Characterizing Big Tech's Competitive Acquisition Behavior: Strategic Convergence and Strategic Persistence

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Abstract

In the rapidly evolving digital landscape, where businesses are interconnected and market boundaries are increasingly blurred, Big Tech companies face complex competition dynamics. With more digital markets dominated by either two or more of these companies, it is important to understand whether their decisions are affected by the other and, if so, how much. What are the dynamics between them that result in their strategic decisions? Addressing these questions can help define the relevant market, which has been a particularly important issue in strategy and competition economics literature. This paper examines the acquisition records of the "big five" – Google, Amazon, Microsoft, Meta and Apple – between 2004 and 2021. We identify two distinct behavioral patterns, which we call strategic persistence (extension of their past strategic decision) and strategic convergence (conforming their decision with the other four). Using an acquisition game model that accounts for the dynamic interplay among these companies, we show varying degrees of firm convergent and persistent behaviors. This finding highlights two interconnected insights: first, each individual Big Tech company pursues a unique strategic positioning; second, the converging tendency shown across these companies underscores the intense competitive pressures they face as close rivals.

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1 Introduction

In the digital landscape, companies often turn to acquisitions as a key growth strategy. Big Tech companies have long used this approach, making it an important feature of their market dynamics (Gautier and Lamesch, 2021; Katz, 2021; Motta and Peitz, 2021; Parker et al., 2021). It has been shown that these types of digital ecosystems exhibit oligopolistic characteristics due to "massive network effects" and "market linkages within ecosystems", where a small group of dominant players compete for user attention (Calvano and Polo, 2021; Bourreau and de Streel, 2020; Katz, 2021). In fact, many scholars have worked to identify anticompetitive behaviors of the dominant companies (Cunningham et al., 2021; Motta and Peitz, 2021; Katz, 2021). While assessing consumer harm and regulating them remain important goals, a more pressing question arises: How do leading tech companies position themselves within a market characterized by a few dominant players and what is the scope of the markets that we should examine to illuminate their competitive dynamics?

In alignment with previous literature (Barsy and Gautier, 2024; Teece, 2023; Arend, 2023; Prado and Bauer, 2022; Cozzolino et al., 2021; Motta and Peitz, 2021; Katz, 2021; Birch et al., 2021; Jacobides, 2020; Teece, 2023; Arend, 2023), we examine GAMMA firms, the big five (hereinafter referred to as "Big Tech") – Google, Amazon, Meta, Microsoft, and Apple – that are 'large technology conglomerates with extensive customer networks and core businesses in social media, telecommunications, Internet search, and e-commerce Bódi et al. (2023). We argue that they are direct competitors to each other, influencing each other's strategic decisions. As will be demonstrated in Section 3, they compete intensively across various digital sectors. They also possess the financial resources, market power, and technological capabilities necessary to respond effectively to the other Big Tech companies' strategic moves.

In just over two years, from 2015 to 2017, Google, Amazon, Microsoft, Meta, and Apple collectively acquired 175 companies (Gautier and Lamesch, 2021). Such acquisitions can help build the capabilities of these companies, allowing them to add product lines or access key data and/or technologies. However, high profile acquisitions and the high number of acquisitions made by such a small number of major technology companies has attracted much attention from antitrust authorities about the potential impact that it can bring to the market, including its negative impact on competition and innovation (Cunningham et al., 2021; Motta and Peitz, 2021; Katz, 2021). This has raised the need for regulatory authorities and scholars to examine the merger behaviors ofBig Tech specifically to determine how and on what basis their market power and anti-competitive behavior should be measured (Katz, 2021; Motta and Peitz, 2021).

Traditionally, competition economics has focused on identifying the "relevant market" and examining market concentration to determine the level of market dominance of a firm. However, many studies demonstrate the difficulties in identifying relevant markets in digital sectors, as market boundaries become increasingly blurred (Jacobides and Lianos, 2021). Some further argue the need to first understand the nature of platform competition and integrate strategic management perspectives into the policy frameworks to complement those limitations (Petit and Teece, 2021). Notably, Teece (2023) points out "ecosystem-to-ecosystem" competition amongst the platform companies that lies across vertical and horizontal markets and argues that the dynamically evolving nature of their acquisition strategies should be accounted for to assess their anti-competitive behavior and formulate corresponding policies/regulations. Others like Arend (2023) are skeptical of this characterization based in large part on the fact that no empirical evidence to date has demonstrated the dynamic nature of platform companies. Therefore, in order to empirically examine the acquisition behavior of these firms, we identify and model their dynamic competitive behaviors.

What are the characteristics of the way Big Tech companies compete? Big Tech competition, as platform-based competition spanning multiple markets and sectors encompassing a range of products and services, cannot be captured by a traditional view of competition based on a single product market, which ignores the"interconnectedness" and "interdependence" of digital markets (Cennamo, 2021) – consider Amazon

Marketplace, which began as an online retailer but has since evolved into a hub for diverse offerings, including video streaming services like Prime Video. Digital markets include e-commerce, e-marketplace, mobile app store, social media service, information search service, digital content distribution, cloud computing service, big data analytics, digital advertisements, and AI services. In these markets, the Big Tech companies have established themselves as dominant players, leveraging their platform capabilities to drive growth and innovation. For example, Google operates cloud computing (Google Cloud), mapping solutions (Google Maps), video-sharing platform (YouTube), and a mobile app distribution platform (Google Play Store). Similarly, Amazon has built a platform that offers its e-commerce marketplace, cloud computing, and web hosting services (Amazon Web Services). Although not all services the Big Tech companies provide are platform-based, their platforms serve as a core infrastructure to expand their market presence.

How do their competition dynamics differ from traditional market competition? Competition in digital markets often involves strategic interactions across multiple stakeholder groups, driven by the creation and capture of multi-sided network externalities (Rietveld and Schilling, 2021). Platforms, characterized as 'inverted firms', create a large share of their value outside the firm rather than inside the firm (Parker et al., 2017). As a platform connecting two or more sides of a network (multi-sided), the thickness (density) of each side becomes a key driver of creating network externalities and intensifying user 'lock-in'. For example, a user would prefer Google Play over competing Android app stores for its substantial offering of apps (sellers) and large user base (which affects the credibility of the rating of an app). Furthermore, the platform can easily expand into adjacent markets to attract the same set or even a larger set of participants. A platform with rich data from both suppliers and consumers on its network can easily offer a range of different products or services with improved targeting, marketing, and optimized services. As such, the platform's objective has been to capitalize on its multi-sided network externalities through creating thick markets.

Another feature of platform competition is the formation of the platform ecosystem (Rietveld and Schilling, 2021; Jacobides et al., 2018). Platforms carefully seek and choose participants of the platform ecosystem to create value within that ecosystem. These participants can be software developers on the app store, hardware vendors (chip, device, data center, utilities) of cloud services, and content providers of video streaming services. Therefore, it becomes a critical strategic decision to determine whether to open or close their ecosystem, define the boundaries of the ecosystem, establish a compelling value proposition, and develop an effective governance framework that accommodates diverse stakeholders (Adner, 2017).

Big Tech competition, therefore, is platform-based ecosystem-to-ecosystem competition. The rivalry goes beyond a single product market competition, as their value chain and profit are derived from the close orchestration of different components that make up the ecosystem, which often lies between multiple vertical and horizontal markets (Parker et al., 2021). In essence, the Big Tech companies compete with each other through their expansive product portfolios (multi-product) and partnerships (multi-actor alliance) that can maximize their value creation (Jacobides, 2022). Their partnerships may also involve traditional incumbent producers, a mix of competitive and collaborative dynamics in vertical relationships (Cozzolino et al., 2021). In this view, Jacobides (2022)'s Big Tech multi-product and multi-actor ecosystem encompasses offline manufacturing firms, marketing firms, and firms providing delivery service. As each Big Tech company pursues its own ecosystem, the key strategic decision in acquisition activities lies in finding the multi-market horizontal and vertical scopes that maximize the overall performance of the ecosystem. This iteration of optimizing acquisition strategy can be viewed as a dynamic capability learning process, where the Big Tech companies continually update their business portfolios in response to changing market environments and the acquisition behaviors of their rivals.

This paper aims to address the following questions: (1) What drives the acquisition of the Big Tech companies?, (2) how do they interact with each other in acquisition activities, and how can we characterize their acquisition behavior?, and (3) what kind of systematic pattern emerges from those interactions in the

Big Tech ecosystem as a whole? In this paper, we build on the existing platform competition literature to answer these questions. In particular, we focus on the strategic interplay of the major platform companies to find how each firm positions themselves strategically to navigate competition within the group. In addition, we examine the degree to which they exhibit the strategic behaviors of imitation and adaptation, which may indicate a greater intensity of competition within the Big Tech companies over a wider range of markets.

The remainder of this paper is organized as follows. Section 2 reviews the literature on Big Tech's acquisition motives and presents key research propositions. Section 3 describes Big Tech's acquisition behaviors as a multi-market diffusion process and provides descriptive evidence of multi-market convergence. Section 4 formulates the acquisition behaviors as a dynamic acquisition game, and Section 5 specifies the estimation procedure of model parameters. Section 6 provides empirical findings and tests the research propositions presented in Section 2. Finally, Section 7 concludes with strategic implications of the main finding and future research areas.

2 Theoretical Foundation

2.1 Literature Review

Extensive research across different disciplines has explored acquisition motives. Some primary acquisition motives of platform companies have been to (1) scale and enforce their presence in the existing market (technology synergies, operational efficiency) (Granstrand et al., 1993; Ruckman, 2005; Desyllas and Hughes, 2008; Faulí-Oller et al., 2018; Mermelstein et al., 2020), (2) expand into adjacent horizontal markets (economies of scope argument) (Gautier and Lamesch, 2021; Mueller, 1997; Teece, 2023), (3) acqui-hire (acquire to access specialized workers), or (4) preempt by killer acquisition (Motta and Peitz, 2021; Zingales et al., 2020). Apart from preemptive acquisitions specifically targeted at eliminating potential rivals through post-buyout discontinuation, the existing literature converges on a broader strategic motive: securing critical resources for platform business development (Argentesi et al., 2021; Gautier and Lamesch, 2021). These resources can be technological capabilities, data assets, supply chain networks, logistics infrastructure, financial capital, and human talent. The implications of acquisition then extend to wider market outcomes, including their effects on market concentration (Stigler, 1950), competitive efficiency, and intensity of innovation (Bryan and Hovenkamp, 2020; Katz, 2021; Norbäck and Persson, 2009).

From a resource-based view, Big Tech's acquisition practices are driven by securing resources to develop sustainable competitive advantages. The key target resource includes technologies associated with the platform, big data on users and ecosystem participants, big data analytics, and the deep learning algorithm for mass customization and targeted marketing (Birch et al., 2021). User data can be another key resource. Big Tech companies generate value by capitalizing the data and transforming it into business assets. This can be improvement of existing products/services or even discovering new business opportunities. Acquisition gives them a means of procuring separate (distinct) user data which they can combine with their existing data resource to create value and synergies (economies of data integration) (Birch et al., 2021). Although each Big Tech company may have a different acquisition portfolio, they share the same objective of retaining and strengthening user engagement and their access to users.

Dynamic capabilities, a firm's "ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997), can be internally developed or externally acquired. Firm capabilities that can dynamically adapt may hold a significant advantage in a high-tech hyper competitive environment. The success of an enterprise in this environment is less about optimizing production on a given set of constraints but rather more dependent on a firm's capabilities in "discovering and developing opportunities" and reconfiguring their ecosystem around externally and internally found innovation (Teece, 2007; Eisenhardt and Martin, 2000). With the rapidly evolving nature of technology sectors, resource acquisition has been a popular means of adapting and developing dynamic capabilities. Strauss and Yang (2024) analyzed 995 acquisitions and 127,226 patents owned by Big Tech between 2000 and 2022 and found a strong correlation between market entry and acquisition of capabilities. Finding acquisition central in developing technological capabilities especially after 2000, the Big Tech firms have acquired assets that are complementary to their existing technologies or that are completely new technological fields. One prominent example is Google's acquisition of DeepMind. The integration of DeepMind's algorithm with Google's vast data assets has not only enabled the firm to develop specialized AI across multiple sectors, but has also allowed it to scalably expand into markets that were previously untapped like healthcare and robotics without significant market barriers (Chivers, 2021).

One of the key characteristics of Big Tech acquisitions is their massive scale. On the one hand, Big Tech's prolific acquisition activity can be seen as a response to their significant investment in research and development (R&D). Acquisition can surge as these companies either shortcut the internal R&D process by acquiring established technologies or innovations (acquisition and development, A&D). Alternatively, the output of R&D (new technologies) may require the acquisition of complementary technologies or business applications. The frequent acquisitions can also be due to the unique characteristics of resources in digital platform-based firms. The "hyper-specialization" (narrow in domain) and "hyper-scaling" (easily scalable) characteristics of the resource bundles can lead them to obtain new resources and capabilities through acquisition and capture new business opportunities (Giustiziero et al., 2023).

Another reason for massive acquisition lies in the *volatility* of acquisition effects as the effects of acquisition do not last long. This can be attributed to several factors, including the hypercompetitive nature of the market and the short time span of technological cycles. Even after successfully acquiring competitive advantage, the intense competition amongst the Big Tech firms makes sustaining competitive advantage increasingly more challenging. As a result, the sustainability of competitive advantage is less about relying on a singular competitive advantage maintained throughout time but more of a concatenation of a series of multiple competitive advantages that change over time (Wiggins and Ruefli, 2005; D'Aveni et al., 2010). In addition, the short-cycle of technology displacement amplifies the volatility. Barsy and Gautier (2024) find innovation effect of technology transfer lasting only 1.5 years. Functional, organizational, and strategic alignment between acquiring and acquired firms during the integration process can also influence the lasting effects of acquisition (Cloodt et al., 2006).

To respond to this volatile environment, Helfat and Raubitschek (2018) argue that"environmental scanning and sensing capabilities" and "integrative capabilities for ecosystem orchestration" are the key dynamic capabilities to lead a digital platform-based ecosystem. When it comes to acquisition, Čirjevskis (2019) highlighs that the key capabilities evolve over time: starting as "sensing and shaping" in the pre-acquisition phase, they shift to "identifying and seizing" during the acquisition stage, and further transition to "transforming and reconfiguring" in the post-acquisition phase. When "sensing and shaping" become important capabilities, how do companies "sense" market opportunities? We posit that there are two primary signals that the Big Tech companies pick up on to determine their next acquisition moves: 1) analyzing past behavior and 2) by observing the actions of their direct competitors. Their past behavior can influence their actions for the current period, as it is highly likely that they have already experimented with the benefits and costs of such purchase decisions. If their decision was successful, the past behavior may be reinforced in the current period; if the opposite is true, their past behavior may not continue in the current period. Regardless, the most straightforward approach for a company is to rely on its past strategy to guide its future strategic decision (Schmid, 2019; Haskamp et al., 2021): either sticking with what has worked in the past or adjusting course to accommodate changing circumstances.

Table 1: Selective Competing Domains of the Big Tech Companies

	Google	Amazon	Apple	Microsoft	Meta
Cloud Computing	✗	✗		✗	✗
Streaming Video Service	✗	✗	✗		✗
Online Advertising	✗	✗			✗
Social Networking Service	✗				✗
Digital Assistant	✗	✗	✗		
E-commerce	✗	✗			✗
Mobile Operating Systems	✗		✗		
Operating Systems	✗		✗	✗	
Personal Computing	✗		✗	✗	
App Store	✗	✗	✗		
Productivity Suite	✗			✗	
Mapping and Navigation	✗		✗		
Augmented Reality			✗	✗	✗

Notes: This table shows each Big Tech company's representative operating business domains. A closer examination shows that many of these 13 domains are shared by two or more Big Tech companies, highlighting their competitive overlap. In a broader tech landscape, Big Tech companies have become mutually direct competitors.

In dynamic markets, competitor behavior can also serve as a crucial signal (Deng et al., 2024). This tendency may be particularly salient if the environmental uncertainties are high (Lieberman and Asaba, 2006), i.e., the likelihood of commercializing target technologies is low (technical difficulties embedded in commercialization), the technology is not yet fully comprehended, if it is hard to determine the compatibility of the technology with its businesses, or if it is hard to determine in advance the exact valuation of the technologies. In such a scenario, firms may engage in frequency-based imitation (Haunschild and Miner, 1997; Ozmel et al., 2017). Table 1 may suggest how the Big Tech companies might have reacted to the signals coming from their rivals; they have encroached each other's domains. This provides an early indication that warrants further investigation. This signaling mechanism can evolve into an iterative process of competitive moves: firms respond to the actions of their competitors, which then provoke counteractions from those same competitors, creating a continuous cycle of strategic moves and countermoves. This iterative process is well-established in the strategic management literature as competitive dynamics (Chen and Miller, 2012; Giachetti and Dagnino, 2021; Rosário and Raimundo, 2024).

The same strategic behavior has also been extensively studied in dynamic game theory. This phenomenon is particularly pronounced in the oligopolistic market, a dominant market structure of digital economies, where a limited number of market leaders closely monitor and respond to the strategic actions of their competitors. The interdependence among these firms means that changes in market conditions, such as new technologies or shifts in financial market conditions, can trigger reciprocal responses from other companies, creating a continuous loop of competition and adaptations.

2.2 Research Propositions

In the midst of rapid technological evolution, where short-lived technologies are quickly replaced by new ones, the Big Tech firms are constantly put in the position of having to make the *right strategic decision to secure the innovative technology.* In this environment, companies that fail to remain responsive to the shifting landscape may miss out substantial benefits and even not be able to sustain. The Big Tech firms in a leadership position may be eager to expand their markets by aggressively acquiring new and adjacent start-ups, while those in a follower position may simply imitate or catch-up those acquisitions to sustain their relative market positions. In what follows, we suggest several research propositions that characterize the evolutionary dynamics of a Big Tech ecosystem as a whole and that specify the strategic interactions between individual companies in their acquisition activities.

Proposition 1. (Multi-market Multi-sector Diffusion) Big Tech's acquisition behavior exhibits collectively a multi-market multi-sector diffusion process and converging competing markets.

All Big Tech companies had distinct core or major business domains at their inception. Microsoft provided operating systems, Apple was a computer manufacturer, Amazon was an online bookstore, Meta provided social network services, and Google provided search engine services. As these companies grew, acquisition enabled each of their business scopes to scale rapidly and expand both vertically and horizontally, exhibiting a multi-market/multi-sector diffusion process. For example, while Google offers a search engine, it also offers other digital services, including an app store, cloud services, and video streaming/social networking services (YouTube). If each firm diffuses across multiple markets, does the collective total number of sectors occupied by Big Tech diverge or converge? Does the total number of sectors in which Big Tech acquired targets grow exponentially (diverge) or does the number remain constant (converge)? If they converge, the Big Tech firms are likely to be present in more common markets, which may yield higher intensity of competition among the Big Tech companies.

Proposition 2. (Strategic Convergence) Big Tech acquisition demonstrates strategic convergence.

As these Big Tech companies enter a growing number of common markets, their acquisition behavior may mimic that of their rivals. One of the reasons for this behavior is that they don't want to miss out on prospective technologies that may change the market . This strategic approach has three potential outcomes. First is that investing in promising initiatives can provide a competitive edge, mitigating the risk of market loss and securing their market position in that market. The second outcome is that even if an individual investment does not yield long-term returns, they can console themselves knowing that their rivals have also struggled. Finally, the global innovation momentum, fueled by Big Tech's significant financial resources, creates an environment where investments are more likely to yield the next groundbreaking technology. In this scenario, it is unlikely that any single firm can either achieve long-term strength or suffer significant losses, as the acquisition impact of an individual company is quickly neutralized by the rapid imitation and adaptation of its peers.

When this tendency reaches its extreme, where one firm quickly responds to the other competitors' strategic decisions, and vice versa, the strategies of these firms become highly correlated. This behavior implies that it is increasingly possible to predict with a high degree of accuracy how one firm will respond to the other firms' decisions. We define such a behavioral pattern as "strategic convergence". This refers to the extent to which a company's strategic behaviors display similar patterns, leading it to converge and compete in overlapping markets and exhibit synchronized decision-making. By examining strategic convergence, one can more easily define who the company considers as their direct competitors. If the strategic convergence is high, it could well be that they consider themselves as direct competitors.

Proposition 3. (Strategic Persistence) Specialization incentives may drive strategic persistence, which leads to sequentially repetitive acquisitions.

When a company's strategic decisions are grounded in specialization, their decision in a particular period may show a similar pattern to their decision-making in previous periods, reinforcing their previous strategic decision. This implies that each firm's focused strategy reinforces its existing technological capabilities. In a scenario where the incentives for specialization prevail, we can expect firms to adhere to their past strategic decisions. We define such a behavioral pattern as "strategic persistence." An example of this is Meta's acquisition of another social networking service, WhatsApp, to complement its existing social networking service of Facebook.

Firms can acquire either capabilities they already possess or acquire a different set of capabilities that could complement their existing capabilities. However, the evolution of firm capabilities remains path dependent, especially for firms that have already developed a path of learning, where knowledge and economic gains increase with similar sets of resources already possessed by a firm (Petit and Teece, 2021).

Proposition 4. (Growth Stage Dependency) Acquisition incentives change as a firm grows..

The acquisition incentives of companies can vary by their growth stage. As platforms grow, they are more likely to have diversified business portfolios, characterized by a broader range of businesses, a solid market presence, and stronger financial resources, which can also lead them to risk-averse decision-making due to higher sunk costs. In contrast, early-stage platform companies may be driven by different incentives, including the desire to rapidly expand their offerings and gain market traction, which can lead to less risk-averse decision-making to bridge the gap between the established industry leaders. They may adopt follower strategies, acquiring and assimilating the latest technologies, innovations, and best practices from peer companies to quickly catch up and match with their pace and capabilities. This can lead to stronger strategic alignment with their peer group, as they seek to close the knowledge and experience gap.

Proposition 5. (Interaction with Environment) Each Big Tech firm may respond differently to the macroeconomic environment.

Another critical factor that may influence Big Tech's acquisition decision is the macroeconomic environment. Klinge et al. (2023) highlights a trend in the digital landscape, where large platforms such as Alibaba, Alphabet, Amazon, Apple, Meta, Microsoft, and Tencent, are becoming increasingly engaged in "corporate financialization" – operating as *de facto* financial institutions – which affects their acquisition strategies. These firms are likely to seek out investments to expand their ecosystems, which in turn affects their decisions regarding cash reserves versus investment opportunities each period. This trade-off can significantly impact their willingness to leverage their assets to acquire new businesses and can lead to a shift in their strategic priorities. Favorable market conditions can create a self-reinforcing cycle of growth, where venture capital markets become increasingly active due to Big Tech's buyout activities, attracting a surge of startups seeking acquisition. As these startups fuel further investment and expansion, they drive even more acquisitions, perpetuating the cycle.

Proposition 6. (Heterogeneous Responsiveness) The ecosystem of an individual Big Tech company may vary depending on when and where they have situated their ecosystem.

The unique features of a firm, such as its dominant market or core technology, can significantly influence the trajectory of its evolution. For example, companies that have achieved strong market position through search engine services may have different trajectories of constructing their ecosystem compared to those that have established themselves through strong software technology; the difference in their trajectory is impacted by the timing of the acquisition and/or the domain of technologies that they acquire. As pointed out by Strauss and Yang (2024), this can be attributed, in part, to the concept of "path dependency", which highlights how a firm's initial choices and actions shape its future decisions and outcomes. The starting point for ecosystem construction can have an impact on a firm's evolutionary path.

3 Big Techs' Acquisition Behaviors

3.1 Data Sources and Background

I use Pitchbook as the main source of data. The data contains the universe of acquisitions, including date of the deal, the name of the acquired company (target information), and the sector or market in which the target operates. It also includes information about acquirers, including the date they were founded and the market/sector in which they primarily operate. Several other studies in the literature have used these data to analyze merger and acquisition activities. For example, Tang et al. (2022) used this database to analyze digital mergers and acquisitions in China. Zingales et al. (2020) used Pitchbook to analyze acquisitions made by Google and Facebook. For my analysis, we used Pitchbook's classification of target industry sectors to examine the acquisition behaviors of the Big Tech firms from the second quarter of 2004 to the fourth quarter of 2021.[1]

The evolution of the Big Tech companies began with Microsoft's founding in 1975, establishing its primary operation in operating systems with Windows PC. Apple followed in 1976, focusing on consumer electronics with its Mac product line. Amazon emerged in 1994, 18 years later, with its Internet Retail service, while Google launched in 1998, concentrating in the IT Consulting and Outsourcing sector. Meta completed the group in 2004, introducing its Social/Platform Software. The first Big Tech acquisition occurred in 1987, marking the beginning of the timeline. From 1987 to 1994, only Microsoft and Apple represented the Big Tech landscape. The group reached its current composition of five members when Amazon, Google, and Meta joined between 1994 and 2004. Since the first acquisition made by Big Tech in 1987, their acquiring sectors expanded into 79 sectors in 2021.

3.2 Multi-market Multi-sector Repeat-purchase Diffusion Process

Multi-market multi-sector diffusion process refers to the recurring acquisitions across multiple markets or sectors (79 in this study). Table 2 , 3, and 4 present the top 10 sectors with the highest acquisition activities of each firm, measured by the cumulative sum of the total acquisition from 1987. This measure provides a comprehensive view of two key trends: (1) the evolution of each firm's top sector over time and (2) the changes in the overlap of priorities across firms. An alternative approach to the accumulated sum since 1987 is to divide the entire time window into discrete time period segments with different starting years and use the aggregated sum between those periods. However, this approach can introduce potential problems associated with arbitrary segmentation choices, which can lead to inconsistent counting of overlapping sectors across the firms and thus inaccurate conclusion.

The stopping years are 2003, 2012, and 2021. These years are either (1) immediate year preceding the establishment of the last member of Big Tech, which is 2003, or (2) the half mark between 2004 and 2021, which is 2012, and (3) the most recent year in our sample, which is 2021, when all members of Big Tech were present and in full operation.

In the early phase of Big Tech competition when only Microsoft and Apple were in business (until 1997), they had quite a few overlapping sectors competing for acquisition, including 1) Software Development Applications, 2) Application Software, 3) Business/Productivity Software, and 4) Network Management Software. It was around these times when both of these firms' primary focus were in developing software

[1] 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, Social/Platform Software provider, was founded.

compatible with their hardware operating systems, and they have been competing mainly on the Personalized Computer market. Although founded in 1994, Amazon did not engage in acquisition until 1998.

As of 2003 shown in Table 2, the acquisition sectors have diverged between Apple and Microsoft, making only two shared sectors among their respective top ten acquisition sectors. Of the four firms present, the three companies, Apple, Microsoft, and Google, had Application Software as the most frequently acquired sector.

This changed in 2012. As of 2012 in Table 3, all members of Big Tech made a significant number of acquisitions in Application Software. It became the highest acquisition activity sector for the four firms, and second to the highest for Amazon. Among the top 10 sectors in which each of the five firms made acquisition, four sectors overlap across four firms – Multimedia and Design Software, Business/Productivity Software, Media and Information Services (B2B), and Information Services (B2C). This makes Google and Meta presumably competing against at least three other Big Tech companies for acquisition in five of their respective top ten sectors. Apple and Microsoft follow suit, where this number reduces to four. Overall, the number of targets acquired within each sector increased significantly between 2003 and 2012.

In 2021 in Table 4, we see a greater number of overlapping sectors. This may imply that their core businesses have become in need of similar technologies, which may contribute to their greater overlap of acquisition sectors. On each company's list of top ten acquisition sectors, two sectors were common across all five companies; Application Software and Business/productivity Software. This makes the five firms compete against the other four firms for acquisition in two of the top ten sectors. Four sectors appear on at least four companies' list: Media and Information Services (B2B), Multimedia and Design Software, Information Services (B2C), and Software Development and Applications. This implies, for example, that Apple shares six common sectors with at least three other Big Tech companies. Similarly, Google and Meta, each shares six of their top 10 sectors with at least three Big Tech companies. The number of overlapping sectors drops to five for Microsoft, while that number becomes three for Amazon.

The evolution of the popular sector has demonstrated significant variation over time, company-wise. A comparison of Table 2 with Table 4 reveals shifts in the sectoral portfolio, which can be partly attributed to business expansion and diversification. If, however, these firms had adhered strictly to their core domains, avoiding the creation of new paths by imitating their rivals, we would likely observe a sectoral portfolio largely consistent with that of earlier years. However, this is clearly not the case. For example,"Multimedia and Design Software" which did not feature as a prominent sector in 2003, emerged as a leading acquisition sector in 2021 for Apple.

Table 2: Top 10 Sectoral Acquisitions from 1987 to 2003 by Acquirer, colored by the Intensity of Overlap

	Apple	Microsoft	Amazon	Google
1	Application Software (4)	Application Software (10)	Internet Retail (4)	Application Software (2)
2	Internet Software (2)	Business/Productivity Software (5)	Social/Platform Software (2)	Communication Software (1)
3	Software Development Applications (2)	Multimedia and Design Software (5)	Information Services (B2C) (1)	IT Consulting and Outsourcing (1)
4	Application Specific Semiconductors (1)	Entertainment Software (3)	Movies, Music and Entertainment (1)	Internet Software (1)
5	Automation/Workflow Software (1)	Information Services (B2C) (3)	Network Management Software (1)	Media and Information Services (B2B) (1)
6	Business/Productivity Software (1)	Communication Software (2)	Other Services (B2C Non-Financial) (1)	Other Software (1)
7	Computers, Parts and Peripherals (1)	IT Consulting and Outsourcing (2)	Systems and Information Management (1)	
8	Distributors/Wholesale (1)	Movies, Music and Entertainment (2)		
9	Education and Training Services (B2B) (1)	Network Management Software (2)		
10	Internet Service Providers (1)	Other Software (2)		

Notes: This table shows the top 10 sectoral acquisitions from 1987 to 2003 categorized by individual acquirer. Overlapping sectors, frequently appearing within the top ten target acquisition areas for the majority of Big Tech companies, are highlighted in color.

Table 3: Top 10 Sectoral Acquisitions from 1987 to 2012 by Acquirer and Sector, Colored by the Intensity of Overlap

	Apple	Microsoft	Amazon	Google	Meta
1	Application Software (8)	Application Software (20)	Internet Retail (10)	Application Software (32)	Application Software (10)
2	Multimedia and Design Software (3)	Business/Productivity Software (15)	Application Software (6)	Information Services (B2C) (10)	Social/Platform Software (5)
3	Automation/Workflow Software (2)	Systems and Information Management (9)	Movies, Music and Entertainment (4)	Communication Software (9)	Vertical Market Software (4)
4	Business/Productivity Software (2)	Media and Information Services (B2B) (8)	Publishing (4)	Internet Software (7)	Communication Software (3)
5	Computers, Parts and Peripherals (2)	Multimedia and Design Software (7)	Information Services (B2C) (2)	Social/Platform Software (7)	Information Services (B2C) (2)
6	General Purpose Semiconductors (2)	Network Management Software (7)	Social/Platform Software (2)	Business/Productivity Software (6)	Media and Information Services (B2B) (2)
7	Internet Software (2)	Communication Software (6)	Specialty Retail (2)	Media and Information Services (B2B) (6)	Multimedia and Design Software (2)
8	Media and Information Services (B2B) (2)	Entertainment Software (5)	Computers, Parts and Peripherals (1)	Multimedia and Design Software (6)	Social Content (2)
9	Movies, Music and Entertainment (2)	Information Services (B2C) (5)	Distributors/Wholesale (1)	Vertical Market Software (6)	Business/Productivity Software (1)
10	Software Development Applications (2)	Other IT Services (4)	Electronic Components (1)	Other Software (4)	Consulting Services (B2B) (1)

Notes: This table shows the top 10 sectoral acquisitions from 1987 to 2012 categorized by individual acquirer. Sectors that appear to be among each company's most sought-after sectors for target acquisition are highlighted in color. The darkness of the color indicates the intensified sectoral overlap between the Big Tech companies.

Table 4: Top 10 Sectoral Acquisitions from 1987 to 2021 by Acquirer and Sector, Colored by the Intensity of Overlap

	Apple	Microsoft	Amazon	Google	Meta
1	Application Software (22)	Application Software (37)	Application Software (11)	Application Software (64)	Application Software (21)
2	Business/Productivity Software (12)	Business/Productivity Software (36)	Internet Retail (11)	Software Development Applications (14)	Social/Platform Software (11)
3	Multimedia and Design Software (9)	Network Management Software (15)	Movies, Music and Entertainment (7)	Communication Software (13)	Business/Productivity Software (8)
4	Media and Information Services (B2B) (8)	Systems and Information Management (14)	Business/Productivity Software (4)	Information Services (B2C) (13)	Entertainment Software (7)
5	Software Development Applications (7)	Entertainment Software (13)	Information Services (B2C) (4)	Social/Platform Software (13)	Media and Information Services (B2B) (6)
6	Entertainment Software (5)	Software Development Applications (13)	Publishing (4)	Business/Productivity Software (11)	Multimedia and Design Software (6)
7	Computers, Parts and Peripherals (4)	Media and Information Services (B2B) (9)	Social/Platform Software (4)	Media and Information Services (B2B) (11)	Communication Software (5)
8	Database Software (4)	Multimedia and Design Software (9)	Specialty Retail (4)	Multimedia and Design Software (10)	Information Services (B2C) (5)
9	Electronics (B2C) (4)	Communication Software (8)	Financial Software (3)	Electronics (B2C) (9)	Software Development Applications (5)
10	Information Services (B2C) (4)	Other IT Services (8)	Systems and Information Management (3)	Internet Software (8)	Vertical Market Software (5)

Notes: This table shows the top 10 sectoral acquisitions from 1987 to 2021 categorized by individual acquirer. Sectors that appear to be among each company's most sought-after sectors for target acquisition are highlighted in color. The darkness of the color indicates the intensified sectoral overlap between the Big Tech companies.

3.3 Multi-market Multi-sector Convergence

The acquisition behavior of Big Tech can be considered as five companies choosing multiple targets to acquire that are distributed across 79 different sectors. In this process, the diffusion may occur among the Big Tech companies and across 79 sectors simultaneously.

Below we formulate a convergence index to measure the overall multi-market multi-sector convergence. It is defined by the average number of Big Tech in a given sector for M sectors scaled within 0 and 1. It is a normalized index, where 0 indicates that there is no presence of Big Tech in any single sector, and 1 indicates that there is a presence of Big Tech in all sectors M.

$$\text{Convergence Index}_t = \sum_{m=1}^{M} \frac{w_{mt}}{M}, \text{ where}$$

$$w_{mt} = \frac{\text{number of Big Tech companies that are present}_{mt}}{\text{number of Big Tech companies}_t}$$

Note that w_{mt} ranges from 0 to 1. If no single Big Tech company is present in sector m in period t, this yields w_{mt} the minimum value of 0. If all Big Tech companies were present in sector m at time t, this yields the maximum of 1. The denominator changes with respect to the point in each company's founding years. In other words, during the period in which only Apple and Microsoft were operating, the denominator used for normalization is two rather than five, so that the maximum value of w_{mt} remains one. With all M sectors having equal weights of $1/M$, the convergence measure is the weighted average of w_{mt}.

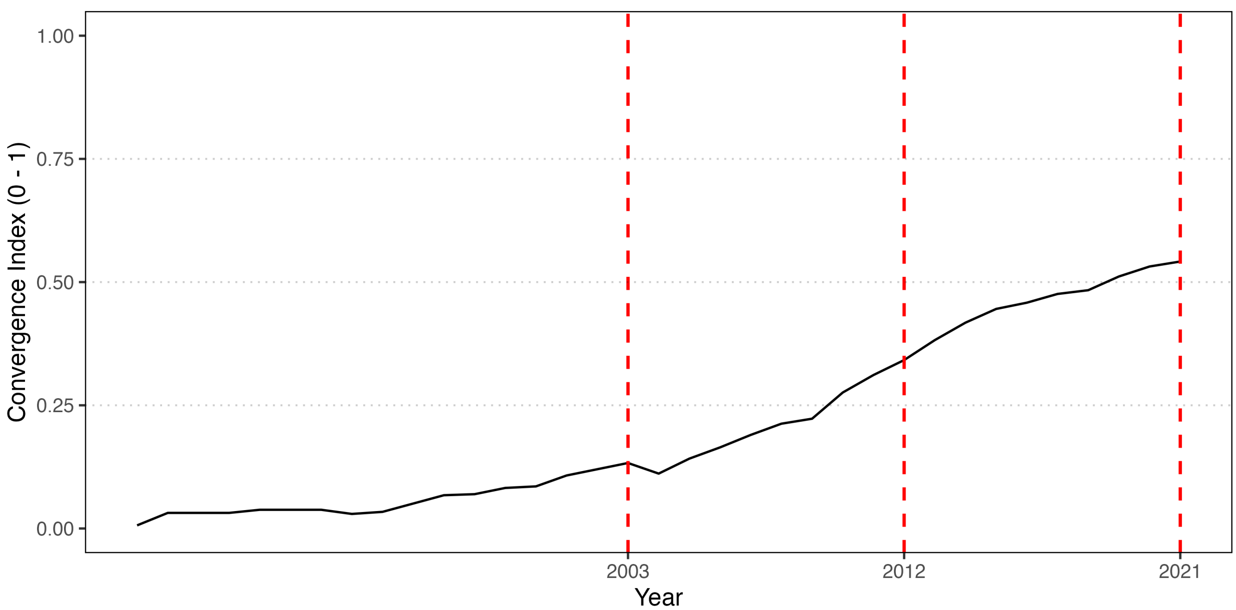

Figure 1: Convergence Index Trend

Notes: Convergence index above represents the average number of Big Tech's presence across 79 sectors from 1987 to 2021 scaled to fall within the range of 0 to 1. The vertical red dashed lines indicate 2003, 2012, and 2021, where we examine in detail the sectors that attracted most acquisition activities by each Big Tech company. Note that the sudden dip in the index in 2004 is attributable to the change in denominator from 4 to 5, following addition of Meta.

Graphing the convergence index over years, it shows a weak S curve, as shown in Figure 1. It started close to 0 in 1987 when one out of two Big Tech companies present at that time was active in acquisition only for one sector, making the index very close to 0. As Big Tech companies diversify and new members join, the index gradually increases. However, the degree of overlap in acquisition sectors was limited until 2004. This is in part because of the tendency that they acquire targets that are directly complementary to their core operation, as they are still in a relatively early stage of their life cycles. Recall that the five companies started in distinct sectors and thus the less likely their acquisition sectors overlap in their earlier stage of the life cycle. Beginning 2004, the convergence of acquisition sectors in Big Tech accelerates; the overlap between acquisition sectors of Big Tech intensifies. During this period, with more Big Tech companies present through acquisition in a growing number of sectors, there has been increased overlap in their business portfolios. This acceleration seems to pace down around 2019. Nonetheless, the growing trend of convergence index supports the **Proposition 1**.

4 Modeling Dynamic Acquisition Game

In this section, we set up a simple acquisition game to empirically validate **Proposition 2** and **Proposition 3** in a dynamic setting. In this dynamic model, each firm responds to *evolving* competitive landscape and optimizes its decision, taking into account how its decision may impact the decision of its rivals' actions. The objective is to quantify the degree of strategic convergence among these firms, as well as to assess the persistence of their acquisition strategies, while accounting for the potential impact of macroeconomic factors on firm-level decisions.

4.1 Outline of the Game

Figure 2 illustrates the dynamic process of the game. The process consists of two interacting components which are agents and environment. The environment is characterized by states and through states it affects the decision of the agents. Given a specific set of states, agents take actions. In turn, agents' actions affect the states which define the environment. With the updated states, agents again take actions, which again feed into updating the states. During this iterative process, agents receive payoffs which are attached to their actions. This iterative process is well described in Figure 2.

Each agent corresponds to an individual Big Tech firm. Their actions are acquisition decisions of whether to engage in acquisition or not. To simplify the model, we assume that their decisions follow the Markov decision process, where their actions are entirely determined by the given states and not the history of those states. The states that their actions are influenced by are the interest rate, the total targets acquired by their rivals, and the total targets acquired by themselves. Under varying combinations of states, they make their decisions to undertake acquisition or not. In each period, every agent participates in an acquisition game. The order of the game is illustrated below.

1. All members of the Big Tech firms observe the previous quarterly interest rate, the number of acquisitions made by themselves and others in the last four quarters, and the firm-specific private shocks, which are identically and independently distributed.

2. Each firm simultaneously makes a discrete choice of whether to acquire a target in that market or not based on the given states and private shocks.

3. The states are updated.

   (a) The total targets acquired by each agent evolves stochastically based on the previous state and the choice they made this period.

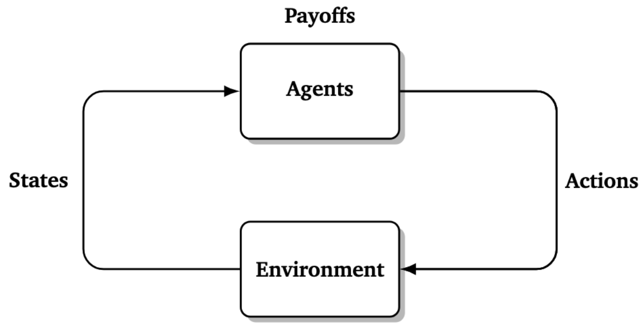

Figure 2: Dynamic Model Capturing Interaction Between Agents and Environment

Notes: This figure presents the interaction between agent and environment. The decision variable of agents is their actions and the environment is defined by a set of states.

(b) The number of acquisitions made by rivals (varying by each agent) evolves stochastically based on the previous state and the choices made by their rivals this period.

(c) The interest rate evolves stochastically based on its previous state.

4. This process of updating states repeats until the terminal period, T.

4.2 Model Description

Time is discrete with each decision period being one quarter. Sectors are indexed as $m = 1, 2, 3, \cdots, M$ and are independent.[2] Subscript m is omitted for a simpler notation. Acquirers are indexed by $i = 1, 2, 3, 4, 5$.

In this model, we assume that the acquisition activities by the five firms are entirely governed by private shocks and the following three states: the number of targets acquired over the past year by firm i, e_{it} , the sum of acquired targets over the past year by firms that are not i, e_{-it}, and the interest rate (int_t). The past number of its own and its rivals' acquisitions help us capture the different responsiveness of each member of the Big Tech firms in response to the intensity of acquisition in a given sector. Given the limited duration of the innovation effect of technology transfer, which has been shown to last approximately 1.5 years (Barsy and Gautier, 2024), we limit the time frame that influences acquisition decisions to a one-year horizon.

To simplify the notation, let

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

where s_{it} is a vector of the three aforementioned states, e_{it}, e_{-it} and int_t. The former two states take different values by each firm i in each period t. The last state, 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

[2] We assume that acquisition activities within a given sector are independent of those in other sectors, i.e., data is generated by the same Markov perfect equilibrium. That is acquisition activities in one sector do not influence or deter activities in other markets. This is a heavy assumption yet reasonable, since Meta's decision to acquire targets in the Social/Platform Software should not influence Microsoft's decision to acquire the targets in Media and Information Services (B2B). 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. We also assume that targets are homogeneous. Again, this is a strong assumption but necessary for the estimation procedures. Future research may benefit from relaxing this assumption

shocks given by[3]

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

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, ν_{0it}, ν_{1it} is firm i's choice-specific private shocks only observable to firm i.[4] The collection of structural parameters are represented by the letter $\boldsymbol{\theta}_i = (\theta_{1i}, \theta_{2i}, \theta_{3i}, \theta_{4i}, \theta_{5i}, \theta_{6i})$ 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.[5]

One of the factors affecting a firm's per-period payoff is the interest rate (θ_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 (θ_3, θ_4) captures the contribution of strategic persistence to the likelihood that a firm makes an acquisition move. In the acquisition game, this indicates the gain that a firm has derived from scale economies. As a firm acquires an increasing number of targets in a given sector, it is more likely to benefit from technological efficiency, thereby achieving scale economies of specialization.

An agent's responsiveness to its rivals' acquisition in scale, represented by (θ_5, θ_6), can be interpreted as an indicator of strategic convergence. What drives strategic convergence? Potential reasons include responding to uncertainty about payoffs, compatibility issues, and valuation challenges related to acquiring targets. In such an environment, rival acquisitions can serve as a strong signal that they may have more information about the target or sector that a company might have missed. Consequently, a company's decision-making may rely heavily on the acquisition strategies of close competitors that are similar in size and hold comparable market positions. It can also be argued that the company's willingness to become part of a preemption group, where rivals buying more targets acts as a bandwagon effect, prompting its acquisition likelihood to increase.

The prospect of targets becoming unavailable can create an incentive for firms to react quickly to mitigate the risk of sold-out targets. In markets characterized by a limited pool of targets available at any given time, there exists a greater risk that the targets are rapidly depleted when competitors acquire a substantial number of targets. As a result, a firm is more inclined to respond quickly to avoid the possibility of targets becoming scarce. Those who react more to their rivals' acquisitions may be signaling their need to stay competitive and adapt to changing market conditions, thereby avoiding missing out on valuable targets.

All states evolve in a stochastic process that follows state transition probabilities that are recovered from the data without using predetermined parameters. Endogenous states (e_{it}, e_{-it}) travel through state space

[3]As shown in Figure, 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.

[4]The detailed illustration of discretization can be found in Section 4.1.

[5]The per-period payoff structure is built upon Rust (1987), which is defined by some function of states and choice-specific shock.

probabilistically based on previous states and actions. The exogenous state (int_t) evolves according to only its own path.

4.3 Equilibrium

In each period, each firm makes an acquisition decision that maximizes its expected discounted future payoffs. Let Markov strategy profiles of all firms be denoted by

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

This maps states and idiosyncratic shocks into actions. With per-period profit, the following Bellman equation (value function of each agent) shows a firm's dynamic programming problem,

$$\begin{aligned} V_i(s_{it}, \nu_{it}, \sigma; \theta) = \max_{\sigma(s_{it}, \nu_{it})} & R_i(s_{it}, \nu_{it}, \sigma; \theta) \\ & + \beta \mathbb{E}[V_i(s_{it+1}, \nu_{it+1}, \sigma; \theta) | s_{it}, \sigma], \end{aligned} \tag{2}$$

where the expectation is over the distribution of ν_{it+1} and s_{it+1}, σ is a vector of strategy profiles of all firms which maps given states and shocks into actions, and $\beta \in \{0, 1\}$ 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 $\sigma_{-i}^* = \sigma^*(s, \nu) \backslash \{\sigma_i^*(s, \nu)\}$ is a vector of Markov strategies of players that are not player i, σ_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 (σ_i^*) yields lower future expected returns.

I assume that the data are generated consistently across all markets, having the same Markov perfect equilibrium. This assumption is necessary to obtain consistent parameter estimates, as indicated in previous research (Bajari et al., 2007; Ryan, 2012).

5 Estimation of Model Parameters

To estimate the model parameters, we use the two-step minimum distance algorithm proposed by Bajari et al. (2007) (hereinafter, BBL). This involves: (1) estimating the optimal policy rule by regressing actions on states in a reduced-form framework, and (2) imposing 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.

In the first step, the conditional choice probabilities for each firm is estimated (Hotz and Miller, 1993), which is later used to estimate the parameters in the second stage. This is done by running a separate binary pooled regression – regressing the likelihood of individual firms making acquisitions on a set of state variables. Then the optimal policy rule or the predicted probability of acquisition is computed from the regression estimates for each firm. In this process, we assume that the acquisition records are the outcomes of firms acting optimally in any single period (optimal in a static environment). To incorporate the dynamic decision-making process of firms however, we use the first stage estimates to inform the next step. In the second step, we run forward simulations that model possible actions and states that evolve over time. Expected future returns under optimal policy and alternative policies are separately computed. With a sufficiently large set of perturbed policies (alternative policies), BBL filters 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, we provide a more comprehensive explanation of the procedures involved in the second step of BBL. To begin, we establish the state space and action space, and also estimate the nonparametric transition probabilities linked to these states. Next, we 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. Then, we simulate possible state paths and action paths. We compute the value function under both the optimal policy and various alternative policies given these simulated paths. Finally, we present the outcomes following these procedures.

5.1 Definition of States, State Transitions and Actions

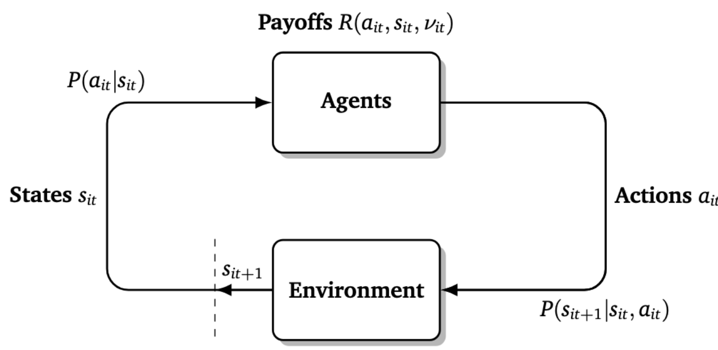

Figure 3: States, State Transitions, and Actions

Notes: The figure depicts an iterative cycle of update in states and actions of agents, where agents continuously adapt their actions in response to feedback from the environment. Agents take actions that yield higher payoffs. Through these actions, states are updated, which in turn informs agents' next set of actions.

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 and the maximum number of acquisitions being 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%.

$$B_1(e_{it}) = \begin{cases} 0 & \text{if } e_{it} = 0 \\ 1 & \text{if } e_{it} = 1 \\ 2 & \text{if } e_{it} \in (1, 15] \end{cases}$$

$$B_2(e_{-it}) = \begin{cases} 0 & \text{if } \sum_{i \neq j} e_{jt} = 0 \\ 1 & \text{if } \sum_{i \neq j} e_{jt} \in (0, 5] \\ 2 & \text{if } \sum_{i \neq j} e_{jt} \in (5, 24] \end{cases}$$

$$B_3(\text{int}_t) = \begin{cases} 0 & \text{int}_t \leq 2.5\% \\ 1 & \text{int}_t > 2.5\% \end{cases}$$

Slightly abusing the notations, we 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 1) with the redefined e_{it} and e_{-it},

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

Action Space In each period, all players choose whether to acquire a target (i.e., enter a market through acquisitions) or not, conditional on given states. 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:

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

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 $S \times A \times S \to [0, 1]$.

The interest rate follows its own path of evolution.

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

where each element in the set $\{0, 1\}$ represents either a low or high-interest state.

5.2 Linearization of Value Functions and Optimality Conditions

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

$$R_i(a_{it}, s_{it}, \nu_{it}) = \Psi_i(a_{it}, s_{it}, \nu_{it})'\theta_i, \tag{4}$$

where $\Psi_i(a_{it}, s_{it}, \nu_{it})$ is a vector of P-dimensional basis functions, $\psi_i^1, \psi_i^2, \cdots, \psi_i^P$. Given that the pay-off function is linear with respect to elements $(a_{it}, s_{it}, \nu_{it})$, ψ_i^p is simply the elements of (s_{it}, ν_{it}) and constant, where each ψ_i^p corresponds to a coefficient for the respective parameter θ_i . 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),

$$V_i(s_i;\sigma) = \mathbb{E}\left[\sum_{\tau=t}^{T} \beta^\tau \psi_i(\sigma_i(s_{i\tau},\nu_{i\tau}), s_{i\tau}, \nu_{i\tau})\theta_i \middle| \sigma_{-i}, s_{it}\right] = W_i(s_i;\sigma)\theta_i, \tag{5}$$

where

$$W_i(s_i;\sigma) = \mathbb{E}\left[\sum_{\tau=t}^{T} \beta^\tau \psi_i(\sigma_i(s_{i\tau},\nu_{i\tau}), s_{i\tau}, \nu_{i\tau}) \middle| \sigma_{-i}, s_{it}\right]. \tag{6}$$

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

$$V_i(s_i;\sigma_i^*,\sigma_{-i}^*) \geq V_i(s_i;\sigma_i',\sigma_{-i}^*), \text{ for all } i, s, \sigma', \tag{7}$$

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

$$\{W_i(s_i;\sigma_i^*,\sigma_{-i}^*) - W_i(s_i;\sigma_i',\sigma_{-i}^*)\}\theta_i \geq 0, \text{ for all } i. \tag{8}$$

Minimizing the violations of the optimality conditions 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 (8)) 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 we evaluate a set of parameters that minimizes the loss function.

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

5.3 Monte Carlo Simulation

In the first stage, we compute the conditional choice probabilities (CCP) or 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}. We also calculate state transitions, which are conditional on the previous state and current actions of players.

In the second stage, we 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. We can then linearly separate this matrix by a vector of parameters and a matrix of basis functions. From Equation (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, we construct a P-dimensional vector of "basis functions", ψ, 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, we can construct W_i matrix by taking the average of the expected discounted sum of ψ from $t = 1$ to $t = T$ over the NS simulated paths.

$$\begin{aligned} W_i &:= W_i(\mathbf{s}; \sigma) && (9) \\ &:= \mathbb{E}\left[\sum_{t=0}^{T} \beta^t \psi_i(\cdot|s_0)\right] && (10) \\ &\approx \frac{1}{NS}\left[\sum_{n=1}^{NS}\sum_{t=0}^{T} \beta^t \psi_{i,n}(\cdot|s_0)\right]. && (11) \end{aligned}$$

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 χ denotes one of the inequality conditions.

Suppose that H is a distribution over the set χ of inequalities. Here, we assume uniform distribution over the set of inequalities that we choose with varying starting states.

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

where NI denotes the number of inequalities, X_k is each chosen inequalities. By varying the number of iterations and optimization methods, we search through a set of θ to find the combination that minimizes $Q(\theta)$. To do so, we create 2000 simulated paths of states and actions that unfold for 100 periods with a 0.95 discount factor using the optimal policy rule.[6] Then we run 6000 times of 200 simulations using the alternative policy rule for a specific player while other players are acting optimally. The alternatives are slight deviations from the optimum such that these differences are drawn randomly from normal distribution with standard deviation of 0.5. We 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 the parameters.

[6] 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 $0.95^{100} = 0.006 \approx 0$.

5.4 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, we 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. We 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, we 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.

6 Empirical Findings

6.1 Estimation Results

Table 5 presents the estimation result. These estimates are the outcome of a two-stage process, where static estimates generated from the first stage are used in the second stage to produce estimates that account for dynamically evolving states. In the first-stage estimation, we conduct a 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 each company's own acquisition, and those of their rivals. These initial results serve as a benchmark for computing conditional choice probabilities and determining optimal cutoffs for each agent at the second stage. In the second stage, we employ a Monte Carlo simulation based on the calculated cutoffs. This simulation generates multiple simulated paths over multiple time periods. We gather these various instances to estimate the associated parameters.[7]

Each variable represents the intensity of acquisitions (detailed in Section 4). These categorizations can also represent the strength of the signal through which the firm responds; few targets acquired indicate a weak signal, while a greater number of targets acquired suggests a strong signal. The likelihood of acquisition is calculated by

$$\frac{p(a=1|s)}{1-p(a=1|s)} = e^{\theta s},$$

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 a low-interest rate environment, where no firm has acquired any targets over the last four quarters.

Estimates can be interpreted as the amount by which each variable affects each agent's predicted probabilities of target acquisition. The results show empirical evidence that (1) companies observe their own past actions and those of their rivals when deciding on acquisition, and (2) the strength of signals measured by

[7] See the Appendix Appendix B for the first-stage estimation results.

Table 5: Model Parameters Estimated from Monte Carlo Simulation (Second-stage Estimates)

	Dependent variable: Acquire/Not Acquire				
	Google	Meta	Microsoft	Amazon	Apple
Constant (θ_1)	-2.479**	-0.544**	-3.702**	-0.419**	-1.075**
	(0.030)	(0.100)	(0.026)	(0.079)	(0.087)
High int. (θ_2)	-0.581**	-3.071**	0.431**	-2.951**	-2.227**
	(0.025)	(0.099)	(0.024)	(0.078)	(0.084)
Own acq. (θ_3)	0.407**	0.770**	0.529**	0.337**	0.523**
estfreq. (=1)	(0.023)	(0.023)	(0.125)	(0.089)	(0.021)
Own acq. (θ_4)	1.301**	1.161**	1.641**	1.503**	0.961**
freq. (> 1)	(0.028)	(0.034)	(0.072)	(0.317)	(0.037)
Rivals acq. (θ_5)	0.901**	0.996**	0.622**	0.197**	0.711**
freq. (1 - 5)	(0.014)	(0.012)	(0.030)	(0.031)	(0.011)
Rivals acq. (θ_6)	1.413**	1.928**	1.392**	1.234**	1.736**
freq. (> 5)	(0.169)	(0.069)	(0.173)	(0.321)	(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 frequencies of past acquisitions matters. Importantly, macroeconomic factors can also influence their decisions. All estimates are found to be statistically significant at the 5% significance level. The constant determines the baseline predicted acquisition likelihood when interest rate is low and no single acquisition was made by an individual company. This constant may thus include 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 Microsoft faces the highest acquisition costs.

6.2 Evaluation of Strategic Convergence

In **Proposition 2**, we propose that the Big Tech companies converge their acquisition strategies by mirroring and synchronizing with those of their rivals. If this is indeed true, the likelihood of acquisition is expected to increase when their rivals undertake a greater number of acquisitions. In fact, the result indicates a substantial *increase* in the projected likelihood of acquisition for all companies in response to the number of targets acquired by their rivals. The estimates for θ_5 and θ_6 are all positive and statistically significant. Ultimately, positive estimates indicate the presence of strategic convergence, which is measured by a firm's sensitivity toward the past activities of their peers. As the firm observes their rivals acquiring more targets, its acquisition likelihood increases, which supports **Proposition 2**. The range of estimates indicates the varying degree to which each firm pursues strategic convergence. In addition, all firms become more active acquirers as the number of previous acquisitions by competitors increases ($\theta_5 < \theta_6$), suggesting a stronger reaction among them towards stronger signals coming from their rivals.

Convergence behavior is not always guaranteed. For instance, when one firm avoids an acquisition that others engage in, their behavior is likely to diverge from the others, as demonstrated by negative coefficient estimates. In this scenario, it is challenging to support Proposition 2. However, no single firm appears to show this pattern. In fact, it is observed that all firms increase their likelihood of acquisition when others acquire, which supports the proposition. Further examination reveals that their response escalate with stronger rivals' engagement. That is, when only a few targets have been acquired by their rivals, these firms may not be overly concerned; however, when the demand for targets by the rivals goes up, they act strongly as this may indicate a strong signal that the market is in high demand.

Table 5 shows that Google, Apple, and Meta stand out as 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 compared to their peers. Meta in particular appears to have the highest strategic convergence, which makes it the most responsive member of the group with regard to the actions of its rivals. Relative to other group members, it seems to have sought aggressive acquisition strategies to grow and solidify its market presence. When rivals seek to acquire more than five firms, it is Apple in addition to Meta that acts, its probability increments escalating (25% probability increments compared to 16%), while Google maintains the same incremental increase of its probability of acquisition (remained 9% probability increments throughout).

6.3 Evaluation of Strategic Persistence

The degree of strategic persistence for **Proposition 3** is also empirically estimated. The parameters of interest are θ_3 and θ_4, indicating the likelihood that a firm will respond to its own past behaviors. It is worth noting that they are *within firm* measures, setting them apart from the parameters associated with strategic convergence, which examine interactions *between firms*. The positive and statistically significant estimates of the parameters ($\theta_3, \theta_4 > 0$) suggest that a firm's own acquisition activities do influence its acquisition decision, which supports the presence of strategic persistence. In addition, all Big Tech companies respond more strongly to stronger signals. That is, the acquisition probabilities for all firms rise in tandem with their own acquisition histories ($\theta_4 > \theta_3$).

Microsoft is pursuing a distinct acquisition strategy compared to other members of the group: Its acquisition strategies are more persistent than convergent. Notably, Microsoft seeks to persistently acquire targets in sectors that are specific to it, which are Network Management Software or Business/Productivity software. In these sectors, Microsoft has acquired almost double the number of targets compared to the second-highest acquirer.

Figure 4 shows individual firm response to weak and strong signals. The strength of the signal denotes the intensity of acquisitions, represented by the number of acquisitions. Along the axis, the response to weak and strong signals is represented in probability increments, respectively. By setting the reference point as the predicted likelihood of acquisition in a low-interest rate environment where no firms had made acquisitions over the last year (baseline predicted probabilities), the incremental probabilities represent the differences in the likelihood of acquisition for each firm between the intensity of the signals and the reference. The 45 degree line indicates that both signals increase the likelihood of acquisition by the same amount. All five firms are positioned above the 45 degree line for both persistent and convergent behavior, indicating that the strong signal increases the likelihood of acquisition more than the weak signal does. As the measure of signal strength is different when estimating persistent and convergent behavior, the parameter estimates between θ_3, θ_4 and θ_5, θ_6 cannot be directly compared. However, different patterns in how each Big Tech company responds to weak and strong signals highlight their unique strategic positioning within the broader Big Tech ecosystem as a whole.

Amazon and Microsoft show a sharp change in their response to a strong signal compared to a weak signal in terms of both strategic persistence and strategic convergence, whereas Meta and Apple exhibit less of this tendency. This demonstrates that Meta and Apple are responding and adjusting their acquisition likelihood

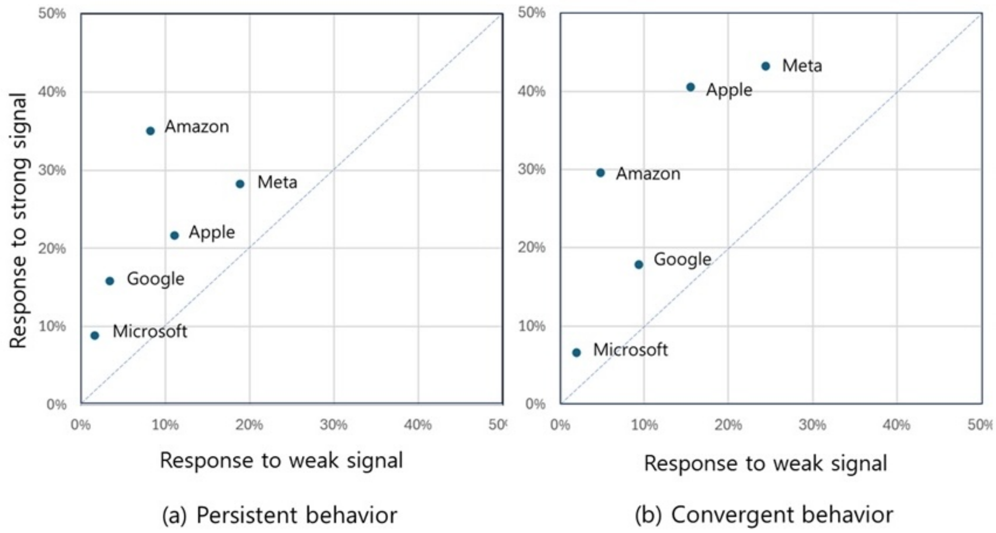

Figure 4: Individual Firm Persistent and Convergent Behavior

Notes: This figure shows persistent and convergent behavior of the five Big Tech companies. The unit of measurement on the horizontal and vertical axes represent percentage points, indicating the marginal absolute increase in acquisition probabilities for weak and strong signals, respectively.

towards weak and strong signals relatively more evenly. Note that the baseline predicted likelihood of acquisition differs between the Big Tech companies, leading to their varied positions on the plane. Comparing persistence and convergence behavior across the firms, Amazon and Microsoft exhibit a stronger tendency of strategic persistence (their acquisition probabilities increase to a lesser extent in their convergence behavior relative to their persistent behavior), while Google, Apple, and Meta exhibit a stronger tendency toward strategic convergence.

6.4 Evaluation of Growth Stage Dependency

The firms are ordered by their operating years as follows:

$$\text{Meta} < \text{Amazon}, \text{Google} < \text{Apple, Microsoft}$$

Simply comparing the *magnitudes* of the parameter estimates, the companies are ordered from the strongest to the weakest strategic persistence as follows:

$$\theta_3 : \text{Meta} > \text{Microsoft} > \text{Apple} > \text{Google} > \text{Amazon}$$
$$\theta_4 : \text{Microsoft} > \text{Amazon} > \text{Google} > \text{Meta} > \text{Apple}$$

To order them by their intensity of strategic convergence:

$$\theta_5 : \text{Meta} > \text{Google} > \text{Apple} > \text{Microsoft} > \text{Amazon}$$
$$\theta_6 : \text{Meta} > \text{Apple} > \text{Google} > \text{Microsoft} > \text{Amazon}$$

Strategic persistence does not appear to be tied to years of operation. Meanwhile, it appears to be partially supported that strategic convergence may be correlated with growth stage. For instance, Meta, the youngest of the five firms, exhibits the strongest strategically convergent behavior. As a result, it is hard to conclude

Table 6: Baseline Predicted Probabilities and Odds Ratio

	Dependent variable: Enter/Not Enter				
	Google	Meta	Microsoft	Amazon	Apple
Baseline Predicted Probabilities of Buying					
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%
Baseline Odds Ratio					
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.

that the Big Tech firm's acquisition behavior, in general, depends on their respective operating years. It may be more reasonable to conclude that Meta's business characteristics and/or strategic orientation are driving its convergent behavior, making its age a necessary but not sufficient condition for this phenomenon. As such, it is difficult to validate **Proposition 4**.

6.5 Evaluation of Macroeconomic Effects

Table 6 presents the baseline predicted probabilities of acquisition and the baseline odds ratios. The former refers to the predicted probabilities when no prior acquisitions were made by any of the five companies during the last year. In that setting, the probabilities are calculated by changing only the interest rate. 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 predicted baseline probabilities of market entry being 25.4%, 7.7%, and 2.4%, as shown in Figure 5.

In a high-interest rate environment, the acquisition likelihood for most firms significantly decreases, making the baseline predicted probabilities for these five firms 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.

On the contrary, Microsoft exhibits a different pattern of changes in acquisition probabilities in response to elevated interest rate. In fact, in a high-interest rate environment, its acquisition probability increased by 1.3% for acquiring in sectors that no Big Tech companies, including itself, have acquired. 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, which may imply a substantial acquisition cost for the company. It is known that Microsoft has been involved in leading high-value acquisitions, including LinkedIn ($26.2 billion). Although how and how much it impacts varies by firm, all five companies show a statistically significant response to the change in macroeconomic effects, and thus **Proposition 5** is validated.

6.6 Evaluation of Heterogeneous Responsiveness

Based on the estimates in Table 5, predicted probabilities are calculated as shown in Figure 6 and corresponding results are shown in Figure 7. Figure 7 shows that the strength of the signals affect differently to each company's predicted probabilities. This suggests that their acquisition strategies are guided by different strategic priorities.

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

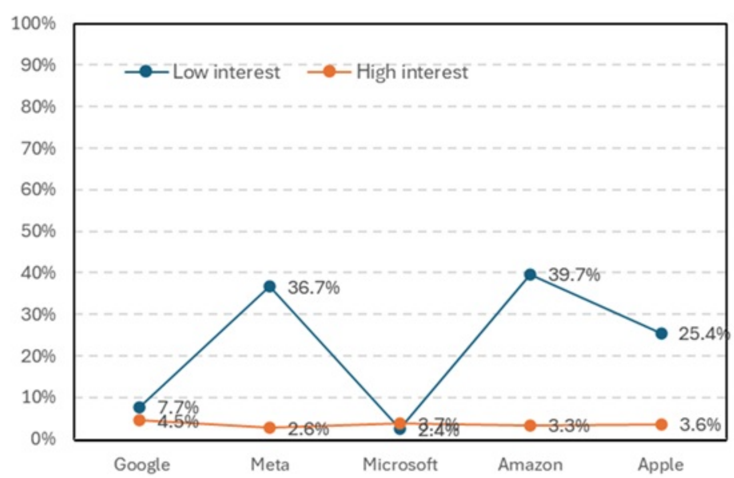

Figure 5: Comparison of Baseline Probabilities Among Big Tech Companies

Notes: This figure presents a comparison of the baseline acquisition probabilities for Big Tech companies, shown separately for low interest and high interest scenarios. The baseline acquisition probabilities that showed relatively high variability across companies become more uniform and drops in the high interest rate scenario.

Strong (freq. > 5)	Baseline + θ_6 probabilities	Baseline + θ_3 + θ_6 probabilities	Baseline + θ_4 + θ_6 probabilities
Weak (freq. 1-5)	Baseline + θ_5 probabilities	Baseline + θ_3 + θ_5 probabilities	Baseline + θ_4 + θ_5 probabilities
None	Baseline probabilities	Baseline + θ_3 probabilities	Baseline + θ_4 probabilities
	None	Weak (freq. = 1)	Strong (freq. > 1)

Figure 6: Acquisition Likelihood Calculation

Notes: This figure shows the parameters involved to compute acquisition probabilities, with various combinations of scenario inputs. This makes nine unique probabilities of acquisition, each resulting from a specific combination of scenarios. The horizontal axis represents the likelihood of acquisition in response to the company's own signal, and the vertical axis represents the likelihood of acquisition in response to those from its rivals. Baseline probabilities represent the acquisition probabilities in the absence of any signals.

Google			Meta			Microsoft			Amazon			Apple		
26	34	56	80	90	93	9	14	34	69	76	91	66	77	84
17	24	43	61	77	83	4	7	19	45	53	78	41	54	65
8	11	24	37	56	65	2	4	11	40	48	75	25	37	47

(a) Acquisition probabilities with low interest rate

Google			Meta			Microsoft			Amazon			Apple		
22	31	53	46	56	59	8	13	33	33	40	55	44	55	62
14	20	40	27	43	49	3	6	18	8	17	42	19	32	43
4	8	20	3	22	31	1	3	10	3	12	38	4	15	25

(b) Acquissition probabilities with high interest rate

Figure 7: Firm-Specific Acquisition Likelihood Based on Contingency Scenarios

Notes: The figure shows the outcome of the computed acquisition probabilities for each company investigated at various combination of scenario inputs. Figure (a) represents acquisition probabilities with low interest rate, and Figure (b) represents acquisition probabilities with high interest rate.

to be the most resilient in response to macroeconomic shocks and consistently maintains modest acquisition strategies relative to others during such macroeconomic shocks. Microsoft appears to place a greater emphasis on growth through the accumulation of targets that can create scale economies. Lastly, Apple and Amazon appear to be responsive to high competitive pressure;, their acquisition likelihood increases by 66% and 69% from the baseline probabilities. However, the results reveal a common pattern across all firms: their acquisition probabilities tend to increase with a higher number of previous acquisitions, i.e., stronger signals.

7 Strategic Implications and Future Research

7.1 Strategic Implications

The acquisition decisions made by these five involve a dynamic process of adapting to changing market conditions while balancing between strategic persistence and strategic convergence. The impact of these two forces may vary depending on the firm characteristics (e.g., firm size, age, etc.) and the idiosyncratic trajectory of each platform ecosystem. My results suggest a greater degree of strategic persistence for a greater number of acquisitions made by its own. This is also true for strategic convergence, which is more inclined to converge for greater investment made by its peers.

This may suggest different market outcomes, the level of competition and innovation, and the regulatory implications. If, for example, strategic convergence among Big Tech is strong, leading to an ever-expanding number of markets in which they compete, a regulatory approach should be different from the one where no single firm strategically converges. That is, if the markets in which Big Tech compete evolve into a group of separated markets, an individual market is likely to have oligopolistic or monopolistic market structure, in which case, each individual Big Tech company has dominant power. However, if these markets grow into a single digital market, it is more likely that such a market is distant from a monopolistic market structure and that all five Big Tech companies are likely to compete against each other. The result of this study shows a growing convergence trend of Big Tech's business scope and their acquisition strategies. Additionally, the growth of the platforms that cuts across multiple vertical and horizontal markets reinforces the need to broaden the scope of the relevant markets to account for the nature of platform expansion and competition.

7.2 Limitation and Future Research

This study is subject to limitations that provide opportunities for future research. The number of companies investigated was restricted to the five leading tech giants in the United States market, allowing for an in-depth examination of their strategic convergence and competitive dynamics. Building on this study, future research may aim to expand the scope to include other major tech companies that have recently gained a significant market cap, such as NVDIA and Tesla. By examining these firms, whose domains are less overlapping with those of the five original companies, future study may be able to assess the extent to which they exhibit their own strategic convergence and persistence, and determine whether the initial findings still apply to the broader set of tech companies. The scope of the firms investigated can be expanded further to include companies originating in other countries. Such scope would require a more comprehensive examination of geopolitical dynamics, national regulatory environments, and regional trade policies that govern global tech industries.

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Appendix A Timeline of Active Big Tech Acquirers

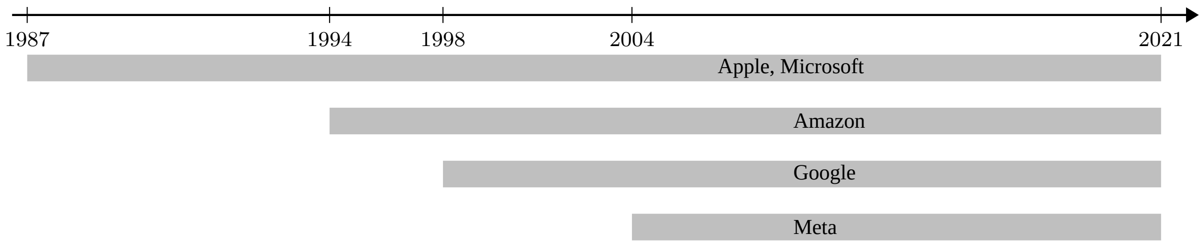

Figure 8: Timeline of Active Big Tech Acquirers

Table 7: Top 10 Sectoral Acquisitions from 1987 to 1993, Colored by the Intensity of Overlap

Apple	Microsoft
Software Development Applications (2)	Business/Productivity Software (1)
Application Software (1)	Multimedia and Design Software (1)
Business/Productivity Software (1)	
Network Management Software (1)	

Table 8: Top 10 Sectoral Acquisitions from 1987 to 1997, Colored by the Intensity of Overlap

Apple	Microsoft
Software Development Applications (2)	Multimedia and Design Software (2)
Application Software (1)	Software Development Applications (2)
Business/Productivity Software (1)	Application Software (1)
Network Management Software (1)	Broadcasting, Radio and Television (1)
	Business/Productivity Software (1)
	Entertainment Software (1)
	Information Services (B2C) (1)
	Movies, Music and Entertainment (1)
	Network Management Software (1)
	Other Communications and Networking (1)

Appendix B Estimation of the First Stage

Table 9: First-Stage Logit Estimates

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