Killers on the road of emerging start-ups—implications for market entry and venture capital financing

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Abstract

The competitive effects of acquisitions made by large US-based technology companies have come under increased regulatory scrutiny over recent years because their acquisition patterns have been viewed as potentially harming competition. This paper studies the impact of acquisitions by large US-based technology companies on the entry dynamics and venture capital financing in their target product markets. We use data from Crunchbase, a global database of start-up companies, from 742 product markets globally, distinguishing the United States and European markets for 2003–2021. Using state-of-the-art econometric developments, we estimate the dynamic treatment effects model in the staggered, dynamic event study setting. Our estimation results suggest that the technology giants' buyouts subsequently reduced market entry rates and decreased the available venture capital funding in the product markets of the acquired companies. The acquisition of technology giants seems to generate a so-called "kill zone," which dissuades the market entry of new companies. Our findings highlight the long-term consequences that technology giants' acquisitions may have, including a decline in venture capital financing and the creation of entry barriers in technology-intensive markets.

Keywords: G24; G34; L1; L41

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1. Introduction

Technology companies' proliferation and intersection with various sectors and industries have significantly shaped the market landscape, raising concerns about market power and its implications for long-term innovation and growth in technology-intensive markets. Cases in point are the billion-dollar deals involving technology giants, such as Microsoft's acquisition of LinkedIn for over USD 26 billion in 2016 and Google's acquisition of Fitbit for USD 2.1 billion in 2021. These landmark acquisitions underscore the centrality of dynamic competition and its complex implications for market power and innovation.

More recently, concerns have intensified around big tech's role in artificial intelligence. High-profile acquisitions of AI firms (such as Google's USD 32 billion purchase of Wiz), partnerships between cloud providers and foundation model developers (notably Microsoft–OpenAI and Amazon–Anthropic), and so-called "quasi-mergers," where incumbents hire key personnel and secure exclusive licenses from start-ups (Kazimirov, 2025).

This article explores the market dynamics surrounding acquisitions by big tech companies, particularly focusing on their impact on the dynamic competition via changes in market entry and venture capital (VC) financing in various product markets.

When two large technology companies merge, a common concern is that the resulting large user base will reinforce the lock-in effects arising from network externalities.[1] In addition to buying companies with large or growing user bases, technology giants have regularly acquired smaller technology companies. Recent studies suggest that the expanding proliferation of technology companies outside of their core business areas has enabled them to accumulate sharable inputs, data, and software algorithms that can be used to exploit the data (see, e.g., Koski and Pantzar, 2019). By the end of 2021, the six US-based technology giants' (Google, Apple, Microsoft, Amazon, Facebook, and IBM—hereafter referred to as "tech giants" in this article) total number of acquisitions amounted to over 950, of which almost 70% took place during the past 10 years.

The increasing market share of the largest technology companies has raised competitive concerns (see, e.g., Crémer et al., 2019).[2] In addition, large companies' buyouts of companies that could potentially grow to be their future rivals—such as Facebook's acquisition of Instagram—have further raised questions about whether the contemporary antitrust enforcement tools are adequate for the acquisition dynamics found in digital markets (see, e.g., Argentesi et al., 2019; Cabral, 2021).[3]

Our article is closely aligned with the theoretical framework of the "kill zone" effect proposed by Kamepalli et al. (2020). This framework suggests that market dynamics in digital markets, driven by network externalities and switching costs, can inhibit new market entries. The threat of acquisition discourages demand from early adopters for new technologies, subsequently dampening VC investment. While Kamepalli et al. (2020) empirically demonstrate a decline in VC investments in start-ups operating in product markets where Facebook and Google execute significant acquisitions, they do not investigate the direct effects on market entry. In contrast, our study offers an empirical analysis of how acquisitions impact, besides VC investments, market entry. In addition, whereas Kamepalli et al. (2020) rely on a limited dataset of companies offering substitute products with seven software companies acquired by Facebook and Google between 2016 and 2018, our dataset includes all acquisitions made by five major US-based technology giants from 2002 to 2021. Our dataset further includes extensive data from 2002 to 2021 on VC investments and market entries across 744 product markets in both the United States and the European Union, providing a deeper and more nuanced understanding on how acquisitions by large US-based technology companies have impacted market entry and VC funding.

As a data source, we use Crunchbase that is a global database of start-up companies that provides detailed information on the market entry of technology companies and the amounts of VC funding attained by companies. A particular advantage of the Crunchbase dataset is that all the listed companies are classified according to their main products (divided into 744 product categories). This data feature allows us to capture the sample firms' product portfolios with a high resolution and identify the major product markets in which the companies are active. Furthermore, Crunchbase has good coverage of start-ups and emerging technology companies, poorly covered in commonly used firm-level datasets such as ORBIS.

We use state-of-the-art econometric developments and estimate the dynamic treatment effects model in the staggered, dynamic event study setting. We employ the estimation method proposed by Sun and Abraham (2021) to explore whether and how the large US-based tech giants' acquisitions have subsequently affected the entry dynamics and VC financing in different product markets in the United States and Europe. We first estimate a benchmark model comprising complete sample data for the treatment years 2003–2021 with 323 treated product markets for the United States and 129 treated product markets for the EU. Secondly, we use the coarsened exact matching (CEM) method to form a control group for the product markets into which the large technology companies entered via their acquisitions. We then estimate corresponding dynamic treatment effect models for the CEM-matched treated and control product markets.

The dynamic treatment effects estimations allow us to make conclusions on the causal economic impacts of acquisitions. We find that the large technology companies' buyouts generally lead to substantially lower market entry rates and less VC funding in the target product markets both in the United States and Europe. The study underscores the importance of examining the potentially detrimental impacts that acquisitions by large technology companies may have on dynamic competition through their effects on firm entry and innovation in technology-intensive markets. However, the presence of a “kill zone” does not inherently signify a negative effect on dynamic competition if it is counterbalanced by positive dynamic effects within large tech firms. Furthermore, other possible explanations for our findings include start-ups and VCs investing in the hope of being acquired, where the acquisition of a particular start-up leads to a perception that the market for similar start-ups is now saturated or that the most promising target has already been taken, thus discouraging further investment and leading to a cooling effect.

The remainder of the article is organized as follows. In Section 2, we present a literature review and discuss hypotheses stemming from the analysis of the literature concerning the competitive effects of acquisitions made by tech giants. Section 3 introduces the data and discusses the strengths and limitations of the subject of the study. In Section 4, we present the empirical model and estimation results. Section 5 discusses the empirical findings and concludes the article.

2. The competitive impacts of acquisitions

Economic literature offers mixed perspectives on whether acquisitions by large companies of start-ups tend to enhance competition or harm it. This debate revolves around the balance between efficiency gains from synergies between the acquirer and the acquired firm, and the potential welfare-reducing consequences of reduced market competition. In this section we provide a selective literature review, and explore how the literature has evolved, examining both the pro-competitive and anticompetitive effects of such acquisitions, with a focus on the unique dynamics of digital markets.

The notion that acquisitions can foster efficiency and innovation traces back to the seminal work of Schumpeter (1934, 1942), arguing that temporary monopoly power due to acquisition drives dynamic efficiency. In this view, acquisitions allow start-ups to contribute innovative ideas and new products, while incumbents possess the competencies, assets, and financial resources needed to further deploy those ideas and products and commercialize them.

Building on this, the literature on dynamic capabilities highlights the importance of synergies in acquisitions. Teece (2007) and Petit and Teece (2021) emphasize that the efficiency gains depend on the acquirer’s ability to absorb the acquired firm’s dynamic capabilities—processes and knowledge that enable competitive advantage. Graebner et al. (2010) and Lee and Lieberman (2010) further argue that acquisitions allow incumbents to access new products, consumer data, and knowledge faster than internal development.

Acquisitions also play a pivotal role in VC markets. Phillips and Zhdanov (2013, 2017) suggest that the prospect of being acquired incentivizes start-ups to innovate, as acquisitions provide a key exit route for investors. Similarly, Crémer et al. (2019) emphasize that buyouts facilitate the private financing of high-risk innovation, ensuring a steady pipeline of new market entrants.

Despite their potential benefits, acquisitions can harm competition by eliminating potential rivals. Gilbert and Newbery (1982) theorize that incumbents may acquire start-ups to preempt competition. This view is supported by Cunningham et al. (2021), who introduced the concept of "killer acquisitions," where incumbents acquire nascent competitors to terminate their innovative projects and preserve market dominance. Their empirical work in the pharmaceutical industry provides causal evidence in favor of this story.

Bryan and Hovenkamp (2019) propose that the strategic behavior of entrants can exacerbate anticompetitive outcomes. Their model suggests that entrants may prioritize technologies aligning with dominant incumbents, increasing the likelihood of acquisition and entrenching market concentration. Motta and Peitz (2021) and Shapiro (2018) argue that such acquisitions reduce consumer welfare by suppressing competition from innovative entrants.

Digital markets introduce additional complexities due to network externalities, economies of scale, and data-driven dynamics (Koski and Kretschmer, 2004). These markets are often characterized by "winner-takes-all" dynamics, where early movers with superior technology or larger user bases attract the majority of users. This leads to strong network effects~~, —~~empirically studied since the 1990s (see, e.g., Gandal, 1994; Saloner and Shepard, 1995; Koski, 1999; Kim et al., 2014)— ~~that lock~~s users into the dominant platforms and make marke~~t entry dif~~ficult for competitors to enter. Acquisitions by incumbents, such as Google or Meta, exacerbate these dynamics by leveraging the acquired firm's technology, user base, and data to strengthen their existing market dominance. Such acquisitions do not merely reinforce the incumbent's position; they also create disincentives for new entrants and investors, leading to what Kamepalli et al. (2020) term a "kill zone."

This counterintuitive dynamic is well-documented in the analysis by Kamepalli et al. (2020). While acquisitions are traditionally viewed as a critical exit strategy for start-ups—encouraging entry and financing—their study shows that the opposite effect can occur in digital markets dominated by incumbents. When these dominant firms acquire promising start-ups, VC investment in the relevant market drops significantly compared to markets without such acquisitions. This decline reflects a broader market-level deterrent effect: by demonstrating their ability to acquire and integrate new technologies or products seamlessly, incumbents signal to potential entrants and investors that the competitive space is effectively "closed." As a result, both entrepreneurs and financiers shift focus away from these markets.

This deterring effect has strong implications. According to Kamepalli et al. (2020), these acquisitions have a "chilling effect" on innovation, not just in the acquired company's particular industry but also in adjacent markets where comparable dynamics are expected. This wider effect highlights the double character of acquisitions in digital markets: whereas they might offer individual start-ups a profitable exit, they can also weaken the competitive environment that encourages more extensive market entry and investment. In this sense, acquisitions help create so-called “kill zones,” where the power of established companies stifles the diversity of innovation ecosystems.

Prufer and Schottmüller (2017) highlight the role of consumer data in reducing the marginal cost of innovation, creating data-driven indirect network effects. When incumbents acquire firms in adjacent markets, they can exploit existing data to dominate new markets, deterring entry and stifling innovation. Prat and Valletti (2012) extend this argument, suggesting that the concentration of data on online platforms can reduce market entry and competition in downstream markets. Wen and Zhu (2019) examine the strategic responses of complementors in the face of entry threats by platform owners. They find that platform-driven acquisitions reduce complementors’ innovation in affected markets, further solidifying incumbents’ dominance.

Recent empirical work has examined the competitive and financial consequences of big tech acquisitions. Gugler et al. (2025) analyze acquisitions by Google, Apple, Facebook, Amazon, and Microsoft and find that such buyouts reduce start-up entry and VC funding in affected markets, consistent with a “kill zone” mechanism. Prado and Bauer (2022), by contrast, document short-term increases in VC activity following big tech acquisitions, though the effect dissipates after a few quarters.

Complementing these VC-focused studies, Affeldt and Kesler (2021) show that rival app developers reduce innovation and product updates after their competitor is acquired by a dominant tech firm, while Eisfeld (2024) finds that the availability of acquisition opportunities stimulates entry in software markets but reduces the diversity of entrants. Other work highlights heterogeneous innovation effects: de Barsy and Gautier (2024) report that acquirers often increase their patenting activity post-acquisition, though evidence of positive spillovers to broader markets is limited; Doan and Mariuzzo (2022) study the cloud computing sector and identify increases in patenting post-acquisition. Ivaldi et al. (2024), drawing on European merger case evidence, find instances consistent with “killer acquisitions,” though outcomes vary across markets. Finally, Jin et al. (2023) compare top acquirers and show that GAFAM acquisitions are not systematically more harmful than those by other large firms but differ in scope and technological expansion. Taken together, recent empirical literature reveals mixed evidence: some studies emphasize deterrent effects on entry and rival innovation, while others point to positive or transient impacts on investment and innovation.

Building on both theory and evidence, it appears that the scope of potential efficiency and innovation gains from acquisitions depends on specific conditions, such as the acquirer’s ability to integrate the acquired firm’s capabilities and the nature of competition in the market (e.g., Teece, 2007; Phillips and Zhdanov, 2013). Recent empirical and theoretical work has raised concerns that in digital markets, acquisitions by large incumbents could result in anticompetitive outcomes due to network effects, data-driven economies of scale, and the creation of kill zones (Kamepalli et al., 2020; Cunningham et al., 2021). Given the growing policy and academic concern about these dynamics, our study focuses on evaluating the potential negative effects of acquisitions, particularly their impact on market entry and VC investments. Based on these insights, we propose the following hypotheses:

Hypothesis 1:
Large incumbents' acquisitions of firms in a product market tend to decrease the entry of new firms to that product market.

Hypothesis 2:
Large incumbents' acquisitions of firms in a product market tend to decrease VC investments in other firms active in that product market.

Although our hypotheses focus on potential harms, we acknowledge the possibility of pro-competitive effects. In spite of potential kill zone effects, acquisitions may still incentivize innovation by providing exit routes for entrepreneurs and investors or signal opportunities for dynamic competition. However, this study emphasizes the negative effects to address gaps in existing literature and inform ongoing policy debates regarding the regulation of acquisitions in digital markets.

3. Data and descriptive findings

3.1. Data

Our dataset is derived from Crunchbase, a leading global database of start-up companies. Crunchbase collects its data through multiple channels, including a partner program in which VC firms share information about their portfolio companies in exchange for access to the database. In addition, it incorporates crowdsourced data provided by companies, which is subsequently verified by Crunchbase's in-house data team to ensure accuracy and reliability.[4]

Crunchbase assembles its data without a predefined sampling frame. The platform sources information from a broad network of data providers, including global investment firms, investors, company executives, and partners, who provide and verify data in exchange for access to the database. Notably, the methodology for data collection implies that the subset of young, internationally oriented technology start-ups actively seeking VC funding—firms that would most likely be targeted by tech giants for acquisition—is likely well-represented. Supporting this claim, Dalle et al. (2017) compared Crunchbase with the OECD Entrepreneurship Financing Database, which relies on survey data from national private equity and VC associations and is considered more representative. Their findings indicate a high correlation between the two datasets, lending credibility to the measures derived from Crunchbase. Consequently, Crunchbase has emerged as the most extensive global database of start-ups and technology companies, offering valuable insights for research in this domain.

The significant advantage of the Crunchbase database for the subject of this study—compared with the datasets using traditional industrial classification (e.g., NACE codes)—is that the companies are classified on a highly granular level according to the main products they provide. The taxonomy within Crunchbase consists of 744 "industries," which are further grouped under 46 "industry groups." Any company can be classified into an arbitrary collection of industries based on its core business activities in various product markets.[5] This classification into product markets corresponds well with the competition-law definition of a relevant market according to product factors (i.e., the product markets of all products or services that can be regarded as substitutable).

The Crunchbase data does not follow a standard panel data format that our analyses would necessitate. Therefore, we transformed the data into a panel format using the following steps. First, we excluded all observations that did not relate to companies.[6] After that, we excluded all firms whose closing date occurred before 2002. For each year from 2002 to 2021, we calculated the annual number of new companies, the annual number of acquired companies, and the stock of companies whose founding date was in the past and whose opening date is either empty or has not occurred. As a result, we get a balanced panel of industries for the years 2002–2021. This allows us to look into the effect of acquisitions on market entry and VC funding in different product markets as well as distinguish shorter-term (i.e., within 5 years after the first entry of a data giant to a market) and longer-term (i.e., within 10 years after the first entry of a data giant to a market) impacts. However, the staggered timing of the first acquisition across product markets implies unbalanced event-time panels in the empirical analysis.

As noted, our definition of "tech giants" comprises the following companies: Amazon, Apple, Facebook, Google, Microsoft, and IBM. We chose the first five of these companies as these are commonly referred to as "big tech" companies that are "impossible to live without." We added IBM to the group as the study of Koski and Pantzar (2019) found that IBM is a major global player in digital markets with vast health databases, and moreover, among the six tech giant companies, IBM has bought the highest number of companies in the two highly data-intensive sectors: financial services and health. The six companies and their subsidiaries have been among the most active acquirers of technology companies according to the Crunchbase data.

Our primary dependent variables are *market entry* and *VC investments*. We operationalize the market entry rate measure as the share of new firms in each product market (i.e., the number of new firms in each product category divided by the stock of existing companies in that product category in a given year). As a measure of VC investments, we use the total funding (in millions of USD) awarded annually in all types of funding rounds to companies within a given product category. Both variables were log-transformed prior to analysis. The left panel of Figure 1 plots the total number of new companies and the stock of companies during the period 2002–2021. Evidently, the yearly number of founded companies peaked in 2015 and has declined since. The right panel in Figure 1 plots the total amount of VC funding by year according to Crunchbase data. In stark contrast to the entry of new companies, VC funding shows a positive trend throughout the observation period, with an average annual growth rate of over 25%.

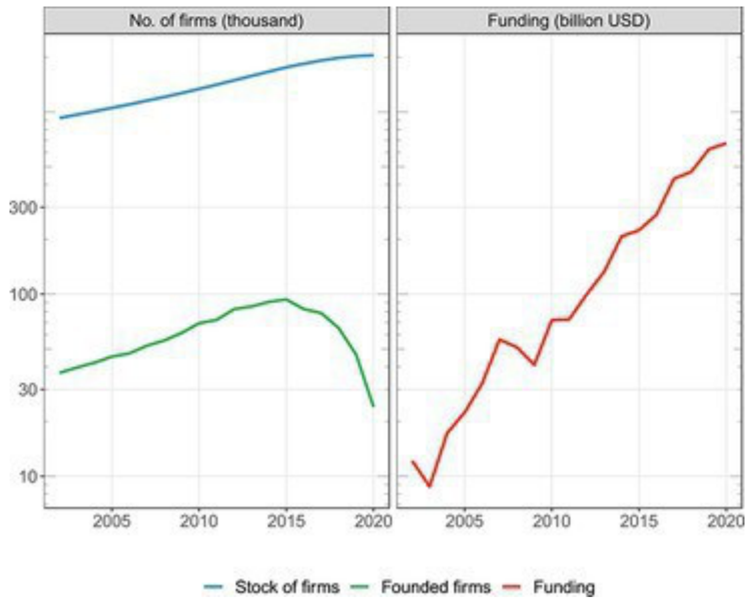


Figure 1 Funding and the number of companies according to Crunchbase

Our unit of analysis is the product market, as defined by the 744 Crunchbase industries. This level of analysis allows the entry rates and VC funding between the product markets in which the tech giants have made acquisitions **t**o be compared with the product markets in which the tech giants have not bought any companies. We undertake the analysis separately for the product markets in the United States and in the EU. The underlying reason for the separate estimations is that there may have been some policy or regulatory changes in either the United States or the EU over time (such as the revision of the horizontal merger guidelines in 2010 in the United States) that changed the overall market environment for all product markets affecting, e.g., to barriers of entry or to VC financing in one of the economies, but not in the other.

The dependent variables and the main independent variables are separately summarized in Tables 1a and 1b for a maximum of 5 years after the first entry of a data giant to a market for the United States and the EU. The log-transformed market entry rate variable equals (about) tech giants' 4% market entry rates in the United States and 5% market entry rates in the EU. On average, VC financing for product markets was higher in the United States than in Europe. In the United States, the *treated* variable equals 0.26 (i.e., the tech giants had acquired companies in 26% of the product markets). In contrast, in the EU, they had acquired companies in 16% of the product markets. The cumulative number of acquired firms was higher after a data giant's first acquisition in a market in the United States (the average and maximum numbers were 0.95 and 97, respectively) than in the EU (i.e., the average and maximum numbers were 0.17 and 20, respectively).

Table 1a Descriptive statistics for the United States

Statistic	Mean	St. dev.	Min	Max
Log entry rate	−3.690	1.280	−6.908	0.001
Log venture capital funding (USD millions)	1.627	5.071	−6.908	11.420
Treated	0.260	0.439	0	1
Cumulative acquisitions by data giants	0.946	3.998	0	97
N	9,458			

Table 1b Descriptive statistics for the EU

Statistic	Mean	St. dev.	Min	Max
Log entry rate	−3.548	1.410	−6.908	0.001
Log venture capital funding (USD millions)	−0.513	5.128	−6.908	10.075
Treated	0.160	0.367	0	1
Cumulative acquisitions by data giants	0.168	0.854	0	20
N	9,477			

Our data does not always include the founding year of the firm. In these cases, we assume that the firm is founded in the year when we first observe it. Incomplete data on firm entry might cause some measurement errors and affect our estimates. However, we note that any measurement errors would only affect the left-hand side of the regression models. Under the reasonable assumption that the missing founding year is uncorrelated with the probability of being acquired by a data giant, this should not jeopardize the econometric setting. Moreover, using the entry rate rather than the number of entries as the dependent variable can mitigate any measurement errors on the dependent variable since entry, and stock variables only show a small correlation with one another.

3.2. The acquisition patterns of data giants

The acquisition history of the global technology giants indicates that they have widely expanded their operations to new product markets and geographical market areas. It is credible that these acquisitions, particularly those concerning platform companies, have contributed to the volume and variety of consumer data possessed by the tech giants. Figure 2 visualizes the geographical acquisition patterns of the digital giants. Each circle represents the headquarters of firms acquired by the tech giants and the large circles represent the headquarters of the digital giants. The acquisitions are highlighted by lines. The overall geographical pattern in North America, Europe, and the rest of the world is displayed as shares of acquisitions in larger bubbles.

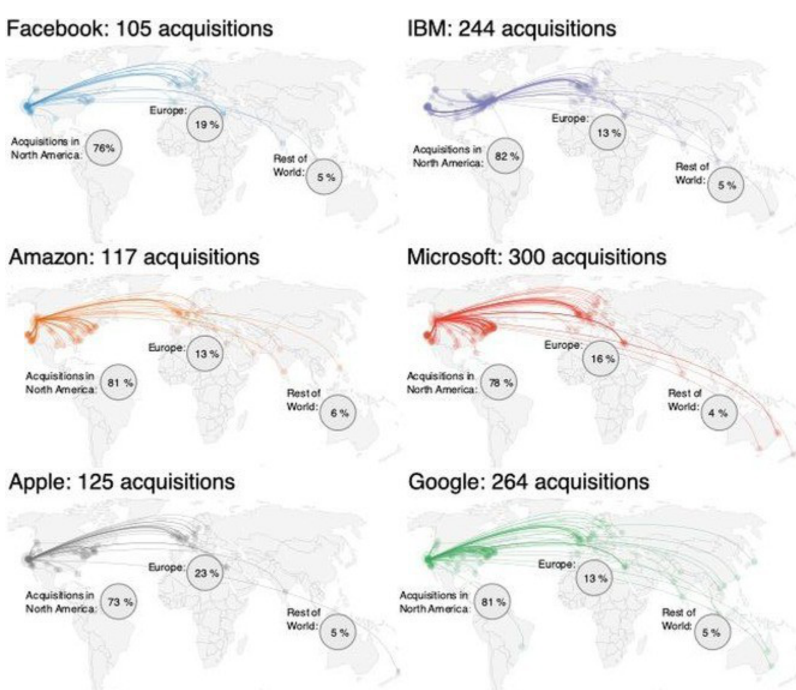


Figure 2 The geographical acquisition patterns of the digital giants

Figure 2 reveals clear commonalities in the acquisition patterns of the digital giants. Most of the acquisitions have taken place in North America, particularly in the densely populated and tech-intensive coastal regions of California, Washington, and the East Coast. For all six giants, 70% or more of all their acquisitions are focused on North American companies. Another geographical focus is Western Europe, with most acquisitions made in London. However, only a sixth to a quarter of all acquisitions took place in Europe. Other relevant acquisition areas are Israel and Australia. The tech giants have conducted some acquisitions in India, New Zealand, China, Hongkong, and Singapore, but the total share of acquisitions outside of Europe and North America accumulates to just 4%–6%.

Figure 3 shows acquisition patterns over time in more detail. The circular heat map visualizes the expansion of the tech giants' scope into an increasing number of product markets from 2002 to 2021. Each cell represents an industry group–year combination. The whole circle contains 920 cells (i.e., 20 years × 46 industry groups). The cells in the center represent the industry groups of the firms at the beginning of the observation period (in 2002); those at the periphery show the industry groups in 2021. Three gray circles give orientation (2002, 2010, and 2021). If a tech giant is not present in a given industry, the cell is empty. The more firms a giant acquires, the darker the cells become. Each cell shows the total number of firms acquired by a giant in a given industry group.

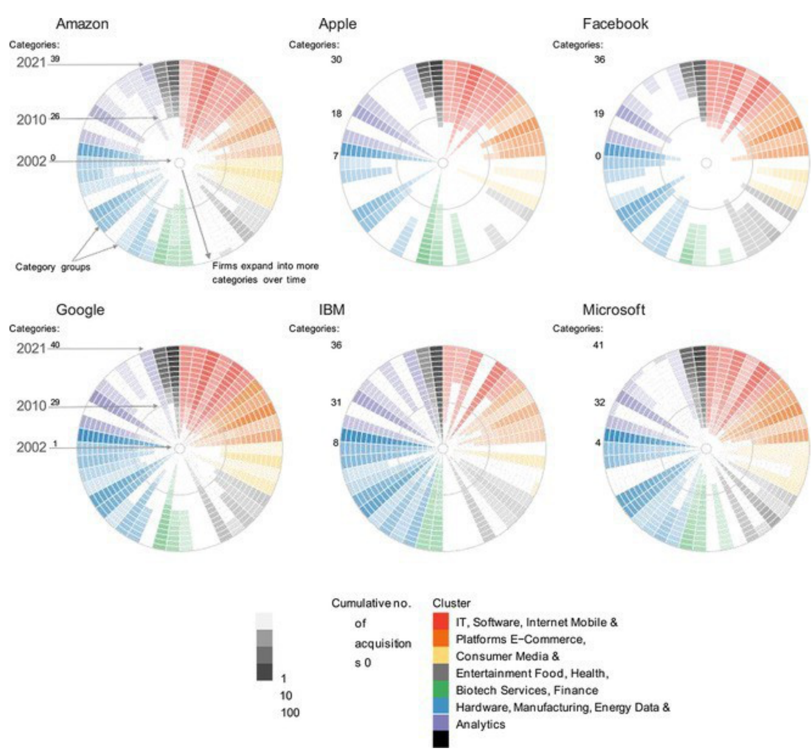
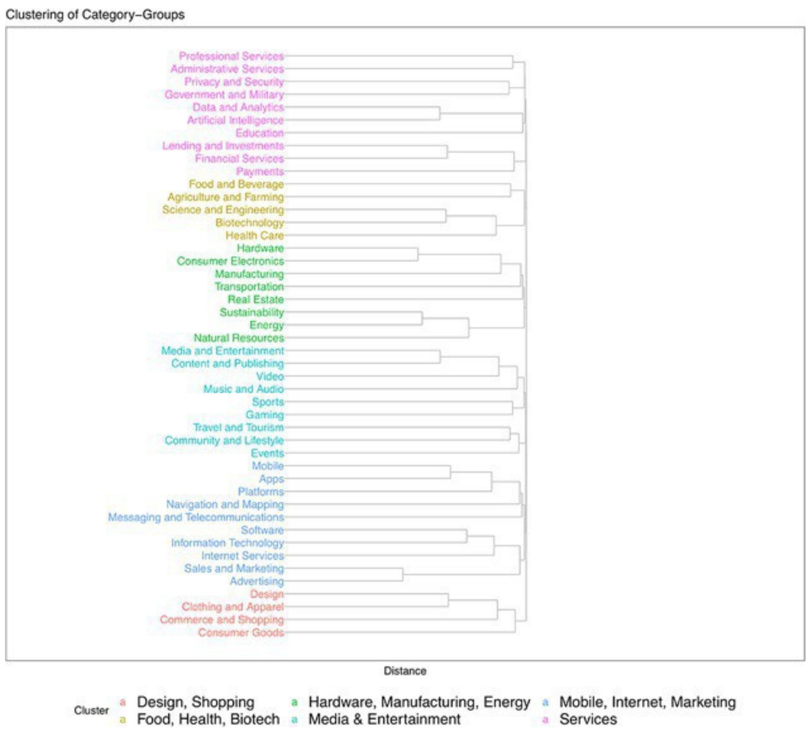


Figure 3 Data giants' acquisition patterns across different product market clusters: 2002–2021

The colors represent clusters of related industry groups, which have been grouped according to a hierarchical clustering algorithm to identify similar industries. The algorithm identifies six main clusters (see the dendrogram shown in Annex 1). We have further split the "services & finance" cluster to isolate "data & analytics" and "IT, software & the Internet" to form a separate "mobiles & platforms" cluster.



Annex 1 This diagram presents a dendogram of the clusters of industry groups used for coloring Figure 3

Figure 3 reveals similarities and differences in the acquisition patterns of the digital giants. For example, while Amazon has focused its activities on “e-commerce, consumer, services,” and “entertainment” early on, Apple entered these markets later and to a lower degree. In contrast, Apple started with a focus on “software, hardware, & media.” With the start of its mobile phone branch, the firm went more intensively into “mobiles & platforms” and “data & analytics.” In recent years, Apple also made its way into “services & finance,” accompanying its mobile payment solutions.

The lower panel reveals a clear focus on services, software, and mobile for Google, IBM, and Microsoft.

Apart from such differences, the figure shows that, by 2021, the giants had expanded into most of the industry groups (see the numbers on the left of each heat map that show the total number of industries the giants had made acquisitions in by 2002, 2010, and 2021).

4. The empirical approach and estimation results

We now turn to empirically studying the hypotheses outlined in Section 2. According to hypotheses 1 and

2, an entry by a tech giant should lead to decreased entry rate and VC funding in a product market. The first acquisition of technology giants varies across the product markets meaning the treatment timing is staggered. Recent developments in the literature indicate that in such cases, a two-way fixed effects regression specification may lead to severely biased estimates (see, e.g., Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Baker et al., 2022; Roth et al., 2023).

To address this issue, we employ a three-stage estimation method of Sun and Abraham (2021) that corrects this potential bias and produces the cohort average treatment effects (CATT) on the treated product markets. Specifically, in the first stage interact the treatment dummy with a cohort indicator representing the year when a tech giant first acquired a company in the product market. We estimate the cohort average treatment effects using a linear two-way fixed effects regression model with interaction terms. This isolates the causal effect of the acquisition over a period of 3 years before and 5 years after the first acquisition. The pretreatment period serves as the reference (Baker et al., 2022). The model is specified as follows:

$$Y_{it} = \mathrm{a}_i + \gamma_t + \sum_{l \# -1} \delta_{\mathrm{g},l} \mathbf{1}\left\{G_g = g\right\} {D_{it}}^l + \mathrm{e}_{it} \quad \textbf{(1)}$$

where Y_{it} captures the (log) number of firms entering product market *i,* divided by the total stock of companies, or (log) VC investments (measured in log millions of USD) in the product market *i* at time *t*.[7] The term a_i and γ_t account for product market-specific and time fixed effects, respectively. The product markets are categorized into different cohorts, *G*, based on their treatment year, $\{G_g = g\}$, where g is the year when a technology giant first time acquired a company in the product market. The variable ${D_{it}}^l$ is a dummy variable that gets a value of 1 for treated product markets in the relative year from the treatment, l, and 0 if technology giants had not acquired any companies in the product market by the end of sample time. In the second stage, we estimate the weights based on the sample shares of each cohort in each respective event period. Finally, we compute the interaction-weighted estimator by taking a weighted average of the cohort-specific CATT estimates from the first stage.

A key assumption in our approach is that product markets mature through distinct stages where net entry rates vary (Gort and Klepper, 1982, Agarwal and Gort, 1996). New markets often begin with a few firms, followed by rapid net entry, a decline, and eventual stabilization. To ensure differences between treated and control markets reflect the acquisition effect rather than market maturity differences, we use CEM (Iacus et al., 2011, 2012) to align markets based on

1. Percentage change in the total stock of firms in the year prior to first acquisition, and
2. Industry classification using the 46 Crunchbase industry groups.

We match the data annually and without replacement during the sample years based on a tech giants' first acquisition that occurred between 2003 and 2021 for the United States and EU product markets.[8] The unmatched product markets are excluded. As a result, we end up having 474 US product markets, of which 123 are treated, for the treatment years 2003–2021, and 475 EU product markets, of which 76 are treated, for the treatment years 2004–2021.

Our empirical strategy relies on standard identifying assumptions to ensure the validity of the causal interpretation of the treatment effects. The central assumption is the parallel trends assumption (Sun and Abraham, 2021). This assumption requires that, in the absence of treatment, the trajectories of entry rates and VC investments would have been similar for treated and control markets.

We assess this assumption by examining pretreatment trends in treated and control markets. As shown in Figure 4, the trajectories of entry rates and investments exhibit consistent patterns across both groups during the pretreatment period. While treated markets show higher absolute levels of entry and investment, the parallel trends suggest that posttreatment differences arise from the treatment effect rather than preexisting disparities.

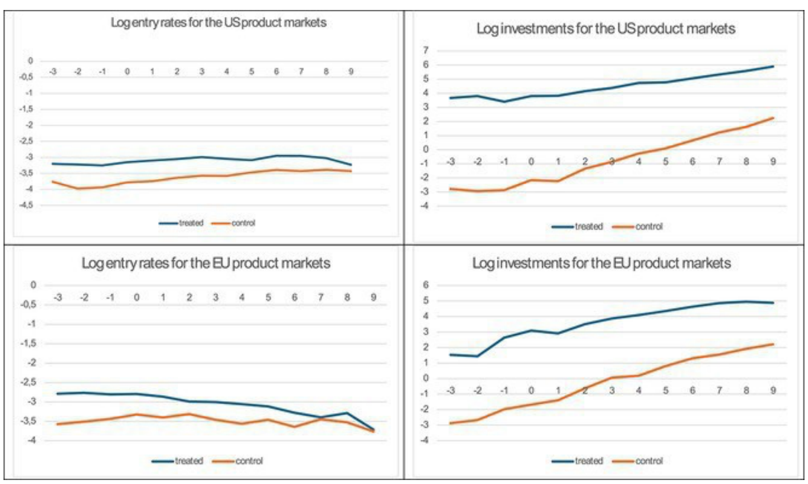


Figure 4 Pretrends for the entry rates and investments

The parallel trends also mitigate concerns that tech giants systematically target ~~product m~~arkets with ~~differen~~t underlying growth trajectories for acquisitions. If such targeting occurred, we would expect to see diverging pretreatment trends. However, Figure 4 shows that both groups exhibit parallel trends in entry rates and VC investments before the first acquisition, suggesting that systematic target~~ing of declining markets is unlikelyalleviating concerns about s~~ystematic targeting of markets with different pre-treatment trajectories.[9]

We estimate our model using two samples. In our benchmark model, we use the complete sample data for the treatment years 2003–2021 with 323 treated product markets for the United States and 129 treated product markets for the EU. Secondly, we use the CEM method to form a control group for the product markets into which the tech giants entered via acquisition to ensure that the underlying differences in the pretreatment evolution of treated and control group markets are not driving the estimation results.

We estimate the benchmark model using equation (1) with the complete sample data for the 3 pretreatment and 5 posttreatment years, allowing the unbalanced panel structure. We next estimate three alternative specifications for the CEM-matched US and EU cohorts to explore the robustness of the estimation results. First, we estimate the model for the 3 pretreatment and 5 posttreatment years with the data of unmatched product markets removed after the CEM. Secondly, we estimate longer-term impacts with 3 pretreatment years and 10 posttreatment years, allowing for an unbalanced panel structure. Thirdly, we restrict the sample to be balanced such that all cohorts in the estimations have 3 pretreatment years (i.e., the first cohort is 2005) and 10 posttreatment years (i.e., we drop the 2012–2021 cohorts).

We estimated equation (1) separately for the United States and EU product markets, with the results presented in Tables 2a1, 2a2, 2b1, and 2b2, and Figures 5a and 5b. The estimation results indicate that US product markets targeted by technology giants' acquisitions during the sample period experienced statistically significantly higher entry rates relative to market size and greater investment prior to the first acquisition compared to control markets. However, the difference in entry rates and investments between treated and control markets began to diminish 1 year after the technology giant's initial acquisition. The benchmark model with complete data and the CEM-matched sample both yielded qualitatively similar results. Notably, the benchmark model without CEM matching indicates that the magnitude of the difference in pretreatment investment levels between treated and control markets is substantially lower than in estimations based on CEM-matched data. Specifically, the CEM-matched data shows that the difference in entry rates between treated and control markets became statistically insignificant from the fourth posttreatment year onward. In addition, the balanced CEM-matched data indicated that investments in product markets targeted by technology giants' acquisitions were statistically significantly lower from the fifth posttreatment year onward.

Table 2a1 The estimation results of the dynamic model for the entry rates for the United States

	Cohorts 2003–2021 (unbalanced)		Cohorts 2003–2021 (unbalanced, CEM)		Cohor (unba
Year relative to tech giants' first acquisition in the product market	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff**
−3	0.166	0.046	0.255	0.076	0.252
−2	0.213	0.044	0.251	0.066	0.258
0	0.160	0.044	0.276	0.070	0.297
1	0.136	0.04	0.253	0.053	0.274
2	0.061	0.045	0.24	0.069	0.261
3	0.072	0.047	0.183	0.073	0.206
4	0.061	0.037	0.083	0.048	0.11
5					0.008
6					0.117
7					0.112
8					0.056
9					−0.05
Nobs	13,885		9,495		9,495

	Cohorts 2003–2021 (unbalanced)		Cohorts 2003–2021 (unbalanced, CEM)		Cohor (unba
Year relative to tech giants’ first acquisition in the product market	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**
R-squared	0.51		0.49		0.48

Table 2a2 The estimation results of the dynamic model for the investments for the United States

	Cohorts 2003–2021 (unbalanced)		Cohorts 2003–2021 (unbalanced, CEM)		Cohor (unba
Year relative to tech giants’ first acquisition in the product market	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**
−3	1.084	0.146	2.280	0.328	2.113
−2	0.956	0.149	2.119	0.304	2.016
0	0.735	0.140	1.951	0.240	1.990
1	0.628	0.124	1.496	0.247	1.534
2	0.27	0.133	1.323	0.233	1.370
3	0.051	0.128	0.973	0.21	1.023
4	−0.043	0.128	0.818	0.196	0.885
5					0.405

	Cohorts 2003–2021 (unbalanced)		Cohorts 2003–2021 (unbalanced, CEM)		Cohor (unba
Year relative to tech giants' first acquisition in the product market	Coeff.	Std. error	Coeff.	Std. error	Coeff.
6					0.285
7					−0.01
8					−0.28
9					−0.36
Nobs	13,920		9,480		9,480
R-squared	0.72		0.72		0.72

Table 2b1 The estimation results of the dynamic model for the entry rates for the EU

	Cohorts 2004–2021 (unbalanced)		Cohorts 2004–2021 (unbalanced, CEM)		Cohorts 2004–2021 (unbalanced, CEM)	
Year relative to tech giants' first acquisition in the product market	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error
−3	0.023	0.051	0.174	0.07	0.114	0.063
−2	0.031	0.058	0.192	0.062	0.132	0.063
0	0.012	0.060	0.142	0.064	0.079	0.070

	Cohorts 2004–2021 (unbalanced)		Cohorts 2004–2021 (unbalanced, CEM)		Cohorts 2004–2021 (unbalanced, CEM)	
Year relative to tech giants' first acquisition in the product market	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**
1	0.045	0.054	0.087	0.07	0.021	0.078
2	−0.036	0.061	−0.001	0.072	−0.069	0.081
3	−0.026	0.058	0.011	0.065	−0.06	0.079
4	−0.042	0.05	−0.007	0.06	−0.082	0.079
5					−0.198	0.108
6					−0.182	0.089
7					−0.268	0.081
8					−0.206	0.088
9					−0.3	0.102
Nobs	13,873		9,477		9,477	
R-squared	0.43		0.41		0.41	

Table 2b2 The estimation results of the dynamic model for the investments for the EU

	Cohorts 2004–2021 (unbalanced)		Cohorts 2004–2021 (unbalanced, CEM)		Cohorts 2004–2021 (unbalanced, CEM)	
Year relative to tech giants' first acquisition in the product market	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**
−3	0.12	0.25	0.551	0.36	0.385	0.356
−2	−0.305	0.249	0.131	0.336	−0.016	0.317
0	0.314	0.224	0.754	0.301	0.607	0.317
1	−0.338	0.22	0.022	0.266	−0.139	0.285
2	0.03	0.212	0.179	0.244	0.006	0.273
3	−0.197	0.194	0.065	0.218	−0.106	0.257
4	−0.235	0.203	−0.133	0.222	−0.316	0.27
5					−0.383	0.292
6					−0.412	0.3
7					−0.54	0.267
8					−0.62	0.27
9					−0.916	0.294
Nobs	13,920		9,500		9,500	
R-squared	0.70		0.70		0.70	

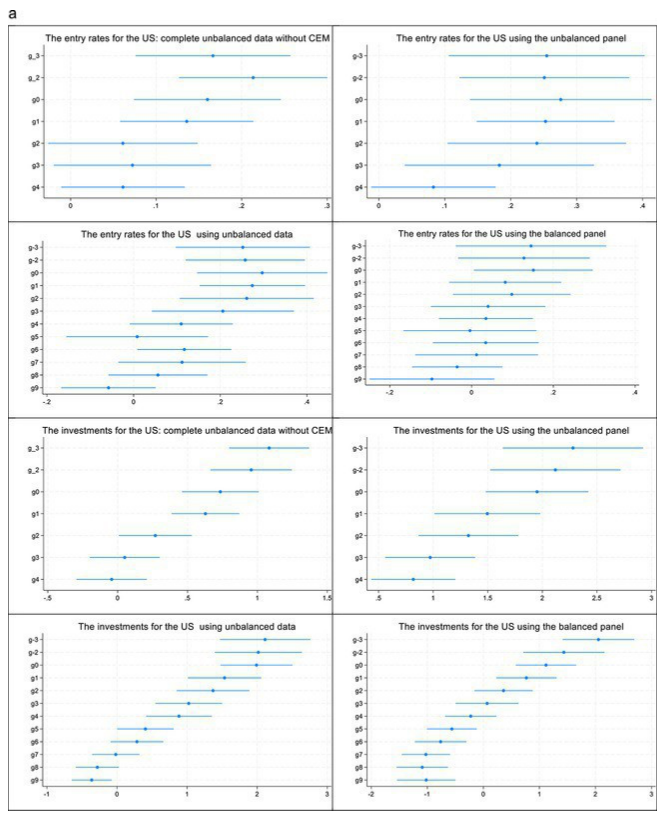


Figure 5a The estimation results of the dynamic models for the entry rates and investments for the United States

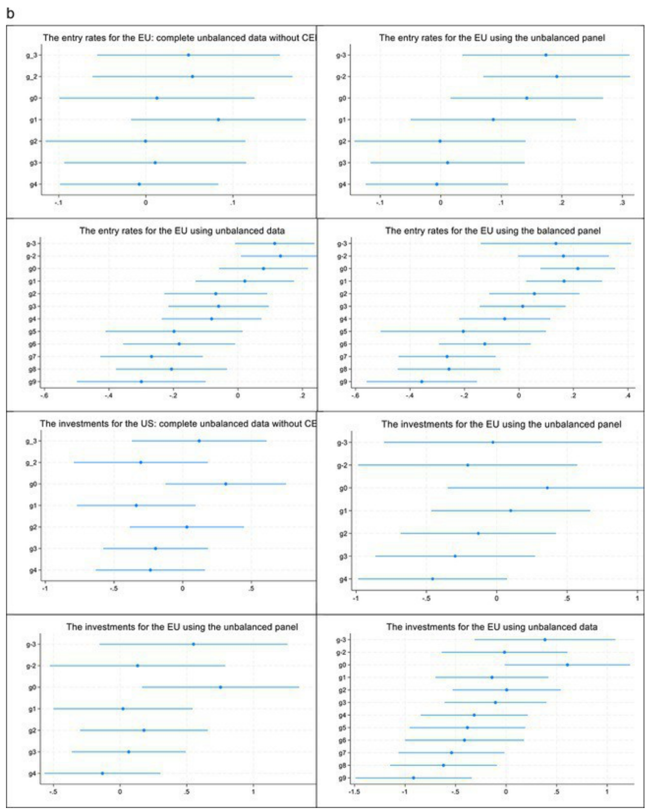


Figure 5b The estimation results of the dynamic models for the entry rates and investments for the EU

The benchmark model without CEM matching shows that the relative entry rates in treated EU product markets did not differ statistically significantly from those in control markets. However, analysis using unbalanced CEM-matched data for the 200~~1~~4–2021 cohorts suggests that entry rates were substantially higher in product markets affected by subsequent acquisitions by tech giants, reflecting trends observed in US-treated markets. In the EU, entry rates in treated product markets were statistically significantly lower than in control markets from the sixth posttreatment onward. Regarding investments, treated EU product markets did not differ statistically significantly from control markets during the pretreatment years. However, investment levels turned negative 3–4 years after the technology giants' first acquisition, becoming statistically significantly lower from the sixth posttreatment years onward.

Using the estimation results for the balanced CEM-matched data with 5 posttreatment years, we find that the difference in market entry rates between product markets targeted by technology giants' buyouts and control markets declined by over 20% in both the United States and the EU during the first 5 years after the initial acquisitions, compared to the average entry rate difference in the 3 and 2 years before the treatment. During the same period, the difference in VC investments decreased by approximately 678% in the United States and 56% in the EU in the markets where technology giants made acquisitions, relative to the control markets.

5. Discussion

In this study, we investigate the effects of acquisitions made by large US-based technology companies on the entry dynamics and VC investment in different product markets. We use data from Crunchbase, covering information about hundreds of thousands of start-up companies in 742 product markets globally from 2002 to 2021. Our estimation results suggest that the tech giants' buyouts ~~tend to reduce~~ market entry rates and decrease the available VC funding over time in the target product markets of the tech giants' acquisitions. In other words, the acquisitions of data giants seem to generate the so-called kill zone effect. Our empirical findings emphasize that the effects of acquisitions in digital markets go far beyond enriching the acquired companies' founders. On the contrary, they seem to reduce the market entry of new firms and reduce VC investments. Venture capital firms are less likely to fund start-ups in markets where the tech giants have already made acquisitions. Furthermore, previous studies suggest that decreased market entry may adversely affect the incumbent companies' incentives to innovate (Aghion et al., 2004).

At the same time, alternative mechanisms may also help explain our findings. One possibility is that ~~venture capitalists fund start-ups primarily with acquisition as the intended exit. In this view, acquisitions~~ do not deter innovation ex ante but represent the natural fulfillment of entrepreneurial finance. Once a leading firm in a product space has been acquired, however, comparable firms lose that exit route, reducing VC interest in further entrants. Our findings of declining VC investment post-acquisition are consistent with this mechanism and align with prior work emphasizing acquisitions as an important exit channel (Phillips and Zhdanov, 2013, 2017; Kerr et al., 2014). Against the backdrop of generally rising entry and VC funding in our data, the relative decline after big tech acquisitions suggests that their effects may differ qualitatively from those of generic acquisitions. Distinguishing empirically between deterrence ("kill zone") and exit-fulfillment remains challenging. The mechanisms differ—deterrence discourages entry ex ante, whereas exit-fulfillment reduces the viability of exits ex post—but both ultimately lower venture funding for new entrants and weaken competitive pressure. As a result, both mechanisms can reinforce incumbents' market power and thereby provide grounds for closer scrutiny of acquisitions by dominant firms, even if exit-fulfillment simultaneously underscores the importance of acquisitions as a natural exit channel in entrepreneurial finance.

It is important to emphasize that our results do not necessarily imply that consumers would be worse off due to tech giants' acquisitions in the short run as acquisitions might enable investments into R&D and innovation that would not have taken place without the acquisition. Notwithstanding this, our results point that the generation of kill zones in various markets may have detrimental effects on competition, innovation, and consumer welfare in the long run. Large technology companies' acquisitions continue to increase their market power both in their existing product markets and in new markets. The tech giants' entry to and presence in various markets is likely to increase market concentration and pose a threat to competition. The empirical findings emphasize that the concerns regarding the insufficient merger control mechanisms involving the global tech giants are highly relevant and require action from policymakers in the United States and Europe. Our findings also highlight a critical gap in current merger control practices, both in the United States and the EU, when it comes to regulating the acquisitions of smaller firms by tech giants. Existing frameworks have struggled to contain the strategic maneuvers of these large players effectively. While the US implemented revised horizontal merger guidelines in December 2023 to intensify the scrutiny of such acquisitions, the long-term impact remains to be seen. Similarly, the EU's Digital Markets Act (DMA), effective in November 2022, mandates reporting by large tech companies of acquisitions involving digital market participants but lacks the authority to directly intervene in these deals.

This discussion is central to the current debates on merger control in digital markets. The recent European Court of Justice ruling in the Illumina/GRAIL case illustrates the limitations of existing tools. By restricting the Commission's ability to review Article 22 referrals that bypass national thresholds, the judgment curtails the expansionist merger control approach adopted in 2021 and reasserts the importance of predictability and legal certainty for merging parties. Proposals such as transaction value thresholds (already implemented in Germany and Austria) or shifting the burden of proof to dominant firms in early-stage acquisitions (Tirole, 2024) illustrate possible ways forward, though each carries limitations.[10] These highlight the need for continued innovation in regulatory frameworks to address acquisitions that may be competitively significant but fall outside traditional thresholds.[11]

In addition to merger control, governments can strengthen start-up ecosystems by supporting the development of early markets and easing financing constraints. Public procurement of innovative products can provide start-ups with independent growth opportunities, while targeted instruments such as fund-of-funds models or quality-signaling grants can improve the supply of VC in the early stages (Islam et al., 2018; Standaert and Manigart, 2018; George et al., 2024). These measures expand the opportunity set for potential competitors without directly constraining incumbents, reducing investor uncertainty and helping start-ups scale without reliance on acquisition exits.

A limitation of our study is that we do not directly capture the perspective of VC investors themselves. While our analysis documents systematic changes in VC investment following acquisitions, we do not observe how investors perceive acquisitions as exit opportunities or how they adjust their strategies in response. Future research could provide a deeper understanding of the mechanisms linking acquisitions, financing, and entrepreneurial dynamics.

Finally, our results should be considered alongside broader regulatory developments in data and digital markets. The General Data Protection Regulation constrains the ability of large technology firms to exploit data-driven network effects, but recent evidence suggests it may also have unintentionally reinforced incumbents' dominance by imposing disproportionate compliance costs on smaller firms (Frey and Presidente, 2024). New EU digital regulations, including the DMA and the Data Act, introduce data-sharing obligations that could shift the balance by enabling smaller firms to access and leverage data more effectively. Assessing how these evolving rules interact with merger control in shaping entry, innovation, and competition presents an important avenue for future research.

Footnotes

1 It is empirically an open question, whether the positive network effects from having a large user base are large enough to generate lock-in effects for users. Giovanetti and Siciliani (2023) and Farrel and Klemperer (2007) provide theoretical models and empirical examples on the emergence of lock-in effects.

2 Courts on both sides of the Atlantic have recently raised concerns about the potential anticompetitive effects of acquisitions by data giants. Notable cases include the DOJ's 2023 antitrust lawsuit against Google, which targets its digital advertising practices and highlights the monopolistic implications of its 2008 DoubleClick acquisition. Similarly, the European Commission's investigation into Google's 2021 acquisition of Fitbit focused on concerns that the deal could enhance Google's data dominance in digital health care and wearable devices. Finally, Microsoft's $68.7 billion acquisition of Activision Blizzard in 2023 faced antitrust scrutiny in both the United States and EU, with regulators expressing concerns about reduced competition in the gaming sector and the availability of popular titles on rival platforms.
Some recently published policy papers, such as those by Bourreau and de Streel (2019) and Hylton (2019), assess the costs and benefits of platform acquisitions.

3 For a thorough discussion on the merger control for digital markets from a legal perspective, see Holmström et al. (2019). For a more general discussion of the topic in the media, see, e.g., the article in *The Economist* (2018), 'American tech giants are making life tough for start-ups' (https://www.economist.com/business/2018/06/02/american-tech-giants-are-making-life-tough-for-startups accessed 2020-03-10).

4 Other recent studies have also relied on Crunchbase to examine related questions. Eisfeld (2024) uses Crunchbase to analyze how acquisition opportunities affect entry in software markets, while Doan and Mariuzzo (2022) employ it to study the impact of digital platform mergers in the cloud computing sector.

5 As a concrete example, the category group "Gaming" includes the following 12 categories: casual games, console games, contests, fantasy sports, gambling, gamification, gaming, MMO games, online games, PC games, serious games, and video games.

6 The Crunchbase database also has observations related to investors, C-suite executives, and board members and events, which we excluded.
7 We add 0.001 to zero values in order to include them in the estimations after the log transformation.
8 Furthermore, simulation evidence presented by Lindner and McConnell (2019) shows that in the absence of parallel trends, matching treatment and control units on past growth rates combined with difference-in-differences for adjusting for reducing bias due to nonparallel trends, at least if the total error variance is small.
9 A possible limitation is that reduced investment in a market might coincide with the technology becoming "old" rather than being directly caused by the acquisition itself. However, we believe this is unlikely to drive our results, as our dataset includes a total of 748 acquisitions of US companies and 129 acquisitions of European companies across various industries over a 20-year period, encompassing diverse technologies and market contexts. The broad scope and heterogeneity of the data reduce the plausibility of such a systematic coincidence as the primary explanation for the observed patterns.
10 For instance, transaction value thresholds may still fail to capture all relevant cases, and shifting the burden of proof could impose significant administrative and evidentiary challenges.
11 [Place text here].

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