expected future returns under the optimal policy and those under alternative policies within these violating cases.

In the subsequent subsections, I provide a more comprehensive explanation of the procedures involved in the second step of BBL. To begin, I establish the state space and action space, and also delineate the nonparametric transition probabilities linked to these states. Next, I proceed to construct the agent's payoffs, which is a function derived from the previously defined actions and states. This process also entails dynamically representing the payoffs while considering the transition probabilities of each state over future periods. In the third step, I simulate possible state paths and action paths. I compute value function under both the optimal policy and various alternative policies given these simulated paths. Finally, I present the outcomes following these procedures.

### 2.4.1 Definition of States, State Transitions and Actions.

**Discretizing the state space** In the model, the acquisition game is governed by three states,  $e_{it}$ ,  $e_{-it}$ , and  $int_t$ . The first two states are divided into three bins, each containing

a reasonable number of observations to capture meaningful transition probabilities for all five firms. The distribution of the number of targets acquired by all five firms is taken into account when determining the bin range. Considering that the average number of acquisitions made over any consecutive four quarters by a single firm ( $e_{it}$ ) is 0.109 with a maximum of 13, the discretization appears to be reasonable. On the other hand, considering that any combination of four firms acquired on average 0.4359, with 22 being the maximum number over any consecutive four quarters, the bins are discretized differently for  $e_{-it}$ . The last state, interest rate is discretized into two bins: high-interest rate bin and low-interest rate bin. The threshold separating the two is set at 2.5%.

$$\begin{aligned}
 B_1(e_{it}) &= \begin{cases} 1 & \text{if } e_{it} = 0 \\ 2 & \text{if } e_{it} = 1 \\ 3 & \text{if } e_{it} \in (1, 15] \end{cases} \\
 B_2(e_{-it}) &= \begin{cases} 1 & \text{if } \sum_{i \neq j} e_{jt} = 0 \\ 2 & \text{if } \sum_{i \neq j} e_{jt} \in (0, 5] \\ 3 & \text{if } \sum_{i \neq j} e_{jt} \in (5, 24] \end{cases} \\
 B_3(\text{int}_t) &= \begin{cases} 1 & \text{int}_t \leq 2.5\% \\ 2 & \text{int}_t > 2.5\% \end{cases}
 \end{aligned}$$

Slightly abusing the notations, I redefine the states such that  $e_{it} = B_1(e_{it})$ ,  $e_{-it} = B_2(e_{-it})$ , and  $\text{int}_t = B_3(\text{int}_t)$ . Rewriting the per-period payoff of each firm (Equation 2.1) with the redefined  $e_{it}$  and  $e_{-it}$ ,

$$R_i(a_{it}, s_{it}, \nu_{it}; \theta) = \begin{cases} \nu_{0it} & a_{it} = 0 \\ \theta_{1i} + \theta_{2i}\text{int}_t + \theta_{3i}\mathbb{1}(e_{it} = 2) + \theta_{4i}\mathbb{1}(e_{it} = 3) & \\ +\theta_{5i}\mathbb{1}(e_{-it} = 2) + \theta_{6i}\mathbb{1}(e_{-it} = 3) + \nu_{1it} & a_{it} = 1. \end{cases} \quad (2.3)$$

**Choice Space** In each period, all players choose whether to acquire a target (i.e., enter a market through acquisitions) or not, conditional on given state. Let  $a_{it} \in \{0, 1\} = A$  denote the player  $i$ 's move at time  $t$ . If  $a_{it} = 1$ , player  $i$  enters a market by acquiring at least one target, while  $a_{it} = 0$  means that they do not. There are five players, making the choice space  $\mathbf{A}_t = (a_{1t}, a_{2t}, a_{3t}, a_{4t}, a_{5t}) \equiv \{0, 1\}^5$ .

**State Transitions** The transition probabilities of all states are computed based on the transition frequencies observed in the data. The transition for  $e_{it+1}$  is determined by its previous state  $e_{it}$ , and decision made by firm  $i$ , which in turn maps 18 different instances into a probability distribution, given by:

$$P(e_{it+1}|e_{it}, a_{it} \in \{0, 1\}) : \{1, 2, 3\} \times \{0, 1\} \times \{1, 2, 3\} \rightarrow [0, 1].$$

The transition probabilities for  $e_{it}$  vary depending on the agent and action it takes. For example, Google may or may not acquire a target in a given period, and its state transition probabilities will differ based on the action it takes in that period. The state transition probabilities maps  $S \times A \times S \rightarrow [0, 1]$ .

Here I illustrate the state transitions probabilities using Google as an example (and using 'g' as a subscript). When Google decides to acquire a target, state transition probabilities look as follows:

$$\begin{array}{c} e_{gt+1} = 1 \quad e_{gt+1} = 2 \quad e_{gt+1} = 3 \\ e_{gt} = 1 \left( \begin{array}{ccc} 0.000 & 0.944 & 0.056 \\ e_{gt} = 2 \left( \begin{array}{ccc} 0.000 & 0.231 & 0.769 \\ e_{gt} = 3 \left( \begin{array}{ccc} 0.000 & 0.000 & 1.000 \end{array} \right) \end{array} \right) \end{array} \right)$$

When Google decides to not acquire a target, state transition probabilities look as follows:

$$\begin{array}{l}
 e_{gt+1} = 1 \quad e_{gt+1} = 2 \quad e_{gt+1} = 3 \\
 e_{gt} = 1 \left( \begin{array}{ccc} 1.000 & 0.000 & 0.000 \\ 0.252 & 0.748 & 0.000 \\ 0.047 & 0.315 & 0.638 \end{array} \right) \\
 e_{gt} = 2 \\
 e_{gt} = 3
 \end{array}$$

Note that switching between discrete bins can occur when acquisition inflow is different from the outflow; the number of acquired targets upcoming quarter is different from the number of targets acquired four quarters ago (Equation 2.4). Note that the state is defined such that it is a four-quarter (one-year) rolling sum of total targets acquired by a specific company. The window moves one quarter at a time and the sum is updated by aggregating the number within that sliding window.

$$\begin{aligned}
 e_{g,t} &= n_{g,t-4} + n_{g,t-3} + n_{g,t-2} + n_{g,t-1} \\
 e_{g,t+1} &= n_{g,t-3} + n_{g,t-2} + n_{g,t-1} + n_{g,t} \\
 e_{g,t+1} - e_{g,t} &= n_{g,t} - n_{g,t-4}
 \end{aligned} \tag{2.4}$$

The transition for  $e_{-it+1}$  is determined by its previous state  $e_{-it}$ , and the number of entering players that are not  $i$ ,  $\sum_{j \neq i} a_{jt}$ . I discretize the sum of player  $i$ 's rivals' actions into three categories: (1) no other agents enter ( $\sum_{j \neq i} a_{jt} = 0$ ), (2) only one other agent enters ( $\sum_{j \neq i} a_{jt} = 1$ ), and (3) more than one other agents enter ( $\sum_{j \neq i} a_{jt} > 1$ ), which in turn maps 27 different combination of instances into a probability distribution, given by:

$$P(e_{-it+1} | e_{-it}, \sum_{j \neq i} a_{jt} \in \{0, 1, > 1\}) : \{1, 2, 3\} \times \{1, 2, 3\} \times \{1, 2, 3\} \rightarrow [0, 1].$$

The transition probabilities for  $e_{-it}$  also vary depending on the agent and actions taken by all other agents except for that agent. Continuing on Google's example, all other agents aside from Google may choose to acquire or not acquire a target, and that affects state

transition probabilities. If no other agents other than Google acquire a target, the state evolves as follows:

$$\begin{array}{l}
 e_{-gt} = 1 \\
 e_{-gt} = 2 \\
 e_{-gt} = 3
 \end{array}
 \begin{array}{l}
 e_{-gt+1} = 1 \quad e_{-gt+1} = 2 \quad e_{-gt+1} = 3 \\
 \left( \begin{array}{ccc}
 1.000 & 0.000 & 0.000 \\
 0.190 & 0.810 & 0.000 \\
 0.000 & 0.333 & 0.667
 \end{array} \right)
 \end{array}$$

When an agent other than Google acquires a target, the state evolves as follows:

$$\begin{array}{l}
 e_{-gt} = 1 \\
 e_{-gt} = 2 \\
 e_{-gt} = 3
 \end{array}
 \begin{array}{l}
 e_{-gt+1} = 1 \quad e_{-gt+1} = 2 \quad e_{-gt+1} = 3 \\
 \left( \begin{array}{ccc}
 0.000 & 1.000 & 0.000 \\
 0.000 & 0.985 & 0.015 \\
 0.000 & 0.063 & 0.938
 \end{array} \right)
 \end{array}$$

Note that this one agent that is not Google can acquire multiple targets, resulting in non-zero probabilities of transitioning from the second bin to the third bin. Likewise, if the number of targets acquired by all agents except Google four quarters ago exceeds the number of targets acquired this period, then a transition from the third bin to the second bin may occur.

The interest rate follows its own path of evolution.

$$P(\text{int}_{t+1}|\text{int}_t) : \{1, 2\} \times \{1, 2\} \rightarrow [0, 1],$$

where each element in the set  $\{1, 2\}$  represents either a low or high-interest state. Note that the interest rate transition matrix closely resembles the identity matrix, with its diagonal elements being very close to 1, as shown below.

$$\begin{pmatrix}
 0.985 & 0.015 \\
 0.021 & 0.979
 \end{pmatrix}$$

## 2.4.2 Linearization of Value Functions and Optimality Conditions.

**Linearization of value function** Using the linearity of pay-off function, I can rewrite the per-period net-gain of firm  $i$  as

$$R_i(a_{it}, s_{it}, \nu_{it}) = \Psi_i(a_{it}, s_{it}, \nu_{it})' \theta_i, \quad (2.5)$$

where  $\Psi_i(a_{it}, s_{it}, \nu_{it})$  is a vector of  $P$ -dimensional basis functions,  $\psi_i^1, \psi_i^2, \dots, \psi_i^P$ . Given that the pay-off function is linear with respect to elements  $(a_{it}, s_{it}, \nu_{it})$ ,  $\psi_i^p$  is simply the elements of  $(a_{it}, s_{it})$ , where each  $\psi_i^p$  corresponds to a coefficient for the respective parameter. In this context, we have six such coefficients with six parameters to estimate for each player. The scaling of the parameter for the difference in choice-specific shock is set to 1 to minimize multicollinearity with the constant term.

Expanding (2),

$$V_i(s_i; \sigma) = \mathbb{E} \left[ \sum_{\tau=t}^T \beta^\tau \psi_i(\sigma_i(s_{i\tau}, \nu_{i\tau}), s_{i\tau}, \nu_{i\tau}) \theta_i \middle| \sigma_{-i}, s_{it} \right] = W_i(s_i; \sigma) \theta_i, \quad (2.6)$$

where

$$W_i(s_i; \sigma) = \mathbb{E} \left[ \sum_{\tau=t}^T \beta^\tau \psi_i(\sigma_i(s_{i\tau}, \nu_{i\tau}), s_{i\tau}, \nu_{i\tau}) \middle| \sigma_{-i}, s_{it} \right]. \quad (2.7)$$

**Optimality conditions** In a Markov-perfect equilibrium, it must be true that

$$V_i(s_i; \sigma_i^*, \sigma_{-i}^*) \geq V_i(s_i; \sigma_i', \sigma_{-i}^*), \text{ for all } i, s, \sigma', \quad (2.8)$$

which means that each player  $i$  acted best response to the other players' strategies and that choosing an alternative policy produces lower expected future returns. Using linearity, this

can be rewritten as

$$\{W_i(s_i; \sigma_i^*, \sigma_{-i}^*) - W_i(s_i; \sigma'_i, \sigma_{-i}^*)\}\theta_i \geq 0, \text{ for all } i. \quad (2.9)$$

**Loss function (Objective function)** Let

$$g_i(\theta_i) = \{W_i(s_i; \sigma_i^*, \sigma_{-i}^*) - W_i(s_i; \sigma'_i, \sigma_{-i}^*)\}\theta_i.$$

Notice that  $g_i(\theta_i)$  is positive when optimal policy yields a greater expected sum of future returns than the alternative policy, is zero when both policies yield the same expected sum of future returns, and negative when the optimal policy yields a smaller expected sum of future returns. The inequality (Equation (2.9)) is only violated when  $g_i(\theta_i)$  is less than 0. The loss function is then defined as follows:

$$Q(\theta) = (\min\{g_i(\theta_i), 0\})^2.$$

Note that by choosing the smaller value between  $g_i(\theta_i)$  and 0, this function will only select cases where the alternative policy results in higher expected total future returns, i.e., those that violate the inequality conditions. Squaring this term creates the loss function that needs to be minimized.

Then I evaluate a set of parameters that minimizes the loss function.

$$\arg \min_{\theta} Q(\theta)$$

**2.4.3 Monte Carlo Simulation.** In the first stage, using the data, I calculate the policy rule for each player  $i$ ,  $P(a_{it} = 1|s_{it})$ , which represents the probability of agent  $i$  choosing  $a_{it} = 1$  given  $s_{it}$ . I also calculate state transitions, which are conditional on the previous state and current actions of players.

In the second stage, I generate  $NS$  simulated state paths, each lasting for  $T$  periods, and corresponding actions taken by each player  $i$ . This allows me to determine a  $NS \times T$  dimensional matrix, composed of per-period reward along each simulated path. I can then linearly separate this matrix by a vector of parameters and a matrix of basis functions. From Equation (2.1), a vector of parameter is denoted by

$$\theta_{1i}, \theta_{2i}, \theta_{3i}, \theta_{4i}, \theta_{5i}, \theta_{6i}$$

for all  $i \in \{1, 2, 3, 4, 5\}$ . Note that for each simulated path, I construct a  $P$ -dimensional vector of “basis functions”,  $\psi$ , where  $P$  is the number of parameters that contribute to the reward function (in this case,  $P = 4$ ). With a total of  $NS$  simulated path, I can construct  $W_i$  matrix by taking the average of the expected discounted sum of  $\psi$  from  $t = 1$  to  $t = T$  over the  $NS$  simulated paths.

$$W_i := W_i(\mathbf{s}; \sigma) \tag{2.10}$$

$$:= \mathbb{E} \left[ \sum_{t=0}^T \beta^t \psi_i(\cdot | s_0) \right] \tag{2.11}$$

$$\approx \frac{1}{NS} \left[ \sum_{n=1}^{NS} \sum_{t=0}^T \beta^t \psi_{i,n}(\cdot | s_0) \right]. \tag{2.12}$$

Recall that  $g(\chi; \theta, \alpha)$  is defined by

$$\begin{aligned} g(\chi; \theta) &= V_i(s_i; \sigma_i^*, \sigma_{-i}^*; \theta) - V_i(s_i; \sigma_i', \sigma_{-i}^*; \theta) \\ &= (W_i(s_i; \sigma_i^*, \sigma_{-i}^*) - W_i(s_i; \sigma_i', \sigma_{-i}^*)) \cdot \theta, \end{aligned}$$

where  $\chi$  denote one of the inequality conditions.

Suppose that  $H$  is a distribution over the set  $\chi$  of inequalities. Here, I assume uniform distribution over the set of inequalities that I choose with varying starting states.

$$Q(\theta) := \int (\min\{g(\chi; \theta), 0\})^2 dH(\chi) \\ \approx \frac{1}{NI} \sum_{k=1}^{NI} (\min\{\hat{g}(X_k; \theta), 0\})^2$$

where  $NI$  denotes the number of inequalities,  $X_k$  is each chosen inequalities. By varying the number of iterations and optimization methods, I search through a set of  $\theta$  to find the combination that minimizes  $Q(\theta)$ . To do so, I create 200 simulated paths of states and actions that unfold for 100 periods with 0.95 discount factor using the optimal policy rule.<sup>10</sup> Then I run 6000 times of 200 simulations using the alternative policy rule for a specific player while other players are acting optimally. The alternative are slight deviation from the optimal such that these differences are drawn randomly from normal distribution with standard deviation of 0.5. I repeat this process for all five firms and find parameter estimates corresponding to each firm that satisfy 6000 moment inequalities, respectively. The estimates are robust to multiple starting values of parameters.

## 2.5 Results

This section presents estimation results, which consist of findings from both the first-stage and the second-stage. The first-stage estimation yields static results, where variables do not exhibit dynamic evolution. These initial results serve as a benchmark for computing conditional choice probabilities and determining optimal cutoffs for each agent.

In the first-stage estimation, I conduct logit regression analysis, using a binary dependent variable to represent acquisitions and non-acquisitions. This regression includes a set of dummy variables that capture the interest-rate levels, the acquisition intensities of

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<sup>10</sup>Note that the selection of the maximum time periods is based on the number of periods in which the additional term does not contribute significantly to the summation of the expected present value of future returns. This is because  $0.95^{100} = 0.006 \approx 0$ .

the agent themselves, as well as those of their rivals. Subsequently, I calculate the specific cutoff points at which each agent decides to take action under varying values of these state variables.

In the second stage, I employ a Monte Carlo simulation based on the calculated cutoffs. This simulation generates multiple simulated paths over multiple time periods. I gather these various instances to estimate the associated parameters.

Table 3. First-Stage Logit Estimates

	<i>Dependent variable: Enter/Not Enter</i>				
	Google	Meta	Microsoft	Amazon	Apple
Constant	−4.052*** (0.119)	−4.995*** (0.200)	−4.438*** (0.137)	−4.538*** (0.161)	−4.595*** (0.165)
High int.	−0.362 (0.221)	−1.976*** (0.723)	0.983*** (0.182)	−0.616 (0.401)	−1.470*** (0.516)
Own acq. freq. (=1)	0.896*** (0.183)	1.357*** (0.280)	1.178*** (0.208)	0.637* (0.387)	0.942*** (0.280)
Own acq. freq. (> 1)	1.772*** (0.213)	1.377*** (0.397)	2.370*** (0.238)	1.631*** (0.591)	1.126*** (0.424)
Rivals acq. freq. (1 - 5)	1.556*** (0.158)	1.648*** (0.251)	1.153*** (0.175)	0.592** (0.257)	1.353*** (0.221)
Rivals acq. freq. (> 5)	2.520*** (0.392)	3.150*** (0.422)	2.249*** (0.375)	2.439*** (0.416)	2.699*** (0.411)
Observations	5,609	5,609	5,609	5,609	5,609

*Notes:* Standard errors are in parenthesis, with statistical significance denoted by \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ . Int., acq., freq. are abbreviations for interest, acquisition, and frequencies, respectively. All 79 markets are treated homogenously. The total number of observations is the multiplication of 79 markets with 71 quarterly periods (from the second quarter of 2004 to the fourth quarter of 2021).

**2.5.1 First-Stage Estimation.** Table 3 presents empirical evidence that (1) the players observe their own past actions and those of their rivals when deciding on market entry through acquisition, (2) the frequencies of past market entries have varying effects on the players' current decisions, and (3) that macroeconomic factors can influence players' market entries.

In all specifications, every estimate is found to be statistically significant at the 1% significance level, with the exception of the estimates associated with indicator variable of high-interest rates. In a scenario with low-interest rates and no prior acquisitions by any party, the constant variable is the sole factor influencing each agent's likelihood of entering the market. In the post-merger equilibrium, this constant includes elements that could deter a company from pursuing acquisitions, such as market entry costs or the expenses associated with acquiring a target. The magnitude of the constant estimate indicates that Meta faces the highest acquisition costs, while Google incurs the lowest.

When calculating the baseline predicted probabilities of entering the market, all agents exhibit relatively low probabilities, ranging from 0.6 percent to 1.7 percent. Notably Google's predicted probability of entering the market under low-interest rates, in cases where no previous entry has occurred, stands out as the highest at 1.7 percent, while Meta displays the lowest likelihood of acquiring a target at 0.6 percent. Holding all other factors constant, the projected probability of market entry decreases by approximately 0.5 percent for all agents except Microsoft when the interest rate surpasses 2.5 percent.

The observed effect of a high-interest rate on market entry, particularly in the case of Microsoft where its probability of entering the market increases, may appear counter-intuitive. This phenomenon could be attributed to one of two possibilities: 1) The threshold I have set to define the 'high-interest rate' period may not accurately capture Microsoft's acquisition behavior, or 2) Microsoft's behavior indeed diverges from the expected pattern.

If the former scenario is true, one potential solution is to adjust the threshold that distinguishes between low and high-interest rate periods. In the current model, this threshold is set at 2.5% but it is adjustable. Another approach involves modifying the calculating of the quarterly interest rate. Currently the model assumes that firms base their acquisition decisions on the *average* of the last four monthly fed funds effective rates. However, considering firms' prompt response to interest rate fluctuations, it may be more reasonable to use the *most recent* month's interest rate rather than the average. Further

research will be conducted to explore the impact of different interest rate thresholds or alternative methods of incorporating quarterly interest rates.

If the latter scenario is true, Microsoft’s behavior may be unique in that it leverages high-interest rates to target highly appreciated startups. It is important to note that while high-interest rates can potentially constrain acquirer’s liquidity and financial resources, they can also lead to reduced valuations for startups. In such case, this hypothesis becomes plausible. Further investigation will be needed to gain a deeper understanding of Microsoft’s specific acquisition strategy in response to varying interest rates. I provide comprehensive interpretations of other coefficient estimates in the subsequent subsection.

**2.5.2 Second Stage Estimation.** Table 4 presents the estimates derived from the second stage estimation. The estimates can be interpreted as the amount that each variable affects each agent’s predicted probabilities of market entry.

The variables ‘Own acquisition’ and ‘Rival acquisition’ are categorical variables representing the intensity of acquisitions, with predefined categories from 1 to 3. When no prior entries have occurred by any agents, both variables are set to 1. ‘Own acquisition’ is assigned a value of 2 when an agent has entered the market once in the past year, and it becomes 3 if an agent has entered more than once during the same period. Similarly, ‘Rivals acquisition’ is categorized as 2 when the number of targets acquired by other rivals over the past year falls within the range of 1 to 5, and it is set to 3 for any number exceeding 5. These categorizations were previously outlined in the subsection titled “Definition of States, State Transitions, and Actions” in Section 4.

The empirical results suggest a greater variations among the players in their cost of acquisition (estimates for constant). This contradicts the static analysis presented in the first-stage estimation. In a dynamic model, agents internalize costs that subsequently affect future returns and contribute to the different estimates between static and dynamic models. This phenomenon appears particularly pronounced in the cases of Amazon and Meta, where their baseline acquisition or market entry costs significantly decrease when comparing static to dynamic results.

Table 4. Second-Stage Estimates

	<i>Dependent variable: Enter/Not Enter</i>				
	Google	Meta	Microsoft	Amazon	Apple
Constant ( $\theta_1$ )	-2.479** (0.030)	-0.544** (0.100)	-3.702** (0.026)	-0.419** (0.079)	-1.075** (0.087)
High int. ( $\theta_2$ )	-0.581** (0.025)	-3.071** (0.099)	0.431** (0.024)	-2.951** (0.078)	-2.227** (0.084)
Own acq. ( $\theta_3$ ) freq. (=1)	0.407** (0.023)	0.770** (0.023)	0.529** (0.125)	0.337** (0.089)	0.523** (0.021)
Own acq. ( $\theta_4$ ) freq. (> 1)	1.301** (0.028)	1.161** (0.034)	1.641** (0.072)	1.503 (0.317)	0.961** (0.037)
Rivals acq. ( $\theta_5$ ) freq. (1 - 5)	0.901** (0.014)	0.996** (0.012)	0.622** (0.030)	0.197** (0.031)	0.711** (0.011)
Rivals acq. ( $\theta_6$ ) freq. (> 5)	1.413** (0.169)	1.928** (0.069)	1.392** (0.173)	1.234 (0.321)	1.736** (0.070)

*Notes:* Standard errors are in parenthesis, with statistical significance denoted by \*\*p<0.05. Int., acq., freq. are abbreviations for interest, acquisition, and frequencies, respectively. Standard errors are computed by (1) bootstrapping  $B = 25$  subsamples of size  $NI/2$  from the simulated data, where  $NI$  represents the number of inequalities, (2) find parameter estimates for each subsample that minimizes squared violations, and (3) calculate the standard deviations of  $B$  number of parameter estimates. A total of 200 simulations are conducted, searching over a set of parameters that are minimizing the violations of the optimality conditions from 6000 inequalities. The alternative cutoffs are drawn from normal distribution of mean 0 and standard deviation 0.5. These estimates are point-identified and robust to the initial parameter guesses.

The coefficient associated with the constant term are the baseline probabilities for each agent in market entry during a low-interest rate period with no prior entries made by any of the firms. When ranking the firms by their highest baseline predicted probabilities to the lowest, Amazon boasts the highest predicted baseline probability with 39.7%, closely followed by Meta with a 3%p lower probability of 36.7%. Apple, Google, and Microsoft trail behind these two firms with their baseline predicted probabilities of market entry being 25.4%, 7.7%, and 2.4%.

**Macroeconomic factor** In a high-interest rate environment, the baseline predicted probabilities for these five firms become quite similar. The impact of the elevated interest rates on acquisition probabilities is particularly strong for the three firms that initially exhibited high acquisition probabilities in a low-interest rate environment – Meta, Amazon, and Apple – driving down their baseline predicted probabilities significantly.

For instance, Amazon, which initially had approximately 39.7% predicted probability of venturing into uncharted market territories under low interest rates, adopts a more cautious approach in a high-interest rate environment, with its acquisition probability plummeting to just 3.3%. A similar pattern emerges for Meta, where high-interest rate state leads to a 34.1%p drop in its predicted probability of entering new markets, reducing it to 2.6%. Apple’s acquisition probability also drops, albeit to a lesser extent, from 25.4% to 3.6%.

One plausible explanation for this pattern in Amazon’s acquisition strategy may be related to its financing structure. A notably high debt-to-equity ratio compared to other firms suggests the likelihood of Amazon relying heavily on debt for financing its acquisitions. Consequently, the company may experience significant financial pressure in a high-interest rate environment, which, in turn, hampers its acquisition activities.

Furthermore, Meta’s high responsiveness to interest rate can be partly attributed to its relatively young age compared to the other firms. In terms of the company life cycle, Meta finds itself in a relatively early stage compared to other members of the group. This positioning may render Meta financially constrained in a high-interest rate environment, restricting its acquisition activities to a greater extent in comparison to other group members.

Table 5. Baseline Predicted Probabilities and Odds Ratio

	<i>Dependent variable: Enter/Not Enter</i>				
	Google	Meta	Microsoft	Amazon	Apple
<i>Baseline Predicted Probabilities of Buying</i>					
Low Interest Rate	7.731%	36.733%	2.409%	39.681%	25.446%
High Interest Rate	4.480%	2.620%	3.660%	3.320%	3.550%
<i>Baseline Odds Ratio</i>					
Low Interest Rate	0.084	0.581	0.025	0.658	0.341
High Interest Rate	0.047	0.027	0.038	0.034	0.037

*Notes:* Odds ratio of one implies an equal split between the probability of buying and not- buying. Odds ratio of less than one implies a greater probability in not-buying while greater than one implies higher probability in buying. The ratio of the predicted baseline probabilities of buying and that of not-buying equals the baseline odds ratio. As the probabilities of not-buying is greater than buying, the baseline odds ratio is substantially less than 1.

On the contrary, Microsoft exhibits a different pattern of changes in acquisition probabilities in response to elevated interest rate. In fact, in high-interest rate environment, its acquisition probability increased by 1.3% for entering new markets that no firms have entered. This may suggest that Microsoft has a propensity to acquire relatively appreciated startups that are likely to experience depreciation during a high-interest rate period. Microsoft may leverage this opportunity to purchase startups that were previously financially out of reach during low-interest rate periods. This interpretation is partly supported by the highly negative constant estimates associated with Microsoft, indicating a substantial market entry cost for the company.

**Competitive Motives** Previously, I introduced the concept of competitive motive, which serves as a representation of competitive aspects of factors affecting firms’ decisions regarding market entry. These factors may include competitive pressure to acquire a company just to keep up with their rivals, firm’s desire to join the preemption group, or

Table 6. Odds Ratio Multiplier

	Google	Meta	Microsoft	Amazon	Apple
Constant ( $e^{\theta_1}$ )	0.084	0.581	0.025	0.658	0.341
High int. ( $e^{\theta_2}$ )	0.559	0.046	1.539	0.052	0.108
Own acq. (= 1) ( $e^{\theta_3}$ )	1.502	2.160	1.697	1.401	1.687
Own acq. (> 1) ( $e^{\theta_4}$ )	3.675	3.194	5.160	4.495	2.614
Rivals acq. (1 – 5) ( $e^{\theta_5}$ )	2.462	2.708	1.862	1.217	2.036
Rivals acq. (> 5) ( $e^{\theta_6}$ )	4.108	6.878	4.022	3.434	5.677

*Notes:* Each estimate represent the corresponding odds ratio multiplier that is multiplied to the baseline odds ratio to get the odds ratio at the given state. The multiplier of 1 will not change the odds ratio from the baseline odds ratio, greater than 1 will make the buying more likely than not-buying compared to the baseline scenario, and less than 1 will make the not-buying more likely compared to the baseline scenario. It is worth noting that  $\frac{p(a=1|s)}{1-p(a=1|s)} = e^{\theta_s}$ , where  $s$  represents a vector of states,  $\theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6)$  represents a vector of parameters, and  $a$  represents acquisition decision. The baseline scenario is in low-interest rate environment, and no firms has entered the market over the last four quarters.

a firm buying companies to mitigate the risk of targets becoming unavailable or preempt targets that could potentially benefit their competitors. However these different factors that I term them collectively as “competitive motive” is often challenging to directly observe and can only be assessed indirectly through revealed actions.

As such, to measure it, I evaluate how each agent responds to changes in the total number of acquisitions collectively made by its competitors. When a firm observes a significant number of targets being acquired collectively by its rivals, it can trigger competitive motives for the two prominent reasons: 1) These targets are likely to be in high demand, which leads to making swift acquisition to be a crucial process to join the preemption group and avoid a potential competitive disadvantage as others secure these assets (keeping up with their rivals), and 2) these targets might offer significant strategic advantages to the rivals, justifying acquisition to prevent the rivals from gaining a competitive edge through these transactions.

The second stage estimation findings present empirical evidence about the degree to which firms respond to their competitors. The estimation results indicate that these

competitive motives by themselves can substantially increase the projected likelihood of acquisition. Across all firms, it appears that competitors' past acquisition records contribute significant share in determining their acquisition activities ( $\theta_5, \theta_6$ ). In particular, as the number of past acquisitions by the competitors increases, all firms become more active in engaging in acquisitions ( $\theta_5 < \theta_6$ ).

This trend, where firms become more active in acquisitions as more targets are acquired by their rivals, suggests empirical evidence of the presence of competitive motives. This can imply that when only a few targets have been acquired in a given sector in the previous year, a potential acquirer may not be overly concerned. However, when more than five targets have been acquired by its rivals, it sends a strong signal that the market is in high demand, prompting the firm to make acquisitions in order to remain competitive.

Google and Meta stand out as among the most responsive members in the group, responding more strongly to the initial actions of their competitors. In other words, even when rivals have acquired only a few targets, these firms seem to be heavily affected by it compared to other group members. Meta in particular appears to have the highest competitive motives which makes it the most responsive member of the group with regard to the actions of its rivals. This can be readily understood considering its relatively early stage in the company life cycle, relative to other group members, where it seeks aggressive acquisition strategies to grow and solidify its market presence.

Microsoft appears to be entering markets and acquiring a greater number of targets in sectors where others are seeking fewer acquisitions. In low-interest rate environment, Microsoft's predicted probabilities amounts to merely 9% for entering markets it has not entered but its rivals have entered more than 5 times during the past one year, a significantly lower probabilities considering Meta and Amazon's probabilities are higher than 65% under the same situation. This suggests that Microsoft is pursuing a distinct acquisition strategy compared to other members of the group. In other words its acquisition strategies are more focused on internal motives rather than defensive ones. Notably, Microsoft's focus on Network Management Software, where it pursues the highest number of acquisitions,

and its acquisition of 31 targets in the Business/Productivity software sector (compared to others who acquired at most a third of that number) exemplify this divergence.

**Scale Economies** Across all agents except for Microsoft, the effect of scale economies on acquisitions appears to be relatively modest when compared to that of competitive motives ( $(\theta_3, \theta_4) < (\theta_5, \theta_6)$ ). The acquisition probabilities for all other firms rise in tandem with their own acquisition histories. This signals the presence of scale economies, as a greater number of past acquisitions appears to increase the probability of acquisitions across all firms. In a low-interest rate environment, when these firms individually have previous acquisition record of buying more than one targets over the past year, Meta's likelihood of market entry reaches to 65.0 percent, Microsoft's climbs to 11.3 percent, and Apple's to 47.1 percent, assuming that no other firms have entered the market in that year.

In summary, the results provide suggestive evidence regarding the focus of the five firms' acquisition strategies. For example, Meta stands out as the most proactive player in the acquisition landscape, displaying high responsiveness to both its internal motives and the actions of others. Amazon appears to be highly affected by interest-rate fluctuations as this may have a significant implication in financing acquisitions. Google seems to be the most resilient in response to macroeconomic shocks and consistently maintains modest acquisition strategies relative to others during such shocks. Microsoft appears to place a greater emphasis on growth through the accumulation of targets that can create scale economies. Lastly, Apple appears to be responsive to high competitive pressure. However, the results reveal a common pattern across all firms: their acquisition probabilities tend to increase with a higher number of previous acquisitions. This suggests that competitive motives and scale economies become more influential as the number of past acquisitions grows.

**2.5.3 Robustness of the Estimates.** Contrary to a standard regression model, calibration is prone to the initial guesses set forth by the econometricians. This holds true when it is challenging to ascertain the form and the shape of a multi-dimensional function,

and when the presence of numerous local minima is a possibility. In order to test whether the reported estimates are robust to the initial guesses, I test this by randomly drawing 5 - 10 different starting parameter values from uniform distribution of  $[-10, 10]$ . The reported estimates are all robust from different starting values. I used LBFGS as an optimization method.

Note that the robustness of parameter estimates to initial parameter values depends on the randomness introduced through cutoff perturbations, along with the magnitude of these perturbations. For example, if the perturbations are such that the agent maintains its action even when the cutoff is perturbed, the differences in the basis functions between optimal and alternative policy are marginal. This likely results in the matrix composed of the differences in the basis functions less than full rank, i.e., not enough information present to identify the parameters. In such cases, there exists multiple solutions, leading to the parameters to be not point-identified. To avoid such scenarios, I introduce enough perturbations (6000 moment inequalities formulated from the differences in the expected future payoffs from optimal cutoffs and the expected future payoffs under alternative cutoffs) to encourage agents to take alternative actions. This, in turn, enables me to formulate sufficient number of moment inequalities such that all the parameters are point-identified.

## **2.6 Conclusion**

This study examined the acquisition behaviors of major players in the tech industry, specifically the GAMMA firms. Different sources that serve as behavioral motives for acquiring a target were identified. The estimation results provide useful insights into each firm's strategies and their sensitivity to their rivals' past actions. The study revealed that the interdependence of each firm's actions is greater than their internal motives for some firms. This suggests that we may see a wider range of markets dominated by GAMMA firms and greater market concentration across these markets.

Different responsiveness to incentives among firms can stem from their unique characteristics and strategic objectives. Variations in firm size, core business focus, and

financing structures of acquisitions can all influence their strategic responses and their degree of reaction to rivals' acquisition moves. However, overall, these firms tend to become more active and strategically responsive when other tech giants become aggressive in acquisitions. This suggests that we may observe intensified acquisition competition, almost exhibiting crowding effects among the tech giants, where many firms become pursuing similar strategies, which would likely lead to a highly competitive yet saturated market environment.

The resulting increase in market concentration can have various welfare implications. For example, as the GAMMA firms compete across broader markets, it is possible that market efficiency improves in multiple sectors. On the other hand, it could also shift the market structure from a competitive market to market structure that is closer to an oligopoly in a wider range of markets, which may lead to controversial impacts on innovation levels. Some argues that it boosts innovation as more startups are likely to enter the market for buyout (Cabral, 2021; Rasmusen, 1988) while others (Cunningham et al., 2021; Kamepalli, Rajan, & Zingales, 2020; Katz, 2021) argue that it hinders innovation. Some conclude the innovation effect from prohibiting acquisitions is weakly negative that depends on market characteristics (Letina, Schmutzler, & Seibel, 2021).

Further extension of study can involve including more behavioral factors that trigger acquisitions, i.e., a state dimension of internal motives for market expansions. This will further help to distinguish the conflicting internal drives for acquisition, scope economies versus scale economies – with constrained financial resources, a firm should choose between spreading versus strengthening. Furthermore, it may be worthwhile to explore the appropriate selections of feasible alternative policies to test the robustness of the estimates.<sup>11</sup> Bajari et al. (2007) note the importance of having large support of inequalities that contains sufficient information to yield identification. They also highlight the approach proposed by Holmes (2011) as a viable solution to mitigate this concern. In this approach, minimal

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<sup>11</sup>For example, the degree and the design of randomness of the perturbed policies introduced by the econometricians tend to determine robustness of parameter estimates. Partially perturbed policies that do not yield agents to take an alternative action can result in deviations from the identification assumptions required for the estimator, potentially leading to parameters to be *set identified*.

or no weight is assigned to perturbed policies that carry little additional information. The parameter estimates in this study, obtained by creating perturbation policies that randomly deviates from the optimal policies, are robust across 100 randomly generated initial guesses. Additionally, their robustness can be further evaluated by using the approach outlined by Holmes (2011).

CHAPTER III  
THE SHORT-RUN EFFECTS OF OPENING MOBILE IN-APP PAYMENT SYSTEMS:  
EVIDENCE FROM SOUTH KOREA

This chapter was co-authored with Keaton Miller. Jointly, we conceptualized and developed the motivational framework, which provides the theoretical background for the analysis. I conducted the empirical investigation and data analysis, while we both contributed to the writing and revising the manuscript.

### **3.1 Introduction**

Many digital platform markets are highly concentrated, dominated by a few players who have built a large share through network externalities (Rochet & Tirole, 2003). These players often employ ‘tying’ strategies to extend their dominance in one market to other markets (Carlton & Waldman, 2002). By foreclosing rivals, tying can lead to the monopolization of the market for the tied good (Whinston, 1990). For example, Microsoft once tied its Internet Explorer browser with its Windows operating system to hamper the growth of competing browsers. The lack of competition from the exclusionary conduct associated with tying raises several anti-competitive concerns. The price of tied products is likely to be above the competitive equilibrium price and the level of product variety is likely to fall, both of which contribute to a decrease in consumer welfare (Whinston, 1990). It can also negatively affect the level of innovation in the tied good market as potential entrants choose not to invest, which in turn further strengthens an incumbent’s dominant market position (Choi & Stefanadis, 2001).

Our study focuses on the market for mobile apps, which features substantial tying. Google and Apple, the leading firms in the market for mobile operating systems, each operate a distribution platform (Google Play Store and Apple App Store) that has near-monopoly power over the sale and distribution of apps to the relevant end-users. These firms have used the power implicit in their access to a large base of mobile users to dictate contract terms to app developers. Among these terms is a requirement to exclusively use the

platform's payment system to process in-app purchases. On both platforms, 30% of every purchase is remitted to the platform owner as a commission.

These contracts have been subject to public and legislative scrutiny in many countries in recent years as developers of large and popular apps have complained that the current system is unfair and limits development effort (see, e.g. Allyn, 2021). The most successful effort, from the perspective of app developers, is a 2021 South Korea law that banned app store operators from enforcing exclusivity requirements for in-app payment processing.

We study the effects of the law and subsequent responses from platform owners on app distribution. The law came into effect on September 14, 2021. On December 18, 2021, Google responded to the law by adjusting its platform policies for apps that serve users in South Korea. Developers of Play-distributed apps may offer such users an in-app billing system that differs from Play's built-in billing system if they complete required forms and agree on additional terms. Apple has not changed its policy until June 30, 2022 (about six months after Google has changed its policy).<sup>12</sup> Our prior is based on the claims of app developers: as the commission payment acts as a tax, developers no longer subjected to the tax (or subjected to a lower tax) may be able to improve the quality of their apps, thus increasing the number of users with the apps installed and increasing the income of developers from in-app purchases. In fact, app developers have incentives to diverge away from their existing use of the platform's proprietary in-app payment processing if enough government protection is insured and significant other developers are shifting away from it (Hwang & Kim, 2022).

We test these hypotheses using app-level panel data on installs and revenue from Appfigures, a market research firm. We define Apple App Store-distributed apps on mobile devices located in South Korea as the treated group and the date of Apple's policy change as the date of treatment. We compare outcomes for apps in this group against outcomes in two sets of potential control groups. First, we consider Apple App Store-distributed apps

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<sup>1</sup><https://developer.apple.com/support/storekit-external-entitlement-kr>

<sup>2</sup>Alike Google, Apple still charges a 26% commission rate to app developers using a third payment option for in-app transactions

in countries with closed billing systems (i.e. those that are not South Korea). Second, we consider Apple App Store-distributed apps in South Korea during the pre-treatment period.

We test for changes in app-level outcomes using difference-in-differences and triple difference-in-differences techniques. While our point estimates suggest that installs decreased and revenues increased post-reform, the effects on app downloads are imprecisely estimated. We therefore interpret findings on app installs as a null result. In other words, we estimate that the law had an effect on app revenue but did not have an identifiable effect on app downloads after the law was implemented.

Our work contributes to the broader literature exploring the theoretical and empirical implications of tying strategies. Within this literature, most of the work has focused on examining the effects of tying (Amelio & Jullien, 2012; Carlton & Waldman, 2002; Choi & Jeon, 2021a; Derdenger, 2014). In contrast, studies that analyze the effects of attempted remedies and/or regulations that seek to unbundle once-tied products are relatively scarce.

The structure of this paper is as follows: Section 2 provides a brief background on the app market and existing platform policies on in-app billing systems. Section 3 illustrates data and descriptive evidence; Section 4 introduces identification strategy to estimate the changes in the outcome variables of interest and provide implications about the empirical results. Finally, Section 5 concludes with some remarks of improvements and a discussion of possible future research.

## **3.2 Background**

**3.2.1 App Stores.** App stores are digital platforms for selling and distributing mobile applications (apps). Developers publish their apps on these platforms while consumers use the platforms to discover, purchase, and access apps. Developers earn revenue through three methods. First, developers may charge an up-front price to download the app. Second, developers may embed advertisements into the app. Third, developers may lock certain features behind in-app purchases. These methods may be combined. For example, a strategy game app may be offered to download for free, but come with advertisements

displayed between each round or before each turn. Users may pay a fee to remove such advertisements. The app may offer additional features in exchange for fees such as in-game performance bonuses (e.g. increases to the rate at which the user progresses through the game) or changes to the appearance of game features (e.g. ‘cosmetic’ changes to the characters in the game that do not affect game outcomes).

App stores offer users (among other features) limited security guarantees, a centralized record of purchases, and convenient re-installation of apps on new devices (e.g. a user changing mobile devices which both use the Google Play Store may reinstall their applications with minimal intervention). These platforms offer developers exclusive access to large user bases (i.e. developers who wish to offer their apps to Android users must do so through the Google Play Store) and baseline functionality related to online communication, payment systems, and cloud-based storage (of e.g. saved documents or play sessions). App stores generate revenue primarily by charging a commission on both purchases of apps with up-front prices and in-app purchases.<sup>3</sup> Historically, the ‘tax rate’ charged by both Google and Apple has been set at 30%. In other words, when a user spent \$10 on either an up-front or in-app purchase, the developer received \$7 and the platform received \$3. In early 2021, both Apple and Google reduced the tax rate to 15% for the first \$1 million of revenue earned by a developer each year.

Other app stores exist. For example, three major South Korean telecommunications companies maintain the ONE store platform which is installed on all mobile devices sold in South Korea that are serviced by the relevant wireless networks. ONE store offers developers a lower commission rate of 20% when using the ONE store payment platform and a 5% service fee when using other platforms.

**3.2.2 The South Korean Law and Responses.** Responding to antitrust concerns, the South Korean National Assembly banned the operators of app store platforms from imposing payment methods on app developers starting September 14, 2021. This policy

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<sup>3</sup>Google also offers a monthly subscription service that includes access to a rotating library of paid apps.

change made South Korea the first country to compel the opening of in-app billing systems by law.

The law required platform operators to submit detailed plans about how they would change their policies to comply. Google implemented changes in December 2021 that allowed developers to offer users in South Korea an alternative in-app billing system. To do so, developers must certify compliance with industry standards for security and fraud prevention, report all transactions from users in South Korea on a monthly basis, and pay a per-transaction service charge equal to the non-South-Korea market rate minus 4%. In other words, while developers may offer users an alternative payment system, most payments are still taxed at 26%. While Apple has indicated an intent to cooperate with the law, it was not until June 2022 that it has announced changes to its Terms of Service to comply and allowed developers to use third-party payment systems. As like Google, Apple App Store offers a rate of 26% per-transaction service charge for developers using an alternative billing system.

Regulators in other countries are considering similar actions. The Netherlands' antitrust authority has ordered Apple to allow alternative payment methods for dating apps. In the United States, the Open App Markets Act is a bipartisan effort to untie payments and implement additional restrictions on app platform providers; the legislation was drafted in part in response to a lawsuit from a prominent app developer challenging Apple's in-app payment restrictions.

### **3.3 Data and Descriptive Evidence**

To study the short-run effect of South Korea's legislation, and the corresponding policy responses of Google and Apple, we obtain panel data on app downloads and revenues from Appfigures. Appfigures is a firm that provides developers tracking and analytics services. Specifically, we obtain Appfigures' 'Public API' dataset of app installations and revenue for 369 apps on Apple App Store offered in five countries at the monthly level from January 2018 to December 2023. We define the pre-reform period as January 2018 to September

2021 and the post-reform period from December 2021 to December 2023. It is important to note up front that these data consist of Appfigures' estimates of the relevant metrics. Appfigures forms these estimates by training prediction models on private data reported by developers who opt-in to its data collection program.<sup>4</sup> We proceed under the assumption that the Appfigures data are noisy measures of the true install and revenue data that have neutral bias relative to the reform. By 'neutral bias' we mean that to the extent that the Appfigures estimates are biased measures of the true data, that bias is not affected by the reform. Thus, comparisons of app performance pre- and post-reform can identify at least the direction of any effects, if not the magnitudes.

The apps we consider are the cross-platform apps that are free to download, monetize solely through in-app purchases, and generated a yearly average revenue no less than \$1000 in South Korean market. These apps were selected as they are most likely to be impacted by the legislation, given their primary revenue source derives from in-app billing and their sufficient revenue exposure in the South Korean market. Any effects of the policy change of Apple App Store in response to the legislation should manifest within this sample of apps that rely heavily on in-app purchase models and have a substantial presence in the regulated country.

We specifically analyze these apps' performance on the Apple App Store for two reasons. First, Apple's in-app purchase policies and commission rate policies have remained stable over the period examined, unlike Google Play. This allows for a cleaner comparison of app performance pre- and post-treatment. Second, this analysis controls for substitution effects across app stores, as iOS users are inherently locked into the Apple App Store with no alternative store options on this operating system. This is less true for apps on Google Play, where developers have flexibility to distribute their apps through third-party app stores that offers different in-app purchase policies. Therefore, the estimated effects of legislation

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<sup>4</sup>In other words, Appfigures observes publicly-available data from Google and Apple for all apps, and private data from developers that opt-in. Appfigures trains prediction models on the set of apps for which private data are available, and produces estimates of the private data for all apps. It is these estimates that we use as the outcome measures in our analysis.

Table 7. Distribution of Developers Based on the Number of Apps Published

Apps Published	Developers
1	289
2	24
3	4
5	1
6	1
9	1
Total	320

*Notes:* In the sample of 369 Apple App Store-distributed apps, the table shows the distribution of developers (publishers) based on the number of apps they have distributed. A total of 320 unique publishers are present, with 31 publishers having more than one app in the sample.

on app performance within the Apple App Store ecosystem can serve as an upper bound, as substitution effects are limited.

We examine the performance of these apps in South Korea, United States, and additionally in Japan, Germany, and France. We chose these countries as their per-capital spending on mobile apps is similar to that in South Korea. According to Statistica, through the first three quarters of 2021, Japan had the highest mobile spending per capital with \$149 US. South Korea was the second with \$95 US, followed by the United States with \$90 US. Germany and France were 7th and 8th, respectively.<sup>5</sup> Although similar legal movements were put forth by developers against the two major app distribution platforms across several countries during the sample period, we observe no significant changes to the commission rate structure imposed by the Apple App Store until the end of 2023. This allows us to use the app performance data from these unaffected countries as a reliable control group for our analysis.<sup>6</sup>

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<sup>5</sup>See Statistica.com (2021).

<sup>6</sup>Note that Apple updated its App Store policies in January 2024 to comply with the 2021 Supreme Court ruling in the Epic Games vs. Apple case. This update allows developers to integrate external payment systems alongside Apple’s billing system while also reducing the commission rate by 3%. (See Apple.com (n.d.-b) for more details.) Apple faced similar pressure by the Japanese Fair Trade Commission, leading it to allow reader app developers to incorporate external payment links. Furthermore, in March 2024, Apple updated its policies to comply with the European Commission’s Digital Markets Act, as detailed in their official communications. (See more Apple.com (n.d.-c) and Apple.com (n.d.-a) for more details.

Table 7 shows the total number of developers in the sample. Among the apps we study, for the majority of cases, each developer has a single app included. However, there are 31 developers who have multiple apps present within the sample. This information regarding the developer-app mapping is important, as it informs whether we should expect behavioral changes in response to the policy at the developer or app level. In cases where developers operate multiple apps, accounting for developer fixed effects rather than app fixed effects may be more appropriate for our empirical analysis. However, as evident from the table, approximately 80% of the sample exhibits a one-on-one mapping between developers and apps. For this dominant subset, accounting for developer-level effects can be reasonably excluded, as each app effectively represents the behavior of a distinct developer entity.

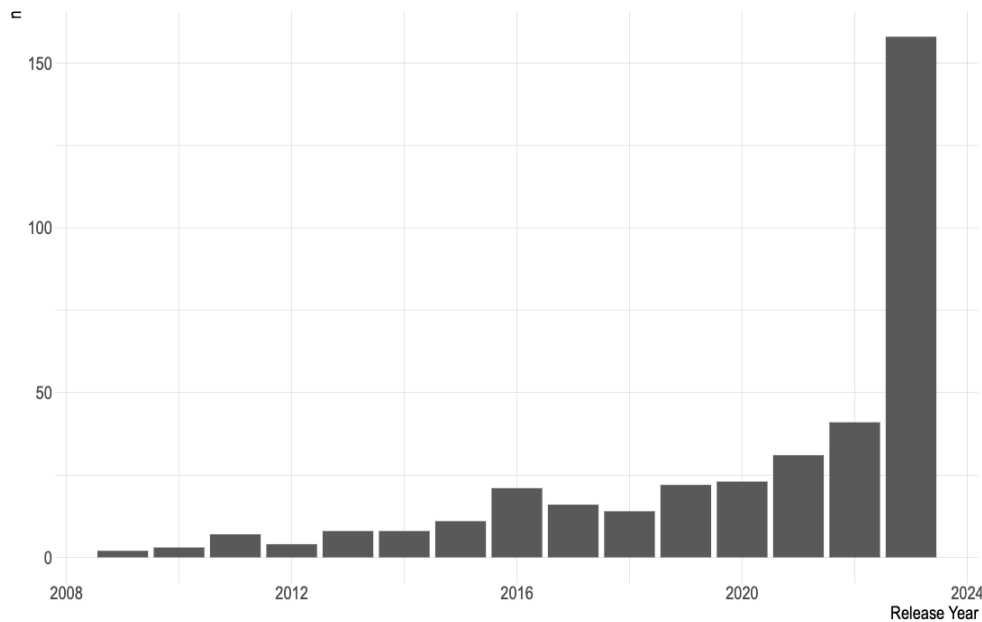
Figure 6 and Figure 7 illustrate the distribution of app release years and primary app categories represented in the sample, respectively. Approximately 43% of the apps were released in 2023. Among the apps in the sample, the top categories were Games (Role Playing, Simulation, Strategy, Action, and Casual subcategories), followed by Entertainment and Social Networking apps.

Table 8. Other Storefronts the Sample Apps Are Available

Other Storefronts (Cross Platform)	N
Google Play	341
Amazon Appstore, Google Play	20
Amazon Appstore, Apple Mac, Google Play	2
Amazon Appstore, Google Play, Windows10	2
Apple Mac, Google Play	2
Amazon Appstore	1
Windows10	1
Total	369

*Notes:* All apps in the sample are cross-platform, using other storefronts apart from the Apple App Store to reach Android users. Besides Apple App Store, of the 369 apps, 341 are only available on Google Play, 24 are available on multiple Android app stores including Google Play, and 2 are available on Google Play and Apple Mac App Store. Only two apps in the sample are available on either Amazon App Store or Windows10 for Android or PC users.

**Figure 6. App Release Year**



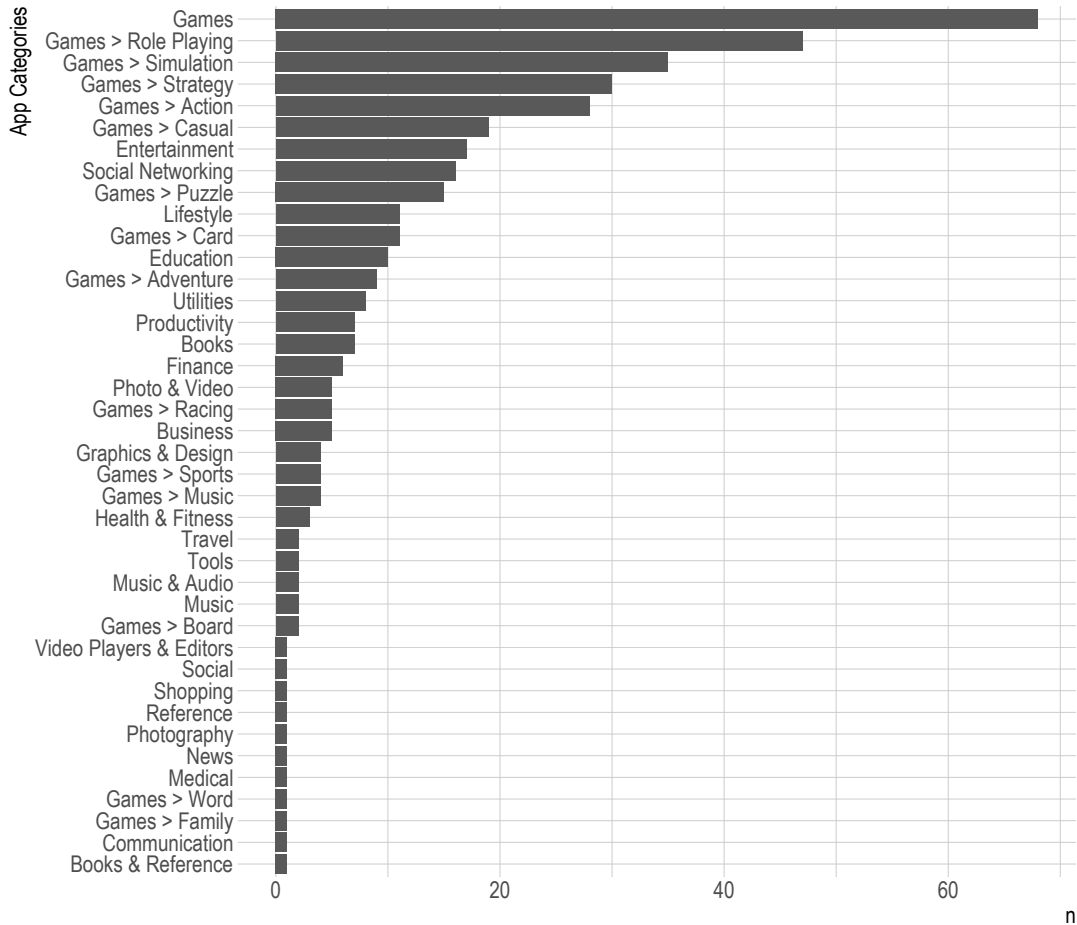
*Notes:* This figure illustrates the number of apps released each year in the sample. Over 150 apps were released in 2023, followed by more than 25 apps each released in 2021 and 2022.

Table 8 displays other storefronts, apart from the Apple App Store, that the apps in the sample are distributed. Approximately 92% of the apps in the sample are distributed exclusively on Apple App Store and Google Play Store, with no presence on other platforms. The remaining apps are listed across multiple storefronts, including Google Play, Amazon AppStore or Windows10. However, only 2 out of 369 sample apps rely on the Windows 10 and Amazon Appstore as their sole distribution channels for Android users. Given our analysis focuses specifically on the legislation’s impact on the Google Play and Apple App Store platforms, we exclude the two apps within the sample.

### **3.4 Identification and Estimation**

**3.4.1 Motivational Framework.** To motivate our empirical work, we consider a model in which a developer seeks to maximize the profit they earn from an app. In the

Figure 7. App Categories



Notes: This figure illustrates the categorization of the apps in the sample. The top six categories in the sample are General Games, Role Playing Games, Simulation Games, Strategy Games, Action Games, and Casual Games. Entertainment and Social Networking are the next most frequent categories in which the apps are classified.

model, the price of an in-app item determines the volume of in-app transactions, and a consumer’s decision to install the app depends on the app’s quality and in-app prices.

Let  $p$  be price of an in-app item and  $w$  be app quality. Let  $q(p)$  be the quantity of in-app purchases per consumer as a function of the in-app price and  $d(p, w)$  be the number of app installs, assumed to be decreasing in  $p$  and increasing in  $w$ . Let  $c(w)$  be the cost of developing the app, assumed to be increasing and convex in  $w$ . Finally, let  $\tau$  be the

commission (or tax) rate assessed on in-app purchases, assumed to be exogenous from the perspective of the developer. The developer chooses a price and quality that solves

$$\max_{p,w} \pi(p, w) = pq(p)d(p, w)(1 - \tau) - c(w). \quad (3.1)$$

Suppose that  $\pi(p, w)$  is globally concave and there is an interior global maximum. The first order conditions for maximization are

$$\{w^*\} : \frac{\partial \pi}{\partial w} = 0 \leftrightarrow pq(p)(1 - \tau) \frac{\partial d(p, w)}{\partial w} = \frac{\partial c(w)}{\partial w} \quad (3.2)$$

$$\begin{aligned} \{p^*\} : \frac{\partial \pi}{\partial p} = 0 \leftrightarrow \\ (1 - \tau)(q(p)d(p, w) + p \frac{\partial q(p)}{\partial p} d(p, w) + pq(p) \frac{\partial d(p, w)}{\partial p}) = 0 \end{aligned} \quad (3.3)$$

By combining these expressions and rearranging terms, we can write an expression for the optimal price,

$$p^* = \frac{-q(p)d(p, w)}{\frac{\partial q(p)}{\partial p} d(p, w) + \frac{\partial d(p, w)}{\partial p} q(p)} = - \frac{\frac{\partial c(w)}{\partial w} \frac{\partial d(p, w)}{\partial p}}{d(p, w)(1 - \tau) \frac{\partial q(p)}{\partial p} \frac{\partial d(p, w)}{\partial w}} - \frac{q(p)}{\frac{\partial q(p)}{\partial p}}$$

Suppose that the cost function is convex in app quality, i.e.,  $c(w) = w^2$ . From (3.2), we can write an expression for the optimal quality,

$$w^* = \frac{1}{2} pq(p)(1 - \tau) \frac{\partial d(p, w)}{\partial w}.$$

It can be shown that  $\frac{\partial p^*}{\partial \tau}$  is calculated to be positive, meaning that as the commission rate drops, the in-app price decreases.<sup>7</sup>

It can be also be shown that  $\frac{\partial w}{\partial \tau}$  to be negative, assuming that app quality improvement attracts higher number of app downloads. Intuitively, in the absence of a quality characteristic to the product, changes in the commission rate would simply be passed through to consumers. However, the quality dimension acts as a additional wedge on which the commission rate acts: when the firm faces a commission rate, it does not receive payment for the ‘full’ quality of the app it has produced and therefore it reduces the quality of app while also acting to decrease the price to some extent. If this factor dominates the pass through effect, this results in increasing the price.

We then examine how profit, the number of app downloads, and app quality respond with respect to change in commission rate  $(\frac{\partial \pi}{\partial \tau}, \frac{\partial d(p,w)}{\partial \tau}, \frac{\partial w}{\partial \tau})$ .

**3.4.2 Stylized Model.** In this section, we introduce a stylized model that presents the effects of reduced commissions on in-app prices, app quality, app installations, and in-app sales volume. Our model is a two-stage nested logit model. It simulates users deciding to make in-app purchases based on their decision to install an app. In this model, once users decide to install an app, firms choose in-app price and app quality to maximize their profits. In the first-stage, users consider the probability of making in-app purchases at a given in-app price. Then in the second-stage, users decide whether to install an app based on its quality and in-app prices. Developers then select the optimal in-app prices and app quality to maximize their profits. We examine three different scenarios: (1) users prefer app quality over in-app prices, (2) users prefer in-app prices over app quality, and (3) users equally value in-app prices and app quality.

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<sup>7</sup>To see this, simplify the notation and write  $c(w) = c$ ,  $q(p) = q$ , and  $d(p, q) = d$ . Let  $B \equiv \frac{\frac{\partial c}{\partial w} \frac{\partial d}}{d \frac{\partial q}{\partial p} \frac{\partial d}} > 0$ . Then

$$\frac{\partial p^*}{\partial \tau} = \frac{\partial(-\frac{B}{1-\tau})}{\partial \tau} = B(1-\tau)^2 > 0 \blacksquare$$

Suppose at the in-app level, indirect utility of a representative user  $i$  associated with choice  $j$  is given by

$$u_{ij} = \theta_p p_j + \varepsilon_{ij},$$

where  $\varepsilon_{it}$  is identically and independently distributed with the Type I Extreme Value distribution. We normalize the mean utility of the outside good to zero so that  $u_{i0} = \varepsilon_{i0}$ .

Let  $y_i$  represent the user's choice from a set of choices between not making and making in-app purchases,  $j \in \{0, 1\} = J$ . The probability of the user making in-app purchases can then be expressed as follows:

$$\Pr(y_i = 1 | \theta_p) = \frac{\exp(\theta_p p_j)}{1 + \exp(\theta_p p_j)}.$$

At the app-download stage, the user decides to download an app based on the overall value (inclusive value) derived from in-app purchases and in-app item prices.

$$\text{Inclusive Value} = \ln(1 + \exp(\theta_p p_j))$$

Let  $z_i$  represent the user's decision from a set of choices, where  $k \in \{0, 1\} = K$  denotes not installing (0) and installing (1). Then, the probability of app installs becomes

$$\Pr(z_i = 1 | \theta) = \frac{\exp(\theta_w w_k + \ln(1 + \exp(\theta_p) p_j))}{1 + \exp(\theta_w w_k + \ln(1 + \exp(\theta_p) p_j))}.$$

Suppose that the cost is a quadratic function of the quality  $w$ , then

$$c(w) = \theta_{c1} w + \theta_{c2} w^2.$$

The profit function can be rewritten as follows:

$$\pi(p, w) = \underbrace{(1 - \tau)}_{\text{after tax}} \underbrace{\Pr(d = 1|w, p, \theta)}_{\text{probability of installing an app}} \underbrace{p \Pr(q = 1|p, \theta)}_{\text{in-app revenue}} - \underbrace{c(w)}_{\text{cost}}.$$

Let parameter set denoted by

$$\Theta = [\theta_w, \theta_p, \theta_{c1}, \theta_{c2}],$$

where  $\theta_w$  represents quality coefficient on utility,  $\theta_p$  represents price coefficient on utility,  $\theta_{c1}$  represents linear quality coefficient on cost, and  $\theta_{c2}$  represents quadratic quality coefficient on cost.

**3.4.2.1 Scenario 1: Quality Sensitive Users.** In this scenario, a user places more weight on the quality of an app over the in-app prices.

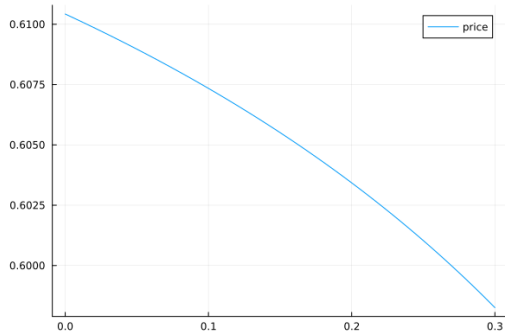
$$\begin{aligned} \Theta &= [\theta_w, \theta_p, \theta_{c1}, \theta_{c2}] \\ &= [3, -2, 0.05, 0.025] \end{aligned}$$

Figure 8 illustrates that app installs go up, app quality improves, in-app prices go up, and in-app sales go down. User's preference for high-quality apps incentivize developers to improve app quality, as commission rate goes down. This in turn affects in-app prices, since quality improvement is costly for developers which they may seek to offset these cost by increasing in-app prices. With higher in-app prices, in-app sales go down. In summary, while app quality improves and in-app prices rise, the number of app installs still increases largely because users value app quality over in-app prices. However, they may spend less on digital goods or services within an app.

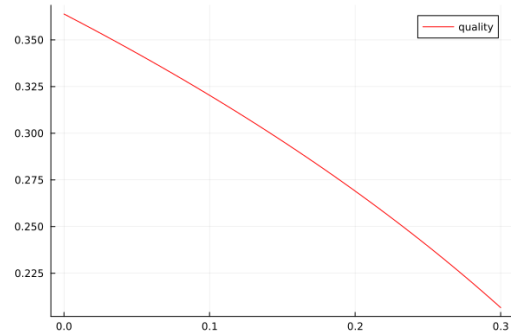
**3.4.2.2 Scenario 2: Price Sensitive Users.**

$$\begin{aligned} \Theta &= [\theta_w, \theta_p, \theta_{c1}, \theta_{c2}] \\ &= [1, -2, 0.05, 0.025] \end{aligned}$$

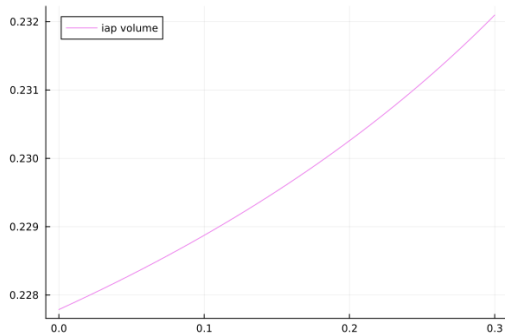
Figure 8. Scenario 1: Quality Sensitive Users



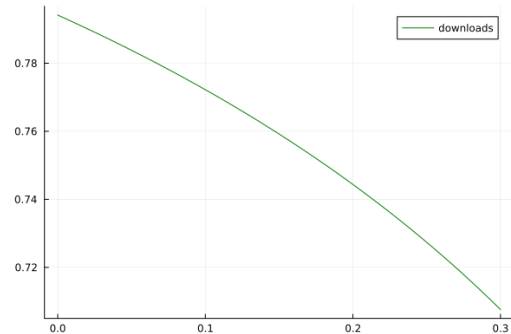
(a) Price Changes



(b) Quality Changes



(c) In-app Volume Changes

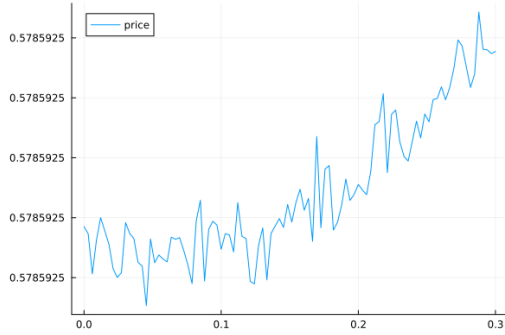


(d) Install Changes

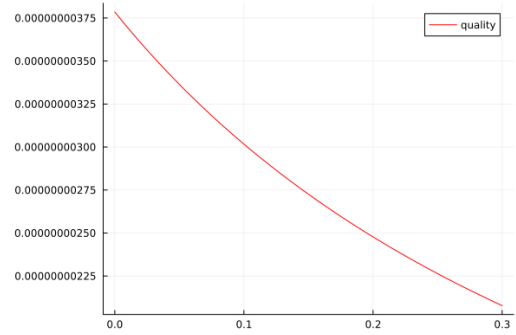
Notes: The figures illustrate the changes in key app performance metrics with respect to changes in the tax rate, under the scenario where users are more responsive to changes in app quality than to changes in in-app prices. Specifically, as the tax rate changes: figure (a) shows the changes in the profit-maximizing in-app item price, figure (b) depicts the changes in the profit-maximizing app quality, figure (c) demonstrates the changes in in-app volume, and figure (d) presents the changes in app installs.

In this scenario, a user values in-app prices more than the quality of an app. Figure 9 shows in-app prices go down, app quality goes up, app installs go up, and in-app sales go up. As users prioritize in-app prices over app quality, developers respond by lowering in-app prices. This in turn increases the in-app sales. Note that developers are striking the balance between lowering in-app prices and its impact on boosting in-app sales to choose their optimal in-app pricing strategies. In summary, as app quality improves and in-app price decrease, there is an increase in app installs. Additionally, users are likely to spend more on digital goods or services within the app in response to the reduced in-app prices.

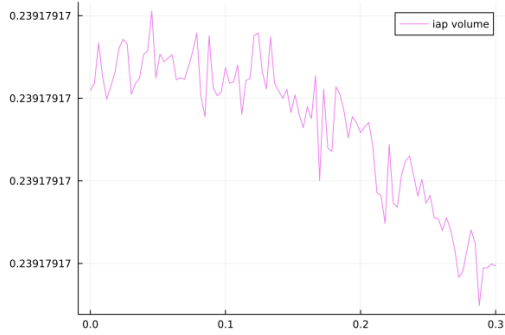
Figure 9. Scenario 2: Price Sensitive Users



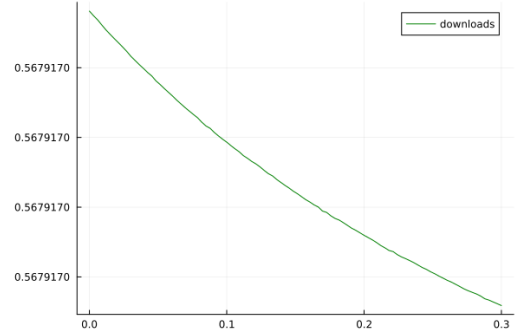
(a) Optimal Price Changes



(b) Optimal Quality Changes



(c) In-app Volume Changes



(d) Install Changes

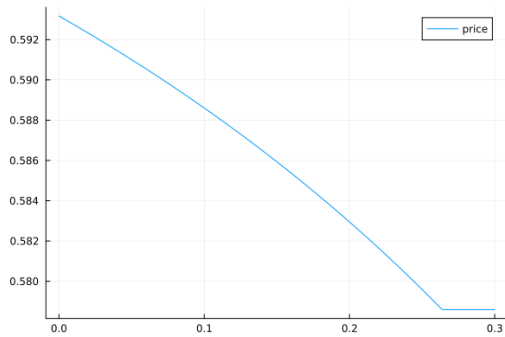
Notes: The figures illustrate the changes in key app performance metrics with respect to changes in the tax rate, under the scenario where users are more responsive to changes in in-app prices than to changes in app quality. Specifically, as the tax rate changes: figure (a) shows the changes in the profit-maximizing in-app item price, figure (b) depicts the changes in the profit-maximizing app quality, figure (c) demonstrates the changes in in-app volume, and figure (d) presents the changes in app installs.

### 3.4.2.3 Scenario 3: Equally Sensitive Users.

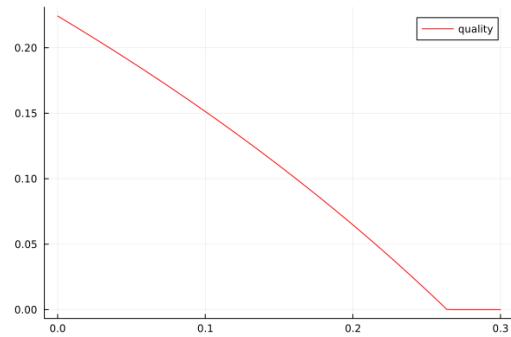
$$\begin{aligned}\Theta &= [\theta_w, \theta_p, \theta_{c1}, \theta_{c2}] \\ &= [2, -2, 0.05, 0.025]\end{aligned}$$

In this scenario, users are assumed to equally prioritize in-app pricing and app quality. Figure 10 illustrates that app installs go up, app quality improves, in-app prices rise, and in-app sales go down. Analogous to the first scenario, higher app installs accompany improvements in app quality. The observed increase in in-app prices may derive from

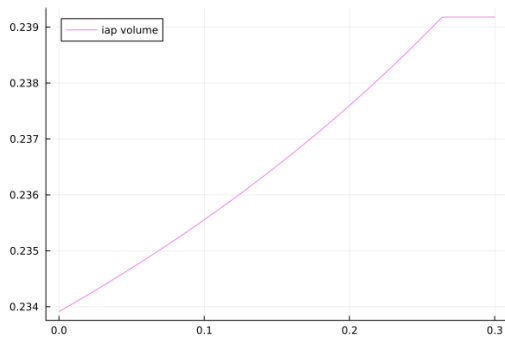
Figure 10. Scenario 3: Equally Sensitive Users



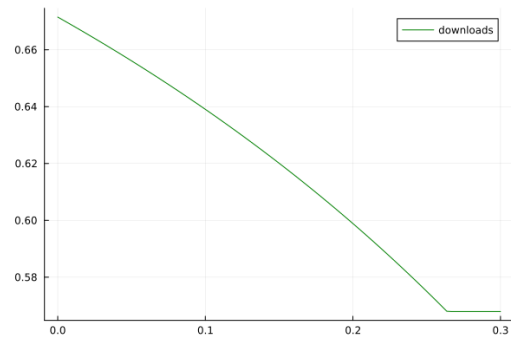
(a) Optimal Price Changes



(b) Optimal Quality Changes



(c) In-app Volume Changes



(d) Install Changes

Notes: The figures illustrate the changes in key app performance metrics with respect to changes in the tax rate, under the scenario where users are equally responsive to changes in in-app prices and to changes in app quality. Specifically, as the tax rate changes: figure (a) shows the changes in the profit-maximizing in-app item price, figure (b) depicts the changes in the profit-maximizing app quality, figure (c) demonstrates the changes in in-app volume, and figure (d) presents the changes in app installs.

developers investing in elevating app quality, with the additional costs recovered through imposing higher optimal in-app prices up to the profit maximizing level. While quality improvements can drive install growth, elevated in-app prices may conversely suppress installs. However, as former effect dominates the latter, we observe a net increase in app installs despite rising prices. Developers continue to prioritize app quality improvements for users equally responsive to quality and pricing. It is important to note that we impose a non-negative constraint on the optimal quality and in-app pricing levels, defaulting to zero when the optimal quality level reaches negative values due to this restriction.

**3.4.3 Econometric Model.** Our framework suggests that a drop in the commission rate should lead to an increase in profits (which we measure with revenues) and downloads. We estimate the effect of the policy change using a two-way fixed effects difference-in-differences (TWFE DiD) that compares the difference in outcomes for the treated group between the pre-treatment and post-treated periods to the difference in outcomes for the control group between the same periods. We estimate the parameters of

$$\log(Y_{ict}) = \beta_0 + \beta_1 D_{ict} + \alpha_i + \zeta_c + \gamma_t + u_{ict}, \quad (3.4)$$

where  $\log(Y_{ict})$  is the logged outcome variable (either app installs or app revenue) for app  $i$  distributed in country  $c$ , at time  $t$ ,  $D_{ict}$  is a treatment dummy that interacts  $\text{PostReform}_t$ , an indicator variable which is equal to 1 if  $t$  is June 2022 or later, and  $\text{Treat}_{ict}$ , an indicator variable which is equal to 1 if app  $i$  for the users in country  $c$  is in the treated group. Fixed effects for cross sectional units are represented by  $\alpha_i$ ,  $\zeta_c$ , which are app-level, country-level fixed effects, respectively.  $\gamma_t$  represents time fixed effects, and  $u_{ict}$  represents idiosyncratic app-platform-country-time disturbances.

The treatment we are interested in is the opening of in-app billing systems and the corresponding decrease in the commission rate paid by firms. This treatment applies only to apps that are distributed by Google Play and installed on mobile devices located in South Korea. This implies there are three sources of variation available in the data: (1) different treatment status across sampled countries (Korea vs. Countries other than Korea), and (2) different treatment status across different “years”<sup>8</sup> (Treated “year” vs. Control “year”).

We consider two sets of potential control groups that could serve as counterfactuals for the treated group based on these sources of variation. The first control group is App Store distributed apps in countries that have closed billing system. In other words, we compare the performance of Apple App Store apps in South Korea to the performance of the same apps in other countries.

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<sup>8</sup>We compare the six-months post treatment against the six prior months.

The second control group consists of apps on Apple App Store years and months prior to the law being implemented. The use of this control group may be particularly helpful in the presence of seasonal trends.

The parameter of interest is  $\hat{\beta}_1$ , which represents the causal effect of Apple’s changed policy on app installs and app revenue, provided that the identification assumption is satisfied. For difference-in-differences estimator to produce unbiased estimates, the parallel trend assumption must hold: the difference between the treated and the control remains constant throughout the analysis period in the absence of the treatment. Since dependent variable is logged,  $\hat{\beta}_1$  estimate can be interpreted as the percent change for treated apps during post-treatment period.  $\hat{\beta}_1$  isolates the change in app installs and app revenue that cannot be explained by what was observed as the difference between the treated and control group in the pre-treatment period. We explore the parallel trends assumption for our different control groups and conclude that the control group most likely to satisfy the assumption is the group of App Store-distributed apps downloaded in other countries.

That said, it is possible that any results stemming from that control group are driven by seasonal trends in download and in-app purchase behavior. To account for this, we explore specifications using two sets of control groups in a triple-difference-style approach. That is, we estimate the parameters of

$$\begin{aligned}
\log(Y_{ict}) = & \beta_0 + \beta_1 \text{PostYear}_t \times \text{PostMonth}_t \times \text{TreatCountry}_{ic} \\
& + \beta_2 \text{PostYear}_t \times \text{TreatCountry}_{ic} + \beta_3 \text{PostMonth}_t \times \text{TreatCountry}_{ic} \\
& + \beta_4 \text{PostYear}_t \times \text{PostMonth}_T \\
& + \alpha_i + v_{ict},
\end{aligned} \tag{3.5}$$

where  $\log(Y_{ict})$  is the logged outcome variable (either app installs or app revenue) at time (year-month)  $t$  for app  $i$  that belongs in country  $c$ ,  $\text{PostYear}_t$ , and  $\text{PostMonth}_t$  are an indicator variable which is equal to 1 if  $t$  is 2022 or later, and July or later, and  $\text{TreatCountry}_{ic}$  is an indicator variable which is equal to 1 if app  $i$ -group  $c$ -country pair is in the treated

group. For example, suppose we have observations about four apps each of which are distributed across five countries. Then  $i \in \{1, 2, 3, 4\}$ , and  $c \in \{1, 2, 3, 4, 5\}$ . If only country 1 is treated,  $\text{TreatCountry}_{ic}$  equals one for all 12 app-platform pairs and is zero otherwise. Fixed effects for cross sectional units are represented by  $\alpha_i$ , and idiosyncratic disturbances are represented by  $v_{ict}$ .

## 3.5 Results

**3.5.1 Using Apps in Countries with Closed Billing System as Control.** Our first estimates of Equation (3.4) come from focusing on Apple App Store-distributed apps and exploiting cross-country variation in treatment status. Specifically, we examine whether Apple App Store apps in Korea experienced differential app revenue and install outcomes relative to the same apps in other countries during the post-treatment period. From the event-study analyses testing the parallel trend assumption during pre-treatment period, we noticed significant revenue drop from the legislation’s effective date until Google’s responsive policy change. The underlying mechanism driving these results remain uncertain. To mitigate potential upward bias, we exclude this interval, as the abrupt pre-treatment revenue drop could lead to overestimating the effects of Apple’s subsequent policy revision if included.

Table 9 summarizes the estimates of  $\beta_1$ . The point estimates suggest that downloads decrease while revenue increases. Specifically, the downloads decrease by 8% post-treatment while the revenue increases by 24%. We note in the later section that the parallel trends assumption is most likely to be satisfied using this comparison group.

**3.5.2 Using Apps in Other Years and Months as Control.** We then examine whether Apple App Store apps in Korea experienced differential revenue and/or install outcomes during the six-month post-treatment period relative to their own performance during the corresponding months in pre-treatment years. This specification allows controlling for monthly seasonality variations by directly comparing app performance on a year-month basis. Under this approach, we observe approximately a 1.8% decrease in app

Table 9. Results Using Other Countries as Control

	<i>Dependent variable:</i>	
	log(downloads)	log(revenue)
	(1)	(2)
Interaction	-0.079* (0.044)	0.240*** (0.046)
Constant	7.774*** (0.110)	8.671*** (0.113)
Observations	33,868	35,165
R <sup>2</sup>	0.527	0.608
Adjusted R <sup>2</sup>	0.522	0.604
Residual Std. Error	1.732 (df = 33502)	1.863 (df = 34803)
F Statistic	102.365*** (df = 365; 33502)	149.689*** (df = 361; 34803)

*Notes:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. Standard errors are in parentheses. The reported coefficients are estimates of the interaction term between post treatment period and treated country (Korea), using 367 Apple App Store-distributed apps installed in Korea and four other countries. The dependent variables are the logged number of installs in Column (1) and logged revenue in Column (2).

Table 10. Results Using Other Years and Months as Control

	<i>Dependent variable:</i>	
	log(downloads)	log(revenue)
	(1)	(2)
Treatment Year:Month	-0.018 (0.047)	0.118** (0.046)
Constant	11.980*** (0.138)	13.817*** (0.140)
Observations	8,920	9,016
R <sup>2</sup>	0.795	0.819
Adjusted R <sup>2</sup>	0.786	0.812
Residual Std. Error	1.055 (df = 8563)	1.046 (df = 8663)
F Statistic	93.232*** (df = 356; 8563)	111.369*** (df = 352; 8663)

*Notes:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. Standard errors are in parentheses. The reported coefficients are estimates of the interaction term between post treatment year and the first six months since the initiation of the treatment, using 367 Apple App Store-distributed apps installed in Korea. The dependent variables are the logged number of installs in Column (1) and logged revenue in Column (2).

installs, though noise in the estimates prevents conclusively attributing a meaningful effect to Apple’s commission rate change. However, we find an around 11.8% increase in app revenue in the treated years and months compared to other periods, indicating Apple’s policy revision allowing alternative billing systems contributed to revenue growth. This represents a roughly 12% divergence from the previous specification’s estimates. Such a gap could partly stem from the different reference groups; while the previous specification compared to average non-Korea market outcomes pre-treatment, this specification benchmarks against average Korea market app outcomes during pre-treatment years, potentially better controlling for cross-country variations in app performance.

**3.5.3 Using Triple Difference-in-Differences.** We now turn to empirical results from triple difference-in-differences. This specification first computes the differences in app outcomes between treated months and non-treated months for both the South Korea market and non-Korea markets. Then, we compare these respective differences to detect any

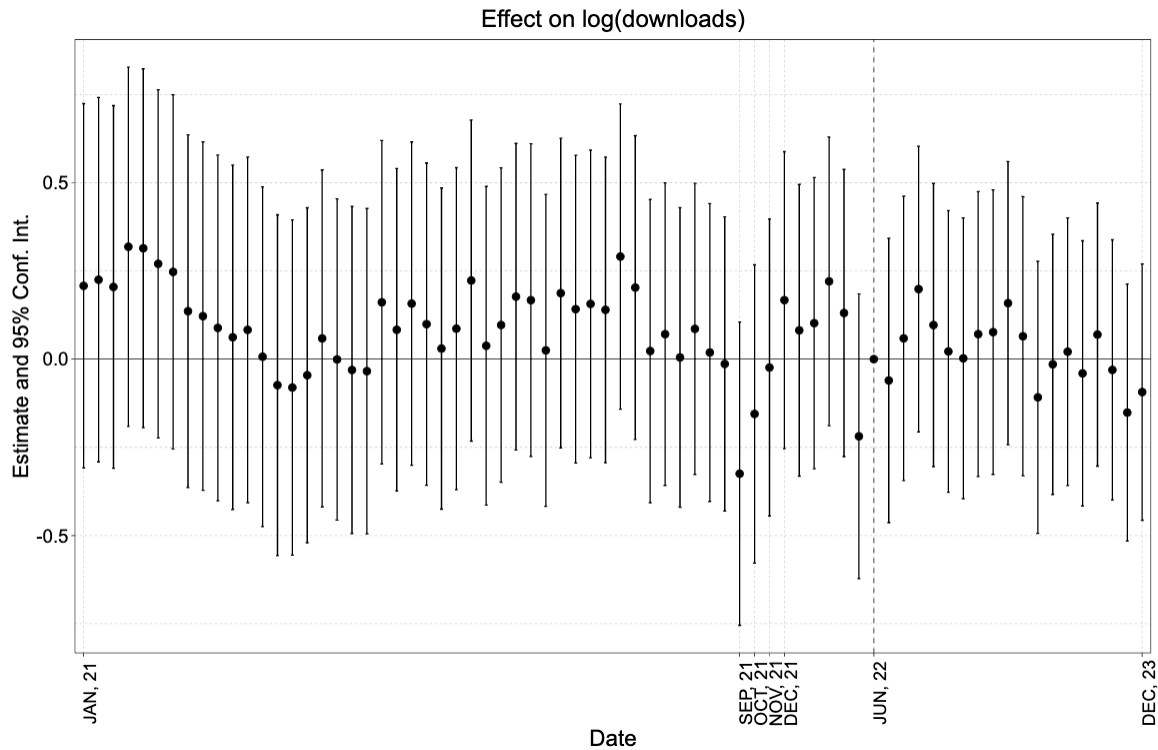
significant changes post treatment. We find around 10% decrease in app installs, a finding consistently observed but lacking sufficient statistical power to draw robust inference. However, we do find higher app revenue by 13.7% under this specification as well. While the sign of this revenue estimate aligns with previous specifications, it contains significant noise, preventing us from extracting statistical inferences from this result alone.

Table 11. Results Using Triple DiD

	<i>Dependent variable:</i>	
	log(downloads)	log(revenue)
	(1)	(2)
KR:Treat Year	-0.029 (0.063)	0.187*** (0.066)
KR:Treat Month	0.022 (0.060)	-0.065 (0.065)
Treat Year:Treat Month	0.003 (0.046)	-0.034 (0.047)
KR:Treat Year:Treat Month	-0.101 (0.087)	0.130 (0.092)
Constant	7.466*** (0.104)	8.642*** (0.105)
Observations	33,868	35,165
R <sup>2</sup>	0.525	0.608
Adjusted R <sup>2</sup>	0.520	0.604
Residual Std. Error	1.737 (df = 33513)	1.863 (df = 34814)
F Statistic	104.475*** (df = 354; 33513)	154.169*** (df = 350; 34814)

Notes: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. Standard errors are in parentheses. The reported coefficients are estimates of the interaction term measuring the joint effect of each combination of post-treatment year, post-treatment month, and treatment group (Korea), using 367 Apple App Store-distributed apps installed in Korea and four other countries. The dependent variables are the logged number of installs in Column (1) and logged revenue in Column (2).

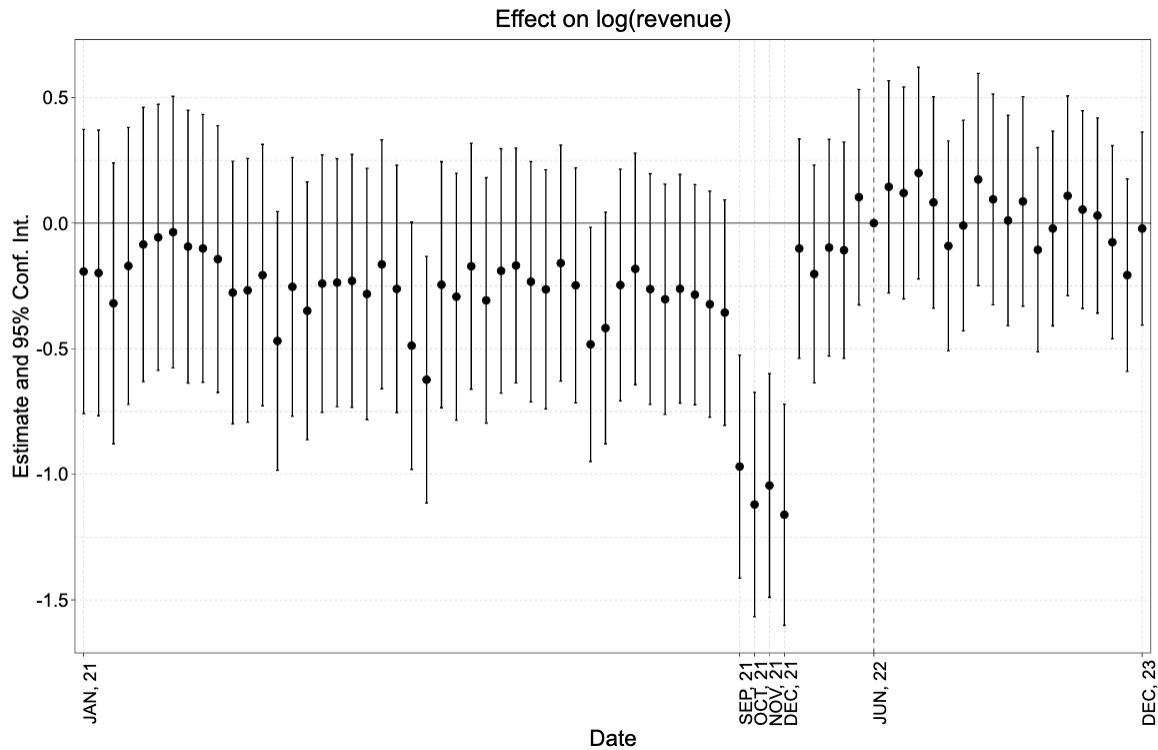
Figure 11. Event Study of the Apple's Response on the Number of App Installs



Notes: These estimates are from an event study regression. The dependent variable is logged number of downloads and the independent variables include app, country, and time fixed effects. The reference month is set on the month of June, 2022.

**3.5.4 Event Study.** To ensure the ongoing consistency of app performance between Korea and other countries during the pre-treatment period, we implement the event study technique. This methodology validates the parallel trend assumption in pre-treatment period. Accounting for app and country fixed effects, the average difference in app downloads during pre-treatment periods should not statistically differ from the period immediately preceding treatment onset. Figure 11 illustrates the event study analysis of app downloads. We systematically compare app performance in the pre-treatment period against the period immediately preceding treatment initiation to identify any deviations in app behavior. The figure confirms no significant differences across time and countries before treatment, validating the parallel trend assumption. However, we observe a steep

Figure 12. Event Study of the Apple’s Response on App Revenue



Notes: These estimates are from an event study regression. The dependent variable is logged app revenue and the independent variables include app, country, and time fixed effects. The reference month is set on the month of June, 2022.

drop, though the confidence interval still includes zero, in the month when the legislation became effective.

Figure 12 presents the event study analysis of revenue. We observe systematic drops in app revenue during November and December each year for Korea compared to non-Korean markets, relative to the baseline period of June 2022, which is just before the treatment. This drop is more notable from September 2021 and December 2021, when the legislation became effective until Google’s policy change. While uncertainty surrounding the policy effects could partly explain the significant revenue decline in South Korean market during this period, the exact cause remains unclear. Therefore to prevent overestimating treatment

effects, we have excluded the four-month period from September 2021 to December 2021 from the current analysis.

**3.5.5 Discussion and limitations.** Taken together, these results suggest that the policy may have resulted in a decreased number of installs and a increased revenue for apps on Apple App Store in South Korea, though we consider this result to be suggestive only.

These results are surprising as we see greater improvements in app revenue than anticipated. If the commission rate reduction were the only factor affecting revenue, assuming in-app pricing and sales volumes remained constant, we would anticipate around a 9% revenue increase. The additional gains suggest either: 1) Developers may have raised in-app prices despite the commission drop, and/or 2) in-app purchase volumes rose, driven by either new paid users or increased spend among existing users. For the first case of developers raising in-app prices: One hypothesis is that developers leveraged this opportunity to enhance app quality, justifying higher in-app prices which increase the revenue. For the second case of increased in-app purchase volumes, which is different from app installs: It is likely that existing users transition from using the apps without in-app purchases to making the in-app purchases. However, these results warrant further analysis to isolate the precise drivers behind the strong-than-project revenue uplift.

It is important to note that our analyses are subject to limitations. First, our identification strategies assume that no event (other than the policy change) systematically affected outcomes for apps distributed on the Apple App Store in South Korea during the analysis period. Second, given that the installed base of smartphone users in the United States is approximately an order of magnitude higher than in South Korea (and the number of smartphone users worldwide is another order of magnitude higher), it is reasonable to believe that firms serving global users and facing high development costs would forgo implementing alternative payment systems even in the context of South Korea's law. Lastly, due to data limitations, we cannot directly observe app-level switching of billing systems, which left us to analyze indirectly the legislation's effects through average app performance

metrics, rather than directly counting affected apps and their individual performance changes caused by the legislation.

### **3.6 Conclusion**

The near-monopoly power of the two leading app distribution platforms have raised antitrust concerns that these platforms leverage their market power to tie in-app billing system with their platform operations and charge developers a dictated commission rate that is higher than would be present in a more competitive market. To prevent leading platform operators from monopolizing in-app billing system, the National Assembly of South Korea recently passed a law that bans app stores from requiring developers to only use the platform's billing system, i.e., preventing app marketplace operators from tying in-app billing system with their platforms. This research serves as a preliminary study to examine the short-term effect of this legislation. We examine whether Apple App Store's response to the legislation has any significant impact on app demand as well as app revenue. While the previous literature has largely focused on negative market consequence of tying (reducing incentives to innovate, price that is charged higher than competitive rate, etc.), the effects of unbundling are less well-studied. Our study is among the first to investigate the market consequence of decoupling in-app billing system from operation of app distribution platforms.

Across specifications, we observe a consistently negative point estimate of the relationship between the reform and the number of downloads, and a consistently positive point estimate of the relationship between the reform and app revenues. The effects of downloads are estimated with substantial noise, however, and we therefore conclude that the policy change was unlikely to significantly affect app installs in South Korea over the period we consider. We note that any quality improvement of an app as a result of cost

reduction is likely to contribute to app revenue, which may be the reason we do see positive policy shock on app revenue as we have anticipated.<sup>9</sup>

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<sup>9</sup>Although the data presents some early evidence of app revenue improvements in response to the policy, we are still unsure and looking for reasons that generated significant dip in app revenues during the first four months after the legislation became effective. We presume users may have temporarily depressed their in-app spending during that period, expecting prices to decrease in response to legislation, only to later discover that Google Play Store still charges a 26% commission rate for developers, before the improvements we've observed more recently.

CHAPTER IV  
DISRUPTING THE APP STORE DUOPOLY: EVIDENCE FROM SOUTH KOREAN  
APP DISTRIBUTION MARKET

#### 4.1 Introduction

I study the effectiveness of a pricing strategy employed by an entrant firm seeking to penetrate duopolistic digital markets. While pricing schemes have traditionally been popular and effective strategic moves in conventional markets, their efficacy is less well-established in markets with strong network effects, which may independently diminish the impact of such tactics. Of particular interest is assessing the viability of pricing strategies within app store markets, where network effects tend to be pronounced, and Google Play and Apple App Store dominate the app distribution landscape, while also serving as providers of mobile operating systems.(Garcia-Swartz & Garcia-Vicente, 2015; Singh, Hosanagar, & Nevo, 2021)

Major legal actions have contested the dominance of these platforms, i.e., whether the fee structure imposed by dominant platform operators can be justified, independent of their market power in app distribution. Some of the key issues at the forefronts include: 1) whether the commission levels charged exceed competitive rates, and 2) whether Google Play has illegally tied its billing system to the app distribution channel. (Bostoen & Mândrescu, 2020; Etro, 2023; Geradin & Katsifis, 2021) These are important issues as anti-competitive tying can act as a entry barrier both to the primary and secondary markets, making harder for entrants to enter the market and reducing the incentives for incumbents to innovate as a result. (Choi & Jeon, 2021b; Etro & Caffarra, 2017) Such legal aims to bring down the commission rate, inviting competition into the market.

This paper analyzes the commission rate policy proposed by the third-party app distribution platform, called “ONE store”, a local app distributor originated from South Korea. The platform proposes a 20% commission rate, 10 percentage points lower than the two leading app distribution platforms, if developers use the ONE store platform and its billing system. Additionally, developers are free to use their own billing system and

only pay 5% commission rate for using ONE store – 21 percentage points lower than the comparable policy of Google Play and Apple App Store. This pricing policy is a dramatic departure from the policies of the two leading platforms (Google Play and Apple App Store), where both of them required developers to pay 30% for using the platform and the platform’s billing system, and 26% if developers use the third-party billing system.

With a proprietary dataset obtained from a third-party app distribution platform that offers different fee structures compared to the main app distributors that covers the period from 2017 to 2023, and I measure (1) whether there is a significant movement of developers from one platform to another, (2) whether this shift resulted in an increase in the number of users on the third-party platform, and (3) whether this shift also resulted in an increase in the usage of the platform.

Using difference-in-differences technique, I find temporary but significant inflow of apps on the platform post policy, increased level of in-app sales within apps on the platform, and higher number of paid-users within an app. However, I find these effects do not sustain in the longer-term horizon, and that the policy does not necessarily lead to higher in-app sales, and conclude by stating that the policy may not be sustainable.

This study adds on to the literature focusing on platform dynamics and pricing policies as a viable strategy for less competitive firms. For instance, Barwick and Pathak (2015) examine how letting brokers compete on commission rate reallocates market share in favor of the more efficient brokers in the Boston real estate market. Marra (2020) presents a case study of an online platform where fees on one side of the platform bring in more participants on the other side. To build on this literature, I explore whether different commission rates alter the competition landscape among app distribution platform operators, specifically whether platforms with smaller user bases can gain a portion of the market share in the app distribution platform market. This study build on to this strand of literature by empirically testing the effectiveness of an entrant’s pricing policies.

Additionally, this research contributes to the extensive literature studying varied strategic approaches under conditions where network effects are present. In app store, two

groups of agents, users and developers, interact through platform or app stores. Given the two-sided nature of the platform, where one side of the participants is indirectly affected by the participation of the other side, it is important for any platform operators to sufficiently attract one side to create positive externalities on the other side.(Armstrong, 2006; Eisenmann, Parker, Van Alstyne, et al., 2006; Rochet & Tirole, 2003) In app store markets, low pricing schemes may effectively draw profit and exposure-maximizing developers to publish their apps through the platform. As sufficient number of apps become available, more users use the platform to search and install apps, generating a positive feedback loop that increases competitiveness through network effects. However, determining which market side to initially attract remains a challenge.(Caillaud & Jullien, 2001) I study whether discrepancies in commission rate policy between platforms can initiate network effect formation by drawing developers, naturally leading to user attraction and a self-reinforcing feedback loop.

The structure of this paper is as follows: Section 2 provides a brief background on the app distribution market and existing policies on in-app billing systems across different app distribution platforms. Section 3 illustrates data and descriptive evidence; Section 4 introduces identification strategy to estimate the effects of pricing cheap strategy in attracting developers and users. Finally, Section 5 concludes with a discussion of possible future research.

## **4.2 Background**

App store is a platform that offers a wide range of apps. The success of app store depends on the large enough user base to attract developers to publish their applications on the platform, but also large number of applications on the platform to attract users. It is a two-sided platform involving two groups, users on one side and developers on the other, where each side is affected by the scale of the other sides.

The operating system of mobile devices has significant implications on which app stores users can use. Apple App Store is the only app store available for users of iOS devices, while

Google Play Store came pre-installed as the default for Android devices. This coupling between operating system and the app store itself has generated enough starting user base to create sufficient incentive for app developers to join the platforms and enrich the app store ecosystem. As a result, Google Play and Apple App Store have become the two leading app stores dominating the app store market in Android devices and iOS devices, respectively. These platforms have leveraged the large user base that they have accumulated from their hardware devices to attract users to successfully create cross-side network effects. Although alternative store exist for Android devices, such as Windows Store and Amazon Store, they hold a relatively small global market share.

ONE store is among the few minor platforms operating on Android devices in South Korea market. It was launched in 2016 by the collective collaboration among three major telecommunication operators (LG Uplus, SK Telecom, and KT Telecom) together with one major search engine online platform (Naver) in South Korea. It is a local app store only operable on Android devices and grew its size to reach a 14% market share in South Korea as of 2021.<sup>1</sup>

To compete against Google Play Store and attract developers toward ONE store, it has introduced a policy of 80:20 and 95:5 in 2018, which indicates the in-app revenue sharing ratio between the developers and the platform, under different billing systems. If developers use ONE store's billing system, 80% of the revenue generated from in-app transaction goes to developers, while the remaining 20% goes to ONE store. Contrary to Google Play Store or Apple App Store, ONE store allowed developers to use a third-party billing system since its launch in 2016, which became only recently available for Google Play or Apple App Store, taking 5% as a service fee.

The proposed policy has priced two separate services, app distribution service from in-app billing service. ONE store separately charged 20% for a bundled fee of the two services, while only charged 5% for the service fee of using the platform for app distribution service, which effectively leaves 15% be the in-app billing system fee. This is a discrepancy from

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<sup>1</sup>See Cha and Park (2023)

the pricing strategies by the dominant app distribution platforms, where these platforms have bundled the two services together to charge 30% commission rate. This fee has later come down to 26% for developers using the third-party billing system, which effectively leaves 4% as the in-app processing fee that the dominant platforms have priced to charge the developers. With difference in commission rate charged by different platforms, I analyze the effectiveness of the low-pricing strategy on app performance on the minor platform and also bringing developers and users onto the platform.

### 4.3 Data and Descriptive Evidence

I use the proprietary data obtained from ONE store that consists of app-level monthly statistics related to app installs and in-app transactions from January 2017 to March 2023.<sup>2</sup> The apps in the sample are apps that are classified “Game” category on ONE store.

Table 12. Game Apps with New Installs on ONE store

Year	N
2017	7183
2018	7525
2019	7846
2020	7707
2021	7247
2022	7885
2023	5643

*Notes:* The statistics are yearly summation of game apps with new installs on ONE store. The statistics for 2023 are significantly lower than those for comparison years, as they represent the fraction of yearly apps in the first four months (January to April).

The table above shows the number of game apps on this platform that had new installs during the period January 2017 and April 2023. The unique apps with new installs have grown by approximately 300 apps between 2018 and 2019, while they have decreased in number by around 150 apps between 2019 and 2020. It has also decreased by 500 apps

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<sup>2</sup>I would like to acknowledge ONE store for providing data resources.

between 2020 and 2021. The number recorded the highest in 2022, which is equivalent to 7885 apps available during that year.

#### 4.4 Identification Strategy and Estimation

**4.4.1 The Timing of the Policy Change.** The policy change took place on three different occasions: (1) July 2018, when ONE store has announced its commission rate policy that is 10 percentage points lower than the competing dominant distribution platforms, (2) September 2021, when legislation to ban Google Play and Apple App Store from requiring developers to use the platforms' payment systems became effective, and (3) December 2021, when Google Play changed its commission rate policy that is 4 percentage points lower than its previous commission rate. Each policy change may have distinct implications for ONE store's performance and the apps listed on the platform. Our analysis primarily focuses on the first occasion, evaluating the effects of ONE store low-commission-rate scheme in 2018.

**4.4.2 Identification Strategy.** I evaluate the effects of the pricing strategy of ONE store on four outcome variables, which are app installs, in-app purchase volume, the number of paid users within an app, and the amount in which they spend on in-app purchases.

$$\log(Y_{it}) = \beta_0 + \beta_1 \text{Post}_t + \alpha_i + \delta_t + v_{it}, \quad (4.1)$$

where  $Y_{it}$  represents the outcome variables (app downloads, in-app transaction volumes, in-app purchase amounts) for app  $i$  at time  $t$ ,  $\text{Post}_t$  indicates the post-treatment period that is on and after July, 2018. The parameter of interest is  $\beta_1$ .

In the second specification shown in Equation 4.2, to control for potential year-to-year seasonality, I compare the app performance in years during and after the policy change with their performance in years before the policy change.

$$\begin{aligned}
\log(Y_{it}) &= \beta_0 + \beta_1 \text{TreatYear}_t \times \text{TreatMonth}_t \\
&+ \beta_2 \text{TreatYear}_t + \beta_3 \text{TreatMonth}_t \\
&+ \alpha_i + \nu_{it},
\end{aligned} \tag{4.2}$$

where  $Y_{it}$  denotes the outcome variables (app downloads, in-app transaction volumes, in-app purchase spending, paid users) for app  $i$  at time  $t$ ,  $\text{TreatYear}_t$  refers to the year 2018 (when the treatment was introduced),  $\text{TreatMonth}_t$  indicates the first six months of post-treatment period,  $\alpha_i$  represents app-level fixed effects, and  $\nu_{it}$  represents idiosyncratic unobservables.

## 4.5 Results

I presents the reduced-form model results on four different outcome variables derived from two specifications – the linear model and the difference-in-differences approach, denoted by Equation 4.1 and Equation 4.2, respectively.

The first column of Tables 13, 14, 15, and 16 reports the results from the linear model specification incorporating a post treatment dummy variable. The results show 4.9% increase in new installs, a 35.7% increase in the number of paid users, a 21.9% increase in the volume of in-app purchase transactions, and 14.9% increase in the amount of in-app purchases. All estimates do not contain considerable noise that limits the precision of these findings. Nevertheless, as the previous plots show, part of these observed increase across all four dimensions may be attributed to general upward trends in app performances over time. While the pricing policy changes may have strong immediate effects, such secular upward trends of app performance could potentially inflate the estimates to some extent. These limitations are accounted for in the difference-in-differences specification, where I focus on isolating the immediate six-month effect, following the policy’s change.

The results from the difference-in-differences model are reported in the second column of Tables 13, 14, 15, and 16. The results from the difference-in-differences framework

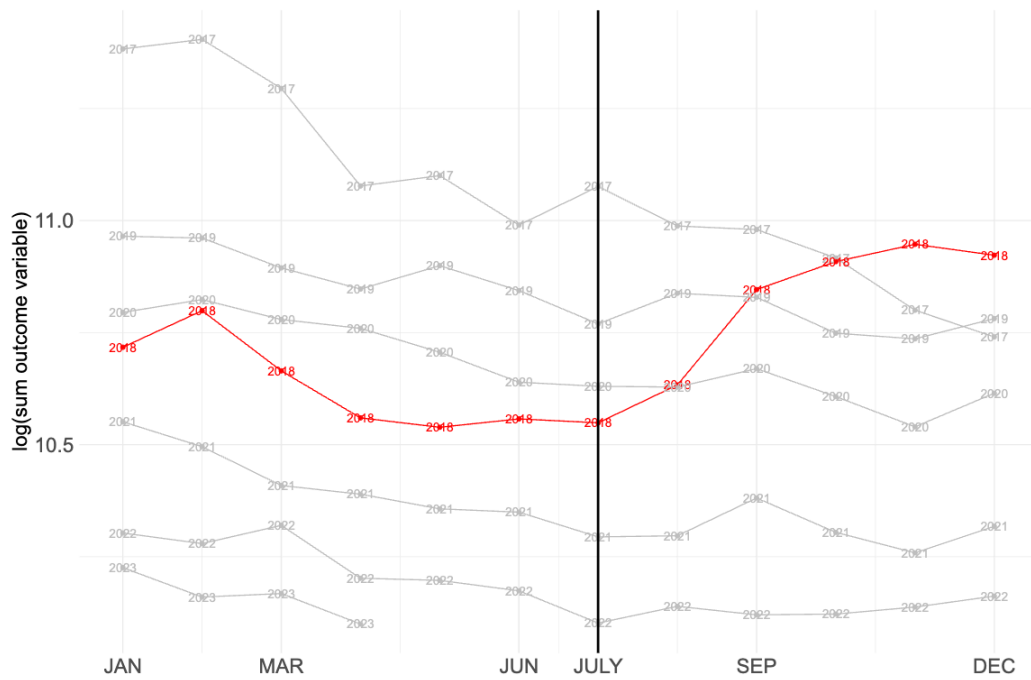
indicates 1% drop in app installs, 25.6% increase in the number of paid users, 11.1% increase in the volume of in-app purchases, and 3.5% increase in the amount of in-app purchases. While the estimates for changes in the number of paid users and the volume of in-app purchases exhibit relatively low noise levels, the estimates for changes in app installs and the amount of in-app purchases are considerably noisier. These results indicate that indeed when adjusting the upward time trend, the policy is only effective in increasing the number of paid users, and consequently increasing the volume of in-app transactions, but less so on the app-level total user spending on in-app purchases. Such results indicate that the low-pricing strategy might draw many first-time-in-app-item purchasers, increasing the overall volume, while those users are not heavy money spender, indicating the overall in-app purchase spending to significantly change. As the business model of app store platform is a fixed-cut (20% in case of ONE store) of the amount of in-app revenue generated by apps published on the platform, the incremental changes on total app revenue can act as a loss for platform operators. This implies that if the amount of in-app spending by users cannot sufficiently compensate the drop in commission rate, the low-pricing strategy may be unsustainable.

#### **4.6 Conclusion**

The findings suggest the platform only benefits from a low-pricing strategy in the short-term. However, while a low-pricing approach appears to drive higher in-app purchase traffic volume, the increase in total in-app spending is insufficient to offset the revenue losses of the app store operator from reduced commission rates. The strategy appears to not generate substantial network effects to retain users on the platforms long-term or spur meaningful substitution away from Google Play toward ONE store.

The effectiveness of the low-pricing strategy appears to be temporary, with its impact diluting over time. Possible reasons for such dilution includes ONE store remaining a locally-focused app store platform. Developers wishing to reach a global user base may

Figure 13. Yearly Comparison of New Installs



Notes: The figure shows a yearly comparison of aggregated app installs on a monthly basis. The policy change occurred in July 2018. The month in which policy change occurred is marked with a vertical line. The aggregated new installs are log transformed. The statistics for 2018 are marked in red.

Table 13. Regressions Using App Installs as the Dependent Variable

	<i>Dependent variable:</i>	
	log(new installs)	
	(1)	(2)
Post Policy Change	0.049*** (0.017)	
Year 2018:Post July		-0.009 (0.018)
Constant	2.008*** (0.013)	2.001*** (0.015)
Observations	308,505	308,505
R <sup>2</sup>	0.006	0.006
Adjusted R <sup>2</sup>	0.006	0.006
Residual Std. Error (df = 308486)	1.763	1.763
F Statistic (df = 18; 308486)	105.504***	105.058***

*Notes:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. Standard errors are in parentheses. The dependent variable is the logged number of app installs. The linear model specification is in Column (1), and the model interacting year 2018 and post-treatment months is in Column (2). The coefficient estimate for the Post Policy Change captures the change in the dependent variable during the policy change month and the subsequent five months. The estimate for the interaction term captures the change in the dependent variable during the first six months starting from the policy change.

Table 14. Regressions Using the Number of Paid Users as the Dependent Variable

	<i>Dependent variable:</i>	
	log(paid users)	
	(1)	(2)
Post Policy Change	0.357*** (0.021)	
Year 2018:Post July		0.256*** (0.023)
Constant	0.524 (0.563)	0.272 (0.618)
Observations	82,346	82,346
R <sup>2</sup>	0.810	0.771
Adjusted R <sup>2</sup>	0.797	0.756
Residual Std. Error	0.975 (df = 77203)	1.070 (df = 77218)
F Statistic	63.991***	50.765***
F Statistic df	(df = 5142; 77203)	(df = 5127; 77218)

*Notes:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. Standard errors are in parentheses. The dependent variable is the logged number of paid users. The linear model specification is in Column (1), and the model interacting year 2018 and post-treatment months is in Column (2). The coefficient estimate for the Post Policy Change captures the change in the dependent variable during the policy change month and the subsequent five months. The estimate for the interaction term captures the change in the dependent variable during the first six months starting from the policy change.

Table 15. Regressions Using In-app Purchase Volume as the Dependent Variable

	<i>Dependent variable:</i>	
	log(iap volume)	
	(1)	(2)
Post Policy Change	0.219*** (0.033)	
Year 2018:Post July		0.111*** (0.036)
Constant	1.212* (0.673)	0.874 (0.734)
Observations	46,845	46,845
R <sup>2</sup>	0.854	0.827
Adjusted R <sup>2</sup>	0.844	0.815
Residual Std. Error	1.165 (df = 43801)	1.271 (df = 43816)
F Statistic	84.456***	68.994***
F Statistic df	(df = 3043; 43801)	(df = 3028; 43816)

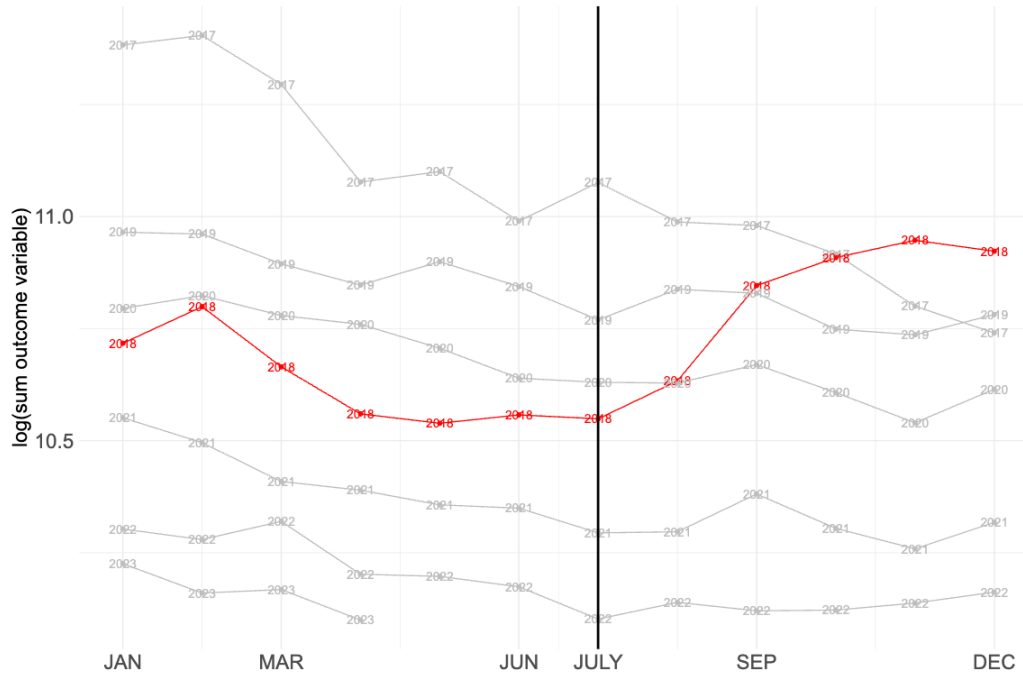
Notes: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. Standard errors are in parentheses. The dependent variable is the logged in-app purchase volume. The linear model specification is in Column (1), and the model interacting year 2018 and post-treatment months is in Column (2). The coefficient estimate for the Post Policy Change captures the change in the dependent variable during the policy change month and the subsequent five months. The estimate for the interaction term captures the change in the dependent variable during the first six months starting from the policy change.

Table 16. Regressions Using In-app Spending as the Dependent Variable

	<i>Dependent variable:</i>	
	log(iap amount)	
	(1)	(2)
Post Policy Change	0.149*** (0.041)	
Year 2018:Post July		0.035 (0.045)
Constant	9.589*** (0.826)	9.173*** (0.900)
Observations	45,347	45,347
R <sup>2</sup>	0.855	0.828
Adjusted R <sup>2</sup>	0.846	0.817
Residual Std. Error	1.430 (df = 42511)	1.559 (df = 42526)
F Statistic	88.632***	72.567***
F Statistic df	(df = 2835; 42511)	(df = 2820; 42526)

*Notes:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. Standard errors are in parentheses. The dependent variable is the logged in-app spending. The linear model specification is in Column (1), and the model interacting year 2018 and post-treatment months is in Column (2). The coefficient estimate for the Post Policy Change captures the change in the dependent variable during the policy change month and the subsequent five months. The estimate for the interaction term captures the change in the dependent variable during the first six months starting from the policy change.

Figure 14. Yearly Comparison of Paid Users



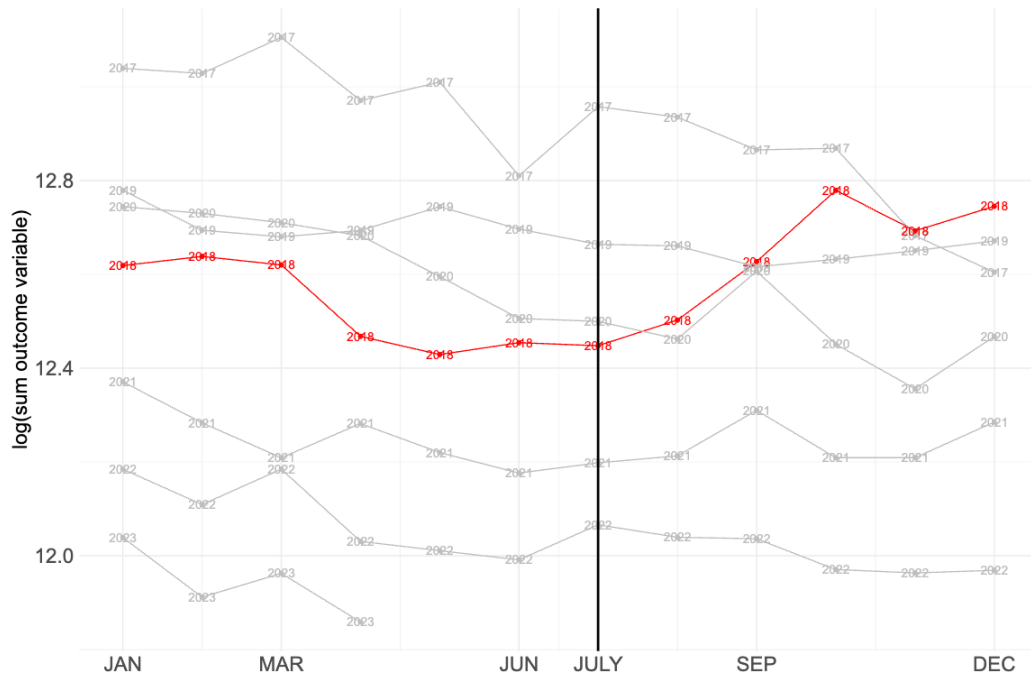
Notes: The figure shows a yearly comparison of aggregated number of paid users on a monthly basis. The policy change occurred in July 2018. The month in which policy change occurred is marked with a vertical line. The aggregated new installs are log transformed. The statistics for 2018 are marked in red.

have diminished incentives to list their apps on ONE store given its regional limitations, restricting the long-term viability of the pricing strategy's effects.

Another reason can be the way app feature algorithm is designed. The algorithm that promotes and features certain apps on an app store is based on the app's gross revenue. If an app goes cross-platform across different distribution platforms, the revenue splits, reducing the probability of being featured. This algorithm discourages developers from going cross-platform, leading them to choose one app store over another. In this scenario, Google Play is often favored over ONE store.

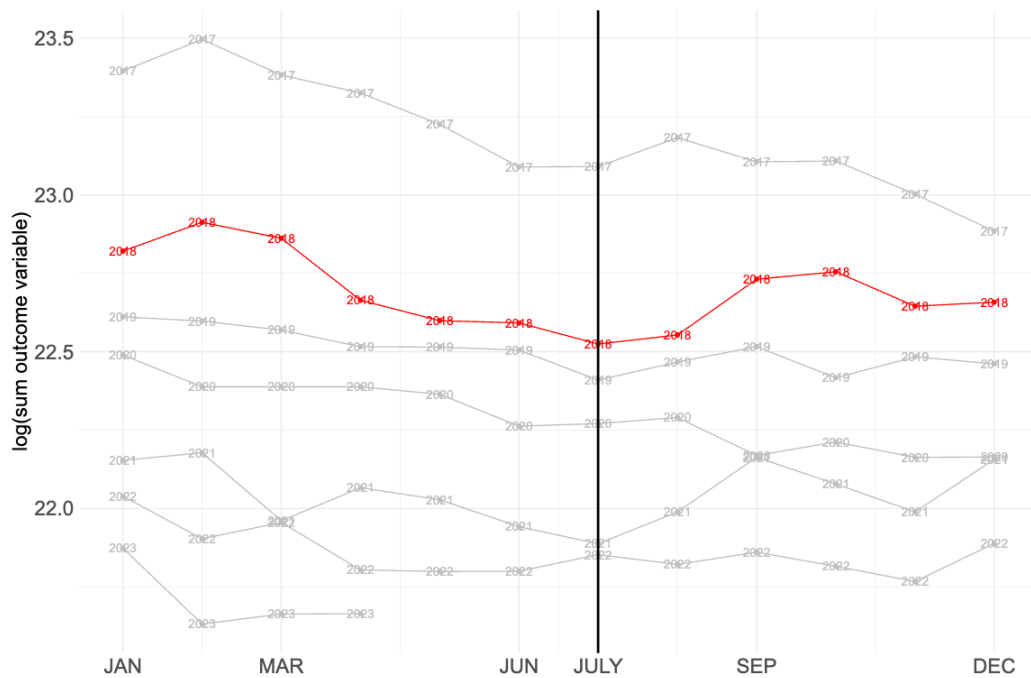
This paper empirically examined the effectiveness of a low-pricing strategy employed by the entrant platform against incumbent platforms in digital markets with duopolistic market structures. The findings suggest such pricing schemes may have limited efficacy in digital markets. Existing network effects have solidified incumbents' positions, with

Figure 15. Yearly Comparison of In-app Purchase Volume



Notes: The figure shows a yearly comparison of aggregated in-app purchase volume on a monthly basis. The policy change occurred in July 2018. The month in which policy change occurred is marked with a vertical line. The aggregated new installs are log transformed. The statistics for 2018 are marked in red.

Figure 16. Yearly Comparison of Total In-app Spending



Notes: The figure shows a yearly comparison of aggregated in-app spending on a monthly basis. The policy change occurred in July 2018. The month in which policy change occurred is marked with a vertical line. The aggregated new installs are log transformed. The statistics for 2018 are marked in red.

developers and users still largely locked into dominant platforms. While the entrant successfully attracted some local developers on its platform, the global user network of the incumbents poses a formidable barrier for developers aiming to grow globally to fully switch or forgo the dominant platform entirely. Consequently, the policy impact remains temporary, with the entrant app distribution platform failing to scale in size to viably compete against established incumbents long-term.

Future research can explore alternative strategies for policymakers and new entrants to penetrate the highly concentrated digital market, which includes investigating the minimum threshold in terms of the number of developers or the level of commission rate that can generate self-reinforcing network effects to make the entrant competitive. Other angles might include inspecting regulatory policies related to data portability, enhancing users and developers to freely select app store platforms as they like without bearing significant switching costs in between those platforms. Policies similar to this aspect may not only enhance competition in digital markets but also enhance both developers and user's surplus as their choice of platform becomes broader. Such research can provide entrants' strategic options and provide effective policies that can create competition in the digital markets.

Another potential area for future research could be identifying and isolating the two different sources of traffic that impact app downloads and revenue changes. These sources are specifically due to the dual nature of platforms. In response to commission rate changes, users can switch at the app level by converting free apps to paid ones. They can also change app stores they use to take advantage of price discrepancies between app distribution platforms. Although challenging, accurately measuring these different traffic sources is crucial as they may impact pricing policies differently.

Lastly, an area that merits further research is to examine the welfare implications of competitive market structures, contrasting duopoly versus triopoly scenarios. Such research could reveal whether introducing an additional competitor enhances or diminishes overall social welfare compared to a duopolistic environment. Empirical analyses regarding consumer surplus, producer surplus, and efficiency ramifications across these market

structures could be academically informative and also support regulatory assessments and antitrust evaluations of competition policy.

APPENDIX A  
CHAPTER 2 APPENDIX

Table A.1. Acquisition Counts by Sector

	Industry	GOOGL	META	MSFT	AMZN	AAPL
1	Aerospace and Defense	1	1	0	0	0
2	Air	1	0	0	0	0
3	Alternative Energy Equipment	2	0	0	0	0
4	Application Software	62	21	26	11	18
5	Application Specific Semiconductors	1	0	0	0	2
6	Automation/Workflow Software	3	0	5	1	2
7	Automotive	1	0	1	0	1
8	Broadcasting, Radio and Television	3	0	0	1	2
9	Buildings and Property	1	0	0	0	0
10	Business/Productivity Software	11	8	31	4	11
11	Casinos and Gaming	0	0	0	0	0
12	Communication Software	12	5	6	2	2
13	Computers, Parts and Peripherals	1	1	3	1	3
14	Connectivity Products	0	0	1	0	0
15	Consulting Services (B2B)	0	1	2	1	1
16	Database Software	3	0	5	2	4
17	Diagnostic Equipment	0	0	0	1	1
18	Distributors/Wholesale	0	0	0	1	0
19	Education and Training Services (B2B)	0	0	1	1	1
20	Educational Software	3	0	3	0	1
21	Educational and Training Services (B2C)	1	0	0	0	0
22	Electrical Equipment	3	1	0	0	3
23	Electronic Components	2	0	1	1	1
24	Electronic Equipment and Instruments	3	1	3	0	0
25	Electronics (B2C)	9	1	1	2	4
26	Energy Storage	0	0	0	0	1
27	Enterprise Systems (Healthcare)	0	0	2	0	0
28	Entertainment Software	5	7	10	2	5
29	Financial Software	1	0	0	3	1
30	General Purpose Semiconductors	0	1	0	0	2

	Industry	GOOGL	META	MSFT	AMZN	AAPL
31	Government	0	0	0	0	1
32	Holding Companies	0	0	0	0	1
33	Household Appliances	1	0	0	0	0
34	IT Consulting and Outsourcing	2	1	4	0	0
35	Information Services (B2C)	13	5	2	3	4
36	Internet Retail	0	0	1	7	0
37	Internet Service Providers	1	0	1	1	0
38	Internet Software	7	2	2	0	0
39	Logistics	1	0	0	2	0
40	Machinery (B2B)	3	0	0	1	0
41	Media and Information Services (B2B)	10	6	9	1	8
42	Medical Records Systems	0	0	0	0	1
43	Monitoring Equipment	0	0	0	0	1
44	Movies, Music and Entertainment	3	3	2	6	3
45	Multimedia and Design Software	10	6	4	1	8
46	Network Management Software	8	2	13	0	1
47	Operating Systems Software	3	0	3	0	0
48	Other Apparel	0	0	0	1	0
49	Other Commercial Products	0	0	1	2	1
50	Other Commercial Services	2	1	1	1	1
51	Other Communications and Networking	1	0	1	0	0
52	Other Consumer Durables	1	0	0	0	0
53	Other Consumer Products and Services	0	0	0	0	1
54	Other Financial Services	2	0	0	0	0
55	Other Hardware	4	1	0	0	0
56	Other Healthcare Technology Systems	0	0	0	0	1
57	Other IT Services	7	4	7	1	2
58	Other Information Technology	2	0	2	0	0
59	Other Media	3	0	0	0	0
60	Other Retail	1	0	0	0	0

	Industry	GOOGL	META	MSFT	AMZN	AAPL
61	Other Semiconductors	0	0	0	1	1
62	Other Services (B2C Non-Financial)	1	1	0	0	0
63	Other Software	4	1	3	1	3
64	Other Transportation	0	0	0	1	0
65	Outcome Management (Healthcare)	0	0	0	1	0
66	Printing Services (B2B)	0	0	0	1	0
67	Production (Semiconductors)	0	0	0	0	1
68	Publishing	2	2	2	4	0
69	Security Services (B2B)	0	0	2	0	0
70	Social Content	1	4	1	1	1
71	Social/Platform Software	13	11	6	2	4
72	Software Development Applications	14	5	11	1	4
73	Specialized Finance	1	0	0	0	0
74	Specialty Retail	1	0	0	4	0
75	Storage (IT)	2	0	2	1	0
76	Systems and Information Management	7	0	12	2	0
77	Telecommunications Service Providers	1	1	2	0	0
78	Vertical Market Software	6	5	2	0	1
79	Wireless Communications Equipment	2	0	1	1	0

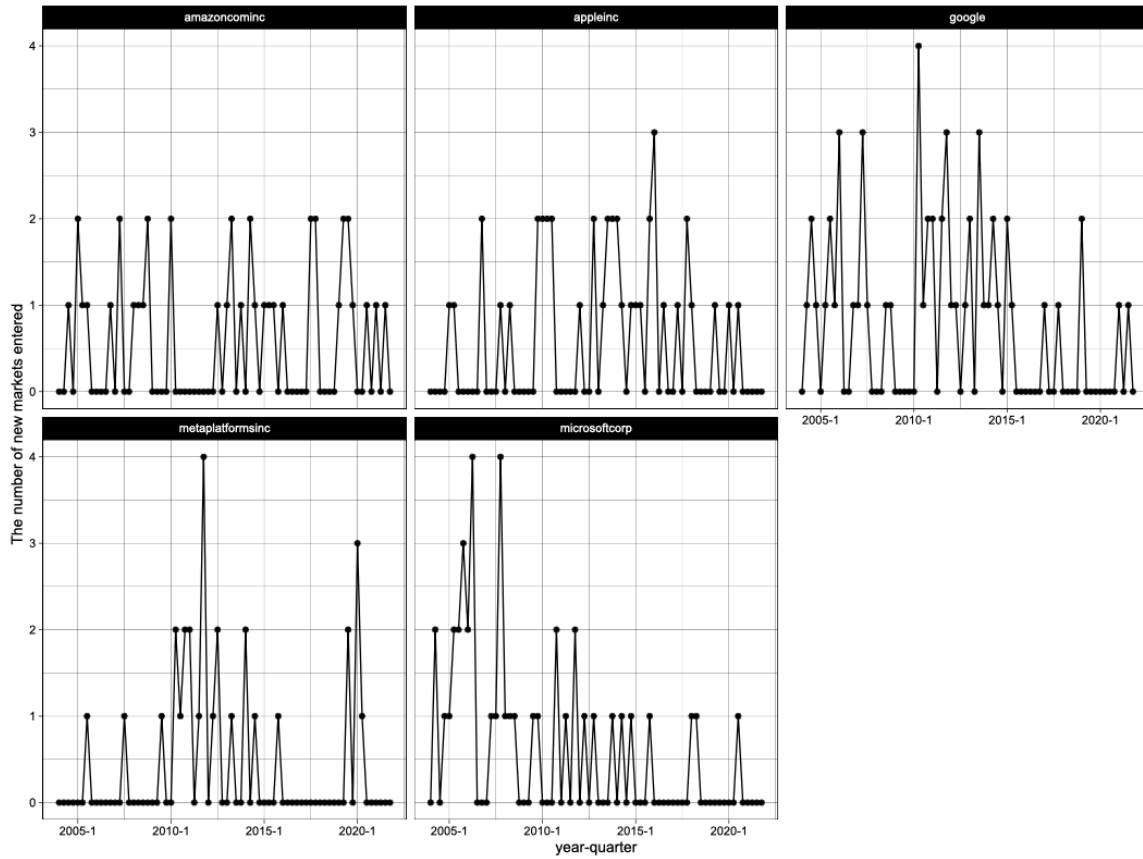
*Note:* Pitchbook’s industry classification is used for the analysis. Each column labeled GOOGL, META, MSFT, AMZN, AAPL represents Google, Meta, Microsoft, Amazon, and Apple, respectively. These 79 sectors are sectors that have been explored through acquisition since their respective founding dates. However, the summary statistics are calculated based on time periods in which all five firms coexisted and conducted business activities. Consequently, certain industries may appear as though they were not explored. For example, Microsoft’s acquisition of Ensemble Studios, classified under Casino and Gaming industry, took place in May 2001 but is recorded zero in the table since this event happened outside the analysis period. Highlighted cells indicate the primary industry of each firm.

Table A.2. Number of Entered Markets by Acquirer

Company	Range of Markets Entered
Amazon	40
Apple	41
Google	55
Meta	29
Microsoft	42

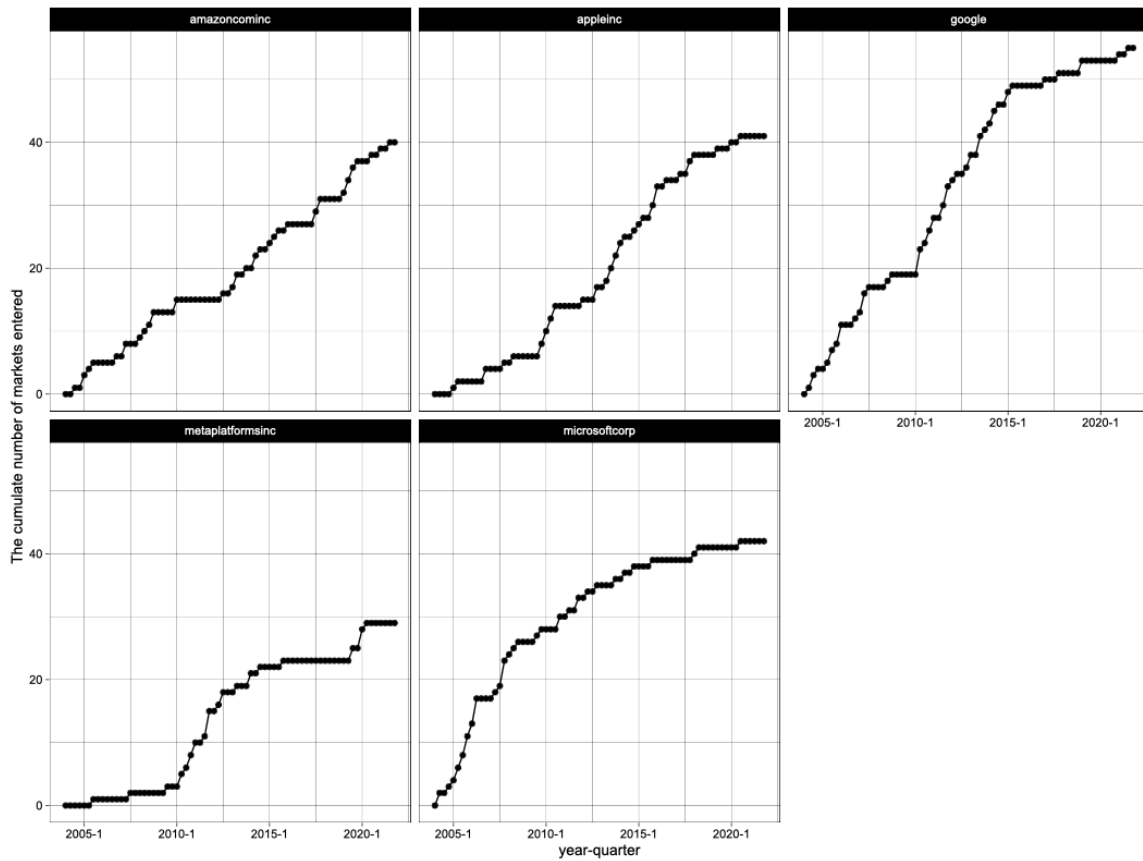
*Note:* The numbers are the cumulative number of a range of markets entered by the GAMMA firms as of 2021. Multiple entrance (multiple targets acquired across different times) to the same market is treated as one entrance.

Figure A.1. The Number of Markets Entered



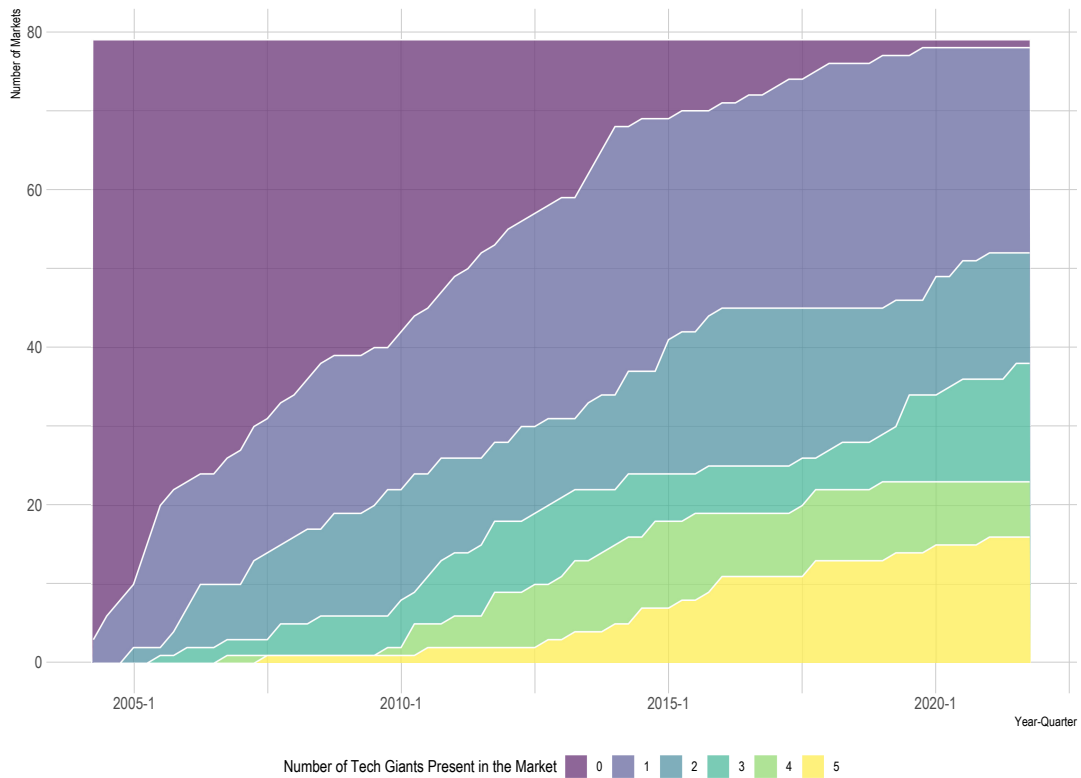
Note: The figure represents the monthly market expansion for each player. This figure can be interpreted as the number of new markets or sectors entered by each firm on a monthly basis.

Figure A.2. The Cumulative Market Expansion



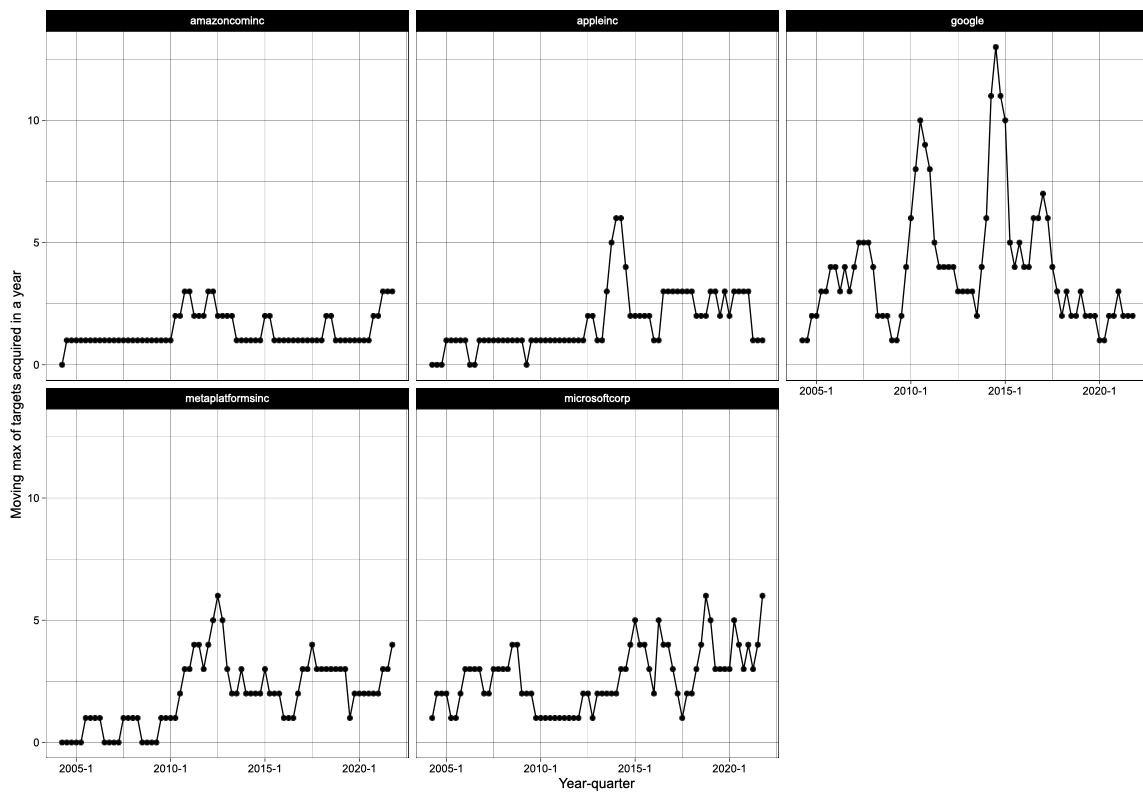
Note: The figure represents the cumulative market expansion for each player. This figure can be interpreted as the cumulative distribution of the Figure A.1 up to a given point in time. Each player has different speed of new market expansion.

Figure A.3. Tech Giant Involvement Across Expanding Markets through Acquisitions



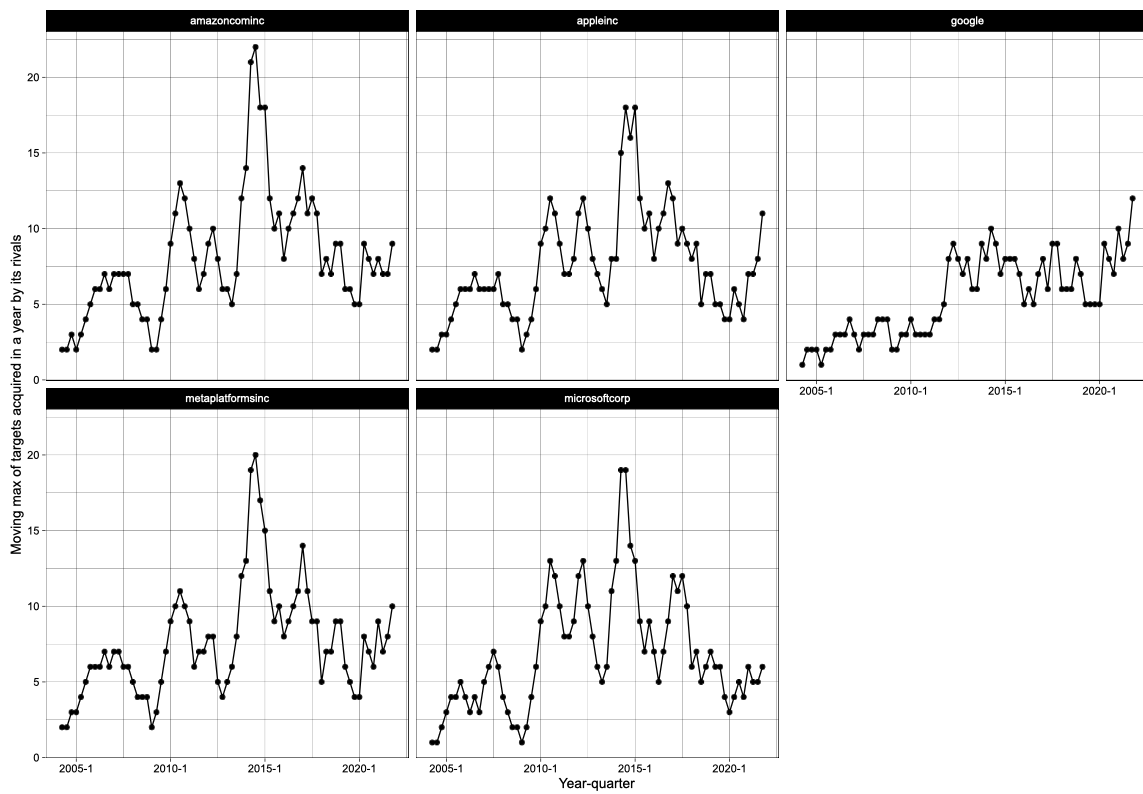
Notes: This figure shows the growing number of sectors in which at least one or more tech giants have been involved in through acquisitions. The yellow colored region represents the trend in the total number of sectors in which all five firms have ‘entered’ through acquisitions. Out of 79 sectors investigated, over 15 sectors have been tapped by the five firms previously, which may suggest intensifying competition between tech giants in acquisitions.

Figure A.4. The Rolling Maximum Sum of Annual Targets Acquired



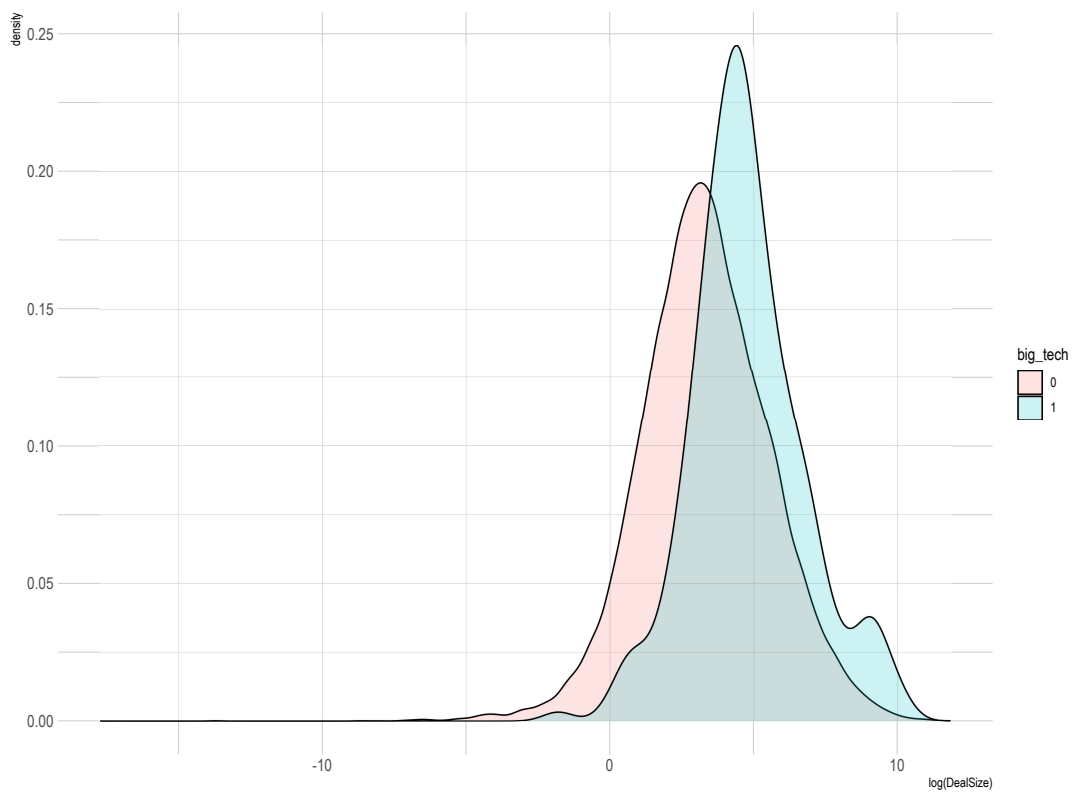
Note: The figure plots the trend of the maximum sum of targets acquired across multiple sectors within a rolling one-year time frame.

Figure A.5. The Rolling Maximum Sum of Annual Targets Acquired by Rivals



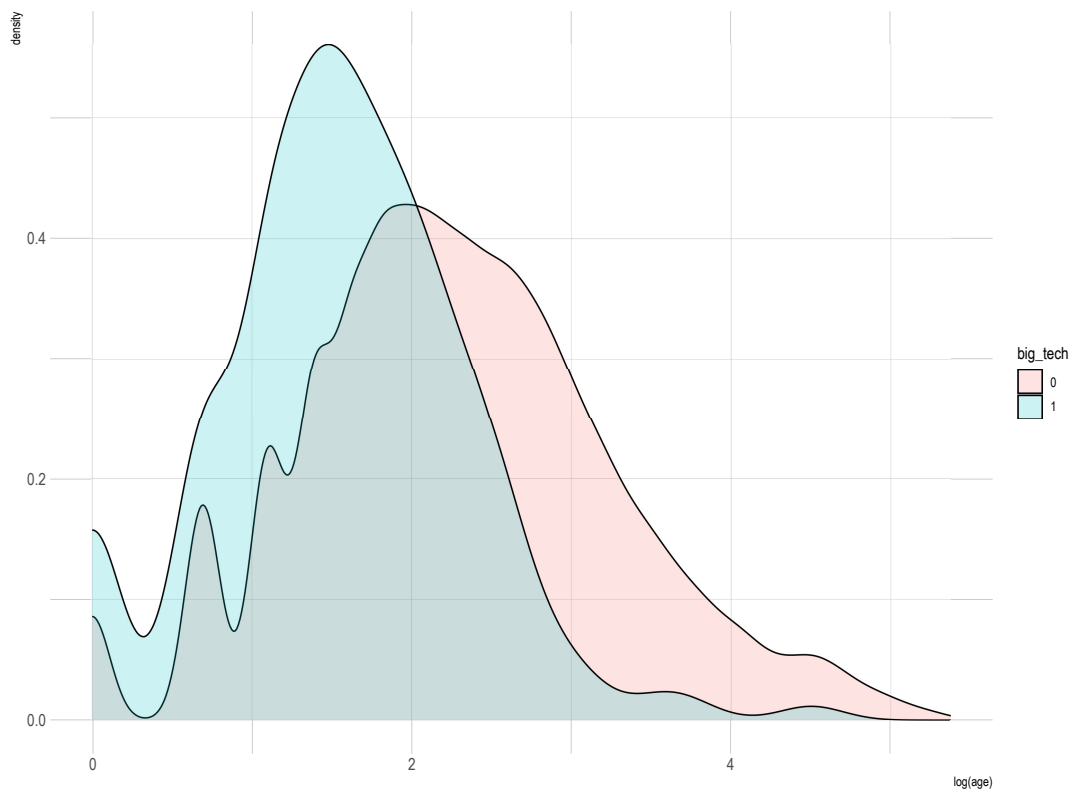
Note: The figure illustrates the trend of the maximum sum of targets acquired by the all other firms, excluding each labeled firm, across multiple sectors within a rolling one-year time frame.

Figure A.6. Deal Size



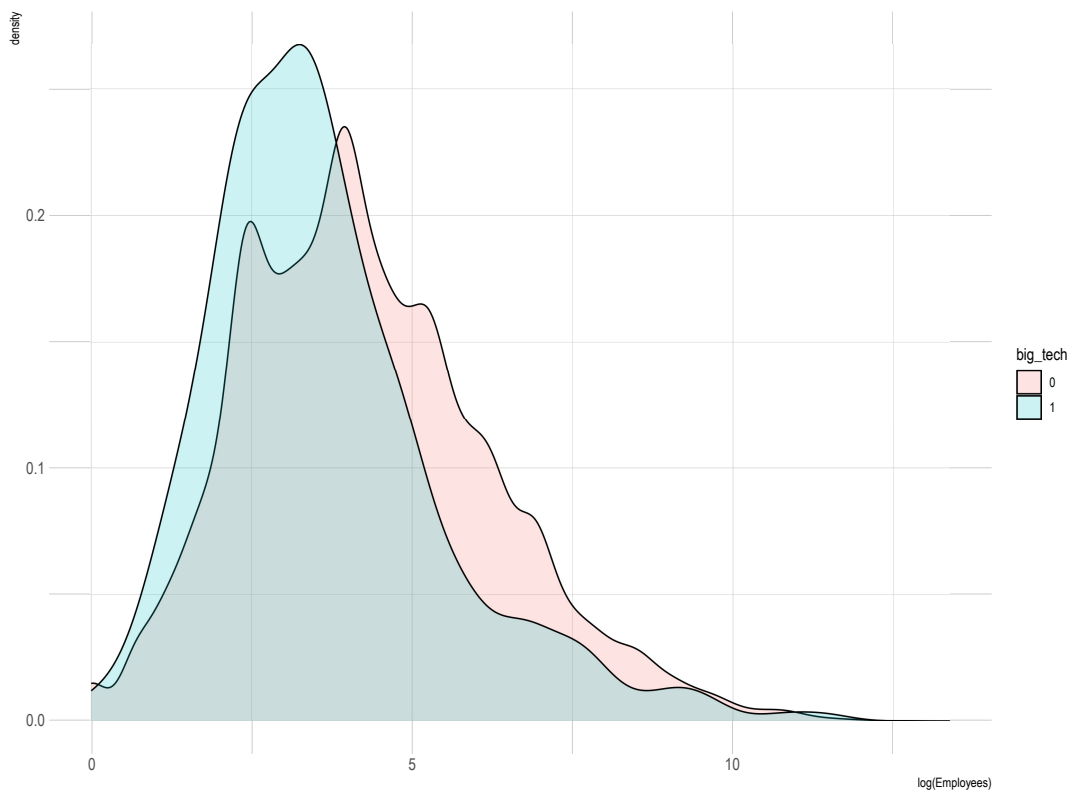
Note: The figure illustrates the comparison of the deal size in the acquisition made by the GAMMA firms and non-GAMMA firms.

Figure A.7. Target Age



*Note:* The figure illustrates the distribution of the target age acquired by the GAMMA firms and non-GAMMA firms. GAMMA firms tend to acquire younger targets.

Figure A.8. Number of Employees



*Note:* The figure illustrates the distribution of the the number of employees at the target company acquired by the GAMMA firms and non-GAMMA firms. GAMMA firms tend to acquire smaller firms.

Figure A.9. Probabilities of Entry  
(high-interest rate, no previous entries from any of the firms for the last one year)

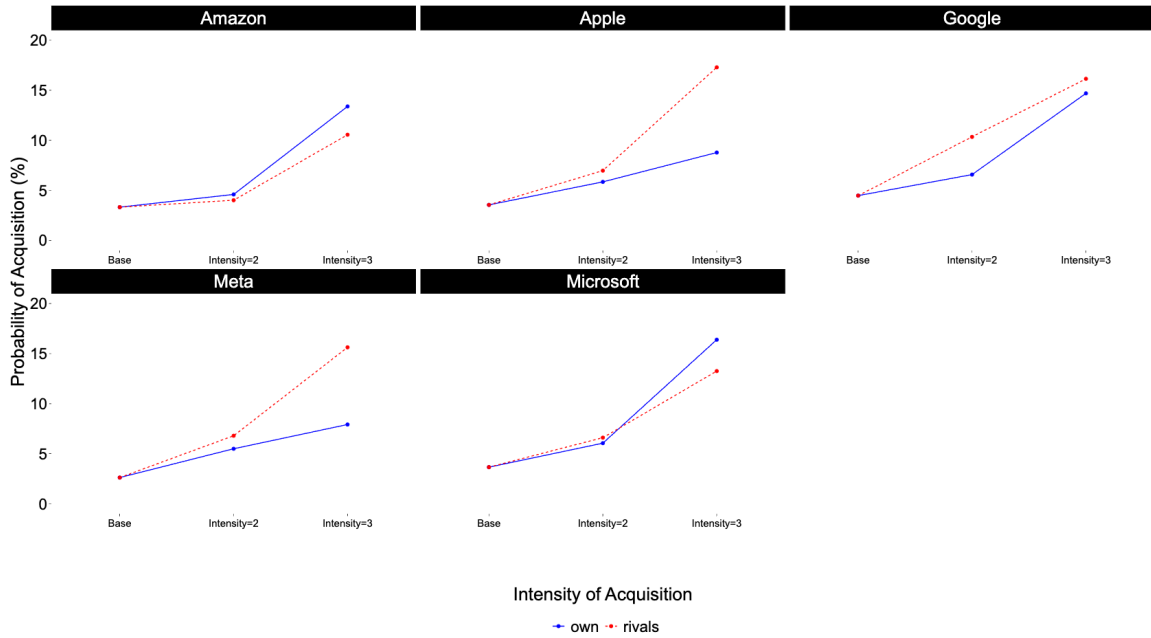
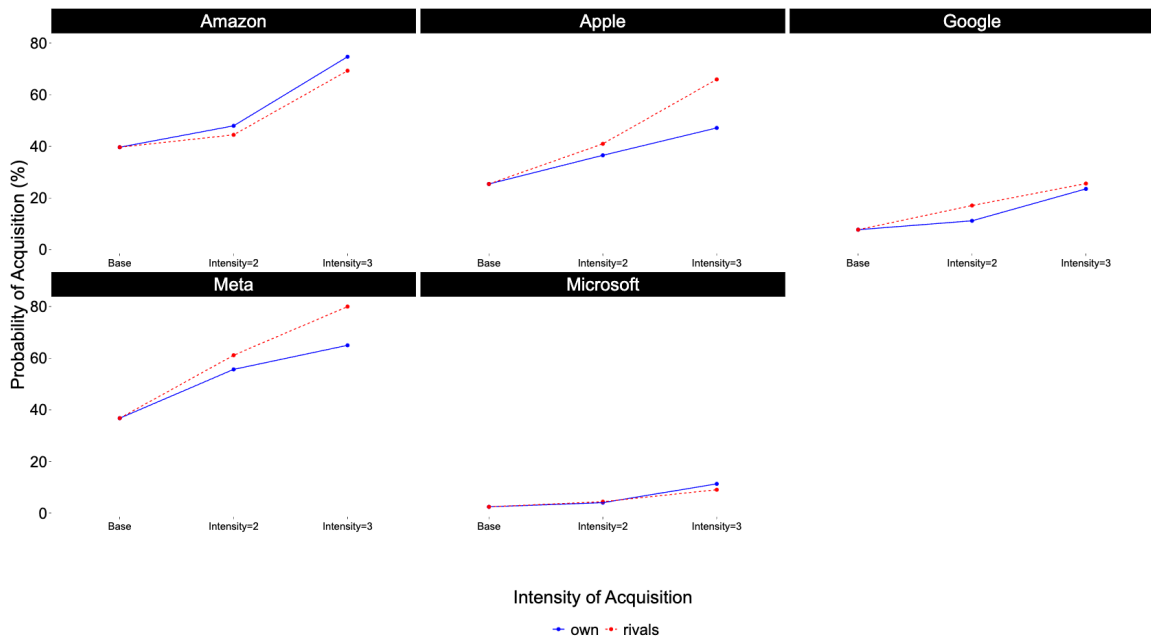
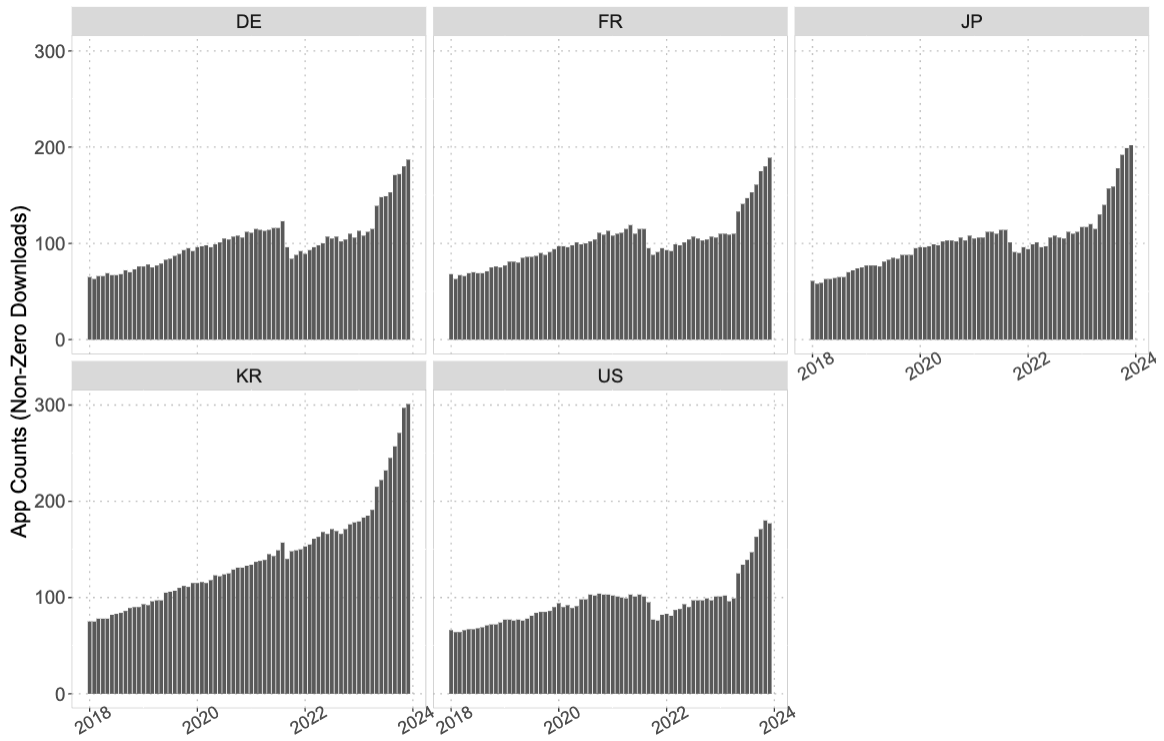


Figure A.10. Probabilities of Entry  
(low-interest rate, no previous entries from any of the firms for the last one year)



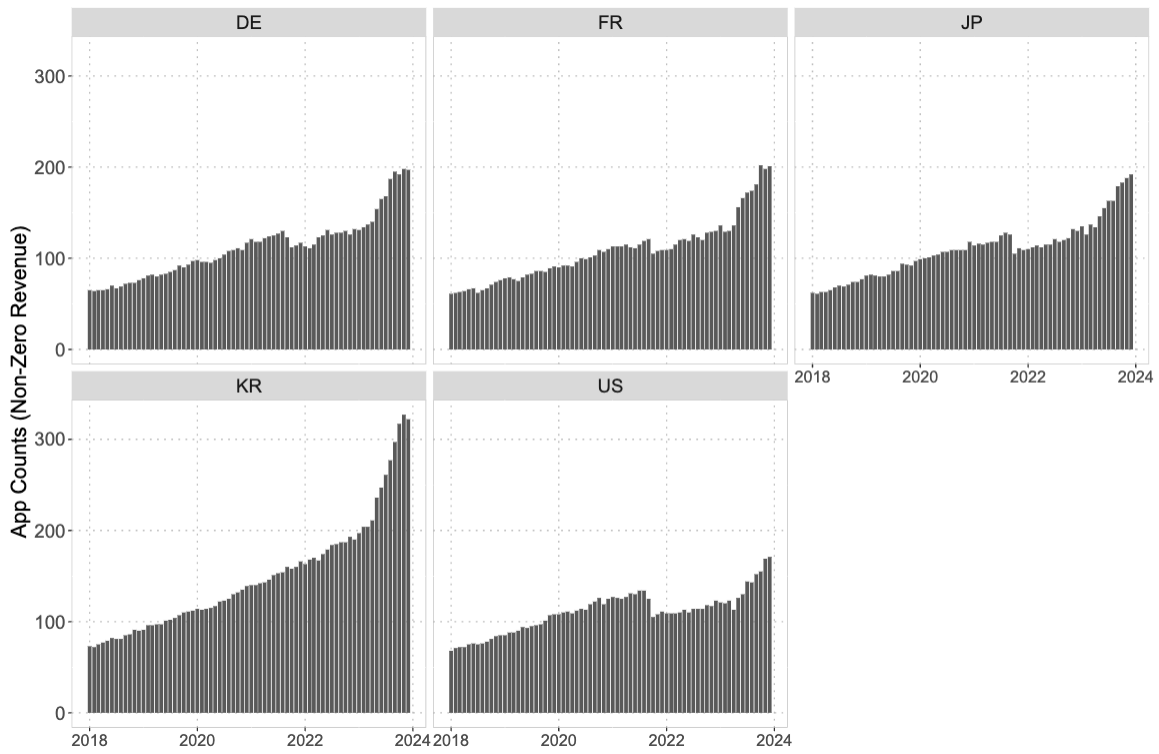
APPENDIX B  
CHAPTER 3 APPENDIX

Figure B.1. App Counts by Country (Apps With Non-zero Installs)



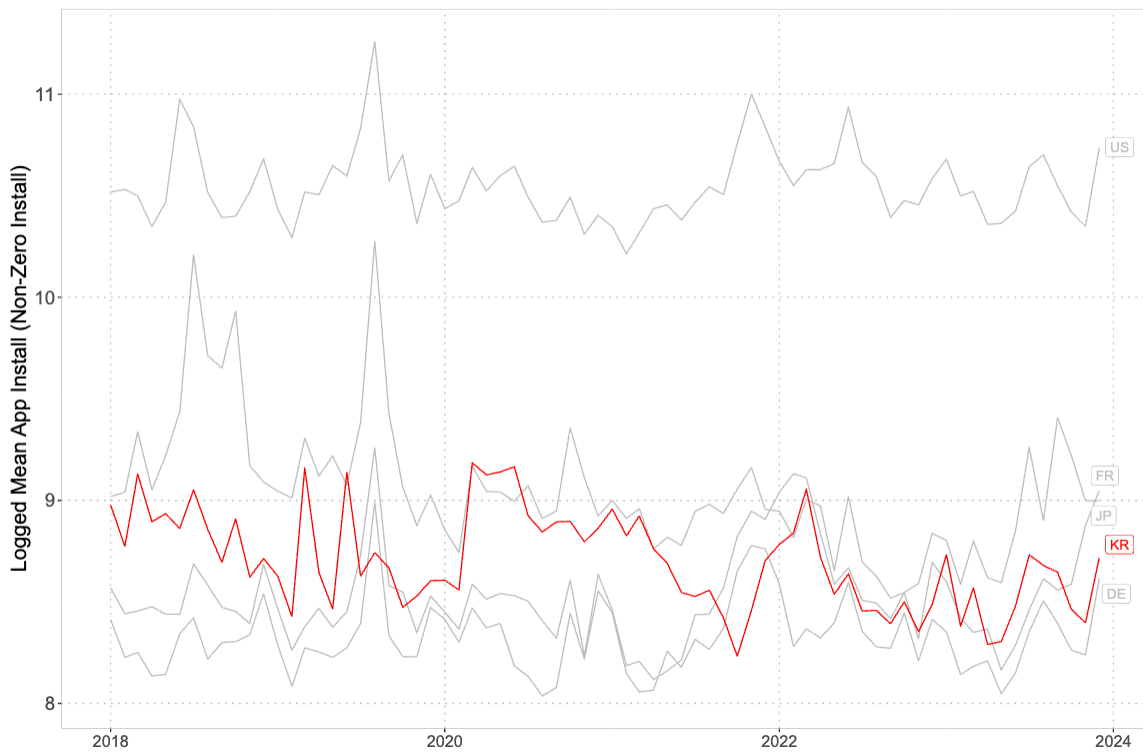
Notes: This figure illustrates the number of apps used for analysis on a monthly-basis across countries. Each month, apps with zero download were dropped from the count. These apps with non-zero install were used for app install analysis.

Figure B.2. App Counts by Country (Apps With Non-zero Revenue)



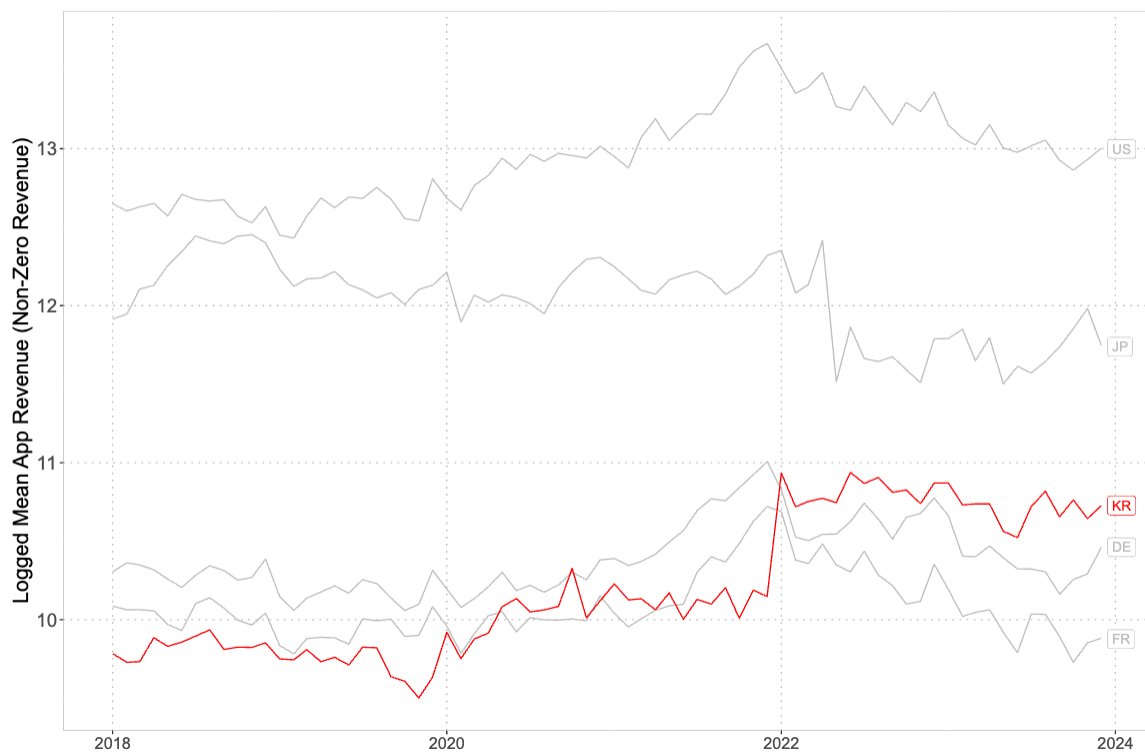
Notes: This figure illustrates the number of apps used for analysis on a monthly-basis across countries. Each month, apps with zero revenue were dropped from the count. These apps with non-zero revenue were used for app revenue analysis.

Figure B.3. Average Monthly App Installs by Country



Notes: This figure shows the varying trends in the logged mean of monthly app install for each country.

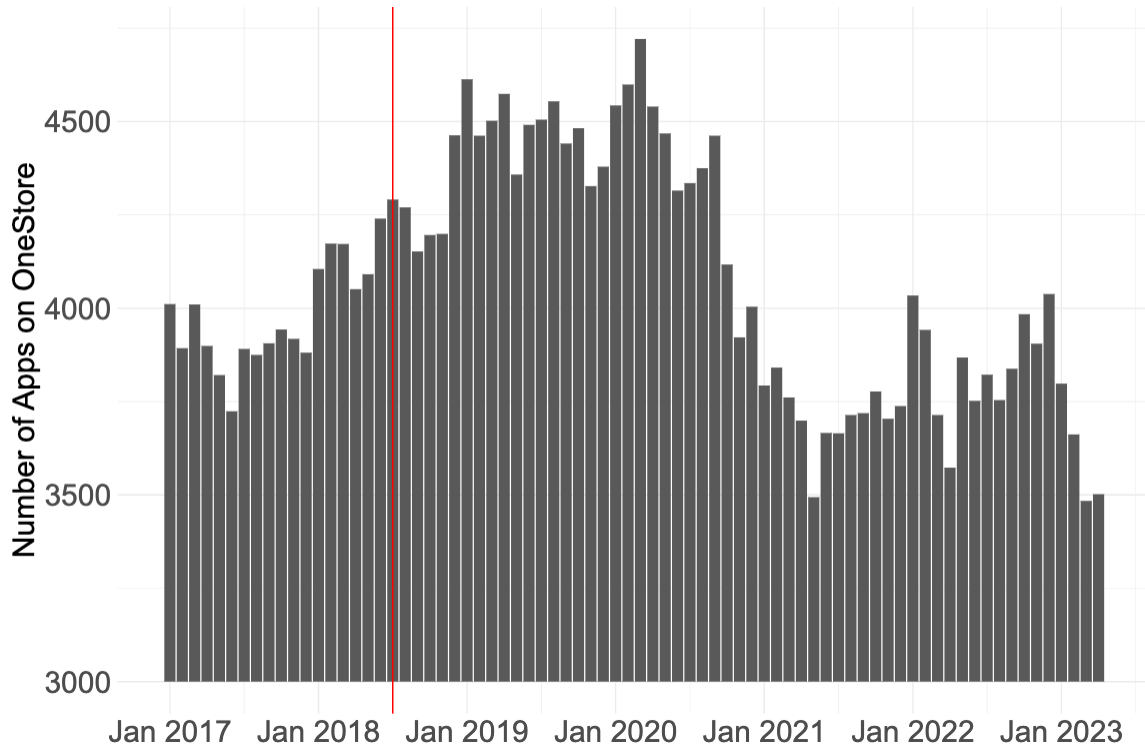
Figure B.4. Average Monthly App Revenue by Country



Notes: This figure shows the varying trends in the logged mean of monthly app revenue for each country.

APPENDIX C  
CHAPTER 4 APPENDIX

Figure C.1. Game Apps with New Installs on OneStore



Notes: The figure shows the number of game apps on ONE store with new installs on a monthly-basis across time. The vertical red line indicates the time of policy change.

## REFERENCES CITED

- Allyn, B. (2021, September 10). What the ruling in the Epic Games v. Apple lawsuit means for iPhone users. *NPR.org*. Retrieved from <https://www.npr.org/2021/09/10/1036043886/apple-fortnite-epic-games-ruling-explained>
- Amelio, A., & Jullien, B. (2012, 9). Tying and freebies in two-sided markets. *International Journal of Industrial Organization*, 30, 436-446. doi: 10.1016/J.IJINDORG.2012.03.002
- Apple.com. (n.d.-a). *Apple announces changes to ios, safari, and the app store in the european union*. (Retrieved June 3, 2024, from <https://www.apple.com/newsroom/2024/01/apple-announces-changes-to-ios-safari-and-the-app-store-in-the-european-union/>)
- Apple.com. (n.d.-b). *Distributing apps in the u.s. that provide an external purchase link*. (Retrieved June 3, 2024, from <https://developer.apple.com/support/storekit-external-entitlement-us>)
- Apple.com. (n.d.-c). *European digital markets act (dma)*. (Retrieved June 3, 2024, from <https://www.apple.com/legal/dma/>)
- Argentesi, E., Buccirosi, P., Calvano, E., Duso, T., Marrazzo, A., & Nava, S. (2021, 3). Merger policy in digital markets: An ex post assessment. *Journal of Competition Law & Economics*, 17, 95-140. Retrieved from <https://dx.doi.org/10.1093/joclec/nhaa020> doi: 10.1093/JOCLEC/NHAA020
- Armstrong, M. (2006). Competition in two-sided markets. *The RAND journal of economics*, 37(3), 668–691.
- Bajari, P., Benkard, C. L., & Levin, J. (2007). Estimating dynamic models of imperfect competition. *Econometrica*, 75, 1331-1370.
- Barwick, P. J., & Pathak, P. A. (2015, 3). The costs of free entry: an empirical study of real estate agents in greater boston. *The RAND Journal of Economics*, 46, 103-145. Retrieved from <https://onlinelibrary.wiley.com/doi/full/10.1111/1756-2171.12082>
- Bostoen, F., & Mândrescu, D. (2020). Assessing abuse of dominance in the platform economy: a case study of app stores. *European Competition Journal*, 16(2-3), 431–491.

- Bryan, K. A., & Hovenkamp, E. (2020). Antitrust limits on startup acquisitions. *Review of Industrial Organization*, 56, 615–636.
- Cabral, L. (2021, 3). Merger policy in digital industries. *Information Economics and Policy*, 54, 100866.
- Caillaud, B., & Jullien, B. (2001). Chicken and egg: Competing matchmakers. *Available at SSRN 278562*.
- Carlton, D. W., & Waldman, M. (2002). The strategic use of tying to preserve and create market power in evolving industries. *The RAND Journal of Economics*, 33, 194-220. doi: 10.2307/3087430
- Cha, J.-H., & Park, J.-K. (2023). *Korean app market one store to raise \$151 mn for kiwoom's exit*. (Retrieved June 3, 2024, from <https://www.kedglobal.com/private-debt/newsView/ked202305080021>)
- Choi, J. P., & Jeon, D. S. (2021a). A leverage theory of tying in two-sided markets with nonnegative price constraints. *American Economic Journal: Microeconomics*, 13, 283-337. doi: 10.1257/mic.20180234
- Choi, J. P., & Jeon, D.-S. (2021b). A leverage theory of tying in two-sided markets with nonnegative price constraints. *American Economic Journal: Microeconomics*, 13(1), 283–337.
- Choi, J. P., & Stefanadis, C. (2001). Tying, investment, and the dynamic leverage theory. *The RAND Journal of Economics*, 32, 52-71. doi: 10.2307/2696397
- Cunningham, C., Ederer, F., & Ma, S. (2021, 3). Killer acquisitions. *Journal of Political Economy*, 129, 649-702.
- Derdenger, T. (2014, 4). Technological tying and the intensity of price competition: An empirical analysis of the video game industry. *Quantitative Marketing and Economics*, 12, 127-165. Retrieved from <https://link.springer.com/article/10.1007/s11129-014-9143-9> doi: 10.1007/S11129-014-9143-9/TABLES/13
- Desyllas, P., & Hughes, A. (2008, 1). Sourcing technological knowledge through corporate acquisition: Evidence from an international sample of high technology firms. *The Journal of High Technology Management Research*, 18, 157-172. doi: 10.1016/J.HITECH.2007.12.003
- Eisenmann, T., Parker, G., Van Alstyne, M. W., et al. (2006). Strategies for two-sided markets. *Harvard business review*, 84(10), 92.
- Ericson, R., & Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *The Review of economic studies*, 62(1), 53–82.

- Etro, F. (2023). Platform competition with free entry of sellers. *International Journal of Industrial Organization*, 89, 102903.
- Etro, F., & Caffarra, C. (2017). On the economics of the android case. *European Competition Journal*, 13(2-3), 282–313.
- Faulí-Oller, R., Sandonís, J., et al. (2018). Horizontal mergers in oligopoly. *Handbook of Game Theory and Industrial Organization, Volume II: Applications*, 2, 7.
- Garcia-Swartz, D. D., & Garcia-Vicente, F. (2015). Network effects on the iphone platform: An empirical examination. *Telecommunications Policy*, 39(10), 877–895.
- Gautier, A., & Lamesch, J. (2021, 3). Mergers in the digital economy. *Information Economics and Policy*, 54, 100890. doi: 10.1016/J.INFOECOPOL.2020.100890
- Geradin, D., & Katsifis, D. (2021). The antitrust case against the apple app store. *Journal of Competition Law & Economics*, 17(3), 503–585.
- Gowrisankaran, G. (1999, 21). A dynamic model of endogenous horizontal mergers. *The RAND Journal of Economics*, 30, 56. doi: 10.2307/2556046
- Granstrand, O., Håkanson, L., & Sjölander, S. (1993, 11). Internationalization of r&d — a survey of some recent research. *Research Policy*, 22, 413-430. doi: 10.1016/0048-7333(93)90010-F
- Holmes, T. J. (2011). The diffusion of wal-mart and economies of density. *Econometrica*, 79(1), 253–302.
- Hwang, S., & Kim, S. (2022). Google’s app store policy change and the responses elicited from mobile content firms: A case study on korea’s app store ecosystem. *Telematics and Informatics*, 72, 101855. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0736585322000880> doi: <https://doi.org/10.1016/j.tele.2022.101855>
- Igami, M., & Yang, N. (2016, 7). Unobserved heterogeneity in dynamic games: Cannibalization and preemptive entry of hamburger chains in canada. *Quantitative Economics*, 7, 483-521. Retrieved from <https://onlinelibrary.wiley.com/doi/full/10.3982/QE478> doi: 10.3982/QE478
- Jin, G. Z., Leccese, M., & Wagman, L. (2023). How do top acquirers compare in technology mergers? new evidence from an sp taxonomy. *International Journal of Industrial Organization*, 89, 102891.
- Kamepalli, S. K., Rajan, R., & Zingales, L. (2020). *Kill zone* (Tech. Rep.). National Bureau of Economic Research.

- Katz, M. L. (2021, 3). Big tech mergers: Innovation, competition for the market, and the acquisition of emerging competitors. *Information Economics and Policy*, 54.
- Letina, I., Schmutzler, A., & Seibel, R. (2021). Killer acquisitions and beyond: policy effects on innovation strategies. *University of Zurich, Department of Economics, Working Paper*(358).
- Marra, M. (2020). *Estimating an auction platform game with two-sided entry*. Retrieved from <https://www.precedenceresearch.com/peer-to-peer-lending-market>,
- Mermelstein, B., Nocke, V., Satterthwaite, M. A., & Whinston, M. D. (2020). Internal versus external growth in industries with scale economies: A computational model of optimal merger policy. *Journal of Political Economy*, 128(1), 301–341.
- Motta, M., & Peitz, M. (2021, 3). Big tech mergers. *Information Economics and Policy*, 54, 100868.
- Mueller, M. (1997). *Universal service: Competition, interconnection and monopoly in the making of the american telephone system*. American Enterprise Institute.
- Norbäck, P. J., & Persson, L. (2009, 12). The organization of the innovation industry: Entrepreneurs, venture capitalists, and oligopolists. *Journal of the European Economic Association*, 7, 1261-1290. Retrieved from <https://dx.doi.org/10.1162/JEEA.2009.7.6.1261> doi: 10.1162/JEEA.2009.7.6.1261
- Prat, A., & Valletti, T. (2022). Attention oligopoly. *American Economic Journal: Microeconomics*, 14(3), 530–557.
- Rasmusen, E. (1988). Entry for buyout. *The Journal of Industrial Economics*, 281–299.
- Rochet, J.-C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, 1, 990-1029. Retrieved from <https://academic.oup.com/jeea/article/1/4/990/2280902> doi: 10.1162/154247603322493212
- Ruckman, K. (2005, 1). Technology sourcing through acquisitions: Evidence from the us drug industry. *Journal of International Business Studies*, 36, 89-103. Retrieved from <https://link.springer.com/article/10.1057/palgrave.jibs.8400110> doi: 10.1057/PALGRAVE.JIBS.8400110/TABLES/9
- Ryan, S. P. (2012, 5). The costs of environmental regulation in a concentrated industry. *Econometrica*, 80, 1019-1061.
- Singh, A., Hosanagar, K., & Nevo, A. (2021). Network externalities and cross-platform app development in mobile platforms. *Available at SSRN*, 3911638.

- Statista.com. (2021). *Leading markets worldwide based on mobile spending per capita from 1st quarter 2021 to 3rd quarter 2021 (in u.s. dollars)*. (Retrieved June 3, 2024, from <https://www.statista.com/statistics/1275323/top-countries-mobile-per-capita-spending-worldwide/>)
- Stigler, G. J. (1950). Monopoly and oligopoly by merger. *The American Economic Review*, 40, 23-34.
- Suzuki, J. (2013). Land use regulation as a barrier to entry: Evidence from the texas lodging industry. *International Economic Review*, 54.
- Tang, H., Fang, S., & Jiang, D. (2022). The market value effect of digital mergers and acquisitions: Evidence from china. *Economic Modelling*, 116, 106006.
- Teece, D. J. (2023). Big tech and strategic management: How management scholars can inform competition policy. *Academy of Management Perspectives*, 37(1), 1–15.
- Whinston, M. D. (1990). Tying, foreclosure, and exclusion on jstor. *The American Economic Review*, 80, 837-859. Retrieved from <https://www.jstor.org/stable/2006711>
- Zingales, L., Kamepalli, S. K., & Rajan, R. G. (2020). *Kill zone*.