Entry and Acquisitions in Software Markets*

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Abstract

New entry is thought to be the primary competitive margin in software markets. I study how acquisitions of venture capital-funded startups affect entry incentives. I assemble a product-level dataset of enterprise software and use text-as-data methods to define markets. I build and estimate a dynamic entry model where acquisitions affect returns to entry via (1) changes in market structure and (2) an entry-for-buyout incentive. In counterfactual simulations, banning all startup acquisitions reduces entry by about 16% in the average market, whereas blocking high-priced deals conducted by incumbents slightly raises entry. These results indicate which acquisitions might merit prioritized scrutiny.

Keywords: Mergers and Acquisitions, Antitrust, Entry, Startups, Enterprise Software, Innovation

JEL Classification: G34, L22, L26, L49, L86, M13

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1 Introduction

Companies active in information technology – most famously, dominant incumbents such as Alphabet and Microsoft, but also much smaller players such as Dropbox and HubSpot – have acquired thousands of other firms over the past two decades. The majority of target firms in these transactions were *startups*: young, innovative, venture capital-funded firms. How do these acquisitions affect startups' incentives to initially *enter* a given market? Due to network effects and economies of scale and scope, software industries tend to be dominated by large incumbents. New, innovative entry is thought to be the main dimension of competition in these markets (e.g., Scott Morton et al. 2019).

On the one hand, the anticipation of being acquired can provide an entry-for-buyout incentive if the returns from being acquired are higher than the returns from competing independently (Rasmusen 1988). In software markets, over 90% of successful, venture-backed startups are acquired by other firms, as opposed to being listed on public stock markets.[1] Acquisitions are reportedly a major goal for startup founders and their investors. This suggests that startup acquisitions can reward innovation efforts and encourage entry *ex ante*.

On the other hand, *ex post*, an acquisition affects the competitive environment that future entrants face. By transferring the startup's technology and capabilities to the incumbent, the acquisition enhances the incumbent's ability to develop and deploy the acquired project, which lowers rivals' expected returns to entry. The affected market may evolve into a "kill zone", where entry and investment are rendered unprofitable and deterred (Teh, Banerjee, and Wang 2022).

I study startups' entry incentives in the face of acquisitions (1) by collecting and assembling new data that enable me to identify competing firms, (2) by producing a set of new, policy-relevant facts on startup acquisitions in software markets, and (3) by building and estimating a dynamic structural model of startup entry that nests the *ex ante* and *ex post* channels. The model features forward-looking potential entrants and is novel in that it captures the realities and motives of venture-backed startups in a stylized way.

Answering the research question requires accurately defining *markets*, i.e., sets of companies that offer substitutable products and that interact strategically with each other. This task is conceptually non-obvious for privately held startups, as these are not subject to public reporting requirements and often operate in new product markets not accurately captured by classic taxonomies. To obtain a notion of competing firms, I collect product descriptions from *Capterra*, a vertical search engine whose purpose is to help consumers find enterprise software. Using text-as-data methods, I cluster a comprehensive sample of thousands of products into markets of close substitutes. I merge these product data with information on firms' entry and acquisition decisions stemming from *Crunchbase* (Crunchbase 2021).

The dataset uncovers new, policy-relevant facts on startup acquisitions in enterprise software markets. Acquisitions of very young, venture-backed targets are not confined to the dominant platforms (GAFAM[2]); a broad set of other software incumbents, but also industry outsiders, behave similarly. Fur-

1. Author's calculations using enterprise software startups with successful exits, 2005–2020 (*Crunchbase* data). In contrast, only about 50% of biotech or pharmaceutical startups exit via acquisition (see Appendix G.2.2).

2. This acronym refers to *Google (Alphabet)*, *Amazon*, *Facebook (Meta)*, *Apple*, and *Microsoft*.

ther, under my market definitions, only about 11% of acquisitions are horizontal, i.e., between firms selling in the same product market.

Importantly, acquirer motives differ, and only some acquirer types are likely to create adverse effects for entry. I distinguish acquirers by incumbency. I label as *strategic acquirers* those incumbents active in enterprise software. Relative to other buyers, strategic acquirers plausibly have both the capabilities and the incentives to acquire startups in ways that may deter future entry. This could manifest itself either anti-competitively – for instance, by leveraging market power into new markets (Carlton and Waldman 2002) or by acquiring and redeploying technologies to preempt rivals (Teh, Banerjee, and Wang 2022) – or pro-competitively through complementarities that make the acquired product more valuable.[3] In contrast, *industry outsiders* (e.g., manufacturing firms adopting software tools) typically acquire to vertically integrate software functionalities, with limited scope to influence competition within a specific software product market. Finally, *financial acquirers* (private equity and similar) are best viewed as transitional owners seeking financial returns via restructuring and resale rather than long-run positioning within the software industry.

Presumably, all types of acquirers may create entry-for-buyout incentives, whereas only strategic acquirers can plausibly deter subsequent entry. I compare entry patterns in the quarters following major acquisitions conducted by different acquirer types using a staggered event study framework. The results indicate that major acquisitions conducted by strategic, but not financial acquirers or outsiders tend to be followed by a decrease in new entry.

The overall effect of acquisitions on entry depends on both, the entry-deterring effect that is transmitted via market structure *ex post*, as well as the *ex ante* entry-for-buyout effect. To quantify both channels, I build a dynamic model of startup entry that nests the two channels. Each period, in each product market, a new set of forward-looking potential entrants makes a one-time entry decision. Upon entry, a startup earns flow profits. These flow profits depend in a reduced-form way on market structure; in particular, on the number of competitors, as well as on past major acquisitions of competitors by strategic acquirers (the *ex post* deterrence channel). Entrants also face stochastic liquidity events – acquisitions or initial public offerings (IPOs) – that deliver a lump-sum return (the *ex ante* entry-for-buyout channel). Future acquisitions and public listings are modeled as stochastic exit opportunities that arrive upon the startup with fixed, market-specific probabilities. All in all, when deciding whether to enter a given market, potential entrants on the one hand take into account the current and expected future market structure. On the other hand, potential entrants form beliefs about the likelihood with which their owners can liquidate their investment through an acquisition or a public listing. Using a revealed preference approach and a two-step estimation method with forward-simulation techniques (Aguirregabiria and Mira (2007) and Bajari, Benkard, and Levin (2007)), I can estimate the parameters quantifying the importance of each of these channels for spurring or deterring entry.

The parameter estimates reveal that markets in which firms are acquired more often also display higher startup entry, holding constant measures capturing market size. Moreover, consistent with the event study but less precisely measured, acquisitions with a large transaction size conducted by strategic

3. Appendix A.3 elaborates on entry-deterring mechanisms.

acquirers tend to be followed by a decline in entry. This negative channel is largely driven by the GAFAM and similar public firms, as opposed to smaller strategic acquirers.

The overall effects from blocking all or a subset of acquisitions are determined by the magnitudes of both channels. I hence conduct policy experiments that simulate how entry would evolve under counterfactual merger policies. As a benchmark, I consider a scenario in which all acquisitions are blocked. In the partial-equilibrium analysis (holding beliefs fixed), startup entry declines by up to 16% in the average market. In contrast, blocking only high-value mergers conducted by strategic acquirers could increase entry, but only modestly by up to 1.5% in affected markets. Taken together, the counterfactuals suggest that preserving the entry-for-buyout option is important for startup formation. At the same time, the event study and model point to a subset of deals that are followed by reduced entry. A case-by-case regime that prioritizes these transactions for heightened scrutiny could modestly raise entry in affected markets compared to the status quo.

Many of the world's most valuable firms in terms of market capitalization offer digital services and are frequent acquirers of startups. Yet the motives for these acquisitions and how these relate to entry dynamics remain poorly documented, and the policy implications are unsettled (Crémer, Montjoye, and Schweitzer 2019; Furman et al. 2019; Scott Morton et al. 2019).[4] Both the descriptive and model-based findings that this paper generates are thus of first-order importance from an antitrust perspective, especially in an era where rising markups and concentration are being discussed by economists (De Loecker, Eeckhout, and Unger 2020; Miller 2025). The types of acquisitions studied in this paper are "stealth mergers" (Wollmann 2019) that rarely meet merger notification thresholds under current rules, as acquired targets are small, albeit highly innovative and potentially disruptive firms. The sheer number of these transactions in software has caught the attention of antitrust practitioners and academics worldwide[5], and have led antitrust regulators to claim that digital platforms could "buy their way out of competing", as Lina Khan, the former Chair of the U.S. Federal Trade Commission, phrased it (Khan 2021).

Because competition in software markets is largely *for* the market rather than *within* it, I treat startup entry as the primary competitive margin. Understanding how acquisitions affect entry is central to assessing market contestability and thus informative for merger policy, even though I do not estimate consumer surplus.

Literature. From a broad angle, this paper contributes to the long-standing question of how competition and innovation interact (see Schumpeter 1942; Arrow 1962; Aghion et al. 2005). I focus on the link between mergers and innovative entry (see Berry and Waldfogel 2001), which has gained renewed importance as regulators debate whether acquisitions by dominant technology firms harm competition and innovation. Lefouili and Madio (2025) survey related theoretical and empirical literature.

Relative to this literature, I quantify two mechanisms through which acquisitions affect venture capital (VC)-backed startup entry: (1) an *ex ante* entry-for-buyout channel and (2) an *ex post* deterrence channel operating through market structure. I do so in enterprise software using novel product-level data

4. For instance, it is not well documented whether "killer acquisitions" (Cunningham, Ederer, and Ma 2021) are as common in software as in pharmaceuticals, or whether software acquisitions are mainly horizontal or instead target complements.

5. From 2010–2019, the GAFAM made 618 acquisitions (excluding patent deals and hires), 85% of which fell below Hart-Scott-Rodino reporting thresholds (Federal Trade Commission 2021).

and a dynamic entry model. To my knowledge, this is the first paper to jointly quantify these channels.

Theory provides reasons for both effects. One set of papers emphasize that acquisitions can stimulate entry by providing startups with an attractive exit route (Rasmusen 1988; Hollenbeck 2020; Mermelstein et al. 2020). At the same time, literature has shown that acquisitions can harm competition by discouraging entry. Mechanisms include strategic tying (Whinston 1990; Carlton and Waldman 2002), the threat to counter-develop acquired technology (Teh, Banerjee, and Wang 2022), the creation of ecosystems (Heidhues, Köster, and Kőszegi 2024), entrenchment through cumulative acquisitions (Denicolò and Polo 2021), and network effects coupled with switching costs (Kamepalli, Rajan, and Zingales 2021).[6]

Empirical research has approached questions on the innovation and entry effect of acquisitions in markets for digital products primarily in two ways. A first strand focuses on acquisitions conducted by the GAFAM firms and documents patterns of acquisitions and their consequences for measures of innovation and product characteristics (Affeldt and Kesler 2021a, 2021b; Argentesi et al. 2021; Gautier and Lamesch 2021; De Barsy and Gautier 2024; Ivaldi, Petit, and Unekbas 2025). Several papers focus on *ex post* effects of these acquisitions using reduced-form methods, measuring changes in VC flows or patenting in directly or indirectly affected firms (Koski, Kässi, and Braesemann 2020; Kamepalli, Rajan, and Zingales 2021; Prado and Bauer 2022; Berger et al. 2025; Gugler, Szücs, and Wohak 2025). A second strand takes a more quantitative lens, either with cross-industry data or general-equilibrium models (Cortes, Gu, and Whited 2022; Vaziri 2022; Fons-Rosen, Roldan-Blanco, and Schmitz 2023), or calibrated applied-theory models of merger policy in digital markets (Cabral 2024). These studies have provided valuable insights but focus either on a very narrow set of GAFAM acquirers or on highly aggregated industry-level patterns, and are unable to explicitly distinguish between different forces. Quantifying both effects jointly is crucial for policy: a counterfactual that blocks acquisitions depends on the balance between these forces. Without modeling both, one cannot evaluate whether current merger policy encourages or stifles entry.

What is unique to the structural model of entry presented in this paper is that it is tailored to startups backed by VC. In particular, future transfers of ownership via an IPO or acquisition are taken into account by potential entrants. While dynamic structural models of entry and acquisitions have been estimated in other settings (e.g., Ryan 2012; Igami 2017; Igami and Uetake 2020; Wabiszewski 2024), they focus on more mature markets with fewer players, or on markets where alternative economic forces are at play. Methodologically, the structural model employs two-step estimation routines (e.g., Aguirregabiria and Mira 2007; Bajari, Benkard, and Levin 2007; Collard-Wexler 2013; L. Wang 2022). Findings from both the model and the descriptive facts refine our understanding of commercialization strategies and exit paths for startups (Gans and Stern 2003).

As the data covers the entire enterprise software sector, I can document differences in the behavior of GAFAM acquirers to other types of buyers, while maintaining the granularity needed to track acqui-

6. Appendix A.3 elaborates on entry-deterring mechanisms. Related theory also studies other implications of startup acquisitions. These include effects on the direction of innovation (Cabral 2018; Bryan and Hovenkamp 2020; Cabral 2021; Katz 2021; Callander and Matouschek 2022; Gilbert and Katz 2022; Dijk, Moraga-Gonzàlez, and Motchenkova 2024; Letina, Schmutzler, and Seibel 2024; Bedre Defolie, Biglaiser, and Jullien 2025); and investment and buyout incentives under learning and information or appropriability frictions (Fumagalli, Motta, and Tarantino 2022; Guéron and Lee 2025). McKeon (2025) and Warg (2021) offer insightful empirical contributions on the direction of innovation and product feature design.

sitions at the *product* level. I find that discontinuations are common but most deals are nonhorizontal, suggesting that most software acquisitions do not resemble a classic "killer acquisition" (Cunningham, Ederer, and Ma 2021; Motta and Peitz 2021). The closest study that documents facts about technology mergers across many acquirers is Jin, Leccese, and Wagman (2023).

My paper builds on the growing literature that uses textual analysis to define markets and measure competitive relationships. Hoberg and Phillips (2016) pioneered this approach using public firms' 10-K filings. More recent work applies these techniques to digital services (Decarolis and Rovigatti 2021; Leyden 2022) and even demand estimation (Compiani, Morozov, and Seiler 2023). I use similar methods to construct markets for *private* startups at the product level.

Structure of the paper. The paper covers the data construction in Section 2, and descriptive analyses on acquisitions in enterprise software in Section 3. Section 4 provides motivating reduced-form evidence for the differential effects of different types of acquisitions. Section 5 introduces the model and explains its estimation. Section 6 presents the results and covers the counterfactual simulation. Section 7 discusses certain findings and assumptions. Section 8 concludes.

2 Setting, Data, and Market Definitions

2.1 Setting: Startup Entry in Enterprise Software

This paper focuses on startup entry in the *enterprise software* industry, which refers to any software product that can be used in a business environment. This includes software marketed primarily to firms (such as customer-relationship or accounting software) and software used by both firms and individuals (such as file-sharing software).

Several facts suggest that the motives for entry and acquisitions may be distinct in software, which motivates an industry-level analysis. Appendix G.2 shows that firms acquiring the largest number of startups globally are predominantly software companies. Furthermore, the relative frequency of acquisitions relative to IPOs is much higher in software than in other industries. Mergers in software have received considerable attention in policy debates, but the effects of these acquisitions on competition and innovative entry are poorly documented and understood.

The enterprise software sector is large, growing, and economically significant. Between 2005 and 2020, enterprise software startups attracted more VC investment than those operating in biotechnology and pharmaceuticals (see Appendix G.1). Software can generate substantial efficiency gains, as it facilitates the adoption of new technologies such as cloud computing and AI.[7]

I consider entry by *startups*, which I define as private firms that have received at least one VC funding round. These young, risky, and innovative companies play an outsized role for innovation, industry

7. Berman and Israeli (2022), for example, find that adopting analytics dashboards increases weekly revenues for e-commerce firms by 4–10%.

dynamics, and welfare.[8]

Startups obtain staged rounds of capital injections, primarily from syndicates of VC investors, in exchange for an equity stake. VC investors manage closed-ended funds and typically divest after a period of 7-10 years, making early consideration of exit opportunities crucial. Optimally, a startup undergoes a successful exit, and is either listed on a public stock exchange (and thus becomes a public company), or (more commonly) is sold to another firm (see Appendix G.2.2). Both events are generally considered a success, and may yield high returns to investors and founders. However, roughly half of all startups end up failing, yielding no or little return to investors.[9]

The GAFAM, which are at the heart of policy debates, are active in the enterprise software industry and part of my sample. Anecdotal evidence is consistent with the existence of both the entry-for-buyout motive and of "kill zones" in this sector (see Appendix A).

2.2 Data

Answering the research question requires data on firms' entry and acquisition decisions within precisely defined markets. I obtain firm-level activity data from *Crunchbase*. To enable a market-level analysis, I augment these data with web-scraped product-level information from *Capterra*, a vertical search engine for enterprise software. Employing text-as-data methods on product descriptions yields granular and economically meaningful market boundaries. The resulting market-quarter panel covers over 24,000 products in more than 400 distinct markets, tracking entrants, incumbents, and different types of acquisitions.

2.2.1 Firm-Level Panel: *Crunchbase*

Crunchbase is a well-established database that tracks financial information on over a million public and private companies, in particular VC-funded firms. It reports founding dates, funding rounds, acquisitions, investments, initial public offerings (IPOs), and closures.

I classify investments as "venture capital" following *Crunchbase*'s *Glossary of Funding Types* (Crunchbase 2022), industry reports, and guidance from prior literature (see Appendix B.1). A "startup" is any privately held firm that has received at least one such investment and remains independent. I define "entry" as a firm's first VC funding round (the moment it becomes a "startup" in my data).[10] *Crunchbase* defines acquisitions as majority takeovers, and I use the resulting transaction histories to reconstruct each firm's parent-subsidiary network over time.

8. Some of today's largest firms began as VC-backed companies, and 50% of firms that list on public stock markets, have been VC-backed (Lerner and Nanda 2020). Startups tend to bring forward a larger number, as well as higher quality and more novel inventions, than established companies (Kortum and Lerner 2000; Schnitzer and Watzinger 2022). In the context considered in this paper, a firm that has received VC funding attracts higher demand (proxied by consumer reviews), even after controlling for other characteristics (see Appendix F, Table F.1).

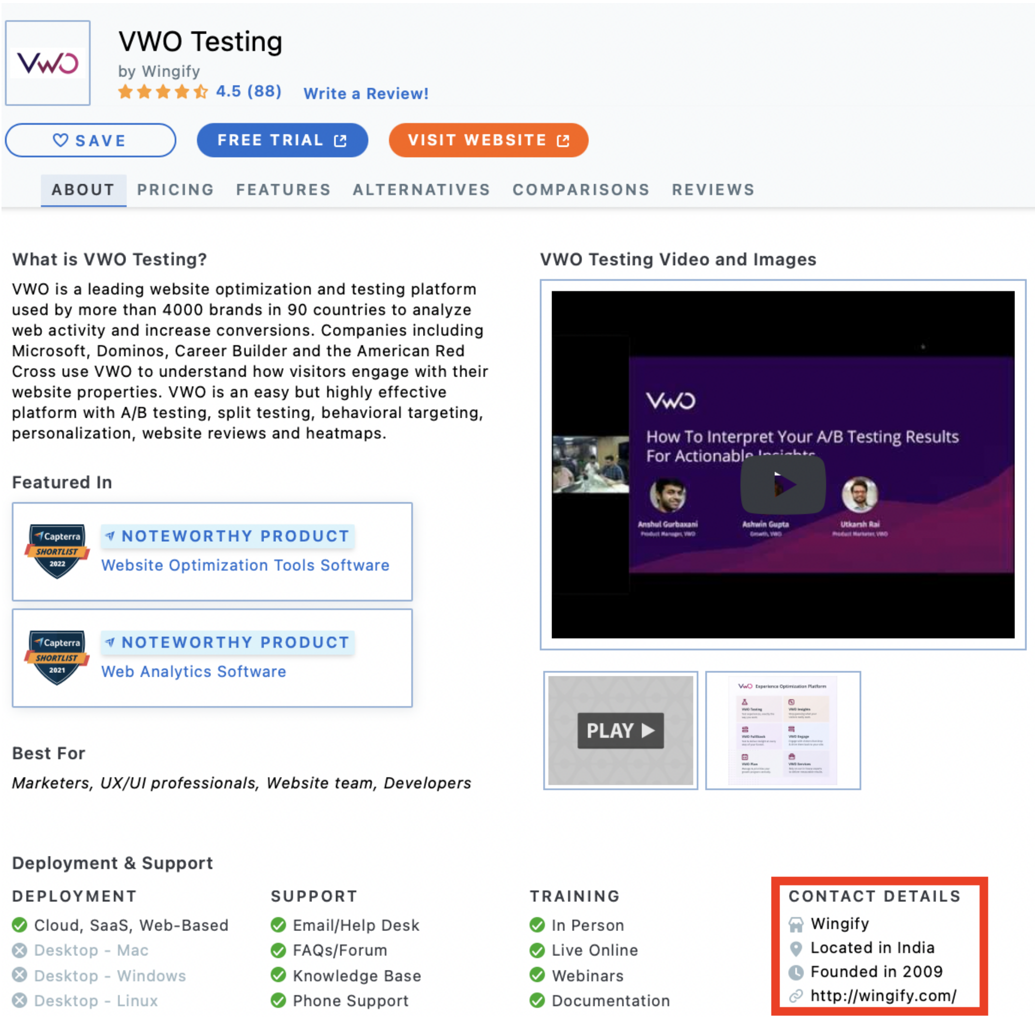
9. The reader may refer to Gompers and Lerner (2001) for further institutional details on VC funding and startup growth.

10. According to this definition, a firm that has had a "founding" event but that has not received any funding has not "entered" the market yet. This is a deliberate feature: entry is interpreted as a joint decision by founders and investors, where the latter are forward-looking agents who internalize expectations about exit opportunities and market conditions. In addition, founding dates in standard databases are often ambiguous – potentially reflecting incorporation, product launch, or even team formation – making them a less reliable proxy for market entry.

2.2.2 Cross-Section of Enterprise Software Products: *Capterra*

Crunchbase alone does not support a market-level analysis of entry and acquisitions. Its industry labels are broad and defined at the firm level, which is especially problematic for conglomerates operating across multiple markets (see Appendix B.1). Alternative classification systems, such as SIC codes or Hoberg and Phillips (2016)'s Text-based Network Industry Classification, restrict coverage to U.S. publicly listed firms, which misses the majority of my sample.

Figure 1: Example of product page on *Capterra*



Notes: Screenshot taken on 11 March 2022. The red frame was added to highlight the company information (in particular, name and URL) that is available and was scraped for all products on *Capterra*.

To overcome this constraint, I collect data from *Capterra*, a leading vertical search engine for enterprise software, using web-scraping techniques. Designed to assist customers in comparing and selecting software solutions, *Capterra* has strong incentives to maintain accurate product information, which I use to construct economically meaningful market boundaries. Appendix B.2 provides additional context and assesses the quality and coverage of the *Capterra* data.

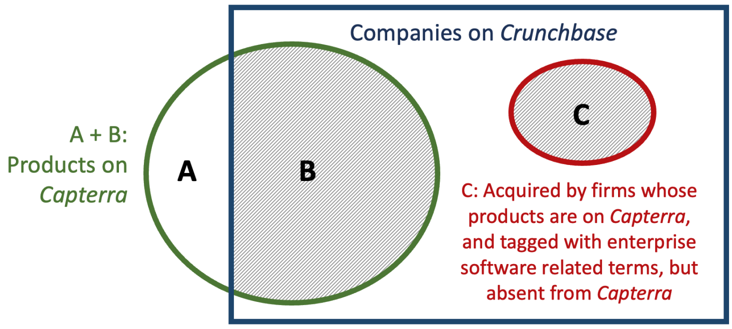
Capterra assigns each software product to at least one of 821 narrowly defined categories (e.g., "Audio Editing Software", "Conference Software", or "Spreadsheet Software"). Each product page contains descriptive text, company information, and user-generated reviews and ratings (see Figure 1). I query all available product pages as of June and July 2021 and download the full set of product-specific information, including the associated firm. Details are provided in Appendix B.3.

I use the *Capterra* data for three main purposes. First, product descriptions and category labels allow me to use Natural Language Processing techniques to cluster products into groups of substitutable offerings (see Section 2.3). Second, the data provide a snapshot of which products are actively offered as of mid-2021, enabling an accurate identification of operational firms and a natural boundary of the whole enterprise software sector.[11] Third, the number of user reviews serves as a proxy for product adoption and usage intensity, allowing me to distinguish strategically relevant competitors from those with a negligible market presence.

2.2.3 Matching *Capterra* to *Crunchbase* Data

I match products listed on *Capterra* to their corresponding firms on *Crunchbase* using company names and URLs (see Appendix B.4 for details). I successfully match 71% of all web-scraped products – and 96% of those with more than 100 reviews – to firms listed on *Crunchbase*. The unmatched products are overwhelmingly characterized by no user reviews, suggesting that they represent minor or inactive competitors with limited relevance in the market.

Figure 2: Illustration of the sample used



Notes: The hatched areas (B and C) point out the sample used. Set B is obtained by matching *Capterra* products to *Crunchbase* firms. Set C is added to account for enterprise software companies acquired in the past, but not on *Capterra* (and hence, not offered to clients) as of 2021. Set A is the (likely insignificant) set of products on *Capterra* that was not matched to companies on *Crunchbase*. (Figure is not to scale.)

A potential limitation of the *Capterra* data is its cross-sectional nature, which means that it does not cover products that were discontinued prior to 2021. To address this, I augment the sample with firms from the *Crunchbase* dataset that (1) are classified as enterprise software–related based on their descriptive text, industry group, or industry code in *Crunchbase*, and (2) have been acquired by a firm that offers a product on *Capterra*. These firms represent cases where products are absent from *Capterra* in 2021, despite having been part of the market in prior periods and undergoing a successful exit. Figure 2 summarizes the composition of the final sample. Further details, along with evidence mitigating concerns about selection, are provided in Appendix B.5.

11. This mitigates a known limitation of *Crunchbase*, where many firms are labeled as "active" despite having ceased operations. *Capterra* thus serves as a U.S.-oriented, product-level sample for enterprise software, which is ambiguous when using *Crunchbase* alone.

Table 1: Overview of matched sample

Number of products	24,582
· % of products active by 2021	84.1%
· % of products with user reviews by 2021	42.2%
Number of companies	20,447
· % of companies VC-backed in 2012–2020	66.9%
· % of companies ever public in 2012–2020	4.6%
Number of acquisitions	6,758
· % of targets with VC funding	42.3%
Number of IPOs	380
· % of companies with VC funding	55.3%

Notes: To show the raw coverage of the matched sample, this table comprises firms active at any point in 2012–2020. 2020 will be excluded from later analyses due to potential disruptions caused by the Covid-19 pandemic (see Figure 3).

2.3 Defining Markets Using Textual Analysis

As laid out above, private firms' operations are not well covered by standard industry classification systems. I therefore delineate markets in a novel way using text-as-data methods (see Gentzkow, Kelly, and Taddy (2019) and Ash and Hansen (2023) for surveys). Each product on *Capterra* is associated with a body of text consisting of one or more categories, and of the product description (the literature calls such a body of text a "document").[12] Each document is hence informative about a product's functionalities. My approach leverages the idea that companies with semantically similar documents should be more substitutable, and hence should form a market.

The procedure of creating markets comprises (1) building a dictionary of meaningful words and extracting these words from each document, (2) vectorizing each document to embed it in a vector space that captures semantic similarities between documents, and (3) clustering documents (and hence, products) into groups of semantically similar and hence likely substitutable products.

I discuss the creation of a dictionary of meaningful terms in Appendix B.6. After extracting these terms from each document, a simple bag-of-words approach is feasible but would ignore semantic relationships between words, resulting in inaccurate product clustering.[13] Instead, I use a word embedding approach, which represents each term as a vector in a high-dimensional semantic space, allowing to capture linguistic similarity (Decarolis and Rovigatti (2021) and Leyden (2022) follow similar approaches in the context of market definition). Specifically, I match each of the extracted terms to a pretrained word vector from *GloVe*, an unsupervised algorithm for learning vector representations of words (Pennington, Socher, and Manning 2014).[14] Each term is thereby embedded in a vector space where semantically similar terms are located near one another. Following standard practice (e.g., Ash and Hansen 2023; Bybee 2025), I then average each product's word vectors to end up with a single vector representation for each document.

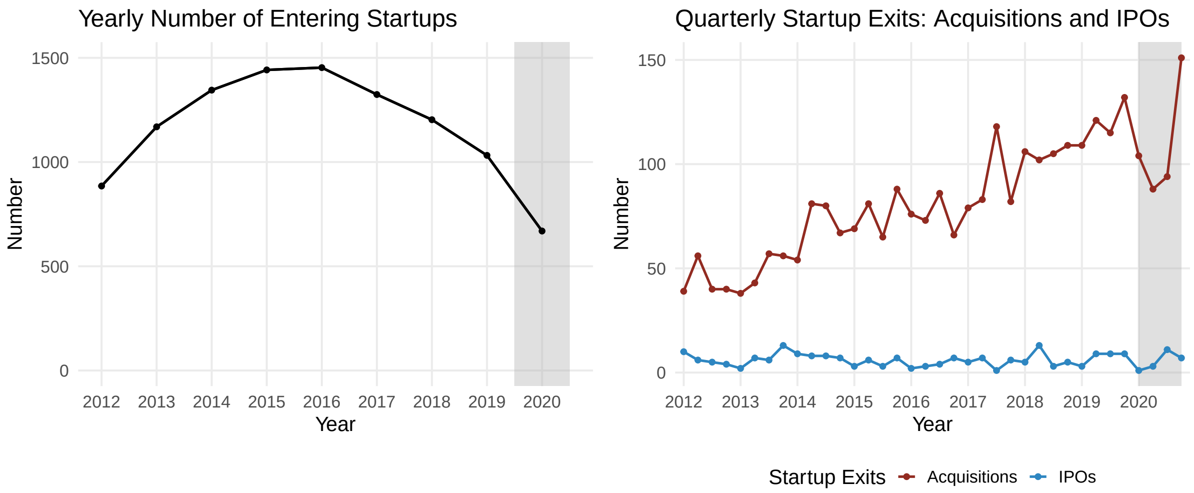
Next, I cluster documents in the embedding space into markets using a k-means clustering algorithm

12. Analogously, each company that has been "acquired-but-discontinued" (set C in Figure 2) is also characterized by a descriptive text and a broader set of categories stemming from *Crunchbase*.

13. For example, terms such as "scheduling" and "calendar", or "billing" and "invoicing", would be treated as unrelated despite referring to similar functionalities, potentially leading to incorrect market segments.

14. The model is trained on *Common Crawl*, a large corpus of web text, making it well-suited for the domain-specific language of enterprise software.

Figure 3: Startup entry and startup exits (acquisitions and IPOs) over time



Notes: The year of 2020 (shaded in both plots) is excluded from all below analyses due to potential disruptions caused by the Covid-19 pandemic. "Startups" are private, VC-backed firms, and for startups, "entry" is defined as the first VC-funding round (see Section 2.2.1).

(see Appendix B.7). Products with nearby document vectors – that is, with similar descriptions and categories – will form a market.

Because k-means requires choosing the number of segments k, I select k by balancing internal fit with external validity. For guidance, I construct an external benchmark from European Commission and UK CMA merger decisions that involve firms in my sample, and a small set of canonical software markets. I then compare candidate partitions by (1) average within-cluster similarity and (2) overlap with this benchmark. Partitions that better recover the benchmark while maintaining high within-cluster similarity are preferred. This procedure points to k in the range of 450-500. The baseline uses k=500 markets (489 after dropping outlier markets). See Appendix B.8 for details.

Table 1 shows descriptive statistics of the dataset for the period of 2012 to 2020. The data cover a sample of over 20,000 firms. The majority of these firms – 67% – is VC-funded, while less than 5% of active companies are (at any point in the observation period) public firms. Only 42% of products have any user reviews on *Capterra*, as of 2021. Figure 3 shows the number of startup entries and exits (acquisitions and IPOs) over time. Entry increases at the beginning of the sample, and then declines, possibly reflecting both a growing and then maturing and increasingly concentrated market, as well as the time lag between a firm's first funding round and product launch. Over the sample period, acquisitions show an increasing trend, while the number of startup IPOs is consistently low. As the year 2020 is affected by the Covid-19 pandemic that initially disrupted funding and M&A activity, I exclude it from the analyses that follow.

Table 2 exhibits descriptives on the market-quarter panel for 2012-2019, highlighting once more the importance of VC-funded startups as competitors in the market. Startup entry is vigorous, with, on average, at least one new startup entering every other market-quarter. Acquisitions occur less frequently (0.2 per market-quarter), and IPOs are very rare.

Table 2: Summary statistics for the market-quarter panel, 2012-2019

Per market-quarter	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
A.1 Market structure (all firms)					
Pre-VC funding firms	4.81	4.56	2	4	7
VC-backed startups (pre-exit)	14.57	13.66	5	11	19
Acquired former startups (active product)	1.43	1.94	0	1	2
Public former startups (active product)	1.22	1.67	0	1	2
Other incumbents	14.76	10.66	7	13	20
Total firms per market-quarter	36.79	26.15	19	31	48
A.2 Market structure (subset: firms with ≥1 product review)					
Pre-VC funding firms	2.01	2.18	0	1	3
VC-backed startups (pre-exit)	6.98	6.46	2	5	10
Acquired former startups (active product)	0.71	1.13	0	0	1
Public former startups (active product)	0.83	1.19	0	0	1
Other incumbents	6.55	4.98	3	5	9
Total firms per market-quarter (with ≥1 review)	17.09	11.94	8	14	24
B. Firm events					
Startups entering	0.68	1.01	0	0	1
Startups being acquired	0.16	0.48	0	0	0
Startups going public	0.02	0.14	0	0	0
Observations: 15,676 (489 markets)					

Notes: Panel A reports descriptives on market structure per market-quarter. Panel A.2 is a subset of A.1, restricting firms to those with ≥1 user review on *Capterra*. Panel B reports market-level flows or events (entry, acquisitions, IPOs). "Pre-VC funding firms" are firms younger than three years that have not yet recorded any event, aside from a founding date, and are therefore not classified as startups. "Other incumbents" are firms that are not startups, but older than three years (since founding date). Many of these are privately operating firms that often do not have a high number of reviews. I exclude 2% of markets characterized by mostly inactive firms.

3 Stylized Facts on Likely Acquisition Motives

This section lays out empirical facts that guide certain modeling assumptions, and serve to better understand acquisition motives in this industry. I distinguish and document different types of acquirers along the dimension of whether the acquirer is active in the industry sector of enterprise software. The main findings are that (1) a broad set of companies act as acquirers, with a little under one third of startup acquisitions undertaken by industry outsiders; (2) many acquired products are no longer actively offered under their original brand name as of mid-2021; and (3) most acquisitions are nonhorizontal.

3.1 Distinguishing Different Types of Acquirers

Different acquirer types likely differ in important ways in their respective motives when acquiring startups. I identify three main types of acquirers, shown in Panel A of Table 3. Out of all acquisitions that are first exits for VC-funded startups, 72% (1,814) are conducted by other industry peers that have their own products listed on *Capterra*. I call these acquirers *strategic acquirers*, as they are active in the enterprise software industry, just like the target firm. 9% of acquisitions are carried out by financial firms, and 19% are carried out by firms that are neither active in enterprise software, nor in finance. Further characteristics on these three types of acquirers can be found in Appendix C.2.

Motivated by the policy focus on the largest and most dominant acquirers, I divide strategic acquirers

Table 3: Acquirer taxonomy: exhaustive types and (non-exhaustive) strategic subtypes

Panel A: Acquirer types (exhaustive)

Acquirer type	**Definition / examples**	**# of startup acquisitions**
Strategic	Companies in enterprise software with own-developed products listed on *Capterra*. *Examples: GAFAM; Cisco; Oracle; Salesforce; Dropbox.*	1814
Financial	Companies active in finance, including private equity firms and investment banks. *Examples: Vista Equity Partners; Thoma Bravo; Marlin Equity Partners.*	225
Outsider	Companies outside enterprise software and finance (no products on *Capterra*); includes holding companies that acquire but do not produce software. *Examples: Synopsys; Intel; WeWork; Verizon; McDonald's; Samsung Electronics; Roche.*	477
Total		**2,516**

Panel B: Strategic acquirer subtypes (distinct but not exhaustive)

Subtype	**Description / examples**	**# of startup acquisitions**
GAFAM	Google (Alphabet), Apple, Facebook (Meta), Amazon, Microsoft and their subsidiaries (e.g., LinkedIn, AWS, GitHub).	122
Old tech	Public companies founded prior to 1995 with over 10,000 employees. *Examples: Cisco, Oracle, VMware, SAP, Dell EMC, HPE, IBM, Adobe.*	178
New tech	Companies founded 1995 or later that started as VC-funded and have exited. *Examples: Salesforce, Palo Alto Networks, Workday, ServiceNow.*	142
Pre-exit	VC-funded startups acquiring before they have "exited" (been acquired or gone public). *Examples: Sprinklr, Freshworks, Ignite Technologies, Dropbox, DataRobot, Stripe, Hootsuite.*	550

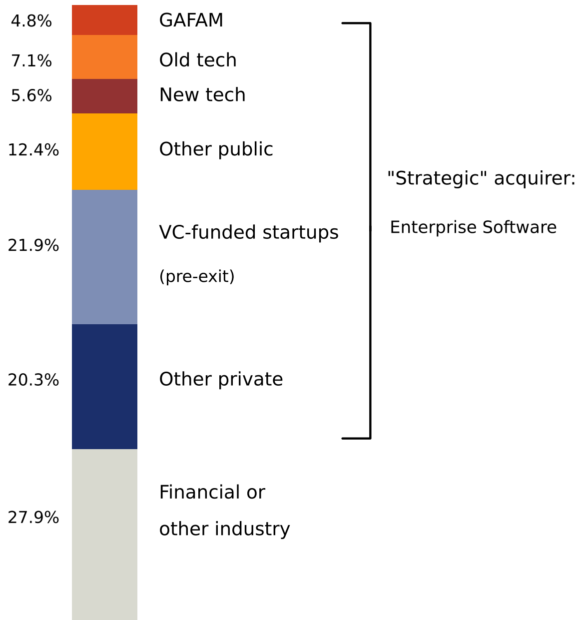
Notes: All figures refer to first exits of VC-backed startups in enterprise software, 2012–2019, counted at the company (not product) level. Types in Panel A are exhaustive and mutually exclusive. Subtypes in Panel B are distinct but not exhaustive; firms can switch subtypes over time (e.g., Dropbox moves from *pre-exit* to *new tech* after going public).

into further (non-exhaustive) sub-groups along the measures of firm age and innovativeness (measured as having received VC funding in the past). Moreover, I segment the GAFAM firms from the others, as the former are deemed to be especially dominant and subject to frequent antitrust scrutiny. All subgroups are detailed in Panel B of Table 3, and their proportions as acquirers are shown in Figure 4. An interesting and perhaps surprising fact is the scale at which acquisitions by *other* startups appear to be a major exit route for growing startups, and that the GAFAM do not account for as many acquisitions in terms of the absolute number of acquired firms.

3.2 Many Acquired Products Are Not Active Post-Acquisition

The data contain companies that were acquired in the past, but whose products are not available any more under the same brand name on *Capterra* (see Section 2.2.3). For the sample of VC-funded enterprise software startups that were acquired in 2012-2019, I find that in a majority – 60% – of cases, the

Figure 4: Shares of first-time acquisitions (exits) of VC-backed startups by acquirer type, 2012–2019



Notes: "Startups" are VC-backed firms, as defined in 2.2.1. Percentages denote the fraction of acquired startups whose buyer is of the indicated type. The total number of such acquisitions is 2,516; the numbers are on the company (as opposed to product) level.

Table 4: Discontinuations by acquirer type

Panel A: Broad acquirer groups (exhaustive)		
Acquirer type	**Discontinuations** (% of acquired startups)	**Discontinuations** (count)
Enterprise software	69.9	1,268
Financial	29.3	66
Other industries	39.6	189
All acquirers	**60.5**	**1,523**
Panel B: Strategic subtypes (distinct, not exhaustive)		
Subtype	**Discontinuations** (% of acquired startups)	**Discontinuations** (count)
GAFAM	82.0	100
New tech	69.3	95
Old tech	74.2	132
Pre-exit	72.7	400

Notes: Panel A covers all acquirers. Panel B subtypes pertain to strategic (enterprise software) acquirers, are distinct but not exhaustive, and firms can switch subtypes over time. Sample: first exits of VC-backed startups in enterprise software, 2012–2019; company-level. Acquirer types and strategic subtypes are defined in Table 3.

acquired startup's product does not exist under the same brand name as of 2021. Hence, findings made for GAFAM-acquisitions in fact carry over to the broad space of strategic acquirers more generally: Affeldt and Kesler (2021a) consider over 50 GAFAM-acquired mobile apps and find that half of these apps are discontinued, and Gautier and Lamesch (2021) find that the GAFAM shut down the companies in 60% of all cases. In my sample, discontinuations are a widespread phenomenon especially for strategic acquirers (69%, see Table 4). They are, as expected, less common for financial acquirers (29%).

Appendix C.3 provides additional details on these acquisitions. Targets whose products are subsequently discontinued are younger at acquisition by roughly one to two years, and sell for lower observed prices than targets whose products remain active (Table C.6).[15]

3.3 Suggestively, Most Acquisitions Are Nonhorizontal

I call acquisitions "horizontal" if the acquired startup's product competes (or has competed, in the case of discontinued products) with the acquirer's product in the same market. According to this definition, only 11% of all acquisitions of VC-funded startups in 2012-2019 can be classified as horizontal. This suggests that acquisitions are likely not driven by the motive of increasing market share within a given market. The finding adds to evidence in Jin, Leccese, and Wagman (2023), who find, using a different taxonomy, that deals in technology markets concern mostly unrelated or adjacent markets.

However, there are caveats to this observation. First, researchers typically do not have access to information on products that are in the development stage within the acquirer's boundaries. If a target's product is complementary to an acquirer's internal product development efforts, the acquisition will then not be classified as horizontal, according to this definition. The second caveat is that, like other research studying digital markets, I take market definitions to be static, whereas a product's market might change over time. These caveats point to the importance of future research in this area.

3.4 Discussion

What explanations are behind the finding that many products are not available post-acquisition? In fact, the finding likely masks a lot of heterogeneity, and thinking of all cases as "shutdowns" might be misguided: it is possible that an acquired startup had not even launched its product yet at the time of the acquisition; that the product was integrated; rebranded; that it simply failed; or that it was "killed" by the acquirer to remove a nascent competitor[16]. Two findings are suggestive that, in enterprise software, alternative interpretations than killer acquisitions may be more relevant for the bulk of acquisitions. First, the young age and low prices of acquired-and-discontinued startups revealed in Section 3.2 suggest that discontinued products had small market shares at the time of acquisition. Given the high failure rates (around 55% on *Capterra*, see Appendix G.2.2), high entry rates, and small odds of building a successful competing product, these acquired firms were perhaps unlikely to pose a real competitive

15. Transaction prices are missing in 84% of acquisitions without active products, and 79% of acquisitions with active products. As it is mostly lower-priced deals that are more likely unreported (in particular "fire sales", see Kerr, Nanda, and Rhodes-Kropf (2014)), the observed price gap is likely a lower bound.

16. Killer acquisitions comprise 5.3 to 7.4 percent of acquisitions in the setting of pharmaceuticals studied in Cunningham, Ederer, and Ma (2021).

threat to the acquirer. Second, the finding that most acquisitions are of nonhorizontal nature suggests that the acquired target was likely not a potential competitor in the acquirer's core business.

A range of anecdotes can help interpret the patterns of acquisitions I observe. For instance, acquired products are oftentimes integrated into the acquirer's existing product as an additional feature or functionality, or to otherwise improve the existing product, if the acquirer is an enterprise software firm.[17] Gautier and Maitry (2024) find integrations to occur in roughly 8% of all discontinued GAFAM acquisitions. Other transactions seem to be so-called acqui-hires in which the acquired startup's employees are paid to become part of the acquiring company.[18] Finally, cases in which the acquired product was rebranded do exist, but any rebranding seems to have gone along with changes to the original product.[19]

4 Reduced-Form Evidence on Acquisitions and Entry

4.1 Specifications

Acquirers differ in both their incentives and their abilities to influence subsequent entry. *Strategic acquirers* possess highly complementary assets (e.g., data, algorithms, an established customer base, or specialized human capital). By integrating these assets into the acquired startup's product, they can realize merger synergies that enhance the target's competitiveness and drive growth in market shares, thereby deterring follow-on entry. Moreover, a dominant software supplier may leverage an acquisition to extend its market power into adjacent niches – for example through tying or by building proprietary ecosystems that reduce contestability (Whinston 1990; Carlton and Waldman 2002; Heidhues, Köster, and Kőszegi 2024) – or may deter entry by threatening to counter-develop the acquired project (Teh, Banerjee, and Wang 2022). This raises entry barriers *ex post*.

By contrast, *financial acquirers*, which are predominantly private equity firms, are interested in short- to medium-term returns on investment, and do not have the means to leverage market power as effectively. They focus on medium-term cash-flow generation through financial engineering or operational changes, and on divesting the target at a profit (Kaplan and Strömberg 2009), rather than on reshaping competitive dynamics in a specific software niche or building ecosystems. Likewise, *outsiders* – firms without in-house software offerings – typically pursue acquisitions to vertically integrate certain software tools, without incentives nor the ability to tilt competition in the acquired startup's market in their favor.

My objective in this section is to study entry patterns around acquisition events by these different

17. For instance, according to news reports, this may have been the case with Amazon's acquisition of the data warehousing company Amiato, see https://techcrunch.com/2015/04/20/amazons-aws-acquired-amiato/; Google's acquisition of app performance startup Pulse.io, see https://venturebeat.com/2015/05/28/google-acquires-mobile-app-performance-startup-pulse-io/; or Upskill's acquisition of Pristine, see https://www.prnewswire.com/news-releases/augmented-reality-industry-leader-upskill-acquires-pristine-300453872.html (all accessed 30/09/2025).

18. For financial acquirers, the motive of discontinuing product might be somewhat different. Anecdotally, it seems that financial acquirers more often merge (and possibly restructure) two companies in their portfolios, rather than entirely discontinuing or acqui-hiring target companies. One example is the alternative data company 7Park Data, which was acquired by Vista Equity Partners and later folded into Apptio, another one of Vista Equity Partners's portfolio firms. Another example is SCIO Health Analytics, which was acquired by the holding group ExlService Holdings and is now part of its product EXL Health.

19. An example is the acquisition of Acompli, a mobile email and productivity app, by Microsoft. The product was rebranded as Outlook Mobile a month after the acquisition; see, e.g., https://www.theverge.com/2015/1/29/7936081/microsoft-outlook-app-ios-android-features (accessed 07/10/2025).

acquirer types, and to understand whether a "kill zone" pattern emerges. As acquisitions of each type affect all markets very regularly, and as any "kill zone" effects should arise for acquisitions of larger startups only, I restrict attention to large acquisitions that did not result in a product discontinuation. Specifically, I focus on transactions valued at over US$100 million or, alternatively, those exceeding US$50 million.[20] For markets that were affected by multiple acquisitions over the sample period, I consider the first acquisition. I moreover estimate separate regressions for different acquirer types.

The empirical analysis is carried out at the level of a market-quarter from 2012 to 2019 using the 489 markets displayed in Table 2, and follows a staggered treatment design. Using the two-stage methods by Gardner et al. (2024), I estimate the parameters of the following linear equation:

$$\text{num\_entrants}_{mt} = \beta\ Acq_{m,t} + \lambda_m + \lambda_t + \varepsilon_{mt} \tag{1}$$

where $\text{num\_entrants}_{m,t}$ denotes the number of VC-funded startups entering in a given market m at quarter t, whereas $Acq_{m,t}$ is an indicator variable that takes the value of 1 if a certain type of acquisition has occurred at any point in the past in market m at time t. λ_m and λ_t denote market and quarter fixed effects, and ε_{mt} is an econometric error term.

To assess pre-trends and investigate the dynamics, I estimate a specification with yearly (4-quarter) bins, over a symmetric three-year window around the acquisition date. Let τ_{mt} denote quarters relative to the first acquisition affecting market m (with $\tau_{mt} = +\infty$ for never-treated observations). I keep observations with $\tau_{mt} \in [-12, 11] \cup \{+\infty\}$ and collapse relative time into six bins with equal widths:

$$\mathcal{B} = \{[-12,-9],\ [-8,-5],\ [-4,-1],\ [0,3],\ [4,7],\ [8,11]\}.$$

I estimate

$$\text{num\_entrants}_{mt} = \sum_{b\in\mathcal{B}} \beta_b\, \mathbf{1}\{\tau_{mt} \in b\} + \lambda_m + \lambda_t + \varepsilon_{mt} \tag{2}$$

In both equations, the omitted category is the never-treated group. Estimation uses the two-stage procedure of Butts and Gardner (2022) (`did2s`) with standard errors clustered at the market level.

Endogeneity and interpretation. When interpreting the results, one must be cautious about the causal meaning of estimated coefficients. Acquisitions by strategic buyers raise the concern that the choice of which market and when to acquire is endogenous to both observed and unobserved conditions. Focusing on *rivals* rather than the merging parties mitigates concerns about which target within a market is selected, as the idiosyncratic acquirer-target "match" factors are less likely to be endogenous to the entry decisions of competitors (see, e.g., Eckbo (1983), Dafny (2009), and Haucap, Rasch, and

20. The median transaction price for VC-funded startups with continued products is US$168 million. As it is mostly lower-priced deals that are more likely unreported (Kerr, Nanda, and Rhodes-Kropf 2014), I believe that I can capture all significant deals that may have affected competition.

Stiebale (2019)).[21] That said, the focus on acquirees' rivals does not by itself resolve market-selection or timing endogeneity. The estimation compares within-market changes around acquisition events to contemporaneous changes in markets without an acquisition, conditioning on market and time fixed effects. Identification requires a parallel-trends assumption across treated and control markets. Finally, I contrast outcomes around acquisitions by strategic versus financial buyers. This comparison is informative if, conditional on controls, markets exposed to each acquirer type would have followed similar rival-entry trajectories absent a deal. I present these estimates as suggestive and use pre-trends, placebo tests, and robustness checks to gauge their credibility.

As treatments, I consider broad, as well as narrower definitions of *strategic* and *financial* acquirer types. The broadest definition of strategic acquirers considers all enterprise software acquirers; narrower definitions consider subsets of these. Similarly, the broadest definition of financial acquirers considers both financial as well as industry outsider firms.[22]

4.2 Reduced-Form Results

Table 5 displays the results from estimating equation 1, using acquisitions with a price of US$100 million or more as treatment events. Entry drops on average by 0.28 entrants per quarter after a major strategic acquisition, which is sizable given that the average number of entrants is 0.68 (see Table 2). The coefficient increases as we restrict attention to major acquisitions by strategic acquirers whose products have at least one review (column (2)), and increases further, although becomes imprecise, when focusing on "New Tech" and GAFAM, or the GAFAM firms only. By contrast, the coefficient is statistically indistinguishable from zero when considering acquisitions by financial acquirers and outsiders (columns (5) and (6)), although negative in sign when considering both outsiders and financial acquirers. To alleviate concerns that markets that are concerned by any type of acquisitions might be different than "never-treated" markets, Table D.1 in Appendix D shows overall similar, although noisier, results when restricting attention to markets that experienced at least one major acquisition by any acquirer type during the period of observation.

Figure 5, which shows estimates from equation 2, reveals that pre-trends (over binned observation periods) are similar and mostly flat. After the treatment, we see that coefficients are negative and marginally significant in the case of strategic acquirers.

Appendix D provides robustness on the static results by showing that qualitatively, the results persist when lowering the threshold of what constitutes a "major" acquisition to a transaction value of above

21. Illustrative accounts suggest that acquirer-target match value often hinges on aspects such as travel distance, network ties, or compatibility of technology stacks. Anecdotally, startups frequently turn down offers they obtain, seemingly for reasons exogenous to market conditions and to rivals' entry decisions. Snap, for instance, received an offer to be acquired by Google and Facebook, but eventually remained independent. The company Clustree received more than three offers before selling to Cornerstone (see https://business.lesechos.fr/entrepreneurs/communaute/0603458127497-podcast-benedicte-de-raphelis-soissan-fondatrice-de-clustree-338661.php, accessed 05/10/2025). An interview I conducted with a startup co-founder who shall remain unnamed revealed that their company received offers from three of the GAFAM, but eventually sold to another digital services company.

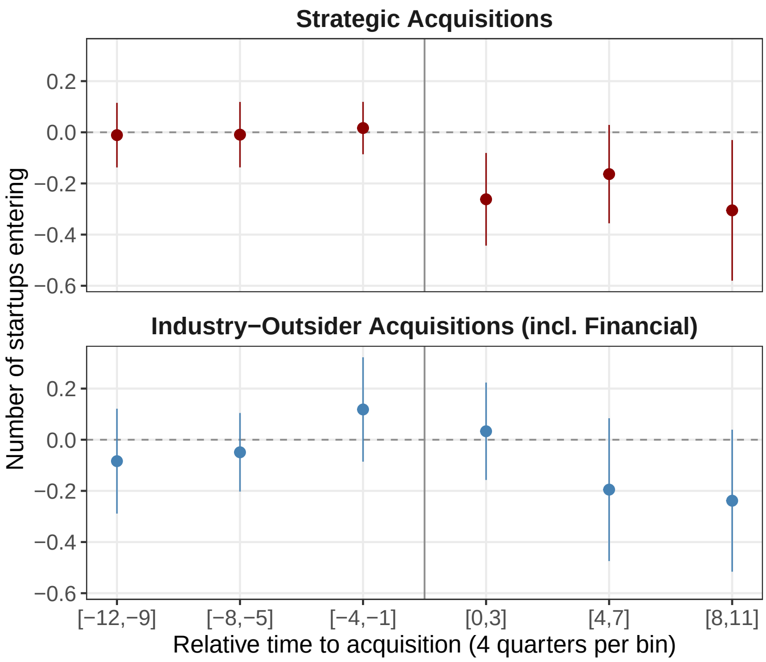
22. To give examples of events used in these regressions: major acquisitions by enterprise software companies include Dropbox-DocSend, Google-Looker, Microsoft-Yammer, Amazon-CloudEndure, Docusign-SpringCM, or Oracle-Moat, for instance. Examples of major acquisitions by financial companies are LiveU-Francisco Partners, Acquia-Vista Equity Partners, or Smartly.io-Providence Equity Partners. Examples of major acquisitions by companies in other industries are Roche-Flatiron Health, McDonald's-Dynamic Yield, Continental-Zonar, or Dupont-Granular.

Table 5: Two-stage DiD estimates of startup entry after major acquisitions, by acquirer type

	Dependent Variable: Number of entrants in market m, quarter t					
	Strategic (enterprise software) acquirers				**Financial / outsiders**	
"Major" acquisition: > US\$100m	(1)	(2)	(3)	(4)	(5)	(6)
1{major acq by strategic}	-0.2778** (0.1323)					
1{major acq by strategic w/ reviews}		-0.3456** (0.1470)				
1{major acq by New Tech or GAFAM}			-0.9201* (0.4764)			
1{major acq by GAFAM}				-1.609* (0.8819)		
1{major acq by Financial or Outsider}					-0.1047 (0.1199)	
1{major acq by Financial}						0.1594 (0.2462)
Market FE	✓	✓	✓	✓	✓	✓
Quarter–year FE	✓	✓	✓	✓	✓	✓
Observations	15,616	15,648	15,648	15,648	15,616	15,648
Adjusted R^2	0.2978	0.2982	0.2981	0.2981	0.2982	0.2976

Notes: "Major" acquisition: > US\$100m (first event per market). Entries are two-stage difference-in-differences (did2s) coefficients, interpreted as post-acquisition average treatment effects on the treated (ATT) for each acquirer group; standard errors clustered by market. The sample is a market–quarter panel, 2012–2019. Column (2) restricts "strategic" to acquirers with at least one product reviewed on *Capterra*; (3) limits to New Tech or GAFAM; (4) isolates GAFAM acquirers; (5) pools financial and outsider acquirers; (6) isolates financial acquirers. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure 5: Major acquisitions and startup entry: event study estimates



Notes: Outcome is the number of VC-funded startups entering a market in quarter t. Event time is relative to the first *major* acquisition in a market (transaction value > US\$100m). We keep $\tau_{mt} \in [-12, 11] \cup \{+\infty\}$ and collapse to six 4-quarter bins: $[-12,-9]$, $[-8,-5]$, $[-4,-1]$, $[0,3]$, $[4,7]$, $[8,11]$. Coefficients plot $\hat{\beta}_b$ with 95% confidence intervals from (2), estimated on a market–quarter panel (2012–2019) with market and quarter–year fixed effects using the two-stage `did2s` estimator; standard errors clustered by market. Panel A: acquisitions by strategic (enterprise software) acquirers with at least one product review on *Capterra*. Panel B: acquisitions by industry outsiders (including financial firms). The omitted category is the never-treated group.

US$50 million. When changing the number of clusters to 475 or 450 markets, results tend to become noisier. Results are qualitatively similar when changing the definition of entry to include also founding dates of pre-funding round firms. Finally, as a placebo exercise, I randomly reassign acquisition dates across treated markets while preserving the timing distribution. Table D.6 shows that the resulting coefficients are statistically indistinguishable from zero. This suggests that the main reduced-form results are not artifacts of event timing, seasonality, or spurious correlation.

Even when not aiming for a causal interpretation of these results, they are interesting and even surprising: as explained in Section 3.4, acquisitions by strategic acquirers seem to often be part of their innovative strategy. At least for some of the acquisitions observed in the data, the motive may be to acquire innovative capabilities in the form of strategic assets or human capital. One may thus have expected strategic acquirers to acquire in markets that experience a rise in demand, and thus an increase in entry. This goes against my findings in Figure 5, which shows that strategic acquisitions are not preceded by more entry, and even tend to be succeeded by a slight decline in entry.

Overall, these reduced-form results offer suggestive support for entry-deterring effects of major strategic acquisitions. They contribute to recent literature, which has found somewhat mixed results on the presence of a "kill zone": whereas Affeldt and Kesler (2021b), Kamepalli, Rajan, and Zingales (2021), Gugler, Szücs, and Wohak (2025), and Koski, Kässi, and Braesemann (2020) document negative effects of GAFAM acquisitions on measures of investment or entry in that market, Prado and Bauer (2022) find an increase in VC investments after an acquisition by a large technology company took place.[23] For a sample of software startups, McKeon (2025) finds that rivals pivot away from the acquired startups' market after an acquisition.

Note that any reduced-form effect blends any effect of an acquisition that is transmitted through market structure, and the entry-for-buyout effect. Studying both types of effects is only possible within a dynamic structural model of startup entry, which is the subject of the next section.

5 Dynamic Model of Entry

To study and quantify both the entry-for-buyout channel and the market structure channel, I build a dynamic model whose parameters can be estimated using the data. The economic agents in this model are potential entrants who decide whether to enter a given market, taking into account the current and expected future market structure, as well as the likelihood of future exit opportunities that arrive with some probability. I model these decisions as a dynamic discrete game with imperfect information, where each firm's choice depends on the anticipated actions of other potential entrants.

A difference from many other dynamic models (e.g., Aguirregabiria and Mira (2007) and Bajari, Benkard, and Levin (2007)) is that each potential entrant can enter at most once. This reflects the nature of venture-backed startups, which are unlikely to wait or time their entry decisions. This assumption simplifies the dynamic game to a one-time discrete choice for each potential entrant. The model is nev-

23. Relatedly, Jin, Leccese, and Wagman (2023) do not find that acquisitions by the GAFAM are followed by a decrease in acquisitions by other firms. All aforementioned papers study the effects of acquisitions conducted by the GAFAM only, and employ alternative methods or taxonomies to define competitors to a focal acquired firm.

ertheless dynamic because firms are forward-looking, face sunk costs upon entry, and understand that their decisions influence state variables, in particular market structure, that evolve over time.

5.1 Setup

Time is discrete and infinite, and each decision period is a quarter. We consider a finite number of independent markets. In every period t and in every market m, there is a new set of entrepreneurs with ideas for new products in that market. These entrepreneurs form an exogenously given cohort of potential entrants. In every period and every market, all potential entrants simultaneously decide whether to enter the market or not, so as to maximize their expected profits. The potential entrants are homogeneous, except for a private i.i.d. shock that each agent draws from a distribution.

If a potential entrant decides not to enter the market, there will be no future chance of entry, and she stays out forever.

If a potential entrant decides to enter, she will earn flow profits in that period. These flow profits depend on a vector of state variables, $\boldsymbol{x}_{mt}$, that capture in a reduced-form way aspects of market structure that are likely to influence firm profits. These state variables are common knowledge among all potential entrants. I interpret period-t flow profits as the expected profits realized after the simultaneous entry game at state $\boldsymbol{x}_{mt}$. Denote $\bar{\pi}(\boldsymbol{x}_{mt};\boldsymbol{\gamma}) \equiv \mathbb{E}[\pi(\boldsymbol{x}_{mt}, a_{mt};\boldsymbol{\gamma}) \mid \boldsymbol{x}_{mt}]$, where the expectation is over the equilibrium distribution of rivals' entry decisions a_{mt}, and where $\boldsymbol{\gamma}$ denotes a vector of structural parameters.

In each period after entry, a startup may "exit" – that is, experience a transfer in ownership – either by being acquired or by listing on the public stock market. These exits allow founders and VC investors to realize returns on their investment. In the model, once a firm exits, it ceases to earn flow profits and instead receives a one-time lump-sum payoff. Acquisitions and IPOs occur as stochastic events that arrive to active startups with some probability each period. If no such event occurs, the firm continues operating, earning flow profits, and transitions to the next period.

Within each period, the timing is as follows:

1. Among the incumbent startups on the market, firms that are acquired in that period earn R^{acq}, and firms that are going public in that period earn R^{ipo}.

2. Each potential entrant i observes the vector of state variables $\boldsymbol{x}_{mt}$ that is common knowledge, and privately observes a cost shock $\boldsymbol{\epsilon}_{imt} = \{\epsilon^0_{imt}, \epsilon^1_{imt}\}$.

3. All potential entrants simultaneously decide: {enter, stay out}, so as to maximize their expected profits.

4. All startups on the market that did not exit in step (1), including the new entrants, earn flow profits based on the realized entry profile at time t, $\bar{\pi}(\boldsymbol{x}_{mt};\boldsymbol{\gamma})$.

5. All state variables transition to the next period.

I normalize the value of staying out to zero. Let θ denote the vector of all structural parameters. The choice-specific value functions for entering and for staying out, excluding the random cost shock, write:

$$U^0(\boldsymbol{x}_{mt};\theta) = 0 \tag{3}$$

$$U^1(\boldsymbol{x}_{mt};\theta) = -\kappa + \bar{\pi}(\boldsymbol{x}_{mt};\boldsymbol{\gamma}) + \beta\mathbb{E}\big[V(\boldsymbol{x}_{mt+1};\theta,\cdot) \mid \boldsymbol{x}_{mt}\big] \tag{4}$$

κ is a parameter denoting the sunk cost of entry, which the potential entrant incurs only once upon entering. $\beta \in (0,1)$ is the discount factor. $V(\boldsymbol{x}_{mt+1};\theta,\cdot)$ is the value of continuing to be active in the market in the next period, defined below. Potential entrant i's decision problem is then given by:

$$\max \quad \Big\{U^0(\boldsymbol{x}_{mt};\theta) + \epsilon^0_{imt}, \quad U^1(\boldsymbol{x}_{mt};\theta) + \epsilon^1_{imt}\Big\} \tag{5}$$

The expected payoffs in future periods can be expressed as follows:

$$\begin{aligned} V(\boldsymbol{x}_{mt};\theta,\cdot) \quad &= \quad \alpha^{ipo}\big(p^{ipo}_m \cdot R^{ipo}\big) + \alpha^{acq}\big(p^{acq}_m \cdot R^{acq}\big) \\ &\qquad + (1 - p^{ipo}_m - p^{acq}_m)\Big[\bar{\pi}(\boldsymbol{x}_{mt};\boldsymbol{\gamma}) + \beta\mathbb{E}\big[V(\boldsymbol{x}_{mt+1};\theta,\cdot) \mid \boldsymbol{x}_{mt}\big]\Big] \end{aligned} \tag{6}$$

R^{acq} and R^{ipo} represent the expected returns for startups upon acquisition and IPO, respectively, which are directly calibrated from data moments to match typically observed market-level exit returns. p^{acq}_m and p^{ipo}_m capture the per-period hazards of being acquired or going public, respectively, and will be estimated to match long-run empirically observed probabilities of startups in market m being acquired or going public (see Section 5.2). The structural parameters α^{acq} and α^{ipo} quantify the degree to which startups' entry decisions are influenced by the likelihood of acquisition and IPO exit opportunities within their respective markets. If the firm is not acquired nor listed on the stock market, which is the case with probability $(1 - p^{acq}_m - p^{ipo}_m)$, then the firm continues to earn flow profits in that period. In the period after, any of the same set of events – {acquisition; IPO; continue} – may occur, and so on. All in all, the vector of structural parameters is therefore given by $\theta = (\boldsymbol{\gamma}, \alpha^{acq}, \alpha^{ipo}, \kappa)$.

The shocks $\{\epsilon^0_{imt}, \epsilon^1_{imt}\}$ are privately observed by firms, but unobserved by the econometrician. I assume that they are independently and identically distributed according to a type-1 extreme value distribution.

As is common in much of the research estimating dynamic games, I focus on Markov Perfect Nash equilibria in pure strategies (Maskin and Tirole 1988a, 1988b). In this equilibrium concept, players' strategies depend only on payoff-relevant state variables (and hence not on factors such as history-dependent variables). Building on the work of Ericson and Pakes (1995), Doraszelski and Satterthwaite (2010) show that when agents' utilities include privately observed shocks – as in the model considered here – a Markov Perfect Nash equilibrium in pure strategies exists.

5.2 Parameterization and Laws of Motion

I do not observe profits, nor demand, for the tens of thousands of firms observed in my dataset. Therefore, I employ a semi-structural approach: I treat profits as a latent variable, as does previous literature that models firms' discrete choices (e.g., Bresnahan and Reiss (1991), Seim (2006), and Collard-Wexler (2013)). This approach makes use of the fact that a firm's presence on a market indicates that it must have been profitable for the firm to enter, by revealed preference. Unobserved profits are modelled as depending on state variables that, according to economic theory, should influence profits. By relating firms' entry decisions to these state variables through the lens of the model, one can estimate the parameters "measuring" the extent to which these state variables affect the profitability of a given market in a given time period.

Per-period flow profits $\pi(\boldsymbol{x_{mt}}; \boldsymbol{\gamma})$ are parameterized as follows:

$$\pi(\boldsymbol{x_{mt}}; \boldsymbol{\gamma}) = \gamma^N \log(N_{mt} + 1) + \gamma^A A^{\text{strat}}_{mt} + \gamma^M_{l(m)} \tag{7}$$

N_{mt} denotes the number of competitors in market m at time t. I define competitors as the stock of incumbent products with at least one user review on *Capterra* produced by either public or VC-funded companies.[24] As N_{mt} is affected by entry, it is thus an endogenous state variable that evolves according to firms' entry decisions, as well as to an exogenous component.[25] A^{strat}_{mt} is an indicator variable that that equals one in the event quarter and the subsequent eleven quarters (i.e., three years) after a rival startup in market m is acquired (and kept alive) by a strategic acquirer. I treat A^{strat}_{mt} as predetermined with respect to period-t entry choices (an observed shock to market conditions) and use it to parsimoniously capture a transitory tightening of competitive pressure that shifts expected profits.[26] Allowing for a 12-quarter horizon allows for the possibility that markets and technology evolves, and the negative effect of a major acquisition might dissipate over time; in other words, a market does not remain "treated" forever. $\gamma^M_{l(m)}$ is an intercept coefficient that varies by market type $l(m)$, with $l = 1, \ldots, L$. It captures a *market-category* effect that is constant over time but differs across markets, and is therefore treated as an exogenous state variable. The coefficient can be interpreted as the baseline profit level associated with a given market. It measures the persistent entry propensity after conditioning on state and time, serves to control for unobserved differences in market size or profitability, following Y. Wang (2022) (see Section 6.1 for details on its construction). The full set of state variables is summarized by $\boldsymbol{x}_{mt} = \{N_{mt}, A^{\text{strat}}_{mt}, l(m)\}$.

Using the logged number of competitors in the profit function captures that, empirically, going from one to two competitors affects firm profits more strongly than going from, say, ten to eleven competitors (see, for instance, Mazzeo (2002)). One can expect γ^N to be negative, capturing that baseline profits

24. I thus exclude companies whose products in a given market do not have any review. I moreover exclude non-VC-funded private and inactive companies. This choice is supported by the better fit in the first stage, indicating firms not captured by this definition may be viewed as a competitive fringe that do not affect entry decisions. Adjusting this definition of competitors does not qualitatively affect the final results.

25. The exogenous component is required to rationalize the data. For instance, a firm may be acquired and shut down (which reduces the number of competitors by one). Alternatively, a non-VC-funded firm may become public (which increases the number of competitors by one).

26. A richer model with heterogeneous firms could map acquisitions into competitive primitives directly (e.g., through productivity or quality). For example, Perez-Saiz (2015) assign the target the acquirer's characteristics, and Igami and Uetake (2020) let mergers alter rivals' productivity paths. Because I do not model firm-level productivity or characteristics, I use A^{strat}_{mt} as a reduced-form shifter to capture the short-run effect of strategic acquisitions on entry incentives.

are declining in the number of competitors N_{mt}. From the reduced-form results in Section 4, γ^A can be expected to be negative as well, i.e., a recent major strategic acquisition of a competing firm lowers returns to entry.

The law of motion of N_{mt} writes as follows:

$$N_{mt+1} = N_{mt} + \text{num\_entrants}_{mt} - D_{mt}^{\text{exit}} + E_{mt}^{\text{entry}} \tag{8}$$

num_entrants_{mt} denotes the endogenous number of entrants that enter in period t. D_{mt}^{exit} and E_{mt}^{entry} are exogenous variables that are included to match the data, as companies occasionally leave or be added to N_{mt} in ways not modelled. I treat these exogenous entry and exit events as random variables:

$$D_{mt}^{\text{exit}} | N_{m,t-1} \sim \text{Binomial}(N_{mt-1}, p_{\text{exit\_exog}}), \qquad E_{mt}^{\text{entry}} \sim \text{Poisson}(\lambda_{\text{entry\_exog}}) \tag{9}$$

As in the event studies, I estimate versions of the model using a broader, and a narrower definition of strategic acquirers. The broad definition encompasses all enterprise software acquirers, whereas the narrow definition accounts for a subset of enterprise software acquirers, namely New Tech and GAFAM acquirers.

In the light of the research question, the key parameters of interest are γ^A and α^{acq}. γ^A measures the extent to which a major strategic acquisition may depress entry. In contrast, α^{acq} measures the extent to which companies have an incentive to enter a market because they face the prospect of being acquired themselves in the future.

Whereas only major strategic acquisitions can affect A_{mt}^{strat}, both strategic as well as financial acquisitions can affect p_m^{acq}. Indeed, any startup acquisition typically yields revenues to the target firm's owners. Therefore, both strategic as well as outsider and financial acquisitions may generally be perceived as a successful exit, allowing entrepreneurs and investors to cash out.[27] I thus take p_m^{acq} and p_m^{ipo} as being the rates of acquisitions and IPOs of VC-funded startups that we observe in the data in each market from 2012 to 2019. Therefore, the entry-for-buyout parameter is identified by variation between markets in the percentage of startups acquired (p_m^{acq}), and observed entry into a given market. The market structure parameter is identified by variation between and within markets in acquisitions conducted by strategic acquirers, and observed entry. I discuss potential endogeneity concerns in Section 7.2.

R^{acq} is set to the median acquisition price for acquisitions of VC-backed startups (US\$120 million), and R^{ipo} is set to the median valuation of startups going public (US\$704 million; see Appendix C.1 Table C.1 for the distribution of these variables).[28] I fix the set of potential entrants in each period, N^{pe}, to the maximum number of entrants ever observed in a given market-quarter, which is equal to eleven.[29]

27. This is the case in particular for buyouts by private equity firms. Anecdotally, see Chopra (2018)'s article in the online news outlet TechCrunch: "In years past, stigma often accompanied private equity sales [...] Today, private equity buyout firms can provide a solid (and on occasion excellent) exit route —- as well as an increasingly common one".

28. I have explored the idea of making R^{acq} and R^{ipo} dependent on the state space, which is complicated by the fact that we observe very few instances of IPOs and acquisition prices. Estimating the model making R^{acq} dependent on broader bins of state variables did not affect final results significantly.

29. Other models of firm entry have fixed the number of potential entrants in a similar way, e.g., Perez-Saiz (2015) or Igami (2017). See the latter paper for a discussion of the rationale for fixing the number of potential entrants to the maximum number of entrants ever observed in the data. Robustness checks with respect to this assumption confirm that parameter values, except for the sunk cost of entry κ, remain roughly the same.

Motivated by first-stage results (see Section 6.1), I set the number of market categories, L, to 20. As the discount factor is not identified, I fix it to $\beta = 0.9$ (see, e.g., Igami and Uetake (2020), who use a discount factor of the same magnitude, also employing quarterly data). Table 6 details all fixed or calibrated parameters.

Table 6: Fixed and data-constructed parameters used in estimation

Parameter	**Symbol**	**Value**	**How set / Source**
Discount factor	β	0.9	Fixed (quarterly data)
Potential entrants per period	N^{pe}	11	Fixed: max entrants observed per market–quarter
Market categories	L	20	Fixed (see first-stage results)
Return from IPO (US$ m)	R^{ipo}	704	Data: median valuation at IPO, startups exiting 2012–2019
Return from acquisition (US$ m)	R^{acq}	120	Data: median acquisition price, startups exiting 2012–2019

5.3 Estimation

The primitives of the model are the structural parameters, $\theta = (\gamma^N, \gamma^A, \{\gamma^M_{l(m)}\}_{l=2}^{20}, \alpha^{acq}, \alpha^{ipo}, \kappa)$. I estimate the parameters using a two-step estimation method (e.g., Aguirregabiria and Mira (2007) and Bajari, Benkard, and Levin (2007)), which is essentially an extension of Hotz and Miller (1993)'s conditional choice probability (CCP) estimator. This approach avoids repeatedly solving the dynamic game across nearly 500 markets by first estimating equilibrium CCPs and state transitions from the data, and then recovering structural parameters in a second step.[30]

5.3.1 First Stage

I use data on agents' choices and state variables to estimate reduced-form regressions – policy functions (or conditional choice probabilities) – that map the state space into potential entrants' actions:

$$\text{num\_entrants}_{mt} = \phi_1 \log(N_{mt} + 1) + \phi_2 A^{\text{strat}}_{mt} + \delta_t + \delta_m + \eta_{mt} \tag{10}$$

δ_t are quarter-year fixed effects that control for time-varying factors common to all markets, such as macroeconomic conditions or seasonal effects. δ_m may either be market fixed effects, or broader, somewhat less flexible market-category fixed effects that account for unobserved market size or profitability (in this case, $\delta_{l(m)}$). Note that this first stage serves to characterize agents' actions given the state space.

Transition probabilities of the exogenously evolving state variables (e.g., A^{strat}) and the parameters of the distributions in equation 9, $\lambda_{\text{entry\_exog}}$ and $p_{\text{exit\_exog}}$, are estimated using a frequency estimated from the residual changes in N_{mt} in the data. Finally, p^{acq}_m and p^{ipo}_m are estimated as the long-run frequencies of acquisitions and IPOs in each market, respectively, over the sample period.

The parameters of the policy function in equation 10 give us an initial insight into the drivers of entry decisions, and in particular into the competitive effects. However, the main purpose of the estimated policy functions and transition probabilities is to forward-simulate the state space in a next step. For each state variable, one can simulate S paths sufficiently far into the future, until discounting renders

30. See Aguirregabiria and Mira (2010) for a survey on these methods.

the payoffs of any additional periods insignificant. Taking the average across these paths, and summing up each period's expected flow profits, yields the expected payoffs of a discrete action, given a set of parameter values.

Using the estimated first-stage policy function with market-category effects (column (4) of Tables 7 and 8), I forward-simulate the state space for each market–quarter observation. I set the simulation length to $T = 100$ quarters and draw $S = 200$ paths. For the endogenous number of competitors, N_{mt}, I use the law of motion in equation 8, where num_entrants$_{mt}$ is generated from the estimated policy function.

The remaining state variables are treated as exogenous processes. The the exogenous exit and entry components are drawn from their respective distributions in equation 9. For the strategic-acquisition state variable, A_{mt}^{strat}, I draw an acquisition event for market m from a Bernoulli distribution with market-specific probability, and set $A_{mt}^{\text{strat}} = 1$ in the event quarter and the following eleven quarters (otherwise $A_{mt}^{\text{strat}} = 0$).

For exit opportunities of the focal entrant, I take market-specific long-run frequencies of startup acquisitions and IPOs, $\hat{p}_m^{acq}$ and $\hat{p}_m^{ipo}$, and forward-simulate Bernoulli arrival processes for each path. Once an IPO or own-acquisition event occurs along a path, I shut down subsequent flow profits and set later occurrences to zero. Returns at exit are R^{acq} and R^{ipo}, as described in Section 5.2.

I summarize each simulated path by discounted expected payoffs, and average them to obtain the period-0 expected value. Flow payoffs depend on $\log(N_{mt} + 1)$, the 12-quarter strategic-acquisition dummy A_{mt}^{strat}, and time-invariant market-category effects, $\gamma_{l(m)}^{M}$. I use $L = 20$ market categories constructed from the first-stage market fixed effects, and keep them constant over time in the simulations. Time fixed effects are set to zero in the forward simulation step.

5.3.2 Second Stage

The second step estimates the structural parameters by imposing optimality on all agents' choices observed in the data. Under the assumption that error terms are type-1 extreme value distributed, one obtains the following conditional choice probabilities for entering:

$$\Psi^1(\boldsymbol{x}_{mt};\theta) = \frac{\exp\left(U^1(\boldsymbol{x}_{mt};\theta)\right)}{\exp\left(U^0(\boldsymbol{x}_{mt};\theta)\right) + \exp\left(U^1(\boldsymbol{x}_{mt};\theta)\right)} \tag{11}$$

These conditional choice probabilities incorporate agents' beliefs about the future, and about their opponents' behavior in a Markov Perfect Nash equilibrium (Aguirregabiria and Mira 2010; Arcidiacono and Ellickson 2011). Based on these conditional choice probabilities as well as agents' observed decisions in the data, one can set up the pseudo likelihood function, following Aguirregabiria and Mira (2007), akin to a standard discrete choice model. Maximizing the pseudo likelihood function yields the estimates of the structural parameters that are the most likely to have generated the data.

Under the assumption that only one equilibrium is played in each market type, it is not needed to specify an equilibrium selection mechanism. The equilibrium that is actually played by the agents in each market type will then be recovered using the conditional choice probabilities.

6 Results

6.1 First Stage: Startups' Entry Decisions

I employ the market-quarterly data used in Section 4 to estimate the model. The results for the first stage can be found in Table 7, using a broader definition of strategic acquirers, namely all firms with enterprise software products that also have at least one user review on *Capterra*. Table 8 reports analogous estimates using a narrower definition, focusing on "New Tech" and GAFAM firms as defined in Section 3. I begin with a linear model with no fixed effects in columns (1) of both Tables. I retrieve a positive coefficient on $\log(N_{mt} + 1)$, which would imply that more competitors attract *more* entrants. This counterintuitive sign when examining strategic interaction effects is a very common result in the empirical industrial organization literature (e.g. Collard-Wexler (2013), Igami and Yang (2016), and Y. Wang (2022)), and stems from unobserved market-specific factors that are not controlled for. In this context, market size and profitability would both lead to more competitors present on the market being correlated with more entry. To control for these unobserved factors, I estimate the model using market fixed effects in column (2). Reassuringly, the coefficient on the number of competitors becomes negative. The coefficient on major enterprise software acquisitions is negative, although not significant when using the broad definition in Table 7. As the dependent variable is a count variable, I also employ a Poisson specification in column (3).

One potential concern with the linear model is the incidental parameters problem. I therefore employ a less flexible version of market fixed effects, which the literature has called market-category effects (Collard-Wexler 2013; Y. Wang 2022). These types of fixed effects equivalently control for unobserved heterogeneity of markets. I follow Y. Wang (2022) and Lin (2015), and first estimate the model with market fixed effects in column (2). From the estimated market fixed effects, I retrieve $L = 20$ quantiles (Appendix E.1 for details). I then associate each market into one of 20 bins, or groups, according to the quantile which its fixed effect estimate falls into. I re-estimate the model, this time using indicator variables describing the group association to each of these L market groups, as opposed to the market itself. Just like market fixed effects, the group-level indicators control for unobserved heterogeneity between markets that is persistent over time. Column (4) shows that this procedure yields similar results.

6.2 Second Stage: Structural Parameters

The estimates of the structural parameters can be found in Table 9. Column (1) shows the results using strategic acquirers with product reviews, using in the first stage the specification of column (4) from Table 7. All parameters have the expected sign. In particular, the effect of more competition, γ^N, is significantly negative, and the effect of a strategic acquisition γ^A is negative, albeit not significant. The returns from being acquired or doing an IPO in the future are both positive, but only significant in the case of acquisitions. This may reflect the fact that IPOs are much rarer events than acquisitions, and that the prospect of being acquired is therefore more relevant to entrepreneurs' entry decisions. Moreover, the market category fixed effects, which are supposed to account for unobserved heterogeneity in

Table 7: First-stage regressions of startup entry (all strategic acquirers)

	Dependent Variable: Number of entrants in market m, quarter t			
	(1) *OLS*	(2) *OLS*	(3) *Poisson*	(4) *OLS*
log(# of competitors + 1)	0.356***	-0.896***	-1.545***	-0.788***
	(0.034)	(0.056)	(0.078)	(0.043)
Major enterprise software acquisition, post-12Q	0.175*	-0.114	-0.145*	-0.110*
	(0.094)	(0.072)	(0.087)	(0.058)
Quarter–year FE	✓	✓	✓	✓
Market FE		✓	✓	
20 market-category FE (estimated)				✓
Observations	15,648	15,648	15,648	15,648
Adjusted R^2	0.09	0.35		0.32
Log likelihood			-14,399.780	
Akaike Inf. Crit.			29,843.560	

Notes: "Post-12Q" equals 1 in the 12 quarters after a major acquisition of a VC-funded startup (transaction value > US\$100m) by a strategic (enterprise software with at least one product review) acquirer in market m, and 0 otherwise. Standard errors clustered by market; Column (4) uses block bootstrap standard errors (5,000 resamples) to account for the estimated market-category fixed effects. Sample: market–quarter panel, 2012-2019. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8: First-stage regressions of startup entry (New Tech / GAFAM acquirers)

	Dependent Variable: Number of entrants in market m, quarter t			
	(1) *OLS*	(2) *OLS*	(3) *Poisson*	(4) *OLS*
log(# of competitors + 1)	0.358***	-0.896***	-1.541***	-0.791***
	(0.034)	(0.056)	(0.078)	(0.043)
Major New Tech / GAFAM acquisition, post-12Q	0.315*	-0.185	-0.076	-0.142
	(0.191)	(0.154)	(0.157)	(0.134)
Quarter–year FE	✓	✓	✓	✓
Market FE		✓	✓	
20 market-category FE (estimated)				✓
Observations	15,648	15,648	15,648	15,648
Adjusted R^2	0.09	0.35		0.32
Log likelihood			-14,403.300	
Akaike Inf. Crit.			29,850.600	

Notes: "Post-12Q" equals 1 in the 12 quarters after a major acquisition of a VC-funded startup (transaction value > US\$100m) by a New Tech or GAFAM acquirer in market m, and 0 otherwise. Standard errors clustered by market; Column (4) uses block bootstrap standard errors (5,000 resamples) to account for the estimated market-category fixed effects. Sample: market–quarter panel, 2012–2019. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

profitability or market size, successively become larger.

Column (2) employs a narrower way to define strategic acquirers by using all major acquisitions by New Tech or GAFAM firms, and employing column (4) of Table 8 in the first stage. Again, parameters have the expected sign.

Interpretation. The estimate for α^{acq} can be viewed as measuring the value (in "utils") of being more likely to be acquired at a given price measured in millions of dollars, from the perspective of an entrepreneur backed by a VC fund considering market entry. It is hence a monetary scaling parameter that translates dollars into "utils" for potential startups. One can then express entrepreneurs' sunk costs of entry in terms of these expected dollars by dividing the estimate of the parameter κ by the estimate of the parameter α^{acq}. Using the results from column (2), I find that the perceived sunk costs of entry must approximately be equal to US\$130 million. This is somewhat more than the lifetime amount of funding

Table 9: Structural parameter estimates

	(1)	(2)
Entry costs, κ	3.250***	3.228***
	(0.150)	(0.115)
$\log(\#\text{ of competitors} + 1)$, γ^N	-0.134***	-0.135***
	(0.015)	(0.014)
Major enterprise software acquisition, post-12Q, γ^A	-0.016	
	(0.013)	
Major New Tech / GAFAM acquisition, post-12Q, γ^A		-0.023
		(0.029)
Own IPO in future, α^{ipo}	0.001	0.001
	(0.001)	(0.001)
Own acquisition in future, α^{acq}	0.025***	0.024***
	(0.002)	(0.002)
Market category 2, γ_2^M (5th–10th perc)	0.041*	0.041*
	(0.023)	(0.024)
Market category 3, γ_3^M (10th–15th perc)	0.072***	0.072***
	(0.021)	(0.022)
...	...	...
Market category 19, γ_{19}^M (90th–95th perc)	0.515***	0.518***
	(0.042)	(0.044)
Market category 20, γ_{20}^M (95th–100th perc)	0.634***	0.638***
	(0.042)	(0.043)
Log likelihood	-15,725.8	-15,724.51
Observations	15,648	15,648

Notes: "Post-12Q" equals 1 in the 12 quarters after a major acquisition (transaction value $>$ US$100m) in market m by the indicated acquirer group, and 0 otherwise. "Major enterprise software" refers to a strategic (enterprise software) acquirer with at least one product review on *Capterra*; "New Tech / GAFAM" is the narrower subset. "Market-category" denotes indicators corresponding to 20 percentile bins (coefficients for labels from 4 to 18 are omitted from table). Standard errors are computed via block bootstrap with 200 resamples. Sample: market–quarter panel, 2012–2019. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

that enterprise software startups have obtained once they go public, according to *Crunchbase* data (see Appendix C.2). Further, I find that the per-period costs of having, in expectation, ten competitors instead of one competitor in the market is equal to US$5 million. Moving up from the least to the most profitable market, in terms of the 20 market-category fixed effects, is worth US$25 million, which emphasizes the importance of market fixed effects. Moving up from the 50th to the 55th quantile is worth around US$1 million.

Several underlying forces might be driving the estimated parameters. In pharmaceuticals, prior work has documents "IPO peer effects", where a private firm is increasingly likely to go public after a close competitor has gone public (Aghamolla and Thakor 2022). In my setting, α^{ipo} is positive but imprecise, plausibly reflecting the rarity and the idiosyncratic occurrence of IPOs among software startups. The positive α^{acq} is consistent with both an entry-for-buyout channel and with shifts in acquisition demand, such as informational herding among acquirers after a salient deal has occurred (Conti, Guzman, and Rabi 2020), which potential entrants might anticipate.

6.3 Counterfactual Simulations

6.3.1 Procedure

One of the purposes of the model is to shed light on how entry evolves if acquisitions by certain types of acquirers were blocked by competition authorities. The ultimate impact depends on the respective magnitudes of the estimated parameters for the entry-for-buyout effect, $\hat{\alpha}^{acq}$, and the estimated market-structure effect of acquisitions, $\hat{\gamma}_A$.

I study two counterfactual changes to the prevailing antitrust regime. In the first scenario, the competition authority blocks only major strategic startup acquisitions.[31] In the second scenario, the competition authority blocks all startup acquisitions altogether, which can be viewed as a benchmark and provides an insight on the size of the entry-for-buyout effect. In each scenario, I assume that the policy change takes place in the first quarter of 2012, i.e., the first period of observation of my data.

To conduct the simulation, I take the empirical values of the state variables in 2012 to be their respective values in this first period. I simulate the entry decisions of N^{pe} potential entrants in this period. Based on the simulated entry behavior, I can calculate the state variables for the next period, and iterate until the end of the sample period. To elaborate, I carry out the following steps (here focusing on the model variant where entry-deterring acquisitions are defined as acquisitions by strategic acquirers with at least one product review (i.e., column (1) of Table 9)):

1. Take $x_{m,2012Q1}$ from the data.
2. Adjust the transition processes to match the counterfactual. For instance, for the "no acquisitions" regime, set the startup's own acquisition hazard $p_m^{acq} = 0$ and suppress the strategic-acquisition state so that $A_{mt}^{strat} = 0$ for all t. Then, forward-simulate the state variables, drawing 500 paths for 100 time periods into the future.
3. Using the estimated parameters from Table 9, column (1), and the forward-simulated state variables, compute the expected discounted value of entering.
4. For each potential entrant, draw i.i.d. cost shocks ϵ_{ijt}^0, ϵ_{ijt}^1 from a type-1 extreme value distribution.
5. Given the expected discounted value of entering from step 3 and the drawn cost shocks from step 4, compute the number of actual entrants (i.e., the number of potential entrants for which the expected discounted value of entering is higher than the value of staying out).
6. Compute and simulate the counterfactual state variables for the next period.
7. Repeat steps 2 to 6 until the last period of observation.

For the forward-simulation in step 2, I alter only p_m^{acq} and/or A_{mt}^{strat} as dictated by the counterfactual, while keeping the original policy function and transition probabilities fixed. I thereby assume that startups hold on to their original beliefs of how state variables will evolve over time. I also assume that

31. This reflects a recommendation by, for instance, US Congress Committee on the Judiciary (2022), see their recommendation for "Restoring Competition in the Digital Economy" on p.14: "Presumptive prohibition against future mergers and acquisitions by the dominant platforms".

blocked acquisitions will not be replaced by IPOs nor alternative bidders seeking to acquire. This simplification can be viewed as an initial impulse by the agents, and an approximation to a full counterfactual simulation. If one were to account for the fact that startups' beliefs regarding the state space evolution were to adjust, one would have to solve for a fixed point that equates startups' beliefs to observed actions in the counterfactual world. Given the large number of observed markets, this is computationally difficult.

6.3.2 Counterfactual Results

I begin by examining entry in the average market under different counterfactual policy regimes. Table 10 displays the effects of blocking only certain, or all, startup acquisitions on the number of entrants and number of competitors across markets and periods. I first simulate the counterfactual in which only strategic acquisitions are blocked: in this scenario, $A_{mt}^{\text{strat}} = 0$ for all market-quarters, and the estimated probability of a future acquisition, p_m^{acq}, is somewhat lower as major strategic acquisitions are excluded. This results in a very slight increase in entry and in competition in the average market: entry increases by 0.5% in the average market, and by 1.1% or 1.5%, respectively, in markets that actually experienced a strategic acquisition in the observed data.

I then simulate the counterfactual in which all acquisitions are blocked. This scenario corresponds to the case in which both $A_{mt}^{\text{strat}} = 0$ for all market-quarters, and $p_m^{acq} = 0$. Entry declines by 15 to 16% in the average market, and by up to 18% in markets that actually experienced an acquisition. For affected markets, the effect is more negative, despite the somewhat entry-supporting effect from blocking strategic acquisitions. My finding of a strong drop in entry if all mergers were blocked seems plausible in light of related literature: using a very different model calibrated to the entire US economy, Fons-Rosen, Roldan-Blanco, and Schmitz (2023) find that, if startup acquisitions in the entire US economy were blocked, the startup rate would decline by 14.9%. Cabral (2024) calibrates a model of innovation for the tech industry, and finds that a complete ban of acquisitions would lead to a 35% welfare decrease compared to a scenario in which all mergers are allowed, which is "primarily due to a significantly lower innovation rate".

Focusing on the model variant where entry-deterring acquisitions are defined as acquisitions by strategic acquirers with at least one product review (i.e., column (1) of Table 9), Figure 6 shows the evolution of entry over time in the average market, and in markets that actually experienced a strategic acquisition in the observed data. Reflecting the averages across markets and periods, it is apparent that blocking all acquisitions leads to a drop of entry in all periods, while blocking strategic acquisitions increases entry only very modestly in certain periods.

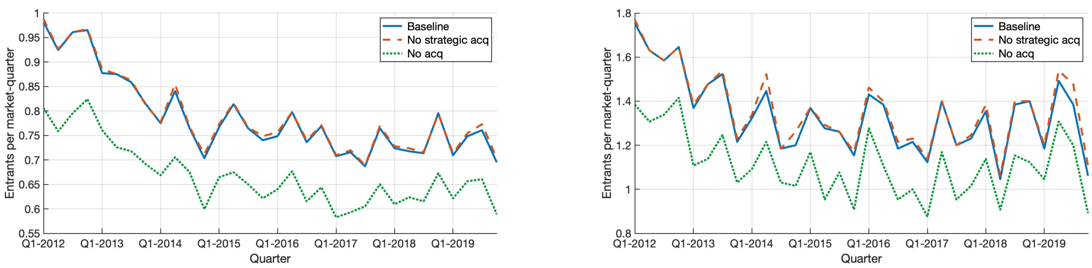
As the data contain many markets, I can explore how the effect of blocking startup acquisitions varies across markets of different types, focusing on markets that were actually subject to strategic acquisitions in the data. Figure 7 shows the counterfactual change in entry when blocking strategic acquisitions, by market fixed-effect quintiles (panel (a)) and by initial number of competitors quartiles (panel (b)). Recall that market fixed effects measure the inherent profitability or size of a market. Strategic acquisitions are more entry-suppressing in more profitable markets, and in markets with more competitors.

Table 10: Counterfactual effects on entry (levels and percent)

Panel A: A^{strat}_{mt} = strategic acquirers with reviewed products				
Policy	**ATE Δ**	**ATE (%)**	**ATT Δ**	**ATT (%)**
Strategic acquisitions (A^{strat}_{mt}) blocked	+0.004	0.53	+0.020	1.47
All acquisitions blocked	-0.119	-15.16	-0.229	-17.11
Panel B: A^{strat}_{mt} = New Tech and GAFAM acquirers				
Policy	**ATE Δ**	**ATE (%)**	**ATT Δ**	**ATT (%)**
Strategic acquisitions (A^{strat}_{mt}) blocked	+0.004	0.52	+0.015	1.13
All acquisitions blocked	-0.124	-15.76	-0.239	-18.10

Notes: Δ is the change in the average number of entrants per market–quarter relative to the baseline model-predicted entry under the observed policy. "ATE" averages across all markets; "ATT" averages across markets that experience at least one strategic acquisition in the observed data (affected markets). The simulations start from the initial state in the first quarter of 2012. "Strategic acquisitions blocked" sets $A^{\text{strat}}_{mt} = 0$ for all market-quarters and uses a somewhat lower estimated p^{acq}_m; "All acquisitions blocked" eliminates all acquisitions by setting $A^{\text{strat}}_{mt} = 0$ and $p^{acq}_m = 0$. Panel A defines A^{strat}_{mt} as acquisitions by enterprise software acquirers with at least one product review on *Capterra*; Panel B defines A^{strat}_{mt} as acquisitions by New Tech or GAFAM acquirers. Counterfactual paths are simulated from the estimated dynamic model using parameters from Table 9, holding other primitives fixed. Percentage changes are computed relative to the corresponding baseline average entry level (ATE: all markets; ATT: affected markets).

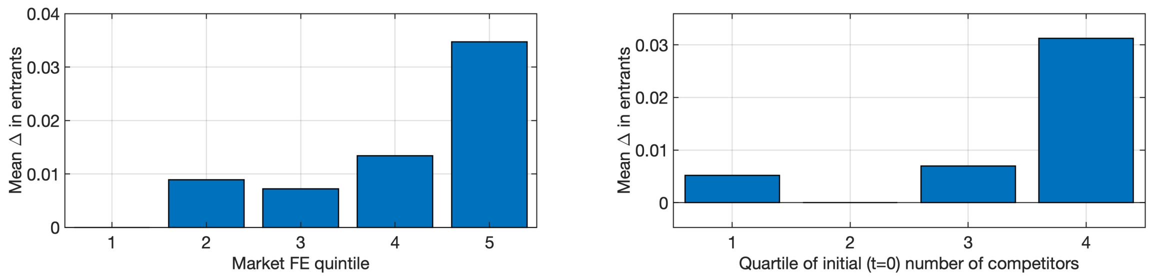
Figure 6: Counterfactual startup entry under alternative merger policies



(a) All markets. (b) Affected markets.

Notes: Lines show the average number of VC-funded startups entering per quarter under (i) the baseline model (model-predicted entry under the observed merger policy) and (ii) two counterfactuals: "No acq" removes all startup acquisitions; "No strategic acq" removes acquisitions by strategic acquirers (enterprise software firms with at least one product review on *Capterra*). Counterfactual paths are simulated from the estimated dynamic model using parameters from Table 9, column (1), holding other primitives fixed. Plot (a) averages across all markets. Plot (b) averages only across markets affected by a strategic acquisition in the data.

Figure 7: Counterfactual change in entry when strategic acquisitions are blocked



(a) By market FE quintile. (b) By initial competitors (quartiles).

Notes: Outcome is the mean change in entrants per market–quarter relative to the baseline prediction. The counterfactual sets to zero acquisitions by *strategic* acquirers (enterprise software firms with at least one product review on *Capterra*). Panel A groups markets into quintiles of the market fixed effect from the CCP policy regression (Table 7). Panel B groups markets into quartiles by their initial number of incumbent products (measured in the first observed quarter for each market). Averages are computed over 2012–2019, restricting to markets that experienced at least one strategic acquisition in the observed data. Counterfactual paths are simulated from the estimated dynamic model using parameters from Table 9, column (1), holding other primitives fixed.

Overall, the counterfactual results suggest that antitrust authorities should continue with case-by-case assessments of startup acquisitions, as this is most beneficial for fostering startup entry. As it seems that particularly large acquisitions have an entry-deterring effect, the findings moreover support the suggestion of using acquisition prices to screen likely harmful mergers (Bryan and Hovenkamp 2020; Fumagalli, Motta, and Tarantino 2022).

7 Discussion

7.1 Limitations of Market Definitions

The market definitions that I employ allow to understand competitive relationships among privately held startups, and thereby allow to make progress on our understanding of the effects of startup acquisitions in software markets. At the same time, these product-level market definitions are subject to some of the same caveats that standard firm-level taxonomies suffer from. In software, startups at times change the focus of their products and pivot from one market into another one, which cannot be captured by static market definitions. The market definitions also cannot account for a possible interdependence between markets which may arises in software, where products with different functionalities can be complementary. Finally, consumer inertia and switching costs are thought to be important in digital markets (e.g., Scott Morton et al. (2019)), which may render products within a market less substitutable than their product descriptions suggest.

These caveats are shared by all other market definitions that do not actually estimate substitution patterns from demand data. How to accurately define markets for software is a frontier research question itself[32], and the discussion highlights the need for future empirical advances in characterizing demand for software and competition between nascent software products.

7.2 Endogeneity of Acquisitions

The identification of the model parameters relies on the assumption that acquisitions are exogenous conditional on market-category effects. To elaborate, let us first consider potential endogeneity concerns regarding the entry-for-buyout parameter, α^{acq}. Each observed market is in a long-run equilibrium of startups entering the market, and startups being acquired in that market. The entry-for-buyout parameter is identified by between-market variation in the market-specific, long-run percentage of startups acquired in a given market (p_m^{acq}), and observed startup entry, after controlling for 20 market-category fixed effects that proxy for persistent profitability. One concern might be that both acquisitions and entry behavior are being driven by an unobserved variable. For instance, technological advances leading to a rise in demand in a given market could make both entry and acquisitions more profitable. However, the inclusion of market-category effects means that identification rests on exogeneity in the variation in acquisitions within a given bin, which is more likely to be exogenous.

The market structure parameter, γ^A, is identified from variation in the number of entrants around

32. See Aridor (2025), who estimates consumer substitution patterns across social media with the help of a field experiment.

the time of a major acquisition by a strategic acquirer both between and within markets, similar to the reduced-form empirical results discussed in Section 4.

Endogenizing acquisitions, as is done in other research (e.g., Igami and Uetake (2020), Cortes, Gu, and Whited (2022), and Wabiszewski (2024)), presents both computational and conceptual challenges in the setting considered in this study.[33]

8 Conclusion

This paper studies the link between innovative entry and acquisitions, and thereby sheds light on a set of questions that is of an enormous importance for economic welfare: what drives the provision of new, innovative products in a market, and how does merger policy affect firms' incentives to do so? New data collection allows to make progress on this question in the context of startup acquisitions in digital markets. Merger policy in the digital economy is being fiercely debated in many jurisdictions, but empirical evidence is still scarce.

The paper provides new descriptive evidence of the likely motives and the effects of acquisitions of VC-funded startups in the enterprise software industry. The structural model endogenizes startups' entry decisions and fleshes out, in a stylized way, an entry-for-buyout effect that fosters entry, and an effect via market structure that deters entry. Counterfactual simulations reveal that an overall ban of all startup acquisitions would decrease entry by up to 16%. On the other hand, acquisitions conducted by strategic acquirers appear to deter entry. If these acquisitions were blocked, entry could increase modestly.

Altogether, these results call for a case-by-case assessment of startup acquisitions by antitrust authorities. The finding that acquisitions conducted at high transaction prices seem to deter entry provides support for the suggestion of using transaction values as a screen to which mergers to scrutinize, emphasized by Bryan and Hovenkamp (2020) and Fumagalli, Motta, and Tarantino (2022).

The data and the evidence gathered in this paper open up several avenues for future research. One important policy concern is not only that firms are able to initially enter, but also that firms are willing to enter and *remain independent* upon successful market entry. Recent literature provided evidence that startups might face barriers to be publicly listed (Lemley and McCreary 2020; Ederer and Pellegrino 2023), or might choose to remain private for efficiency reasons (Davydova et al. 2024). Future research could study what affects firms' willingness to remain independent in software markets, possibly with a model endogenizing the decision to agree to a buyout.

The paper's strength lies in generalizable results on an entire industry sector, comprising tens of thousands of companies. However, while entry is likely the main dimension of competition in software markets, the lack of demand data precludes me from making any strong conclusions regarding welfare

33. First, in model with endogenous acquisitions, there would be thousands of potential acquirers at any given time, as I study an entire industry with over 400 markets at once. Second, it is far from obvious how to write down a model that accurately describes acquiring firms' decision making in my setting. In fact, if it was easy, then VC investors could anticipate acquisitions, and we would not observe such high startup failure rates and risks associated with VC. The setting that, for instance, Igami and Uetake (2020) study, is more tractable: products are homogeneous, and firms can be described by a single profitability parameter that is plausibly very influential for merger decisions in their context.

implications. In this respect, my findings invite a number of follow-up questions, such as: to what extent does new product entry in software markets contribute to welfare? What is the welfare consequence of the frequently observed discontinuation and integration of products? – I leave these questions for future research.

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Supplementary Appendix

Entry and Acquisitions in Software Markets

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Contents

A Anecdotal Evidence and Theoretical Mechanism

A.1 Anecdotal Evidence: Entry-for-Buyout Effect

A.1.1 Benedict Evans, VC investor & analyst, August 2022

Benedict Evans, VC investor & analyst, comments on the FTC's proposal to block Meta from acquiring Within, as well as on the FTC's approach towards M&As in Tech more generally:

> "M&A is a central part of the Silicon Valley ecosystem [...] How do you fund companies if both IPOs and M&A are off the table?" — (Evans 2022)

A.1.2 Bénédicte de Raphélis Soissan, founder of Clustree, July 2020

The following quote stems from an interview with Clustree founder Bénédicte de Raphélis Soissan, who previously successfully sold her startup to Cornerstone.

> "Market assessment is something that I'd do right from the beginning. [...] If I were to start a company again, I wouldn't just see if I could raise funding. I would rather test my idea with potential buyers, to see what exit opportunities there are. [...] From the start, the best way to test the market for me would be to go see potential competitors / buyers (even if it can be risky - so you have to see how you do it) to really test what the market is in terms of exit, what the willingness to pay is, whether there is interest for this type of product, this type of technology, etc."[A1] — (Les Echos Entrepreneurs (2020), minute 51 ff., translated into English.)

A.1.3 Incubators ask entrepreneurs to think about potential acquirers from the beginning

To apply to the startup incubator program by Y Combinator, one of the questions contained in the initial applicant survey was:

> "Which companies would be most likely to buy you?" – (Shontell 2013)

A.2 Anecdotal Evidence: Kill Zone Effect

In "How I Screwed Up My Google Acquisition", Jason Roberts, founder of *Preezo*, talks about his attempt at selling his startup to Google:

> "I heard nothing from Google until the following June when I read that they had acquired Zenter, a YCombinator startup working on the same problem. At that point my heart sank as it was obvious that the window of opportunity had closed and it wasn't a few months later that Google Presentations itself was released. While the Google

A1. Original, in French: "L'assessement du marché, c'est ce que je ferais dès le départ. [...] Si je devais remonter une boîte, ça [ne] serait pas voir si j'arrive à lever les fonds. Ça serait quasiment tester les acquéreurs potentiels avec ton idée, pour voir en fait quels sont les exits. [...] Dès le départ, la meilleur façon de tester le marché ça serait pour moi d'aller voir des compétiteurs / acquéreurs potentiels (même si ça peut être risqué - donc il faut voir comment tu le fais) pour vraiment tester quel est le marché en terme d'exit, quel est le consentement à payer, est-ce qu'il y a intérêt pour ce type de produit, ce type de techno, etc."

> version wasn't quite as powerful or polished as Preezo, being that it was free, solidly good enough and integrated into a complete productivity suite meant it was going to be very tough going for Preezo as a standalone product. To make matters worse, Yahoo and Microsoft had continued to abstain from the web office race, shunting any hopes that acquisition offers might be soon forthcoming." — (Roberts 2010)

Teh, Banerjee, and Wang (2022) provide further anecdotal evidence of the "kill zone" effect in the context of Facebook's acquisition of Instagram.

A.3 How Can Acquisitions Deter Entry? - Summary of Theoretical Literature

Through which economic mechanisms can an acquisition in digital markets prevent entry? The theoretical literature has put forward several economic channels that seem applicable to the setting considered in this paper. Perhaps most directly related is a paper by Teh, Banerjee, and Wang (2022), which shows the conditions under which an acquisition can lead to a "kill zone", in a framework featuring several startups. In their model, a dominant incumbent who acquires a late-stage target can lower a rival startups' payoffs from entry by threatening to counter-develop the acquired technology. The rival redirects its R&D efforts toward an outside project instead. Overall, this can reduce total project development, sometimes with the acquired project ultimately being shelved.

The practice of strategic tying is an alternative mechanism. Whinston (1990) shows that a monopolist in one market can have an incentive to use tying with the purpose of monopolizing a second market. Motivated by real-wold antitrust cases in the tech industry, Carlton and Waldman (2002) investigate the dynamic motives for tying. The authors analyze how tying of a complementary product can allow an incumbent to preserve a monopoly in the future and to extend the monopoly into a newly emerging market. In software markets, it is common practice to integrate core functionalities of a target's product into the acquirer's product post-acquisition, thereby tying different services together. These theories thus provide realistic rationales for entry-deterring effects of takeovers in the context considered in this paper.

A recent working paper by Heidhues, Köster, and Kőszegi (2024) considers the incentives to build digital ecosystems, i.e., to create a portfolio of interconnected digital services. The model builds on the premise that firms can employ "cross-market leveraging" by steering consumers from one market into another market, for instance through default effects that are very effective in digital services. The authors show how these firms have high incentives to acquire targets in other markets, outbidding rivals, and thereby reduce market contestability. Again, the theory is applicable to this paper's context.

Motivated by the acquisitions in digital markets, a dynamic model proposed by Denicolò and Polo (2021) shows that a cumulative number of acquisitions can entrench a dominant position of an incumbent. This cumulation of market power leads to less entry in the long run, even in the presence of an entry-for-buyout effect.

Finally, Kamepalli, Rajan, and Zingales (2021) study a setting with network effects and consumer switching costs. In their model, consumers anticipate that startups' products are highly likely to be acquired and integrated into the acquirer's product. To avoid switching costs, consumers grow reluctant to experiment with new products, which leads to low adoption of products provided by new startups, and subsequently to a lack financial investments into those new entrants. However, this model predicts a lack of funding *ex ante* in expectation of an acquisition, rather than a lack of funding after an acquisition occurred. Moreover, the model depends on the presence of strong network effects and hence seems more applicable to social networks or communication software.

Also see Bryan and Hovenkamp (2020) who discuss further strategies that dominant acquirers buying nascent startups can employ to deter rival entry.

B Supplementary Information on Data Construction

B.1 Construction of Firm Panel Using *Crunchbase*

Crunchbase chronicles over a million public and private firms, including firms that existed in the past but have been closed. The database documents all important company events (funding rounds, acquisitions, IPOs, etc.). Firms recorded on *Crunchbase* may be headquartered all over the world and may span all sectors of the economy, but industry insiders mentioned to me that coverage is likely most accurate for firms located in North America and Europe (which is suitable given that *Capterra* caters to clients in North America, too). Information are sourced using Machine Learning, an in-house data team, a venture program, and via crowdsourcing.

Unlike most other venture databases, *Crunchbase* includes firms even if they never raised VC. *Crunchbase* is well-established in academic literature, and captures early-stage funding rounds and acquisitions of small sizes more completely than competing sources (Jin 2019; Yu 2020).

For all firms in my sample, *Crunchbase* provides me with the dates and characteristics of the firm events *founded*, *getting funding*, *investment*, *being acquired*, *acquiring*, *IPO*, and *closed*. I define an additional event *inactive* as the date five years after the last recorded relevant activity for any private, non-acquired company, following conventions in the existing literature.[B2] I also construct the parent-subsidiary structure for all firms and, for each focal firm, I trace ownership two levels up (i.e., focal, parent, ultimate parent). This structure allows for consistent treatment of acquisitions within corporate hierarchies. For example, if LinkedIn acquires a company after having been itself acquired by Microsoft, the transaction can be attributed to Microsoft as the ultimate parent. Additional levels are not required for the companies in my sample.

As pointed out in the main text, *Crunchbase* defines acquisitions as majority takeovers. This definition includes majority investments. Counting majority investments as acquisitions is reasonable, as a majority investment allows startup founders and early investors to cash out, and transfers ownership and control rights to a new entity[B3]. I exclude takeovers defined as LBO or Management Buyout by *Crunchbase*.

B2. Prior studies have classified firms as inactive if they do not raise venture capital within 3, 5, or 7 years; I adopt the midpoint of this range.

B3. For anecdotal support, see TechCrunch reporting on Vista Equity Partner's majority investment of Pipedrive: "[...] as is the case with these type of private equity buyouts, many of Pipedrive's early shareholders will have exited or partially exited, including employees/management and early backers. This is either voluntary or mandatory as part of a shareholder agreement "drag-along" clause." See /web/20221105105842/https://techcrunch.com/2020/11/12/european-unicorns-are-no-longer-a-pipe-dream/, accessed 05/11/2022.

While *Crunchbase* includes investments of different types, I only consider funding rounds that involve early-stage, high-risk investments, consistent with standard definitions of VC. I adopt the following definitions:

Definition: VC funding round	Any funding round of the following type: *Angel, Pre-Seed, Seed, Series A to Series J, Unknown Series, Corporate Round, Convertible Note, Undisclosed*. (Hence, funding types such as *Post-IPO Debt*, *Grant*, or *Product Crowdfunding*, for instance, are not considered as VC investments.)
Definition: Startup	A privately held company that has received at least one round of VC funding. A firm ceases to qualify as a startup upon experiencing any of the following events: (i) acquisition, (ii) IPO, (iii) closure, or (iv) transition to inactive status.

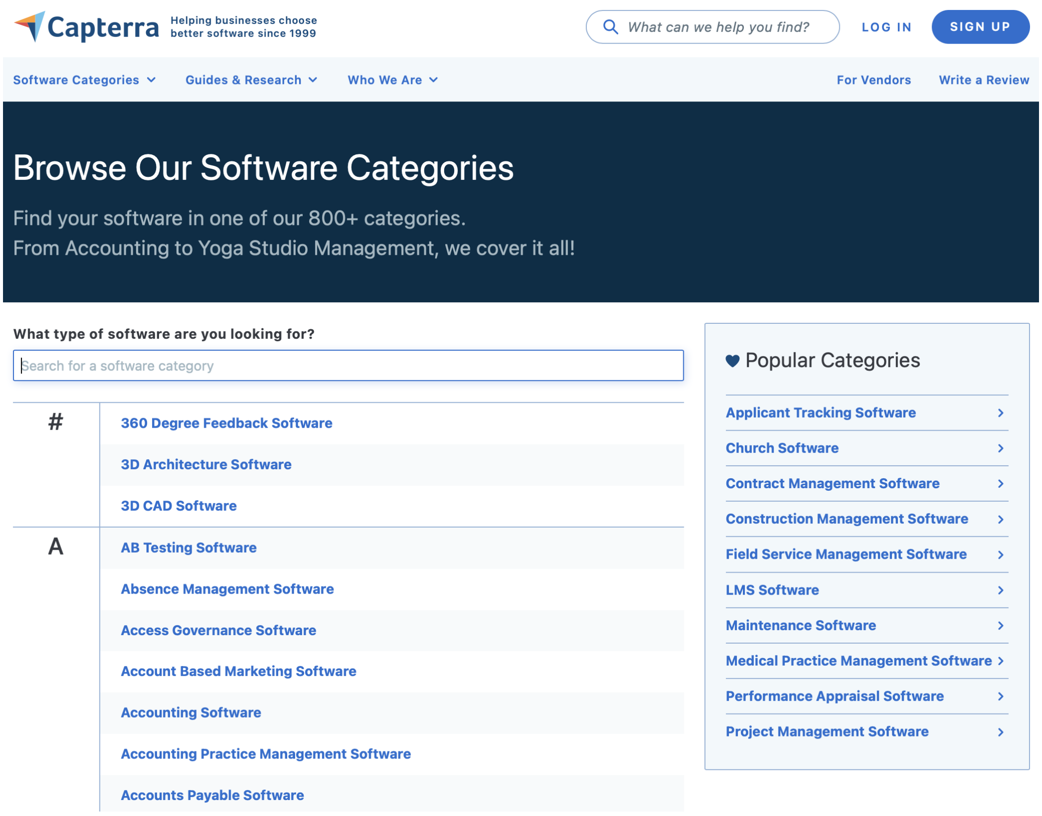
B.2 Assessing Coverage and Quality of *Capterra* Data

Capterra is owned by *Gartner*, a large public consulting and technological research company. Its main competitor is the platform *G2*, which provides a similar vertical search engine with reviews, categories and descriptions on enterprise software products. As of July 2021, the three *Gartner* owned websites had a somewhat larger number of monthly visits (over 10 million) than the platform *G2* (8.5 million). Looking at individual products, the relative number of reviews across products – an indicator of demand – seemed comparable between *G2* and *Capterra*. Using the Internet Archive ("Wayback Machine"), I found that, anecdotally, products whose discontinuation was publicly announced were removed earlier from *Capterra*'s than from *G2*'s website, implying high timeliness. Reviews and ratings on *Capterra* are pooled across the *Gartner Digital Markets network*, which comprises *Capterra* as well as two other subsidiary websites (*GetApp* and *Software Advice*). Information seem to be accurate, representative, and of high quality based on comparisons with *Capterra*'s competitors.

To gauge the overall accuracy and consistency of *Capterra*'s classification system, I inquired about the company's internal process for assigning products to categories. According to the company, when a new product is listed, it is initially assigned to a single category by default. Vendors may then request placement in additional categories, which are reviewed by a dedicated catalog team. Approval is granted if the product is deemed a good fit for the requested category. Figure B.1 displays a screenshot of *Capterra*'s taxonomy, comprising over 800 distinct product categories that are presented to users browsing the site.

To assess potential sources for selection bias, I investigate the set of enterprise software related firms listed on *Crunchbase* but not included in my ultimate sample. While this alternative set of companies is twice as large, it actually contains only 60% of the sample of firms found on *Capterra*, and hence excludes many active, relevant, enterprise software producing firms (especially multi-product firms like Facebook). A detailed manual and systematic investigation reveals that the vast majority of arguably enterprise software related firms not found on *Capterra* are either inactive, based in China, Japan or Korea (and hence likely not available in English), or are misclassified on *Crunchbase*. Only approximately 2–3%

Figure B.1: Screenshot of *Capterra*'s categories page



of enterprise software related firms listed on *Crunchbase* but not appearing on *Capterra* could plausibly have belonged in the sample, but are missing for reasons that are likely random. One may therefore conclude that *Capterra* covers all U.S.-facing enterprise software products in a comprehensive fashion.

B.3 Web-Scraping *Capterra*

I first web-scrape the list of categories available on *Capterra* (see Figure B.1). For each category, I then query the listings page, which I fully expand to obtain a list of all the products that are associated with that given category. For each product in that list, I download the hyperlink that directs to the specific product page (see Figure 1). I end up with 72,986 unique links to product pages on *Capterra*, which I query one-by-one in June and July of 2021.

In some instances, a single product can have multiple product pages on *Capterra*. I therefore define unique products based on product name and the first sentences of the descriptive text. For each product, I collect all the categories which it appears in. I end up with approximately 70,000 unique product-level observations.

For each product, I obtain and save the product and company name; the company's web domain; all product categories; the product description; user rating and number of reviews. I also save, but do not currently use, a text describing the intended audience for the given product; pricing information; company headquarter location; the year in which the company was founded; and the time and date of each instance of scraping. Pricing information is likely not very meaningful: prices for enterprise software tend to be negotiated at the company-level, or vary depending on company size or features included (such as storage space or additional tools).

B.4 Merging *Capterra* Products to *Crunchbase* Companies

The procedure for matching *Capterra* products to *Crunchbase* companies works as follows. First, firms with a unique URL on both *Capterra* and *Crunchbase* – that is, with URLs not shared by any other firm – are matched based on URL alone. Second, for cases where URLs are non-unique in either *Capterra* or *Crunchbase*, I implement a fuzzy matching algorithm that requires both an exact match on URL and a minimum degree of similarity in firm names. For a small number of remaining cases (fewer than 1% of all products), I perform manual matching by searching for the product's company through *Crunchbase*'s web interface and extracting the corresponding firm identifier.

An additional step is necessary in cases where a product originated with a startup but is now offered by the *acquiring* firm. The above matching algorithm associates such a product with its current owner, rather than the original company. To identify the *originating* firm in such cases, I exploit the empirical regularity that early-stage startups typically offer a single product, often bearing the same name as the company. Thus, whenever a product's current producer (as listed on *Capterra*) has previously acquired a company whose name closely resembles the product name, I attribute the original market entry to the acquired firm. Table B.1 provides a few examples of this matching logic.

Table B.1: Illustrative matches linking products to acquired developers (name similarity)

Product Name	**Current Seller on Capterra**	**Original Developer** (Final Match)	**Matching Rationale**
AWS Cloud9	Amazon Web Services	Cloud9 IDE	Amazon acquired Cloud9 IDE
Widevine DRM	Google	Widevine	Google acquired Widevine
Yammer	Microsoft	Yammer	Microsoft acquired Yammer

Notes: "Current seller" is the vendor shown on *Capterra* at the time of data collection. "Original developer (final match)" is the acquired firm I assign using the name-similarity rule. The rows are illustrative examples.

B.5 Including Acquired Firms with Discontinued Products

As noted in the main text, the product-level data obtained by *Capterra* is cross-sectional in nature, covering enterprise software products available in June and July of 2021. I extend my sample to account for potentially relevant competitors that were acquired at a given point of time and then discontinued. To do so, I carry out the following steps:

1. For all the 827 companies acquired by GAFAM firms or any of their subsidiaries on Crunchbase, I manually designate acquired startups into enterprise software related (e.g., Zenter, Sparrow, or LiveLoop) and not enterprise software related by manually looking up information on each of those companies on *Crunchbase* and the World Wide Web.

2. Based on this manually classified sample, I develop selection criteria that employ *Crunchbase*'s descriptive text, industry group, and industry variable, and that allow me to select enterprise software related companies from *Crunchbase* systematically. Essentially, I detect key terms that should

or should not be contained in those bodies of text. Testing these criteria on the initially manually classified sample, the criteria have an accuracy of 81%, a false positive rate of 10%, and a false negative rate of 31%. The majority of the false positive cases are edge cases where the "correct" classification is ambiguous.

To extend the sample, I take into account any company that was an acquisition target from 2005 onwards by a company with products on *Capterra*. Employing these selection criteria, I end up including an additional 3,901 companies that have been acquired by enterprise software companies in the past and are also tagged with enterprise software related terms.

I deliberately choose to not include (non-acquired) enterprise software related firms that previously left the market. These firms are likely irrelevant, non-viable competitors, or firms with products not available in English language.

B.6 Text Processing and Embedding Products in Linguistic Vector Space

Each product on *Capterra* appears in one or more predefined product categories (the average number of categories per product is 1.9, the median is 1), which prevents me from using *Capterra* categories directly as a market classification. Instead, I use textual information from both product descriptions and category names from *Capterra* to classify products into distinct markets (analogously, for products no longer listed on *Capterra*, I use company descriptions and categories from *Crunchbase*). Each product is thus associated with a body of text, which the literature calls a *document*. With the help of vector representations of words (*word embeddings*), I can capture the semantic meaning from the words contained in each document, enabling me to cluster products based on the semantic similarity of their respective documents. Since semantically similar products tend to share functionalities, this approach naturally groups likely competitors into markets. The procedure for embedding each product into a linguistically meaningful vector space consists of: (1) preprocessing the text to extract meaningful terms; (2) creating the embedding by mapping each term to a pre-trained word vector from an unsupervised learning algorithm, Global Vectors for Word Representation (*GloVe*, provided by Pennington, Socher, and Manning (2014)); and (3) averaging word vectors to determine the product's specific location in semantic space. In a final step (described in Section B.7), clustering these product representations in semantic space identifies groups of products with shared functionalities – i.e., markets.

Both the text preprocessing and the clustering method require the researcher to make methodological and hyperparameter choices. These choices are typically not fully data-driven but instead rely on substantive judgment and domain expertise (as discussed in Athey and Imbens (2019) and Ash and Hansen (2023)). Accordingly, I choose any parameters and procedures to maximize the performance of the external validity exercises described in Section B.8.

Step 1 involves extracting likely meaningful terms from all documents. By limiting the analysis to these terms, I exclude irrelevant words (e.g., stopwords) and focus on semantically rich information that enables me to detect commonalities between product descriptions, and to delineate between products that have different functionalities. To select meaningful terms in a systematic fashion, I create a dictionary with the help of all product descriptions and categories on *Capterra*. I first preprocess both category names and product descriptions according to standard procedures. In particular, I remove stopwords ("and", "to", etc.); convert all text to lowercase; remove accents, numbers, and product or company names; replace or expand a small number of acronyms; and create bi-grams. Even after this, the processed body of text contains almost 48,000 distinct terms, some of which are unlikely to be useful for creating product-level embeddings and should therefore be excluded (those are, for instance, names of other companies, or misspelled words that introduce noise). To refine the dictionary, I therefore compute a term frequency–inverse document frequency (TF-IDF) score for all terms. I retain terms that rank among the top five TF-IDF terms for at least ten different products, and then exclude the ten most common terms across the corpus to remove generic words such as "software".[B4] This procedure helps identify words that are both representative and relevant across the sample, while filtering out overly specific, noisy, or mis-spelled terms (e.g., "15-second", "barefoot","bot-aware", or "communicacion"), thereby balancing specificity and generality. The final dictionary contains 6,755 distinct terms. Table B.2 shows the original text as well as the processed text exemplarily for three products.

In step 2, I map each extracted term in a given document to its corresponding vector representation, using pre-trained word vectors from the GloVe model provided by Pennington, Socher, and Manning (2014). Word vectors from GloVe are widely used in prior research due to their ability to quantify semantic relationships between words (e.g., Decarolis and Rovigatti (2021) and Kogan et al. (2023)).[B5] Specifically, I use the set of 1.9 million pre-trained word vectors that were learned by training the GloVe model on 42 billion word tokens from the Common Crawl corpus, and are publicly available at https://nlp.stanford.edu/projects/glove/. I embed all pre-processed terms by matching them to these pre-trained vectors, ignoring words not present in the GloVe dataset.

To illustrate this using the example from Table B.2, GloVe places related words such as "animation", "3d", "graphic", and "design" in proximity to each other in a 300-dimensional vector space. Hence, even if the three products figuring in the Table only share few terms that are identical, the semantics are very similar, and this will be captured through the embedding. This is a key advantage over traditional bag-of-words approaches, which do not account for the semantic meaning of words.

To generate an embedding at the document (i.e., product) level, in step 3 I follow the common approach of averaging all processed tokens (including repeats) in each document (Ash and Hansen 2023; Bybee 2025). This results in each product being represented as a 300-dimensional vector, where a product's location reflects its semantic characteristics.

B4. TF-IDF is a widely used weighting metric that captures the importance of a term in a document relative to its prevalence in the entire corpus. The term frequency (TF) component measures how often a term appears in a product description, while the inverse document frequency (IDF) component penalizes terms that occur frequently across many products. Thus, high-frequency terms across all documents receive lower weights, whereas terms that are frequent within individual documents receive higher weights, as the latter carry more discriminatory, informational value. Selecting top five TF-IDF terms per product filters out unimportant terms, while requiring that a term shows up in the top five TF-IDF terms for at least ten products ensures broader applicability.

B5. BERT (Bidirectional Encoder Representations from Transformers, see Devlin et al. (2019)) is another widely used language model that additionally captures contextual information in which words appear, but is computationally intensive. I use GloVe instead, as the precise contextual nuances of words (i.e., variations in meaning of words based on surrounding text) is straightforward and not central to the analysis of short, relatively standardized product descriptions. (Context-aware models like BERT would be more important in tasks such as question answering or sentiment analysis, where word meaning is highly dependent on context.)

Table B.2: Examples of product descriptions and categories, before and after processing

Product name	**Document** = product description and categories	**Processed text** = terms to be vectorized
Adobe XD	Prototyping and UX solution designed to help businesses of all sizes sketch wireframes and design websites as well as applications. Using Adobe XD, designers can collaborate across teams to add animations, create prototypes, and collect feedback in real-time. The platform allows operators to create 3D and reusable designs to eliminate recreating efforts. Teams can also use the system to create, resize, and utilize the drag-and-drop functionality to align content-based layouts. Prototyping Software, Animation Software, UX Software	prototyping, ux, designed, businesses, sizes, wireframes, design, websites, applications, designers, collaborate, across, teams, add, animations, create, prototypes, collect, feedback, real-time, platform, operators, create, 3d, reusable, designs, eliminate, efforts, teams, system, create, resize, drag-and-drop, functionality, align, layouts, user-experience, prototyping, animation, ux, user-experience
Figma	Cloud-based and on-premise platform that enables businesses to create custom designs, share prototypes among team members. Graphic Design Software, Prototyping Software	cloud-based, on-premise, platform, businesses, create, customise, designs, share, prototypes, among, team, members, graphic-design, prototyping
Justinmind	Justinmind is the best solution to prototype any web or mobile app you want. You can define websites and apps for Web, iOS, and Android with our intuitive drag-and-drop interface. No code involved. Just start from the template of your choice and customize it. Add our pre-loaded UI kits and give life to your design with clickable regions and link interactions. Finally, test the final user experience in a click! Wireframe Software, Application Development Software, Prototyping Software	prototype, web, mobile, app, define, websites, apps, web, ios, android, intuitive, drag-and-drop, interface, no-code, gui, involved, template, choice, customise, add, ui, kits, life, design, regions, link, interactions, test, final, user-experience, click, wireframe, application, development, prototyping, application-development

B.7 Dimensionality Reduction and k-Means Clustering

Next, the products are partitioned into groups based on their respective location in the vector space. High-dimensional spaces, such as the one created by word embeddings, can be challenging for clustering algorithms like k-means due to the curse of dimensionality, which can obscure the underlying structure of the data and make it difficult to identify meaningful clusters (Hastie, Tibshirani, and Friedman 2009; Zimek 2013). To address this, in my preferred approach, I first apply a dimension reduction technique called Uniform Manifold Approximation and Projection (UMAP, see McInnes, Healy, and Melville (2018)). UMAP reduces the dimensionality of the data while preserving its intrinsic geometric and topological structure. UMAP is moreover faster and than other dimension reduction methods and generally applicable. While not strictly necessary, I obtain improved results (in the sense of the validation exercises performed below) and also higher processing speed when using this dimension reduction technique as a first step.

After reducing the dimensionality (from 300 to, e.g., 25 or 50 dimensions), I employ the commonly used k-means clustering algorithm to group products into disjoint sets (Hartigan and Wong 1979; Athey and Imbens 2019). For a given number of clusters k, k-means partitions the observations into groups by minimizing the within-cluster variation, defined as the sum of squared Euclidean distances between each product and the centroid of its assigned cluster.

Both UMAP and k-means require me to choose certain hyperparameters. In the case of UMAP, I need to set the number of dimensions I wish to collapse the product vectors to. I find that 25 dimensions yield reasonable results; changing this number to, e.g., 50 has no meaningful bearing on the clusters that are created. Choosing the right number of clusters k requires more care, as it governs the market size. I use both the below validation exercises as well as the average within-cluster cosine similarity as guidance, and provide robustness checks.

B.8 Validation of Market Definition

B.8.1 Choice of Hyperparameters

As a first "sanity check", I recover the three most frequently mentioned terms across all documents of each market, and find that they are indeed different from each other as well as meaningful. How to validate whether the markets created are also economically sensible is less straightforward. As the vast majority of the firms in my dataset is *not* publicly listed on U.S. stock exchanges, more standard industry classification systems such as SIC codes, or the text-based classification by Hoberg and Phillips (2016), are not helpful for validating my market definitions.[B6]

Instead, I survey the decision texts of merger cases involving enterprise software firms that have been published by antitrust authorities. The market definitions in these official documents are derived from in-depth market investigations and structured economic analysis, and therefore provide a reasonable benchmark for evaluating my market definitions. Table B.3 lists the mergers considered, along with the firms identified in the reports as competing in the same market. As merger decisions typically define markets at the firm (as opposed to product) level, and as firms often supply multiple products, I select each company's respective relevant product on *Capterra*.

In addition to the official merger decisions, I compile a short list of further well-known products, or markets that are arguably straightforward to delineate, such as the market for web browses (see Table B.4). This gives me an additional benchmark to gauge the extent to which my market definitions are appropriate.

To assess the fit of my market clusters with the benchmarks provided in Tables B.3 and B.4, I compute two indices that provide an estimate for overlap: the adjusted Rand Index and the Normalized Mutual Information (Manning, Raghavan, and Schütze 2008). In addition, I compute the mean within-cluster similarity for each of my candidate hyperparameters and approaches, which measures the "average closeness" of all entities within one cluster. When choosing between different word pre-processing techniques or between variants to create a dictionary, I take these indices as guidance. In particular, while the mean within-cluster similarity increases in the number of clusters, it does so at a decreasing rate. The

B6. I attempted to match the publicly listed U.S.-based firms, and hence a small subset of my data, to SIC codes using Compustat data. However, over 72% of these firms fall into just two distinct 4-digit SIC codes ("Computer programming, data programming, etc." and "Prepackaged software"). This illustrates the limitations of SIC codes in capturing competitive relationships or consumer substitution patterns. Similarly, *Crunchbase* industry labels are often too coarse to be useful for my purposes. For instance, many firms are tagged with only general labels like "Information Technology" or "Software".

Table B.3: Markets defined in official merger decisions (validation set)

Merger case	**Market definition**	**Firms in this market** (products in parentheses)
Adobe-Figma (Competition and Markets Authority (2023), p.30)	All-in-one screen design software	Figma, Adobe (Adobe XD), InVision (InVision App), Sketch, Axure, Framer, UXPin, Justinmind, PenPot*, others
Salesforce-Tableau (Competition and Markets Authority (2019), p.19&21)	Modern business intelligence	Salesforce (Salesforce Analytics Cloud), Tableau, Microsoft (Microsoft Power BI), SAP (SAP BusinessObjects Business Intelligence and SAP Analytics Cloud), Oracle (Oracle Business Intelligence), IBM (IBM Cognos Analytics), Qlik (Qlik Sense), SAS (SAS Visual Analytics), MicroStrategy (MicroStrategy Analytics), TIBCO (TIBCO Spotfire), Looker, Information Builders (ibi), Alteryx (Alteryx Designer), others
Microsoft-LinkedIn (European Commission (2017), p.78)	Online recruitment services	LinkedIn, Indeed (additional local providers are mentioned but could not be identified on *Capterra*)
Facebook-Kustomer (Competition and Markets Authority (2021), p.17)	B2C communications	Messenger, WhatsApp, Instagram, Kustomer, others
Facebook-Kustomer (European Commission (2022), p.46)	Customer service and support CRM software	Kustomer, Salesforce (Salesforce Service Cloud), Oracle (Oracle Service), Genesys (Genesys Cloud), SAP*, Zendesk, Verint (Telligent Systems), NICE (NICE Workforce Management), Cisco (Cisco Unified Contact Center Express), Microsoft (Dynamics 365 Customer Service), Avaya*, others
NortonLifeLock-Avast (Competition and Markets Authority (2022), p.47-48)	Consumer endpoint security	NortonLifeLock (Norton AntiVirus), BullGuard*, Avira (Avira Antivirus for Endpoint, Avira Antivirus for Small Business, and Avira Antivirus Pro), Avast (Avast Business, Avast Business Antivirus, Avast Business Antivirus Pro), McAfee (McAfee Endpoint Security, McAfee Network Security Platform), Aura*, ESET (ESET Endpoint Security, ESET Cloud Office Security), F-Secure (F-Secure Business Suite), Kaspersky (Kaspersky Endpoint Security), Panda (Panda Adaptive Defense 360 and Panda Cloud Office Protection), Sophos*, TotalAV*, TrendMicro*, Malwarebytes (Malwarebytes Endpoint Protection, Malwarebytes for Teams), others

Notes: The "Market definition" entry follows the authority's wording. "Firms in this market" lists competitors named in the decisions; for multi-product firms, likely relevant products on *Capterra* are shown in parentheses. An asterisk (*) marks firms cited by the authority that could not be linked to a specific *Capterra* product as of the 2021 scrape. This table is used only to validate the clustering method; it does not define markets for the analysis.

adjusted Rand Index and the Normalized Mutual Information, however, decline after 400 to 500 clusters, which suggests diminishing returns from adding more clusters beyond this range. In my preferred approach, I therefore choose to create 500 clusters (markets).

B.8.2 Descriptive Statistics on Market Definitions

For a few well-known products, Figure B.2 shows word clouds that visualize the most frequently mentioned terms in the product descriptions of all products that are clustered into the same market as the given product. These word clouds illustrate exemplarily that the clustering algorithm groups products

Table B.4: Markets defined from domain knowledge (additional validation set)

Market	**Products that should be part of this market**
Filesharing Software	Google Drive, Dropbox Business, OneDrive, Box, iCloud, FolderShare, Sendoid
Presentation Software	Microsoft PowerPoint, Pitch, Prezi, Slidebean, Prezentor, Google Slides
Webbrowsers	Google Chrome, Safari, Microsoft Edge, Firefox, Tor Browser, Yandex Browser, Chromium, Vivaldi Browser, Opera, SRWare Iron
Campground Management Software	RDPWin, Open Campground, RoverPass
Hotel Channel Management Software	Sirvoy, RMS Cloud, eZee Absolute, eviivo, Cloudbeds

with similar functionalities into the same market.

Figure B.2: Frequent terms in market clusters (MATLAB; Doodle)

(a) Matlab

(b) Doodle

Notes: Each panel shows the most frequent terms in product descriptions for products assigned to the same cluster (market) as the focal product. Text is sized by within-cluster term frequency.

As a further descriptive statistic, I assess the fit with Capterra's pre-defined 812 categories. For this purpose, I compute the Purity, which measures the extent to which each cluster (market) contains predominantly products from a single set of *Capterra* categories (Manning, Raghavan, and Schütze 2008).[B7] When using my preferred approach with 500 markets, I find that purity (computed across all clusters) is 0.52, which implies that on average, half of the products clustered into a certain market also belong to the same *Capterra* categories.

C Further Descriptive Statistics

C.1 Exit-Level Summary Statistics

Table C.1 shows exit-level summary statistics for VC-backed startups that exited in 2012-2019, either via acquisition or IPO, and for which either the transaction price or the valuation at IPO is available. The large difference between mean and median stems from the fact that exit prices and valuations are highly right-skewed, which is in line with prior literature.

B7. Purity is calculated by assigning each cluster to the most frequent category (or rather, set of categories, since a product can belong to multiple categories) within it, and then measuring accuracy as the proportion of "correctly" assigned products relative to the total number of products. It is defined as $\text{Purity}(\Omega, \mathcal{C}) = \frac{1}{N}\sum_k \max_j |\omega_k \cap c_j|$, where $\Omega = \{\omega_1, \ldots \omega_K\}$ is the set of clusters, and $\mathcal{C} = \{c_1, \ldots, c_J\}$ is the set of external categories. See Manning, Raghavan, and Schütze (2008), p.356f.

Table C.1: Summary statistics: exit values of VC-backed startups

	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Acquisitions: transaction price (US$m)	480	331.6	1,068.4	32.8	120	300
IPOs: valuation (US$m)	137	2,560.2	9,671.2	337.6	703.9	1,561

Notes: An observation is an exit of a VC-backed startup in the data from 2012-2019 where (in the case of acquisitions) the transaction price or (in the case of IPOs) the opening valuation, respectively, is available.

Table C.2: Acquisitions of startups and other firms by different types of acquirers, 2012-2019

Panel A: Broad acquirer groups (exhaustive)

	Target type:				**Total**
Acquirer type	<3 years and no VC funding	VC-funded, pre-exit (startup)	VC-funded, post exit	Not VC-funded	
Enterprise Software	6.8	46	3.2	41.1	100
Financial	3.2	27.9	5.8	62.1	100
Other Industries	4.4	36.7	4	53.6	100

Panel B: Strategic subtypes (not exhaustive)

GAFAM	10.2	67.8	2.2	16.9	100
New tech	6.3	70.9	4.8	14.9	100
Old tech	1.5	63.4	7.1	22.4	100
Pre-exit	11.4	49	3.9	32.2	100

All figures in %

Table C.3: Post-money valuations at exit of VC-funded startups by exit type, 2012-2019

Panel A: Broad acquirer groups (exhaustive)

Acquirer type	**Post-money valuation at exit** (US$m, median)	% valuation data is not available
Enterprise Software	21	95
Financial	81.5	95.6
Other Industries	18.6	94.4

Panel B: Strategic subtypes (not exhaustive) and IPOs

GAFAM	65.1	91
New tech	241	94.9
Old tech	587.3	93.3
Pre-exit	3.8	94.7
IPO	1000	70.9

Notes: Table shows the latest post-money valuation that can be obtained from *Crunchbase* prior to a startup's exit.

C.2 Characteristics of Targets Acquired by Different Types of Acquirers

Table C.2 shows the breakdown of acquisitions of startups and other firms by different types of acquirers. It shows that enterprise software firms acquire startups more frequently than other types of acquirers. Table C.5 shows the pattern of funding rounds received by different startups at the time of exit. It closely mirrors the patterns observed for startup age, price and valuation (Tables C.3 and C.4) at exit.

C.3 Products Discontinued After the Acquisition

Acqui-hires. Acquisitions on *Crunchbase* may be tagged with an "acqui-hire" tag. I find that 2.6% of acquisitions of startups in which the product was shut down are recorded as acqui-hire events; exam-

Table C.4: Age at exit of VC-funded startups by exit type, 2012-2019

Panel A: Broad acquirer groups (exhaustive)

	Average age at exit:	
Acquirer type	Years since founding date	Years since first funding round
Enterprise Software	6.8	4.6
Financial	10.5	5.8
Other Industries	7.2	5.2

Panel B: Strategic subtypes (not exhaustive) and IPOs

GAFAM	4.4	3.6
New tech	5	3.7
Old tech	7	5
Pre-exit	5.5	3.8
IPO	10.5	7.6

Table C.5: Number and volume of VC funding rounds at exits of VC-funded startups, 2012-2019

Panel A: Broad acquirer groups (exhaustive)

Acquirer type	**Number of funding rounds** (mean)	**Volume of funding** (US$m, median)	% funding volume is not available
Enterprise Software	2.6	7.2	12
Financial	2.5	12.8	13.3
Other Industries	2.8	8	14.6

Panel B: Strategic subtypes (not exhaustive) and IPOs

GAFAM	2.6	10	12.3
New tech	2.8	8.8	12.4
Old tech	3.2	24	9.6
Pre-exit	2.4	3.5	14.2
IPO	4.5	98.8	3.6

ples are Dropbox-Verst, Google-Bebop, Apple-Union Bay Networks, Twitter-tenXer, and Box-Wagon. I believe the actual number of acqui-hires to be rather higher. For instance, whenever the acquirer announced the shutdown at the time of the acquisition, the acquisition may quite likely have been an acqui-hire. Note that, interestingly, Ng and Stuart (2021) find that a acqui-hired employees turn over at a much higher rate compared to organically hired employees. For products that are active as of 2021, only 0.7% of acquisitions are recorded as an acqui-hire on *Crunchbase*.

Timing. I do not observe the timing of the shut-down in the data. However, anecdotally there are both, cases in which the shut-down was announced right at the time of the acquisition (e.g. Box-Wagon, Dropbox-CloudOn, Dropbox-Verst, Google-AppJet), or after a few years (e.g. Microsoft-Wunderlist, Dropbox-Mailbox, Qlik-DataMarket, or Oracle-Ravello Systems, whose products were shut down between two and four years after the acquisition).

For those startups that were acquired and kept active, I can compile further descriptives using the web-scraped product-level data. I first consider the number of products produced by an acquired firm. I find that those startups that exited via IPO or via an acquisition by a financial acquirer have on average 2 or 1.4 products respectively, as of 2021. In contrast, companies exiting by GAFAM or pre-exit firms

Table C.6: Age at acquisition and deal size by post-acquisition status

	Median age at acquisition:		**Median acquisition price:**
	Years since founding	Years since first funding round	US$ million
Products discontinued	6.2	4.1	100
Products kept active	7.8	5.2	130

Notes: "Years since founding" and "years since first funding round" are measured at the acquisition date. Median acquisition prices are computed among deals with non-missing prices. Sample: startups acquired in 2012–2019.

Table C.7: Number of reviews, VC-funded startups with continued products only, 2012-2019

Panel A: Broad acquirer groups (exhaustive)

	Number of reviews per acquired startup:	
Acquirer type	Median	Mean
Enterprise Software	2	106.2
Financial	1	50.7
Other Industries	1	56.0

Panel B: Strategic subtypes (not exhaustive) and IPOs

	Median	Mean
GAFAM	16.5	848.8
New tech	1.5	34.5
Old tech	2	43
Pre-exit	2	11.8
IPO	12.5	670.4

Notes: For multi-product firms, I sum the reviews across all products supplied by a given firm.

are always single-product in my data. Next, study at the number of reviews of products acquired and continued, which could be an indication for demand. Table C.7 reveals that products acquired by the GAFAM tend to have many more reviews. However, it should however be born in mind that the GAFAM are also especially likely to discontinue products. Moreover, it is not clear whether high number in reviews indicates that the acquisition has boosted demand for these products, or whether these products were previously successful ones.

Note that Ivaldi, Petit, and Unekbas (2025) do not find shut-down rates this high. Two reasons might explain the difference: first, the authors trace products only during one year following the merger, whereas shut-downs anecdotally may happen much later (see Appendix C.3). Second, the authors focus on a selected subset of twelve large merger cases that were subject to investigation by the European Commission. However, I find that shut-downs are especially prevalent for acquisitions of very young companies, in transactions that would not be likely to be subject to an investigation.

D Robustness on Reduced-Form Results

Table D.1: Two-stage DiD estimates of startup entry after major acquisitions, by acquirer type: here, markets with ≥1 major acquisition

	Dependent Variable: Number of entrants in market m, quarter t					
	Strategic (enterprise software) acquirers				**Financial / outsiders**	
"Major" acquisition: > US$100m	(1)	(2)	(3)	(4)	(5)	(6)
1{major acq by strategic}	-0.1719					
	(0.1445)					
1{major acq by strategic w/ reviews}		-0.2595				
		(0.1595)				
1{major acq by New Tech or GAFAM}			-0.8176*			
			(0.4812)			
1{major acq by GAFAM}				-1.520*		
				(0.8842)		
1{major acq by Financial or Outsider}					-0.0067	
					(0.1360)	
1{major acq by Financial}						0.2999
						(0.2554)
Market FE	✓	✓	✓	✓	✓	✓
Quarter–year FE	✓	✓	✓	✓	✓	✓
Observations	3,296	3,328	3,328	3,328	3,296	3,328
Adjusted R^2	0.3848	0.3850	0.3854	0.3860	0.3853	0.3849

Notes: Same specification and variable definitions as Table 5; entries are two-stage difference-in-differences (did2s) coefficients, interpreted as post-acquisition average treatment effects on the treated (ATT) for each acquirer group. Standard errors clustered by market. Sample restricted to markets that experience at least one "major" acquisition (disclosed value > US$100m) during 2012–2019; market–quarter panel. Column (2) restricts "strategic" to acquirers with at least one product reviewed on *Capterra*; (3) limits to New Tech or GAFAM; (4) isolates GAFAM acquirers; (5) pools financial and outsider acquirers; (6) isolates financial acquirers. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.2: Two-stage DiD estimates of startup entry after major acquisitions (> US$50m), by acquirer type

	Dependent Variable: Number of entrants in market m, quarter t					
	Strategic (enterprise software) acquirers				**Financial / outsiders**	
"Major" acquisition: > US$50m	(1)	(2)	(3)	(4)	(5)	(6)
1{major acq by strategic}	-0.2432**					
	(0.1203)					
1{major acq by strategic w/ reviews}		-0.3043**				
		(0.1311)				
1{major acq by New Tech or GAFAM}			-0.9097**			
			(0.4223)			
1{major acq by GAFAM}				-1.584**		
				(0.7964)		
1{major acq by Financial or Outsider}					-0.0793	
					(0.0913)	
1{major acq by Financial}						0.0016
						(0.1705)
Market FE	✓	✓	✓	✓	✓	✓
Quarter–year FE	✓	✓	✓	✓	✓	✓
Observations	15,584	15,648	15,648	15,648	15,616	15,648
Adjusted R^2	0.2979	0.2985	0.2987	0.2988	0.2979	0.2978

Notes: "Major" acquisition threshold is > US$50m (first event per market). Estimates are two-stage difference-in-differences (did2s); standard errors clustered by market. Sample: market–quarter panel, 2012–2019. Column (2) restricts "strategic" to acquirers with at least one product reviewed on *Capterra*; (3) limits to New Tech or GAFAM; (4) isolates GAFAM acquirers; (5) pools financial and outsider acquirers; (6) isolates financial acquirers. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.3: Two-stage DiD estimates of startup entry after major acquisitions (> US$100m), by acquirer type, under alternative market definition

	Dependent Variable: Number of entrants in market m, quarter t				
	Strategic (enterprise software) acquirers			**Financial / outsiders**	
"Major" acquisition: > US$100m	(1)	(2)	(3)	(4)	(5)
1{major acq by strategic}	-0.2476 (0.1701)				
1{major acq by strategic w/ reviews}		-0.3249* (0.1916)			
1{major acq by New Tech or GAFAM}			-0.8716 (0.6586)		
1{major acq by Financial or Outsider}				-0.0975 (0.1355)	
1{major acq by Financial}					0.1696 (0.2448)
Market FE	✓	✓	✓	✓	✓
Quarter–year FE	✓	✓	✓	✓	✓
Observations	14,848	14,880	14,880	14,848	14,880
Adjusted R^2	0.3084	0.3089	0.3086	0.3092	0.3084

Notes: "Major" acquisition threshold is > US$100m (first event per market). Estimates follow the two-stage difference-in-differences (did2s) specification with market and quarter–year fixed effects; standard errors are clustered by market. This appendix table uses the alternative market definition where the clustering algorithm specified k =475 clusters (465 after removing outliers), from 2012-2019. Columns (2)–(3) refine "strategic" to acquirers with *Capterra* reviews and to New Tech or GAFAM, respectively; columns (4)–(5) consider financial/outsider acquirers and financial acquirers only. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.4: Two-stage DiD estimates of startup entry after major acquisitions (> US$100m), by acquirer type, under alternative market definition

	Dependent Variable: Number of entrants in market m, quarter t					
	Strategic (enterprise software) acquirers				**Financial / outsiders**	
"Major" acquisition: > US$100m	(1)	(2)	(3)	(4)	(5)	(6)
1{major acq by strategic}	-0.2476 (0.1701)					
1{major acq by strategic w/ reviews}		-0.3249* (0.1916)				
1{major acq by New Tech or GAFAM}			-0.8716 (0.6586)			
1{major acq by GAFAM}				-1.534 (1.310)		
1{major acq by Financial or Outsider}					-0.0975 (0.1355)	
1{major acq by Financial}						0.1696 (0.2448)
Market FE	✓	✓	✓	✓	✓	✓
Quarter–year FE	✓	✓	✓	✓	✓	✓
Observations	14,848	14,880	14,880	14,880	14,848	14,880
Adjusted R^2	0.3084	0.3089	0.3086	0.3085	0.3092	0.3084

Notes: "Major" acquisition threshold is > US$100m (first event per market). Estimates follow the two-stage difference-in-differences (did2s) specification with market and quarter–year fixed effects; standard errors are clustered by market. This appendix table uses the alternative market definition where the clustering algorithm specified $k = 475$ clusters (465 after removing outliers), from 2012–2019. Columns (2)–(3) refine "strategic" to acquirers with *Capterra* reviews and to New Tech or GAFAM, respectively; (4) isolates GAFAM acquirers; (5) considers financial/outsider acquirers; (6) financial acquirers only. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.5: Two-stage DiD estimates of entry by VC-funded startups or young firms after major acquisitions, by acquirer type

	Dependent Variable: Number of VC-funded startups or young firms entering market m, quarter t					
	Strategic (enterprise software) acquirers				Financial / outsiders	
"Major" acquisition: > US\$100m	(1)	(2)	(3)	(4)	(5)	(6)
1{major acq by strategic}	-0.6104***					
	(0.2345)					
1{major acq by strategic w/ reviews}		-0.6117**				
		(0.2657)				
1{major acq by New Tech or GAFAM}			-1.274			
			(0.9103)			
1{major acq by GAFAM}				-2.113		
				(1.819)		
1{major acq by Financial or Outsider}					-0.3243	
					(0.2373)	
1{major acq by Financial}						0.4352
						(0.2938)
Market FE	✓	✓	✓	✓	✓	✓
Quarter–year FE	✓	✓	✓	✓	✓	✓
Observations	15,616	15,648	15,648	15,648	15,616	15,648
Adjusted R^2	0.3881	0.3878	0.3876	0.3868	0.3892	0.3865

Notes: "Major" acquisition threshold is $>$ US\$100m (first event per market). Estimates follow the two-stage difference-in-differences (did2s) specification with market and quarter–year fixed effects; standard errors are clustered by market. The dependent variable counts first funding rounds of VC-funded startups, and founding dates of non-VC funded young firms. Columns (2)–(3) refine "strategic" to acquirers with at least one *Capterra*-reviewed product and to New Tech or GAFAM, respectively; (4) isolates GAFAM acquirers; (5) considers financial/outsider acquirers; (6) financial acquirers only. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.6: Placebo two-stage DiD with randomized treatment timing

	Dependent Variable: Number of entrants in market m, quarter t					
	Strategic (enterprise software) acquirers				Financial / outsiders	
Placebo: randomized timing of treatment	(1)	(2)	(3)	(4)	(5)	(6)
1{major acq by strategic}	-0.0898					
	(0.0854)					
1{major acq by strategic w/ reviews}		-0.0804				
		(0.0824)				
1{major acq by New Tech or GAFAM}			-0.7651			
			(0.5763)			
1{major acq by GAFAM}				-1.171		
				(1.197)		
1{major acq by Financial or Outsider}					-0.0922	
					(0.1894)	
1{major acq by Financial}						-0.1367
						(0.1327)
Market FE	✓	✓	✓	✓	✓	✓
Quarter–year FE	✓	✓	✓	✓	✓	✓
Observations	15,616	15,648	15,648	15,648	15,616	15,648
Adjusted R^2 (placebo)	0.2977	0.2982	0.2983	0.2975	0.2985	0.2978

Notes: Placebo assignment randomly reassigns acquisition dates across treated markets while preserving (i) the share of treated markets and (ii) the empirical distribution of event timing. Estimates follow the two-stage difference-in-differences (did2s) specification with market and quarter–year fixed effects; standard errors clustered by market. Coefficients are statistically insignificant across specifications, consistent with the main results not being driven by spurious timing patterns. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

E Details on Model Estimation: Market-Category Effects

E.1 Market-Category Effects

I follow Wang (2022) and Lin (2015) to estimate market-category fixed effects. In principle, different numbers of market-categories can be constructed. The more groups I use, the closer the estimates to the results using market fixed effects in column (2) of Tables 7 or 8, but the more likely one will face the incidental parameters problem. In order to strike a balance between those effects, I choose to group markets into 20 categories.

The market-category effects are created by first ranking markets by the estimated market fixed effect coefficients, and then slicint them into equal-sized quantiles.

As a rough validity check, I investigate which types of markets have a high, and which have a low estimated market-category effect. I find that markets with the lowest estimated market-category effect (and thus likely low profitability and/or size) tend to be markets that appeal to narrow customer segments. Among small markets, for instance, are markets containing products in industry-specific or declining niches such as "Winery Software", "Pet Grooming Software", or "Fax Server Software". In contrast, markets with the highest estimated market-category effect appear to be more general-purpose. Among these are, for instance, software tools in areas such as "Payment Processing Software", "Cybersecurity Software", or "Marketing and Analytics Software".

E.2 Forward Simulation

I set the parameters of the time fixed effects to 0 for the purpose of the forward simulation.

F Products by VC-funded Startups Tend to Have More Reviews

In manual checks using a small set of companies, I found a high correlation of a product's reviews and revenue estimates by data providers. Reviews could hence likely be interpreted as a proxy for product demand, or for product quality.

Table F.1 shows results from cross-sectional regressions, either at the level of a firm or at the level of a product, to find whether VC backing is related with product reviews. In particular, columns (1) and (2) show the results of a regression of the number of reviews of a given product on firm characteristics; in particular, on the number of VC funding rounds (column (1)) and on whether or not the firm has received any VC funding round (column (2)). Columns (3) and (4) show the results of a regression of the average number of reviews of a given company's products on the same set of regressors.

It is remarkable that funding rounds seem positively correlated with the number of reviews, even after accounting for company cohort, company employee size, and "status" (acquired, IPO, operating, inactive, closed). This could be a result either of VC funding causally affecting demand; or at VC investors selecting startups whose products are in high demand. The insignificant coefficient of "Firm status: IPO" in columns (3) and (4) is likely due to the fact that public firms have few heavily reviewed “flagship” products, and many lower-review niche offerings. Averaging then shrinks the IPO coefficient mechanically. In general, however, the low adjusted R^2 indicates that factors not captured in this regression are important in explaining reviews.

Table F.1: Cross-sectional correlates of review volume (product- and firm-level)

	Dependent variable			
	Product-level data: # of product reviews		Firm-level data: Avg # of reviews across products	
	(1)	(2)	(3)	(4)
VC financing rounds (count)	9.917**		10.101**	
	(4.081)		(4.459)	
1{Ever VC-financed}		11.193		24.357***
		(9.397)		(8.300)
Firm status: Acquired	5.549	1.036	21.742*	19.167
	(11.701)	(11.666)	(12.857)	(12.601)
Firm status: IPO	126.151***	124.138***	28.803	28.372
	(36.485)	(36.452)	(29.270)	(29.598)
Firm status: Inactive	−2.367	−11.239**	3.257	−6.686
	(6.775)	(5.105)	(7.153)	(4.973)
Firm status: Closed	−33.089***	−36.212***	−24.688***	−28.429***
	(7.686)	(7.600)	(5.953)	(5.777)
Employees: 11–50	−2.805	1.004	−0.228	3.418
	(3.061)	(2.656)	(3.174)	(2.621)
Employees: 51–100	1.739	10.068**	5.669	13.777***
	(4.921)	(3.982)	(5.112)	(3.707)
Employees: 101–250	13.745	25.367**	21.866	34.059***
	(11.362)	(10.006)	(13.717)	(11.655)
Employees: 251–500	21.132**	33.068***	40.134***	54.171***
	(8.644)	(9.004)	(10.619)	(10.935)
Employees: 501–1,000	100.700***	112.842***	128.001***	141.344***
	(27.445)	(27.764)	(32.987)	(34.058)
Employees: 1,001–5,000	185.149***	198.286***	253.182***	269.078***
	(39.962)	(42.969)	(69.918)	(74.679)
Employees: 5,001–10,000	86.452**	95.043***	103.251**	113.446**
	(35.063)	(35.327)	(50.856)	(50.926)
Employees: 10,000+	308.974***	315.326***	155.699***	166.299***
	(65.807)	(65.407)	(49.599)	(49.973)
Employees: Unknown	21.994***	25.531***	16.048***	23.032***
	(7.169)	(7.736)	(5.954)	(6.613)
Firm founding-year FE	✓	✓	✓	✓
Mean of dependent variable	53.47	53.47	36.22	36.22
Observations	20,693	20,693	16,557	16,557
Adjusted R^2	0.031	0.030	0.018	0.016

Notes: Columns (1)–(2) use product-level data; the outcome is the number of user reviews of a given product on *Capterra* as of the scrape date. Columns (3)–(4) aggregate to the firm level; the outcome is the simple average of review counts across all products the firm lists on *Capterra*. "VC financing rounds" are defined as in Section 2.2.1; "Ever VC-financed" is an indicator for at least one such round. "Employees" are taken from *Crunchbase*. "Firm status" is taken from *Crunchbase*, with the addition that status "inactive" is assigned to firms that are designated as "operating" but have not recorded any event within five years (see Appendix B.1). Reference categories: (i) *Firm status*—private and "operating" (according to *Crunchbase*); (ii) *Employees*—1–10 employees. All specifications include firm founding-year fixed effects. Heteroskedasticity-robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

G Facts on the (Enterprise) Software Industry

G.1 Size of the Enterprise Software Industry

The below descriptive statistics are based on the entire *Crunchbase* data (instead of only *Crunchbase* firms that are matched to *Capterra*), and thus separate from the sample considered in this paper. I compare companies operating in enterprise software, and companies operating in biotechnology or pharmaceuticals, as both of these industries are thought to be captured especially well on *Crunchbase*, and characterized by high innovation. As *Crunchbase* does not specifically distinguish industries, I define these industries as follows:

Definition of Enterprise Software. I define as belonging to *enterprise software* all *Crunchbase* organizations that have any of the following categories:

- Sales Automation, Enterprise Software, Advertising, Developer Tools, Web Development, SaaS, Digital Marketing, Analytics, SEO, Business Intelligence, CRM, Web Hosting, Cyber Security, Cloud

I then exclude all organizations that have any of the following categories:

- Biotechnology, Pharmaceutical, Hardware, Insurance, Physical Security, GreenTech, Oil and Gas, Farming, Wine and Spirits, Packaging Services, Solar, Air Transportation, Aerospace, Consulting, Robotics, Semiconductor, Wearables, Sensor, Power Grid, Audiobooks, Video Game, Medical Device

Definition of Biotech and Pharma. I define as belonging to *biotechnology and pharmaceuticals* all *Crunchbase* organizations in any of the following categories:

- Biotechnology, Pharmaceutical

I then exclude all organizations that have any of the following categories:

- Enterprise Software, SaaS, Machine Learning, Artificial Intelligence

I then consider only relevant VC funding rounds, with VC funding rounds defined as in Appendix B.1. I find that between 2005 and 2020, enterprise software startups worldwide have raised US$237 billion, whereas pharmaceutical and biotechnology startups have raised US$177 billion. Looking at all investments (not only VC investments), the enterprise software industry has received US$319 billion, whereas the pharmaceutical and biotechnology industry has received US$278 billion.

G.2 Prevalence of Startup Acquisitions in Software Markets

I first document the high prevalence of startup acquisitions in the software industry compared to other industries: firms active in software are among the most important *acquirers* of VC-backed startups (Section G.2.1), and successful *targets* active in enterprise software predominantly exit via acquisition (Section G.2.2). These findings suggests that the motives for these numerous startup acquisitions may be specific to the software industry, which provides a motivation for conducting the study *within* this industry.

Rank	Acquirer name	# startups acquired	Acquirer name	Billion US$
1	**Alphabet**	139	**Facebook**	24.3
2	**Microsoft**	75	Walmart	19.6
3	**Apple**	68	**Alibaba Group**	15.3
4	**Cisco**	67	**Cisco**	15.0
5	**Facebook**	66	**Alphabet**	12.8
6	**Dell EMC**	64	**Microsoft**	12.4
7	Vista Equity Partners	54	**eBay**	10.8
8	**Amazon**	53	**SAP**	8.7
9	**Yahoo**	49	Illumina	8.7
10	**Salesforce**	48	**Intuit**	8.5
11	**Twitter**	45	**Didi**	8.0
12	**Oracle**	38	**Amazon**	7.5
13	**Intel**	37	Johnson & Johnson	6.9
14	**eBay**	34	Merck	6.8
15	Thoma Bravo	32	**Dell EMC**	6.3
16	**IBM**	32	Investor AB	6.3
17	Walmart	29	Roche	6.3
18	**Alibaba Group**	26	**Uber**	6.0
19	**Groupon**	25	Bristol-Myers Squibb	5.9
20	**IAC**	22	AbbVie	5.8

Table G.1: This Table considers all VC-funded startups on *Crunchbase* that were acquired in 2005-2020 – i.e., *not* just the *Capterra*-matched sample. I show the top 20 acquirers in terms of number of acquired startups (left) and transaction volume (right). **Bold** indicates companies active in digital technology or software. Acquisition prices are missing in 82% of observations, most likely for smaller acquisitions and startups in financial distress ("fire sales", see Kerr, Nanda, and Rhodes-Kropf (2014)).

G.2.1 The most important acquirers of startups of any industry are software firms

Table G.1 shows the top twenty acquiring firms of VC-funded startups in 2005-2020.[G8] For each acquirer, I sum up both the number of acquired firms, as well as the transaction prices.[G9] Looking at the names of the top 20 acquirers in terms of the number of acquired firms (left column), what is striking is that most of the listed companies are producers of software. The GAFAM are among the top 10 acquiring firms, but many other digital technology firms are very active in startup acquisitions as well. Looking at top acquirers of VC-funded startups in terms of dollar volume, a different set of companies shows up, with financial and biotechnology firms appearing as top acquirers. Overall, this pattern hints at the idea that acquisitions of startups may be important for essentially all software firms. However, software firms tend to acquire companies at lower prices, but more of them, compared to companies active in finance or pharmaceuticals.

G.2.2 Startups in software are more likely to exit via acquisition than startups in other industries

This section describes exit strategies by software startups, juxtaposing these to those of biotechnology and pharmaceutical startups. As explained in Section 2.1, startups can successfully exit either by being acquired, or by being listed as a public company on a stock exchange. Whereas I find that failure rates are

G8. Note that I here do not place any restriction on the type of industry or geographic location of acquirer or target firm, and use the entire *Crunchbase* database, as opposed to the *Crunchbase-Capterra* match.

G9. Acquisitions conducted by subsidiaries of a parent firm are counted as the parent firm's acquisition. This means: acquisitions conducted by Flipkart after Walmart purchased a majority stake in Flipkart are counted as acquisitions by Walmart, for instance. If I do not take into account these acquisitions by subsidiaries, the left column in fact contains only software firms.

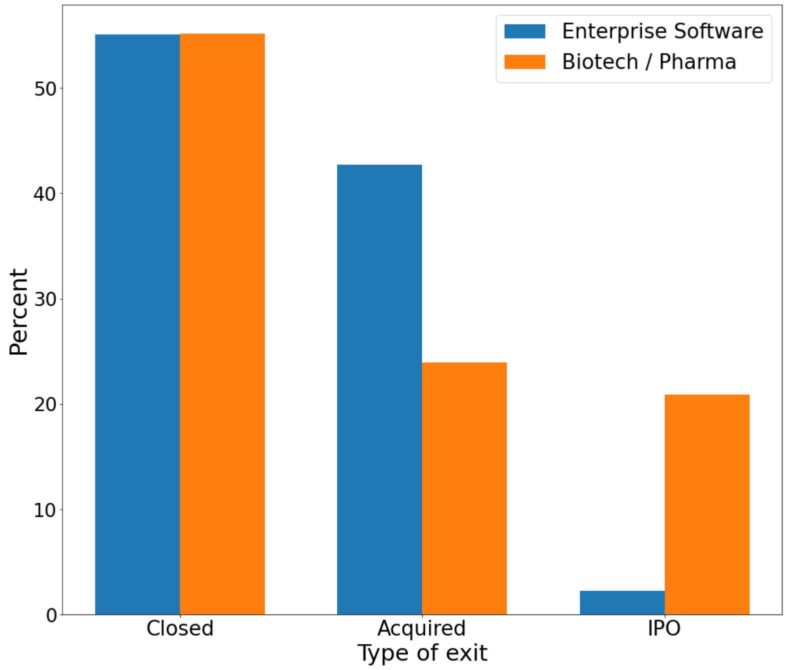


Figure G.1: This Figure shows the type of exits of all US-based startups on *Crunchbase* that were founded after 2001 and exited in 2005-2020, either via acquisition or IPO, and that belong to either the biotechnology & pharmaceuticals or enterprise software industries. Details on the industry definitions are provided in Appendix G.1.

remarkably similar (55%) for startups active in both industries[G10], Out of all successfully exiting startups in enterprise software, 95% exit by acquisition. In the biotechnology and pharmaceutical industry, the common exit routes are strikingly different: here, 53% of successful startups exit by acquisition. The finding highlights once again that motives for entry and acquisitions might be fundamentally different across industries (due to different production technologies etc.), and that within-industry studies are needed to fully comprehend the effects of startup acquisitions.

More recently, startups have been able to postpone their exit and stay private for longer. In those cases, early investors have often sold their shares to investors specialized on later-stage companies (so-called crossover investors). I do not consider those cases here.

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G10. This rate is in line with empirical finance literature: Kerr, Nanda, and Rhodes-Kropf (2014) find that 55% of startups that received VC funding were terminated at a loss.

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