Entry and Acquisitions in Software Markets*

Luise Eisfeld†

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Abstract

How do acquisitions of young, innovative, venture capital-funded firms (startups) affect firms' incentives to enter a market? I create a product-level dataset of enterprise software, and use textual analysis to identify competing firms. Motivated by new stylized facts on startup acquisitions in software, I build and estimate a dynamic model of startups' entry decisions in the face of these acquisitions. In the model, acquisitions can affect returns to entry (1) by affecting market structure, and (2) by providing an entry-for-buyout incentive to potential entrants. Using the parameter estimates, I simulate how startup entry would evolve over time if merger control was tightened. The simulations reveal that, if all startup acquisitions were blocked, entry would decline on the order of 8-20% in some markets. In contrast, I find suggestive evidence that blocking mergers between established industry players and more mature startups might increase entry. These findings indicate that case-by-case merger review can best foster sustained startup entry.

Keywords: Mergers and Acquisitions, Entry, Startups, Enterprise Software, Innovation
JEL Classification: G34, L22, L26, L49, L86, M13

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†University of Lausanne, Faculty of Business and Economics (HEC Lausanne), 1015 Lausanne, Switzerland. Email: luise.eisfeld@unil.ch.

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* into a given market? By their nature, software industries tend to be dominated by large incumbents. New, innovative entry is thought to be the main dimension of competition in these markets.[1]

On the one hand, the anticipation of being acquired can provide an entry-for-buyout incentive if the returns from the merger are higher than the returns from competing (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.[2] Acquisitions are reportedly a major goal for startup founders and their investors.[3] 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 new entrants will be facing. An acquisition can transfer both market power and synergystic value to the acquired startup, allowing it to become a stronger competitor and to capture a larger market share. This can *decrease* the returns to new entry, and render a market niche into a so-called "kill zone" where entry and investment are not profitable (Kamepalli, Rajan, & Zingales, 2021).

I study startups' entry incentives in the face of acquisitions (1) by collecting and assembling new data that enable 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 in a stylized way. The model is novel in that it builds on approaches developed to model entry, but also captures the unique motives and financial realities of venture-funded startups.

Answering the research question requires to accurately define *markets*, i.e., sets of companies that produce substitutable products and that interact strategically with each other. To obtain such a notion of competing firms, I construct a new dataset by web-scraping product-level data from *Capterra*, a vertical search engine for enterprise software. As *Capterra*'s purpose is to assist consumer search, I take its product descriptions and categories and employ text-as-data methods to segment products into clusters of likely substitutes. Unlike previous literature that employs firm-level industry classification systems, this new approach enables the construction of granular markets at the product, instead of firm, level. I merge these product data with information on firms' entry and acquisition decisions stemming from *Crunchbase*.

[1]See Crémer, de Montjoye, and Schweitzer (2019), Scott Morton, Jullien, Katz, and Kimmelman (2019), and Furman, Coyle, Fletcher, Marsden, and McAuley (2019).

[2]Author's computation, using a sample of enterprise software startups with successful exits in 2005-2020 from the data portal *Crunchbase*. In contrast, only 50% of startups in the biotech or pharmaceutical industry exit via acquisition. See Appendix C.11.2.

[3]Venture capital investors typically manage closed-ended funds, and thus wish to divest from their investments typically after a period of 7-10 years. Thinking about exit opportunities early-on is thus deemed crucial; see Section 2 for more background on this.

The data produce new, policy-relevant descriptive facts on startup acquisitions in software markets. I find that acquisitions of particularly young startups are very prevalent in enterprise software. Recent policy discussions have focused on a few dominant incumbents (in particular, on the so-called GAFAM[4]). However, the data reveal that other acquirers show a similar pattern of acquisitions. At the same time, acquisition patterns in software are markedly different from observed patterns in biotechnology or pharmaceuticals, which motivates the industry-level focus of this study.

I distinguish between different types of acquirers along the dimensions of industry incumbency and measures of size, and argue that these acquirer types are likely driven by different motives. I call acquirers that, like the target, are active in enterprise software, *strategic acquirers*. Strategic acquirers are the most likely to possess the capabilites and the incentives to drive down the payoffs to entry ex post. This can manifest either anti-competitively - by leveraging market power into new markets (Carlton & Waldman, 2002) or creating ecosystems (Heidhues, Köster, & Kőszegi, 2024) - or pro-competitively through synergies. In contrast, companies outside enterprise software (e.g., manufacturing firms) seem to acquire enterprise software startups to vertically integrate new tools, and should not have incentives to affect a particular software market's development in the long run. Finally, financial acquirers tend to be transitional owners, seeking financial returns rather than aiming to influence long-term market dynamics.

Presumably, all types of acquirers may generate an entry-for-buyout incentive, whereas only acquisitions conducted by strategic acquirers can lead to entry-deterring effects. I compare entry patterns in the quarters following major acquisitions conducted by either financial or strategic acquirers, akin to an event study framework. The results indicate that major acquisitions conducted by strategic, but not financial or unrelated, acquirers 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. Quantifying these two channels requires a structural model of startup entry that can account for and disentangle the two. I thus set up a dynamic model that can explain startups' entry decisions in a stylized way, and that captures the realities of a venture capital-funded firm. In the model, in each period and in each market, a new set of forward-looking potential entrants considers whether to enter the market.[5] Upon entry, firms obtain flow payoffs every period. These flow profits depend in a reduced-form way on market structure; in particular, on the number of competitors, as well as on large, strategic acquisitions of competitors in the past. In future periods, firms may moreover be acquired themselves, or be listed on the public stock market. Whenever such a transition in ownership occurs, firms stop earning flow profits, and instead earn a single lump-sum return. Future acquisitions and listing events are modeled as stochastic shocks that arrive upon the startup with varying frequencies across markets, and are assumed exogenous conditional on proxies for market size. 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, the entrants form beliefs about the likelihood with their owners can "exit" (in a financial sense) either

[4]This acronym refers to the firms *Google (Alphabet)*, *Amazon*, *Facebook (Meta)*, *Apple*, and *Microsoft*.

[5]The model therefore does not endogenize the decision regarding the timing of entry; nor the decision to exit a market; nor the decision which market to enter.

by being acquired, or by going public. 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 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 at a higher frequency also display higher startups entry, conditional on proxies for market size. Moreover, reflecting the findings of the event study, certain types of acquisitions – those conducted by major industry incumbents and targeting more mature startups – are followed by a decline in entry. The overall effects from banning all or a subset of acquisitions are determined by the magnitudes of both channels. Based on preliminary counterfactual simulations, I find that startup entry may decline if all startup acquisitions were blocked. In particular, in markets in which the profits from competing are low relative to the returns from being acquired, entry drops in the order of 8 to 20% in the counterfactual. In those markets, the entry-for-buyout incentive is strong, and firms barely enter in order to compete. In contrast, if we allow for a causal interpretation of strategic acquisitions, blocking only mergers conducted by large, strategic acquirers would boost entry by over 4% in affected markets. Overall, this suggests that, in order to foster entry, competition authorities should continue reviewing mergers on a case-by-case basis.

Both the descriptive and the model-based findings that this paper generates are of first-order importance from an antitrust perspective. The types of acquisitions that are the focus of this paper are "stealth mergers" (Wollmann, 2019) that rarely meet merger notification thresholds, 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.[6] At the same time, software is an industry where entry is highly valuable, as strong network effects can lead markets to "tip" in favor of a single incumbent. The competitive forces ensuring that incumbents have sustained high rates of innovation therefore come from potential entrants competing *for* the market, instead of companies *within* the market. This has led antitrust regulators to claim that digital platforms could "buy their way out of competing", as Lina Khan, the current Chairperson of the US Federal Trade Commission, phrased it (Khan, 2021).

By studying innovative entry, this paper is linked to the long-running question of how firms' innovation incentives are affected by their competitive environment, going back to Schumpeter (1942) and Arrow (1962). Moreover, entry dynamics and the motives of acquisitions in software markets are still poorly documented and understood.[7] As these markets are bringing vast welfare gains in the years to come, understanding any frictions that entering startups face is economically important.

Literature. This paper has two main contributions to the literature. New findings on startup acquisitions and entry in software markets, of both descriptive and model-based nature, make up the first contribution. The first distinction with respect to existing literature on startup acquisitions in technol-

[6]According to a report by the US Federal Trade Commission, the GAFAM conducted 618 acquisitions (excluding patent acquisitions or hiring events) in 2010-2019 (Commission, 2021). 85% of those acquisitions took place below the reporting thresholds provided by the Hart-Scott-Rodino Act.

[7]For instance, it is not documented whether "killer acquisitions" (Cunningham, Ederer, & Ma, 2021) are as common in software as in pharmaceutical markets. It is also not ultimately clear whether acquisitions concern mostly targets that are active in the same core market as the acquired company, or in complementary markets.

ogy markets is that, to my knowledge, this paper is the first to build and estimate a structural model that disentangles different channels through which acquisitions can increase startup entry. A second distinction is in respect to the level of focus on a particular firm or industry. One strand of previous empirical literature has centered on the GAFAM or few other firms, and has characterized patterns of acquisitions and follow-on market evolution (Affeldt & Kesler, 2021a, 2021b, Argentesi et al., 2021, Gautier & Lamesch, 2021, Ivaldi, Petit, & Unekbas, 2023). Another strand looks at the link between M&As and innovation or business dynamism from a macro perspective using cross-industry data and studying general equilibrium effects (Fons-Rosen, Roldan-Blanco, & Schmitz, 2023, Vaziri, 2022), calibrates a model to study the effect of different merger control regimes on welfare (Cabral, 2023), or models firms' acquisitions and innovation decisions (Cortes, Gu, & Whited, 2022). My perspective lies in between those approaches: I study acquirers beyond the GAFAM, which allows for comparisons of the big five acquirers to other acquirer types, and for more general conclusions. At the same time, however, I focus on acquisitions of startups active in a single industry – enterprise software. To my knowledge, this has only been done by G. Z. Jin, Leccese, and Wagman (2022) in technology markets, or by Cunningham et al. (2021) for pharmaceutical markets. My dataset thus covers an entire industry branch and tens of thousands of companies, but at the same time enables me to follow acquisitions at the *product* level. I can thus characterize the effects of acquisitions in software at a higher level of granularity compared to earlier work (coming somewhat closer to data used in the context of the pharmaceutical industry, where project-level data is abundant, but where acquisition motives and patterns are markedly different[8]).

To generate these new insights, I create a comprehensive dataset of software products, and I apply textual analysis to delineate which firms compete with each other. Such an approach has been pioneered by Hoberg and Phillips (2016), who employ textual analysis to 10-K reports of publicly listed firms. In contrast to those authors, however, I use a text base that covers *private* firms (which in fact constitute 95% of companies in my dataset, see Table 1). I moreover define markets on the product, as opposed to the firm, level, which allows for multi-product companies being active in multiple markets. Textual analysis to distinguish industries and to define competitors is increasingly made use of in academic literature, especially when the focus is on the digital services industry. Decarolis and Rovigatti (2021) define competing advertisers in the context of online ad auctions by means of textual analysis, and I follow their methodology for word vectorization. Leyden (2022) clusters mobile apps into categories using natural language processing and machine learning techniques.[9]

The second contribution is a model that allows to disentangle and to quantify two channels – one ex-ante, one ex-post – through which acquisitions can affect returns to entry. Previous empirical literature focuses on only one of these channels by means of reduced-form techniques. Investigating ex-post effects of GAFAM-acquisitions, prior research has examined measures of VC investment (Bauer & Prado, 2021, G. Z. Jin et al., 2022, Kamepalli et al., 2021, Koski, Kässi, & Braesemann, 2020), patent count (Gu-

[8]See, e.g., Cunningham et al. (2021), Khmelnitskaya (2021), or Majewska (2022).

[9]Even in competition practice, the use of textual analysis for defining markets is seemingly at the forefront of innovative approaches to define markets in the context of merger cases: see https://www.compasslexecon.com/the-analysis/using-natural-language-processing-in-competition-cases/03-22-2022/ and https://www.compasslexecon.com/measuring-of-competition-using-natural-language-processing/, both accessed 18/12/2022.

gler, Szücs, & Wohak, 2023, Warg, 2021), and citations of acquired patents (De Barsy & Gautier, 2024). Speaking to an ex-ante entry-for-buyout channel, Warg (2021) finds that startups "cater" to potential acquirers by investing into adjacent technology areas that may be useful for potential acquirers, and Phillips and Zhdanov (2013) find for a sample of public firms that R&D expenditures increase in expectation of an acquisition. The counterfactual scenario in which all acquisitions are blocked, however, depends on both effects. A linear regression cannot disentangle the different channels of effect that are associated with acquisitions. The model I set up explicitly intends to quantify the two channels, which allows to simulate how entry would evolve under counterfactual antitrust regimes. The most closely related work that incorporates entry decisions into a dynamic structural model, among various other firms' decisions, can be found in the studies by Igami (2017) and Igami and Uetake (2020). However, these papers address different research questions and focus on analyzing a single mature market, leading to a much smaller number of economic agents whose decisions are modeled. Consequently, my modeling approach diverges significantly due to these variations. The descriptive findings of this paper shed new light on startups' commercialization strategies, as highlighted in Gans and Stern (2003).

Prior theoretical research has pointed out a potential entry-deterring effect of acquisitions. Possible theoretical mechanisms by which an acquisition can deter entry are strategic tying (Carlton & Waldman, 2002, Whinston, 1990), the creation of an ecosystem that controls crucial access points (Heidhues et al., 2024), entrenchment of an incumbent via cumulative acquisitions (Denicolò & Polo, 2021), or a lack of early product adoption in the presence of switching costs and network effects (Kamepalli et al., 2021).[10] I am the first to quantify any potential negative effect of acquisitions on entry with the help of a structural model of entry, but my results cannot speak to the precise source of any decline in entry, or potential welfare effects.

More broadly, this paper contributes to the open question on the link between market structure (including mergers and breakups) and innovation. This paper therefore relates to theoretical models, some of which emphasize the entry-for-buyout effect (Hollenbeck, 2020, Jullien & Lefouili, 2018, Mermelstein, Nocke, Satterthwaite, & Whinston, 2020, Nocke & Whinston, 2010), as well as empirical studies of mergers or antitrust enforcement and innovation (Haucap, Rasch, & Stiebale, 2019, Poege, 2022, Watzinger, Fackler, Nagler, & Schnitzer, 2020). Finally, I contribute to research studying the enterprise software industry (see Cockburn and MacGarvie (2011) and Huang, Ceccagnoli, Forman, and Wu (2012) for work on the relationship between intellectual property and market entry).

Roadmap. The paper is organized as follows. I cover the data construction in Section 2, and extensive 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 covers its estimation. Section 6 presents the results and covers the counterfactual simu-

[10]For a more thorough elaboration of possible entry-deterring effects outlined by the abovementioned theory literature, see Appendix B. Further literature has described conditions under which incumbents have an incentive to merge with a nascent competitor in order to discontinue the target's product and remove a future competitor (Cunningham et al., 2021, Motta & Peitz, 2021). Moreover, theoretical literature has proposed further implications of the acquisitions of nascent competitors, such as effects on the direction of innovation, which however I cannot speak to (Bryan & Hovenkamp, 2020, Cabral, 2018, 2021, Callander & Matouschek, 2020, Dijk, Moraga-Gonzàlez, & Motchenkova, n.d., Fumagalli, Motta, & Tarantino, 2022, Gilbert & Katz, 2022, Guéron & Lee, 2022, Hege & Hennessy, 2010, Katz, 2021, Letina, Schmutzler, & Seibel, 2023). Lemley and McCreary (2020) propose policy changes that provide alternatives to acquisitions as exit routes, thereby likely fostering startup entry.

lation. Section 7 discusses the findings and assumptions. Section 8 concludes.

2 Setting, Data, and Market Definitions

2.1 Setting: Startup Entry in Enterprise Software

I study startup entry in the *enterprise software* industry, by which I refer to any software product that can be used in a business environment. This definition captures both, products that are targeted specifically to business clients (i.e., B2B software such as customer relationship management software or accounting software), as well as products for use in both professional as well as private contexts (such as filesharing software).[11]

The choice of the industry is motivated by two facts. First, acquisitions of startups are a very prevalent feature in the enterprise software industry. In fact, the companies acquiring the highest *number* of startups of any industry worldwide are mostly active in software. The presence of substantial industry-level differences in the rates of startups exiting the industry via acquisition, as opposed to via IPO (see Appendix C.11), suggests that the motives of entry and of acquisitions might be software specific, and therefore warrant an industry-level investigation.

Second, the enterprise software industry is large and growing. Between 2005 and 2020, enterprise software startups received more VC funding than all startups belonging to the biotechnology and pharmaceuticals industry (see Appendix C.10). Enterprise software is likely to bring along important welfare gains in the years to come. Software enables the adoption of new technology in enterprises, such as cloud computing or analytics, which can substantially reduce costs or increase efficiency.[12]

I consider entry by *startups*, by which I refer to young, risky, very innovative, VC-backed, privately held companies. These firms tend to play an outsized role for innovation, industry dynamics, and welfare.[13] Upon being founded by entrepreneurs, startups obtain staged rounds of capital injections, primarily by groups (syndicates) of VC investors. These financial intermediaries are specialized in providing funding, as well as advice, to these risky, but potentially high-growth firms in exchange for an equity stake. VC investors manage closed-ended funds, which implies that they need to divest after a period of 7-10 years. Optimally, a startup makes 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 C.11.2). Both of these events are generally considered a success, and may yield a high return to investors and founders. However, roughly half of all startups end up failing, yielding no or little return.[14]

All GAFAM firms, which are at the heart of policy debates, are active in the enterprise software industry. Moreover, there exists anecdotal evidence for the entry-for-buyout as well as the kill zone effect

[11] This definition therefore excludes software products for uniquely private use, such as gaming or social networks.

[12] Berman and Israeli (2022) for instance find that the adoption of analytics dashboards by e-commerce websites increases firms' weekly revenues by 4-10%.

[13] In the past, startups have redefined markets and out-competed large incumbents in some industries. Startups tend to bring forward more inventions (Kortum & Lerner, 2000), as well as higher quality and more novel inventions (Schnitzer & Watzinger, 2022), than established companies. VC-funded startups have contributed to economic welfare in meaningful ways, as illustrated recently with *BioNTech*'s development of Covid-19 vaccines.

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

in this industry, For anecdotal evidence of the entry-for-buyout and kill zone effect in the enterprise software industry, see Appendix sections A.1 and A.2.

2.2 Data

Answering the research question requires data on companies' actions – in particular, on entry and acquisition decisions – in clearly defined markets. I obtain information on firms' actions from the data portal *Crunchbase*. To distinguish which firms actually compete with each other, I additionally web-scrape data product characteristics and descriptions from *Capterra*, a vertical search engine for enterprise software. The web-scraped product-level data allows to use text-as-data methods to classify products into distinct markets, and to produce new descriptive findings on startup acquisitions in software.

The final dataset used for the reduced-form analyses and structural model is a market-quarter panel detailing the number of entering firms, number of competitors, and types and number of acquisitions, in over 400 different markets.

2.2.1 Firm-level Panel: *Crunchbase*

Crunchbase is a data portal that tracks financial information on over a million public and private companies, in particular VC-funded firms. It records companies' founding dates, funding rounds, acquisitions, investments into other companies, initial public offerings (IPOs), and closures. Unlike other financial databases, having received a VC investment is not a pre-condition for being present on this database. *Crunchbase* is well-established in the empirical finance literature, and is believed to capture early-stage funding rounds and acquisitions of small sizes especially well compared to other data sources (Z. Jin, 2019, Yu, 2020).

I use *Crunchbase*'s "Glossary of Funding Types" (Crunchbase, 2022), industry reports, and prior literature as guidance to know which types of investments to classify as venture capital.[15] I then define "startups" as companies that have received at least one such VC-type investment. I further define a startup's "entry" event as the first VC-funding round for a firm in my data.[16] *Crunchbase* itself defines acquisitions as majority takeovers. Using information of all acquisitions in a company's lifetime, I then reconstruct the parent-subsidiary structure of all firms over time.[17]

[15] I define investments of the following types as being VC investments: *Angel*, *Pre-Seed*, *Seed*, *Series A* to *Series J*, *Series Unknown*, *Corporate Round*, *Undisclosed* and *Convertible Note*. I consider VC investments as financial investments into very early-stage, high-risk companies. The listed investment types' descriptions in *Crunchbase*'s *Glossary of Funding Types* match these characteristics (Crunchbase, 2022). Thus, investment types such as, for instance, *Post-IPO Debt*, *Grant* or *Product Crowdfunding* are not considered as typical VC investments. See Appendix C.2 for details.

[16] 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. I do not view this as a restriction, but rather a feature: this way, one can interpret entry decisions as being taken jointly by investors and entrepreneurs. The literature typically assumes that investors are rational, forward-looking agents who take into account the prospects of exit and the development of the market environment when deciding to fund a company in a given market. The decision of focusing on the first round of financing is moreover driven by the fact that founding events in standard databases are typically ill defined: in principle, they could signify, for instance, the date at which the founders first got together; the date of product launch; the date of incorporation; etc., and it is unclear whether these capture market entry very well.

[17] With help of the parent-subsidiary structure, one can classify acquisitions in which, e.g., LinkedIn acquires a firm after itself having been acquired by Alphabet, as a GAFAM-acquisition.

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

The *Crunchbase* dataset also contains information on a startup's industry in the form of industry labels and descriptive text. However, *Crunchbase* alone is not sufficient to perform a market-level analysis of entry and acquisitions, for reasons associated to the labels being too broad and vary on the firm, as opposed to on the product, level, which is inaccurate for conglomerates that span many markets (see Appendix C.3). Alternative industry classifications, among them the text-based ones pioneered by Hoberg and Phillips (2016), are available for public firms only.

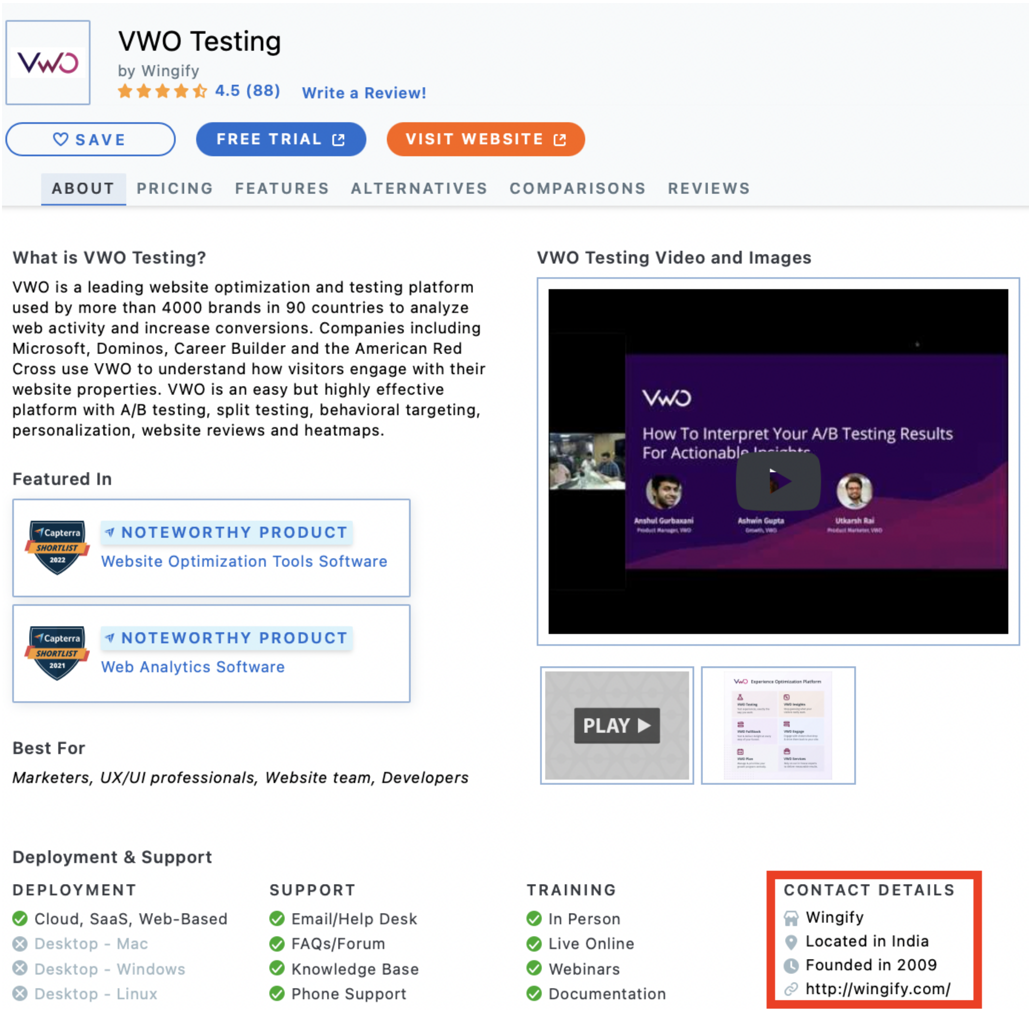


Figure 1: Example of product page on *Capterra*. The red frame highlights the company information (in particular, name and URL) available for all products on *Capterra*.

I therefore obtained the permission to web-scrape information from a platform called *Capterra*. The platform provides one of the leading vertical search engines for enterprise software, and is thus designed to assist customers with comparing and finding suitable enterprise software products. The website classifies enterprise software products into at least one of 821 narrow categories – for example, "Audio Editing Software", "Conference Software" or "Spreadsheet Software". It provides descriptive text, information on the producing company, as well as user reviews and ratings for each product (see Figure 1). The range of enterprise software products covered on *Capterra* is exhaustive and up-to-date. By virtue of being a search engine that assists consumers with finding suitable business software, *Capterra* has an incentive to provide accurate product categories and descriptions. This setting therefore offers a natural structure that can be used to identify substitutable and thus competing products.

I hence query all existing product pages from *Capterra* as of June and July 2021. I download and save, among others, product and company names; the categories that a product is assigned to; the company's web domain; a text describing the product; and the user rating as well as the cumulative number of user reviews. Details on the web-scraping process can be found in Appendix C.4.

In summary, I make use of the *Capterra* data for the following purposes: first, the textual data allows to cluster products into groups of substitutable products, with the help of a pre-trained data set stemming from a machine learning model that allows me to vectorizes the textual data (see Section 2.2.3). Second, the data indicates which enterprise software startups' products are actually active and available as of July 2021. Third, the information on the number of reviews yields an indication of whether a given product is being used at all. This allows me to differentiate companies that are actually "relevant" competitors that act strategically in a given market, and which ones might be considered a non-strategic fringe.

2.2.3 Matching *Capterra* to *Crunchbase* data

I match products on *Capterra* to their respective firms on *Crunchbase* using company URL and company name. I ensure I match products whose companies were acquired in the past to their *originating* firm profile on *Crunchbase*, as opposed to the acquiring firm's profile, with the help of the names and URLs of all *targets acquired* in the past by each active acquirer. Details of the matching procedure are provided in Appendix C.5.

71% of all web-scraped products (accounting for 96% of products with over 100 reviews) are hereby matched to firms on *Crunchbase*. Almost all remaining non-matched products do not have many reviews, and are thus likely insignificant competitors that do not play a major role in this market. Manual checks confirm a high accuracy.

A potential issue is that the *Capterra* data, being cross-sectional in nature, does not contain information on products provided by companies that were shut down in the past. From the remaining firms in the *Crunchbase* data, I therefore include firms into my sample that (1) are enterprise software related based on their descriptive text, industry group or industry variable, and that (2) have in the past been acquired by an enterprise software firm (i.e., by a firm that owns a product on *Capterra*). Essentially, the products are not present on *Capterra* as of 2021, even though they should have been, had their products been continued. Figure 2 summarizes the types of firms that are part of the sample. Appendix C.6 provides further explanations as well as evidence against potential selection issues.

The final dataset contains 46,186 currently existing products that were matched to *Crunchbase*, as well as information of 5,034 additional enterprise software companies that were acquired in the past and whose products are not existing under the same name on *Capterra* any more.

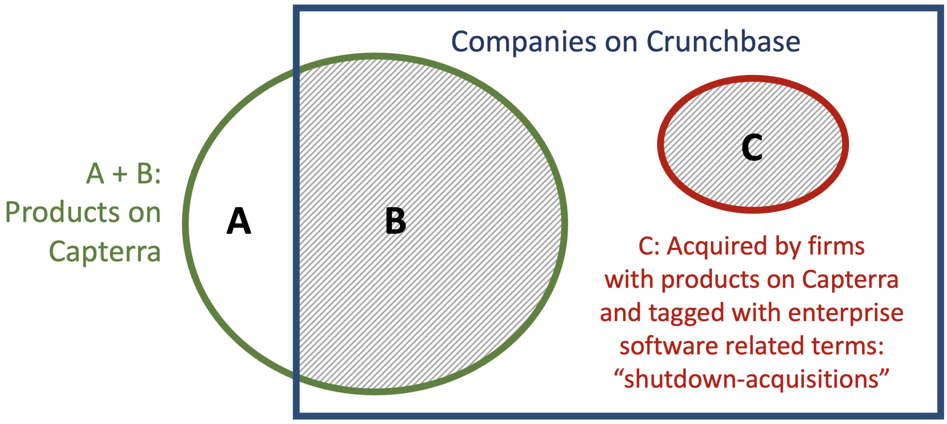


Figure 2: Illustration of sample construction. The hatched areas (B and C) point out the sample used. Set B is obtained by matching *Capterra* products to *Crunchbase* firms. Set C is added to account for enterprise software companies acquired in the past, but shut down as of 2021. Set A is the (likely insignificant) set of products on *Capterra* that was not matched to companies on *Crunchbase*. (Figure is not to scale.)

2.3 Defining Markets using Textual Analysis

I create markets of substitutable products by using text-as-data methods (see Gentzkow, Kelly, and Taddy (2019) for a review). Each product on *Capterra* is associated with a body of text. This text consists of the names of one or more software categories, and of the product description. As a given product may be associated to more than one category, one cannot create disjoint sets of products using *Capterra*'s categories alone. I therefore (1) extract keywords contained in the category name or in the descriptive text, (2) vectorize this textual data (following Decarolis and Rovigatti (2021)), and (3) use a clustering algorithm that creates non-overlapping groups of likely substitutable products.

The textual information on *Capterra* are informative about a product's functionalities, in the sense that companies present in the same (or similar) categories, and described with similar keywords, should be more substitutable. I build a dictionary of meaningful keywords by using all *category names* (e.g., “filesharing” for “Filesharing Software”), as well as additional keywords that are frequently occurring in *Capterra*'s product description. Details can be found in Appendix C.7.

To cluster all products into disjoint markets, I first embed the textual information into a vector space that carries linguistic meaning. I follow the approach taken by Decarolis and Rovigatti (2021): I first match each keyword, for instance, “file-sharing” or “collaboration”, to a pretrained word vector stemming from *GloVe*, an unsupervised learning algorithm for obtaining vector representations for words (Pennington, Socher, & Manning, 2014).[18] I thereby place each keyword at a certain location within a 300-dimensional vector space. Synonyms and terms that are linguistically close to each other tend to be located close to each other in this space. For each product, I then take the average of all its word vectors, so that each product is associated with a single location.

Next, I cluster products (based on their respective locations in the vector space) into distinct markets

[18] The word vectors were trained on Common Crawl, i.e., textual data stemming from craweling the web, which is very suitable for my purpose.

using a k-means clustering algorithm (see Appendix Section C.8). Products whose vectors are located close to each other, and thus, whose descriptors are close in meaning, will be clustered into the same product group.

The k-means algorithm requires the researcher to provide a number of segments ex ante. I employ the silhouette score as guidance, which measures the goodness of a given clustering technique. I find that clustering into 500 to 600 markets maximizes the silhouette score, and results in reasonable market definitions based on various manual validation checks. For instance, when comparing my market definitions to the market definitions from merger decisions by the UK Competition and Markets Authority, I find that the majority of products are correctly categorized as substitutes (see Appendix Section C.9).

Number of products	25,552
· Percent of products alive	80.9%
Number of companies	21,419
· Percent of companies ever VC-funded in 2012-20	63.9%
· Percent of companies ever public in 2012-20	4.5%
Number of acquisitions	6,778
· Percent in which target is VC-funded	42.4%
Number of IPOs	384
· Percent in which firm going public is VC-funded	54.4%

Table 1: Basic descriptives of entire matched data, 2012-2020. I do not count LBOs or management buyouts as acquisitions.

	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
"Pre-event" firms (count)	4.396	4.926	1	3	6
VC-funded, pre-exit startups (count)	15.362	15.377	5	10	20
Acquired & alive startups (count)	1.547	2.149	0	1	2
Public firms (count)	3.777	3.721	1	3	5
Startups entering (count)	0.651	1.033	0	0	1
Startups acquisitions (count)	0.161	0.542	0	0	0
Startups IPOs (count)	0.020	0.141	0	0	0
Startup acquisitions: transaction price (US$)	395.2	945.8	40	130	360
Startup IPOs: valuation (US$)	3,774.7	13,875.4	352	885.4	2,165.2

Table 2: Descriptives using market-quarter panel, comprising 474 markets (after dropping outlier markets), 2012-2020. "Pre-event firms" are companies that are less than 3 years old (based on their founding date) and have not recorded any other event yet (in particular, no funding round). I do not consider these as startups.

Table 1 shows basic descriptive statistics of the matched raw dataset for the period of 2012 to 2020. The dataset covers a sample of over 20,000 firms. The majority of these firms – 64% – are VC-funded. In contrast, only 4.5% of producing companies are (at any point in the observation period) public firms, showing that much relevant entry behavior would be missed if one were to use only data on public firms. Table 2 exhibits descriptives on the market-quarter panel, showing that many of the variables tend to be right skewed.

3 Stylized Facts

This section lays out empirical facts that motivate the research question, guide the modeling assumptions, and are building blocks towards the model-based results. I distinguish and document different types of acquirers, along the dimensions of whether the acquirer is active in the industry sector of enterprise software, and based on measures of age (Section 3.1). The findings can be summarized as follows:

1. Different types of companies are active as potential acquirers.
2. Many acquired products are discontinued (Section 3.2).
3. There is suggestive evidence that most acquisitions are nonhorizontal (Section 3.3).

3.1 Distinguishing Different Types of Acquirers

I identify three main types of acquirers.

- *Companies in enterprise software*: these companies have existing, own-developed products on *Capterra*. I call these acquirers that are themselves active producers of enterprise software *strategic acquirers*.
  - Examples: the so-called GAFAM; Cisco; Oracle; Salesforce; VMware.
- *Financial companies*: these companies are active in finance, based on *Crunchbase* information.[19] Among these are private equity firms. I call these acquirers *financial acquirers*.
  - Examples: Vista Equity Partners; TransUnion; Thoma Bravo.
- *Other industries, i.e. companies outside of Enterprise Software and Finance*: these companies do not have existing products on *Capterra*, and are thus mainly active in other, at times unrelated, industries. I call these companies *outsider acquirers*.[20]
  - Examples: The We Company; Verizon; McDonald's; Samsung Electronics; Ericsson.

The percentages of these three main acquirer types are displayed in Figure 3. Over 65% of acquisitions of exiting startups are conducted by other industry peers. 14% of acquisitions are carried out by financial firms, and 20% 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 D.

I divide enterprise software acquirers into further (non-exhaustive) sub-groups along the measures of age or firm maturity, and innovativeness (measured as having received VC funding in the past). Moreover, I segment the GAFAM firms from the others, as the former have been the focus of attention by competition policy practitioners, and are deemed to be especially dominant in many markets. These

[19] To do so, I use *Crunchbase*'s industry tags. Moreover, *Crunchbase* tags companies that act as investors with an "investor type" variable (this may be, for instance, "Investment Bank" or "Private Equity Firm").

[20] Among these are also holding companies: I define these as all companies that do not produce software products themselves, but acquire software companies and seem to hold software products in a portfolio. Using *Crunchbase*'s industry tags, I find that over half of Industry Outsider acquirers are active in related industry sectors, such as (other) software (e.g., StackPath), advertising (e.g., Amobee), data/artificial intelligence (e.g., Amdocs), media/content (e.g., Groupon), or hardware/telecom (e.g., Verizon). The other half of Industry Outsider acquirers is active in unrelated industry sectors, such as transportation, consumer products, e-commerce, or biotech.

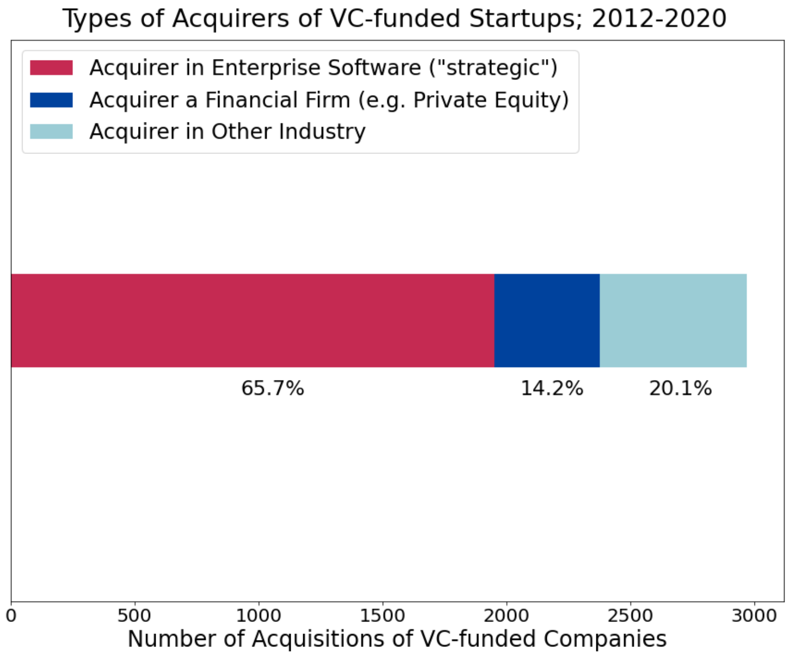


Figure 3: Types of acquirers for first-time acquisitions ("exits") of VC-funded startups worldwide in the domain of enterprise software, for acquisitions occurring between 2012 and 2020. The total number of such acquisitions is 2,973. Acquisitions are counted on the company (as opposed to the product) level. I exclude acquisitions of the types LBO or management buyout.

Sub-dividing strategic (enterprise software) acquirers

Acquirer subtype (# of startup acq)	Description	Examples
GAFAM (156 acq)	Google (Alphabet), Apple, Facebook (Meta), Amazon, Microsoft and their subsidiaries.	GAFAM; subsidiaries such as LinkedIn, AWS, GitHub.
Old tech (190 acq)	Public companies founded prior to 1995 with over 10,000 employees.	Cisco, Oracle, VMware, SAP, Dell EMC, HP Enterprises, IBM, Adobe.
New tech (174 acq)	Companies founded 1995 or later that started off as VC-funded companies, but that have exited.	Salesforce, Palo Alto Networks, Workday, Servicenow.
Pre-exit (630 acq)	VC-funded startups acquiring at a time at which they have not "exited" (been acquired / gone public) yet.	Sprinklr, Freshworks, Ignite Technologies, Dropbox, DataRobot, Stripe, Hootsuite.

Table 3: Definitions of subgroups of enterprise software acquirers. These groups are distinct, but not exhaustive. The number of acquisitions focuses on exiting VC-funded startup acquisitions that were carried out in the years of 2012-2020. (For the category "new tech", using only VC-funded companies avoids taking into account spin-offs from older companies that have a very recent founding date, such as Hewlett Packard Enterprise.)

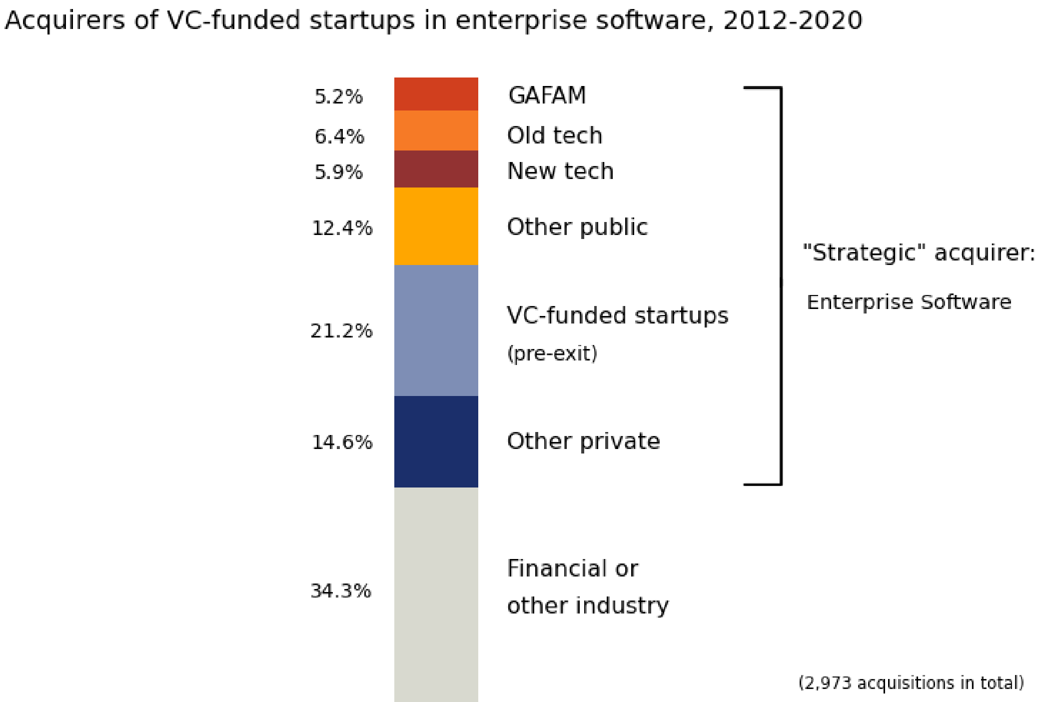


Figure 4: Subgroups of acquirers for first-time acquisitions ("exits") of VC-funded startups worldwide in the domain of enterprise software, for acquisitions occurring between 2012 and 2020. As in Figure 3, the total number of such acquisitions is 2,973; the numbers are on the company (as opposed to product) level; and I exclude acquisitions of the types LBO or management buyout.

sub-groups are detailed in Table 3, and their proportions are shown in Figure 4. Note that companies may switch between these categories as they grow: for instance, Dropbox acquisitons are contained in the category *pre-exit* for the years in which Dropbox had not exited yet, and are contained in the category *new tech* after Dropbox has become a public company.

An interesting and perhaps surprising fact is the scale at which *other* startups appear to be a major exit route for growing startups: companies within the groups GAFAM, Old Tech and New Tech conducted each roughly 150-200 startup acquisitions in the years of 2012-2020, whereas pre-exit firms account for over 600 startup acquisitions. Therefore, out of all startups exiting via acquisition in 2012-2020 in the domain of enterprise software, 21% were sold to other startups. In contrast, only somewhat more than 5% were sold to GAFAM firms.

3.2 Many Acquired Products are Discontinued After the Acquisition

As explained in Section 2.2.3, the data I created contain companies that were acquired in the past, but whose products are not available any more under the same brand name. For acquisitions of VC-funded, enterprise software related startups in 2012-2020, I find that in a majority – 57% – of acquisitions, the product brand must have been discontinued after the acquisition, as of 2021. These numbers align with recent literature studying GAFAM-acquisitions: 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. The results presented here show that

Panel A: "Broad" groups of acquirers (exhaustive)

Acquirer type	**Discontinuations,** percent	**Discontinuations,** count
Enterprise Software	67.1%	1322
Financial	36.1%	153
Other Industries	38.3%	231
All acquirers	56.9%	1706

Panel B: Subgroups of enterprise software acquirers

GAFAM	80.8%	126
New tech	64.9%	109
Old tech	72.1%	137
Pre-exit	66.8%	432

Table 4: Discontinuations of products post-acquisition, for different types of acquirers, and for startups acquired in 2012-2020.

	Age: years since founding (median)	**Age**: years since first funding round (median)	**Price** in US$ million (median)
Products discontinued	6.2	4.0	100.0
Products kept alive	7.8	5.2	136.8

Table 5: Heterogeneity in age at acquisition and in transaction price, for startups whose products were either discontinued (top), or kept alive (bottom).

these findings carry over to non-GAFAM acquirers active in the software industry, and that shut-downs appear to be a widespread phenomenon in software.[21]

Shutdown rates vary by acquiring firms. Shutdowns are especially prevalent for acquirers that are enterprise software firms themselves (Table 4); these companies discontinue the acquired product in 67% of all acquisitions. Financial firms, in contrast, discontinue the acquired product in only 36% of all acquisitions.

The acquired companies whose products are shut down are at the median one to two years younger at the time of acquisition (Table 5), and are acquired at 75% of the price, compared to continued products[22]. The shutdown rate is even higher and amounts to 75% for companies that were acquired at an age of less than 3 years and that have not received any funding yet. These facts suggest that many of the shutdown products did not have a large share of demand at the time of acquisition, and possibly did not yet have a fully developed product. Appendix E contains further details on these acquisitions.

[21] Ivaldi et al. (2023) 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 E). 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.

[22] Not in Table. Prices are missing in 83% of shut-down acquisitions, and in 77% of continued acquisitions. As low prices not available in the data more often (Kerr, Nanda, & Rhodes-Kropf, 2014), the difference in median acquisition prices might therefore well be even higher.

3.3 Suggestively, Most Acquisitions Are Nonhorizontal

I call acquisitions "horizontal" if a startup supplies a product that competes with an acquirer's existing product in the same narrow market as of 2021. According to this definition, and using the above narrow market definitions, only 8% of all acquisitions of VC-funded startups in 2012-2020 can be classified as horizontal. Anecdotally, it seems that most acquisitions could instead be classified as either vertical, or conglomerate type.

However, there are caveats to this observation. First, it is impossible to obtain information on products that are in the development stage within the acquirer's boundaries: an acquirer acquiring a target supplying a product that is complementary to its internal research efforts (which are unobserved) are therefore not classified as being horizontal, according to this definition. The second caveat is that I take market defintions to be static, whereas a product's market might in principle change over time. These caveats point to the importance of future research in this area.

3.4 Discussion

What are the motives behind the shutdown acquisitions that I find? Product shutdowns could in principle be so-called killer acquisitions[23]. The data however suggest that these types of acquisitions might be rare in the context of enterprise software. First, the vast majority of acquired firms in this industry are very young and sometimes have not even raised a single funding round. Thereby, the bulk of firms seem to not be very likely to be a serious threat to a major incumbent such as Google. Second, the finding that most acquisitions are nonhorizontal makes them less likely to be killer acquisitions. Moreover, as Table 4 shows, shutdowns are prevalent among companies with much less market power than Google and the likes. Even startups that have not exited yet and that are very young shut products down in 67% of the acquisitions they undertake. Preexit startups or "new" tech firms account for a much larger share of discontinued startups than the GAFAM.

What may the purpose of acquiring and discontinuing products be? Anecdotally, 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.[24] Some of the transactions seem to be so-called acqui-hires in which the acquired startup's employees are paid to become part of the acquiring company.[25] 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

[23]Killer acquisitions comprise 5.3 to 7.4 percent of acquisitions in the setting of pharmaceuticals studied in Cunningham et al. (2021).

[24]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 07/08/2022).

[25]Examples are *Dropbox-Verst*, *Google-Bebop*, *Apple-Union Bay Networks*, *Twitter-tenXer*, and *Box-Wagon*. In 3% of startup shutdown-acquisitions, the *Crunchbase* data in fact indicate that the acquisition is an acqui-hire. 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.

target companies.[26] I have also found cases in which the product was rebranded. However, any rebranding seems to have gone along with a number of changes to the original product.[27]

The difference in the age profile of acquired startups between enterprise software and financial firms is in line with the fact that financial firms acquire tested products, as presumably these firms are interested in obtaining cashflows. In contrast, enterprise software firms might even be interested in acquiring startups whose products do *not* yet have a customer base. As software is based on communication protocols and programming languages, different pieces of software are interoperable, and software can be created in a modular way. Moreover, a startup producing a tool that is in principle functioning, or that was created by a capable team, might be an interesting target for another software firm even if these products failed to attract demand. This aspect is very different in the pharmaceutical market and may thus be an explanation for why we do not see as many acquisitions of very young startups in the domain of pharmaceuticals or biotech, as shown in Appendix C.11.

4 Reduced-form Evidence on Acquisitions and Entry

Acquirer types likely differ in important ways in their respective motives when acquiring startups. One can argue that only certain types of acquirers have the capabilities and the incentives to deter follow-on entry upon acquiring a startup in a market.

First, only firms active in the industry of enterprise software – which I call *strategic acquirers* – possess highly complementary assets (e.g., data, algorithms, a customer base, or human capital). Upon a merger, these could create synergies and improve the acquired product's capabilities to compete in a given market, thus deterring entry. Furthermore, Whinston (1990) and Carlton and Waldman (2002) show that a company that is a monopolist in market A can transfer monopoly power into a market B by the use of tying. This scenario relevant in software markets: as we have seen, acquirers tend to often buy startups in complementary markets and subsequently integrate product features.

The intentions and capabilities of strategic acquirers contrast with those of acquirers in financial and other industries. Financial acquirers tend to be private equity firms, which are typically transitional owners of the acquired firms, focused on generating cashflows in the medium term by changing a companies' management, with the intention of later reselling the company. For acquirers active in other industries, acquisitions in enterprise software may often be vertical integrations of software products. I also count as other industry an acquirer who does not produce software itself, but may be a holding company that hold a portfolio of software products and that yield stable returns.[28] Therefore, acquisitions by a non-enterprise software acquirer are transitions in startup ownership that should, however, not fundamentally affect market structure and competition in a way that deters follow-on entry.[29]

[26] 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*.

[27] 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 07/08/2022).

[28] Examples are *Valsoft* or *Ropers Technologies*.

[29] At best, the effect should be positive, for instance if the acquired product is subsequently used in-house, but discontinued to previous customers. New entrants should then expect more demand.

Therefore, I pose the following hypothesis:

- **Hypothesis**: Acquisitions conducted by a strategic acquirer may subsequently decrease entry into a given market. This effect should be stronger if the strategic acquirer is large. The effect is absent for acquisitions undertaken by a acquirers active in other industries.

I attempt to shed light on this hypothesis with the help of an event study framework. I employ quarter-market panel data ranging from 2012-2020, and study this hypothesis using the following linear model:

$$num\_entrants_{m,t} = \beta \sum_{\tau=0}^{K} acquisition_{m,t-\tau} + \lambda_m + \lambda_t + \epsilon_{m,t} \quad (1)$$

$num\_entrants_{m,t}$ denotes the number of VC-funded startups entering in a given market m at quarter t. The variable $acquisition_{m,t-\tau}$ is a binary variable that takes on the value 1 if an acquisition of a certain type took place in market m and quarter $t-\tau$, and 0 otherwise. K is the event window, which I set to 4 in my preferred specification. The coefficient of interests is therefore β. λ_m and λ_t denote market and quarter fixed effects, and $\epsilon_{m,t}$ is an econometric error term.

Entry-deterring effects are expected to be more likely when the acquired startup is more valuable, and when the startup's product continues to be developed and marketed after the acquisition. I therefore study acquisitions of VC-funded, private startups at a transaction price above 100US$ million, and focus only on acquisitions in which the product has not been discontinued.[30] I drop LBOs or management buyouts. I consider broad, as well as more narrow definitions of "strategic" and "financial" acquirer types. The broadest definition of strategic acquirers considers all enterprise software acquirers; more narrow definitions consider subsets of these. Similarly, the broadest definition of financial acquirers considers both financial as well as industry outsider firms.[31]

Table 6 displays the first set of results. In columns (1), (2) and (3), the acquirer is a strategic acquirer, whereas in columns (4) and (5), the acquirer is a financial acquirer or an acquirer from another industry. The results provide suggestive support for the hypothesis. Major startup acquisitions by strategic acquirers – both using wide as well as more narrow definitions – tend to be followed by a decline in entry. This pattern is less prevalent for financial acquirers. The result holds when decreasing the threshold of "major" acquisition to a transaction price of 50US$ million.

Table 6 displays a regression of entry on the cumulative sum of a certain type of acquisitions. Here, all coefficiences are negative and significant except for when one only counts financial companies acquiring a startup.

[30] The median transaction price for these VC-funded startups with continued products is 168US$ million. I drop acquisitions that occurred in the first τ or the last τ quarters of the time period under study. In case there are multiple such acquisitions in a given market-quarter or just in adjacent time periods, I continue to set the indicator equal to 1. Finally, note that, as mentioned previously, acquisition prices are often not observed. However, I expect that prices are highly likely to be observed conditional on the price being high; thus, I expect to capture all major acquisitions in this analysis.

[31] 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*. Exmaples of major acquisitions by companies in other industries are *Rocke-Flatiron Health*, *McDonald's-Dynamic Yield*, *Continental-Zonar*, or *Dupont-Granular*.

One concern might be that "treated" markets, i.e., markets in which a large acquisition took place at *any* point, might differ in terms of observables or unobservables compared with markets in which no such acquisition occurred. In Table 8, I perform the event study using only markets in which *any* major acquisition occurred. Even in this setting, which has a much smaller sample size, the coefficients retain the same sign as before.

I perform test for a possible anticipation effect by asking: are acquisitions of these different acquirers *preceded* by a decline, or by an increase, in entry? Table 21 in Appendix G suggests that only major acquisitions by public enterprise software companies may be preceded by a significant drop in entry.

Table 6: Event study: acquisitions and entry patterns, using an event window of 4 quarters. Market-quarter panel, 2012-2020.

	Dependent variable:				
	Number of entrants in market m, quarter t (Sample mean: 0.65)				
	Strategic acquirer			Financial acquirer	
"Major acq" = startup acquisition >$100M	(1)	(2)	(3)	(4)	(5)
Major acq by enterprise software company (89 acquisitions)	-0.112^{*} (0.059)				
Major acq by public enterprise software company (59 acquisitions)		-0.158^{**} (0.075)			
Major acq by GAFAM or 'New Tech' (21 acquisitions)			-0.401^{***} (0.135)		
Major acq by company not in enterpr softw (incl. financial) (40 acquisitions)				−0.101 (0.072)	
Major acq by financial company (13 acquisitions)					0.032 (0.119)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.299	0.299	0.3	0.299	0.299
Observations	17,064	17,064	17,064	17,064	17,064

Standard errors in parentheses, clustered at market level. *p<0.1; **p<0.05; ***p<0.01

Even though these regression results do not allow for a causal interpretation, 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 Tables 6 and 21, which both show that strategic acquisitions are not preceded by more entry, and even tend to be succeeded by a fall in entry.[32]

A concern may be that these results could be driven by the year of 2020 which was affected by the beginning of the Covid-19 epidemic, or by a trend. The results of GAFAM and New Tech acquisitions hold when studying the time period of 2014-2019, which is the time period under study in the model.

[32]I also tried employing the estimator suggested by Callaway and Sant'Anna (2021), which correctly accounts for the staggered nature of the events and which does not require treatment effects to be constant. Due to the fact that events are "too staggered" and too rare when using the market-quarter panel, I end up with too few observations per "group" – i.e. per treatment period – to allow for reliable estimates. When collapsing the data into a market-year panel and using the estimator suggested by Callaway and Sant'Anna (2021), I obtain a negative but imprecisely estimated coefficient on strategic acquisitions.

Table 7: Cumulative sum of major acquisitions of a given type in a given market and startup entry. Market-quarter panel, 2012-2020.

	Dependent variable:				
	Number of entrants in market m, quarter t (Sample mean: 0.65)				
"Major acq" = startup acquisition >$100M	(1)	(2)	(3)	(4)	(5)
Major acq by enterprise software company (ranges from 0 to 4)	−0.142*** (0.053)				
Major acq by public enterprise software company (ranges from 0 to 4)		−0.133** (0.065)			
Major acq by GAFAM or 'New Tech' (ranges from 0 to 2)			−0.297*** (0.085)		
Major acq by company not in enterpr softw (incl. financial) (ranges from 0 to 2)				−0.141* (0.072)	
Major acq by financial company (ranges from 0 to 1)					−0.129 (0.105)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.3	0.299	0.3	0.299	0.299
Observations	17,064	17,064	17,064	17,064	17,064

SEs clustered on market level. *p<0.1; **p<0.05; ***p<0.01

Table 8: Same event study as in Table 6, but as control group, use only markets in which a major acquisition of *any* type has occurred.

	Dependent variable:				
	Number of entrants in market m, quarter t (Sample mean: 0.65)				
	Strategic acquirer			Financial acquirer	
"Major acq" = startup acquisition >$100M	(1)	(2)	(3)	(4)	(5)
Major acq by enterprise software company (89 acquisitions)	−0.108* (0.062)				
Major acq by public enterprise software company (59 acquisitions)		−0.159** (0.072)			
Major acq by GAFAM or 'New Tech' (21 acquisitions)			−0.383*** (0.138)		
Major acq by company not in enterpr softw (incl. financial) (40 acquisitions)				−0.078 (0.074)	
Major acq by financial company (13 acquisitions)					0.110 (0.129)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.252	0.252	0.253	0.251	0.251
Observations	3,420	3,420	3,420	3,420	3,420

Standard errors in parentheses, clustered at market level. *p<0.1; **p<0.05; ***p<0.01

In contrast, the coefficient for the broader groups of strategic acquirers become insignificant. The results moreover roughly hold for a longer event window of 5 quarters, but fade for a shorter event window of 3 quarters. I also consider an event study where I consider all acquisitions with a transaction price of above 50US$ million (as opposed to 100US$ million), with similar results. A Poisson instead of a linear model obtains similar results as in the baseline. See Appendix G for these robustness checks and a further placebo test. One issue in all versions seems to be that acquisitions conducted by companies in other or financial industries tends to be negative as well, albeit not significant, despite using quarter fixed effects that should control for time trends. This is especially prelavent when regressing on the cumulative sum of acquisitions, or using a standard difference-in-differences analysis.

Overall, these reduced-form results offer suggestive support for entry-deterring effects of major strategic acquisitions, subject to the caveat of endogeneity. They contribute to recent literature that has found mixed results on the presence of a "kill zone": whereas Affeldt and Kesler (2021b), Kamepalli et al. (2021), Gugler et al. (2023) and Koski et al. (2020) are aligned with my findings, G. Z. Jin et al. (2022) and Bauer and Prado (2021) find an increase in VC funding after an acquisition by a large technology company took place.[33]

Any reduced-form approach will shed light on a mix of the short-run effect of an acquisition that is transmitted through market structure, and the more long-run 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 Section 5.

5 Dynamic Model of Entry

In order to study and quantify the entry-for-buyout, as well as the market structure effect, I build a dynamic model that I can take to the data. The economic agents in this model are potential entrants deciding whether or not to enter into a given market. I model these entry decisions as a dynamic discrete game with imperfect information that captures the competitive effects of other firms' entry decisions. The framework leans on models of dynamic discrete choice (Aguirregabiria & Mira, 2007, Bajari et al., 2007), but is markedly different to the extent that agents only get one single chance to make their decision of entering, or staying out of the market, instead of taking a new decision every period, which is natural in this setting. What renders the model dynamic is the fact that agents are forward-looking, that they incur a sunk costs, and that their actions affect state variables that change every period. Acquisitions and IPOs are assumed exogenous in this model conditionally on twenty market-category effects that control for unobserved variables in the 440 markets.

[33]Except for G. Z. Jin et al. (2022), all mentioned papers study the effects of acquisitions conducted by the GAFAM only. With the exception of Affeldt and Kesler (2021b) who take a focused approach and study 50 acquisitions conducted by the GAFAM in the mobile app market, those papers focus on many industries and employs alternative, firm-level (and thus possibly less precise) market definitions.

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 and in every market, there is a new set entrepreneurs with ideas for a new product in that market. These entrepreneurs form an exogenously given, fixed set of potential entrants in every period and every market.[34] In each period, 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 private i.i.d. shocks 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 each period. These flow profits depend on a vector of state variables that are common knowledge, $\boldsymbol{x}_{mt}$. The state variables capture in a stylized way aspects of market structure that are likely to influence firm profits.

In every period following the entry decision, companies may be able to "exit" (i.e., experience a transfer in ownership) by being target in an acquisition, or by listing on the public stock market. These exit events allow the entrepreneurs to cash out: once acquired or listed on the stock market, a firm stops earning flow profits, and instead earns a single lump-sum return. I model acquisitions and IPOs as stochastic shocks that arrive upon active startups. If no acquisition or IPO opportunity arrives in a given period, the firm continues earning flow profits, and transitions into the next period.

Within each period, the timing is as follows:

1. All potential entrants observe the vector of state variables $\boldsymbol{x}_{mt}$ that is common knowledge, and privately observe a cost shock $\boldsymbol{\epsilon}_{imt} = \{\epsilon^0_{imt}, \epsilon^1_{imt}\}$.
2. All potential entrants simultaneously decide: {enter, stay out}, so as to maximize their expected profits.
3. All companies on the market earn payoffs:
   - Firms that are acquired in this period earn R^{acq};
   - firms that are going public in this period earn R^{ipo};
   - all other firms, including the new entrants, earn flow profits that depend on the new vector of state variables and a vector of parameters, $\pi(\boldsymbol{x}_{mt+1}; \boldsymbol{\gamma})$.

Without loss of generality, the value of staying out is normalized to zero plus the random shock. The shock can be viewed as components of a sunk costs associated with a given action. Let θ denote the set of all structural parameters. The choice-specific value functions for entering and for staying out, excluding the random cost shock, write:

$$U^0(\boldsymbol{x}_{mt}; \theta) = 0 \tag{2}$$

$$U^1(\boldsymbol{x}_{mt}; \theta) = \mathbb{E}\big[\pi(\boldsymbol{x}_{mt+1}; \boldsymbol{\gamma}) - \kappa + \beta V(\boldsymbol{x}_{mt+1}; \theta, \cdot) \mid \boldsymbol{x}_{mt}\big] \tag{3}$$

[34]Other models of firm entry have fixed these potential entrants in a similar way, e.g., Perez-Saiz (2015) or Igami (2017). I run robustness checks with respect to this assumption.

so that potential entrant i's decision problem is given by:

$$\max \quad \left\{ U^0(\boldsymbol{x}_{mt};\theta) + \epsilon^0_{imt}, \quad U^1(\boldsymbol{x}_{mt};\theta) + \epsilon^1_{imt} \right\} \tag{4}$$

$\pi(\boldsymbol{x}_{mt};\boldsymbol{\gamma})$ denote the flow profits that the firm obtains in each period, which depend on the state variables, $\boldsymbol{x}_{mt}$, and a vector of parameters affecting these flow profits, $\boldsymbol{\gamma}$. 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. The expected payoffs in future periods can be expressed as follows:

$$\begin{aligned} V(\boldsymbol{x}_{mt};\theta,\cdot) \quad &= \quad \alpha^{ipo}\big(p^{ipo}_m \cdot R^{ipo}\big) + \alpha^{acq}\big(p^{acq}_m \cdot R^{acq}\big) \\ &\quad + (1 - p^{ipo}_m - p^{acq}_m)\mathbb{E}\big[\pi(\boldsymbol{x}_{mt+1};\boldsymbol{\gamma}) + \beta V(\boldsymbol{x}_{mt+1};\theta,\cdot) \mid \boldsymbol{x}_{mt}\big] \end{aligned} \tag{5}$$

As stated above, in every period following the entry decision, a firm may receive an opportunity to "exit" in the form of an acquisition or an IPO at probabilities p^{acq}_m and p^{ipo}_m. Such an exit yields returns (either acquisition price, or firm value) R^{acq} or R^{ipo}, respectively. In the model's current version, R^{acq} and R^{ipo} enter as data moments into the model. α^{acq} and α^{ipo} are parameters that essentially measure the extent to which startups' profits are influenced by exit opportunities in their given market. If the firm is not acquired nor listed on the stock market, which is the case at probability $(1 - p^{acq}_m - p^{ipo}_m)$, then the firm continues to earn flow profits in that period. p^{acq}_m and p^{ipo}_m are data moments, in particular, the observed frequency at which startups are acquired, or go public, in market m (more on this in Section 5.2). In the next period, any of the same set of events – {acquisition; IPO; continue} – may occur, and so on. The vector of structural parameters is given by $\theta = (\boldsymbol{\gamma}, \alpha^{acq}, \alpha^{ipo}, \kappa)$.

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

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), Collard-Wexler (2013), Seim (2006)). 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.

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

5.2 Parameterization and Laws of Motion

Per-period flow profits, $\pi(\boldsymbol{x_{mt}};\boldsymbol{\gamma})$, depend on a vector of common knowledge state variables that are relevant to firms' profits. They are parameterized as follows:

$$\pi(\boldsymbol{x_{mt}};\boldsymbol{\gamma}) = \gamma^N \log(N_{mt}) + \gamma^A A^{\text{strat}}_{mt} + \gamma^M_{l(m)} \tag{6}$$

N_{mt} denotes the number of competitors in market m at time t. It is thus an endogenous state variable that evolves according to firms' entry decisions, as well as to an exogenous component[35]. A^{strat}_{mt} denotes the cumulative number of major competing startups that have been acquired (and kept alive) by a strategic acquirer, and evolves exogenously. This state variable is assumed to be exogenous and captures in a heuristic way that, if a major startup competitor is acquired by a strategic acquirer, this affects competition in market m, and thus expected profits.[36] $\gamma^M_{l(m)}$ is the intercept coefficient, which differs by market type $l(m)$, with $l = 1, \ldots, L$. It captures *market-category* effects that are constant over time and only vary at the market level, and is thus an exogenous state variable. These can be interpreted as measuring baseline profits that can be earned of a given market, and are required to control for a market's unobserved size or profitability, following Wang (2022) (see Section 6.1 for how I construct these). The state variables are summarized by $\boldsymbol{x}_{mt} = \{N_{mt}, A^{\text{strat}}_{mt}, l(m)\}$.

I use the logged number of competitors as affecting flow profits in order to capture 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 are declining in the number of competitors N_{mt}. γ^A can be expected to be negative as well (based on the reduced-form results in Section 4), i.e., the number of major strategic acquisitions of competitors A^{strat}_{mt} lowers returns to entry.

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.

I define competitors in a market m at time t, N_{mt}, as consisting of products with at least one review produced by the following firms: VC-funded startups; public companies; acquired startups whose products have been continued; "pre-event" firms that have been founded within the last three years;

[35] The exogenous component is required to rationalize the data; see Section 5.2.

[36] Previous research has modelled firms as heterogeneous agents, which enables to capture the effects of acquisitions on competition and entry incentives in more explicit ways. For instance, in Perez-Saiz (2015), the acquired firm obtains the acquiring firms' characteristics, which affects competition. Similarly, in Igami and Uetake (2020), a merger between firms affects competing firms' productivity profiles. As I do not model firm productivity or firm characteristics, I use this stylized variable to capture that the acquisition affects comeption in the market. In an alternative specification covered in Appendix I, I consider instead a state variable denoted $A^{\text{strat in } t-K}_{mt}$ that mirrors the event study indicator variables employed in Section 4, and is equal to 1 in the event of a strategic acquisition in the past K quarters, and 0 otherwise.

and non-acquired private firms.[37] The law of motion of N_{mt} writes as follows:

$$N_{mt} = N_{mt-1} + num\_entrants_{mt} - D^{exog}_{\text{exit}} + D^{exog}_{\text{entry}} \tag{7}$$

$num\_entrants_{mt}$ denotes the endogenous number of entrants that enter in period t. In contrast, D^{exog}_{exit} and D^{exog}_{entry} are *exogenous* variables that are included to match the data, as companies may leave or be added to N_{mt} in ways not modelled.[38] I model these as random variables that follow a Bernoulli distribution with parameters p^{exog}_{exit} and p^{exog}_{entry}, respectively. I estimate these parameters in a first step using a frequency estimator.

As in the event studies, I estimate versions of the model using a broader, and a more narrow 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.

Whereas only major strategic acquisitions can affect A^{strat}_{mt}, both strategic as well as financial acquisitions can affect p^{acq}_m. 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.[39] I thus take p^{acq}_m and p^{ipo}_m as being the rates of acquisitions and IPOs of VC-funded startups that we observe in the data in each market from 2010 to 2020. Therefore, the entry-for-buyout parameter is identified by variation between markets in the long-run percentage of startups acquired (p^{acq}_m), 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 the median acquisition price for acquisitions of startups (130US$ million in the data), and R^{ipo} the median valuation of startups going public (768US$ million), between 2010 and 2020. [40] 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 six.[41] I fix the number of market categories, L, to 20, motivated by first-stage results (see Section 6.1). As the discount factor is not identified, I set it to $\beta = 0.9$ (see, e.g., Igami and Uetake (2020), who calibrate the discount factor to the same magnitude, also employing quarterly data). Table 9 details all fixed or calibrated parameters.

[37] I thus exclude companies whose products in a given market do not have any review. I moreover exclude acquired non-VC-funded private companies, as well as private companies that have been coded as "inactive" based on them not having recorded any "event" on *Crunchbase* for 5 years. This choice is supported by the better fit in the first stage, indicating that products without any reviews may be viewed as a competitive fringe. Adjusting this definition of competitors does not qualitatively affect final results.

[38] For instance, a firm may be acquired and shut down (which leads to a reduction in the number of competitors by 1). Alternatively, a firm that is not VC-funded may enter (which leads to an increase in the number of competitors by 1).

[39] 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".

[40] 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. I am continuing to explore this.

[41] The rationale for fixing the number of potential entrants to the maximum number of entrants ever observed in the data is laid out in Igami (2017).

Parameter		Value
Discount factor	β	0.9
Number of potential entrants	N^{pe}	6
Number of market types	L	20
Return from IPO	R^{ipo}	768
Return from acquisition	R^{acq}	130

Table 9: Parameters that are fixed, calibrated, or constructed using data moments.

5.3 Estimation

The primitives of the model are the structural parameters, $\theta = (\gamma^N, \gamma^A, \{\gamma^M_{l(m)}\}^{20}_{l=2}, \alpha^{acq}, \alpha^{ipo}, \kappa)$. I employ a two-step estimation method (e.g., Aguirregabiria and Mira (2007), Bajari et al. (2007)), which is essentially an extension of Hotz and Miller (1993)'s conditional choice probability estimator. It circumvents the need to solve a dynamic discrete game in over 400 independent markets, which would make the estimation computationally infeasible. Instead, agents' equilibrium beliefs are obtained from the data. This approach deals with the problem of multiple equilibria. The underlying assumption is that the data have been generated by the same equilibrium, conditional on market observables.[42]

5.3.1 First stage

In a first step, 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:

$$num\_entrants_{mt} = \phi_1 N_{mt} + \phi_2 A^{\text{strat}}_{mt} + \delta_m + \eta_{mt} \tag{8}$$

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, $\delta_{l(m)}$). Transition probabilities of the exogenously evolving (components of) state variables are estimated nonparametrically using a frequency estimator. Note that this first stage is essentially model-free. Policy functions characterize agents' actions given the state space, and transition probabilities describe how the state space evolves.

Note that we are not ultimately interested in the parameter estimates from the policy function in equation 8, but in the set of structural parameters, θ, estimated in the second step. Nevertheless, the parameters of the policy function 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 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.[43]

[42] See Aguirregabiria and Mira (2010) for a survey.

[43] It may occur that the simulated number of competitors in a future time period reaches a value below 0, due to the exogenous entry and exit rates. I found that this is the case in far less than 0.1% of simulated observations, and if it occurs, then only far in the future (at which, due to discounting, it would hardly matter for firms' decisions). In case the forward-simulated number of competitors does hit 0, I set these equal to 0.5 to be able to take logs.

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:

$$\Psi^1(\boldsymbol{x}_{mt};\theta) = \frac{\exp\left(U^1(\boldsymbol{x}_{mt};\theta)\right)}{\exp\left(U^0(\boldsymbol{x}_{mt};\theta)\right) + \exp\left(U^1(\boldsymbol{x}_{mt};\theta)\right)} \tag{9}$$

These conditional choice probabilities incorporate agents' beliefs about the future, and about their opponents' behavior in a Markov Perfect Nash Equilibrium (Aguirregabiria & Mira, 2010, Arcidiacono & 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. Instead, the equilibrium that is actually played by the agents in each market type will be recovered using the conditional choice probabilities.

6 Results

I use market-quarterly data to estimate the model. After excluding a few markets that I regard as outliers, I end up with 440 markets in the years of 2014-2019 (24 periods), yielding 10,560 observations.

6.1 First Stage: Startups' Entry Decisions

The results for the first stage can be found in Table 10, using a "broad" definition of strategic acquirers, and Table 11, which reports analogous estimates using a "narrow" definition. I begin with a linear model with no fixed effects in columns (1) of both Tables. I retrieve a positive coefficient on $\log(N_{mt})$, 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), 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 insignificant when using the broad definition in Table 10. As the dependent variable is a count variable, I also employ a Poisson specification in column (3), which yields negative significant coefficients, albeit at somewhat lower magnitude.

One potential concern with the linear model might be 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, Wang, 2022). These types of fixed effects equivalently control for unobserved heterogeneity of markets. I follow 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 H for details regarding the choice of the number of categories). 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. Finally, I employ market fixed effects along with quarter fixed effects in column (5) to control for seasonal effects which are present in the data. I again recover similar results.

Table 10: First stage, using a broad definition of "strategic" acquirers. Standard errors are clustered at the market level. In column (4), they are computed using block bootstrapping with 5,000 bootstraps to account for the estimated market-category fixed effect.

	Dependent variable:				
	Number of entrants in market m, quarter t				
			Poisson		
	(1)	(2)	(3)	(4)	(5)
# of competitors	0.021***	−0.165***	−0.120***	−0.069***	−0.163***
	(0.001)	(0.015)	(0.017)	(0.012)	(0.015)
Cumulative # of major Enterprise Software acquisitions	0.026	0.094	0.137	0.161**	0.107
	(0.056)	(0.088)	(0.086)	(0.070)	(0.088)
1{quarter=2}					−0.126***
					(0.020)
1{quarter=3}					−0.152***
					(0.019)
1{quarter=4}					−0.214***
					(0.019)
Market FE		✓	✓		✓
20 market-category FE				✓	
Adjusted R^2	0.11	0.34		0.24	0.35
Log Likelihood			−9,809.514		
Akaike Inf. Crit.			20,503.030		
Observations	10,560	10,560	10,560	10,560	10,560

Standard errors clustered at market level. *p<0.1; **p<0.05; ***p<0.01

Using any of these policy functions, and using frequency estimates of the parameters p^{exog}_{exit} and p^{exog}_{entry} ($\hat{p}^{exog}_{\text{exit}} = 0.061$ and $\hat{p}^{exog}_{\text{entry}} = 0.0076$), I can use the law of motion in equation 7 to forward simulate the endogenous state variable N_{mt}. I employ the estimates of column (2), and draw 200 paths of 100 time periods.

The remaining state variables are exogenous. In order to forward-simulate the state variable A^{strat}_{mt}, I estimate the empirical frequency with which a strategic acquisition occurs. I then forward-simulate occurrences of major strategic acquisitions by drawing from a Bernoulli distribution each period, and construct the forward simulated flow of A^{strat}_{mt} so that it reflects the cumulative number of competing firms acquired by a strategic acquirer.

Table 11: First stage, using a narrower definition of "strategic" acquirers. Standard errors are clustered at the market level. In column (4), they are computed using block bootstrapping with 5,000 bootstraps to account for the estimated market-category fixed effect.

	Dependent variable:				
	Number of entrants in market m, quarter t				
			Poisson		
	(1)	(2)	(3)	(4)	(5)
# of competitors	0.022***	−0.163***	−0.117***	−0.066***	−0.161***
	(0.001)	(0.015)	(0.017)	(0.012)	(0.015)
Cumulative # of major New Tech or GAFAM acquisitions	−0.118	−0.083	−0.026	−0.080	−0.068
	(0.135)	(0.219)	(0.245)	(0.148)	(0.220)
1{quarter=2}					−0.125***
					(0.020)
1{quarter=3}					−0.151***
					(0.019)
1{quarter=4}					−0.212***
					(0.019)
Market FE		✓	✓		✓
20 market-category FE				✓	
Adjusted R^2	0.11	0.34		0.24	0.35
Log Likelihood			−9,813.854		
Akaike Inf. Crit.			20,511.710		
Observations	10,560	10,560	10,560	10,560	10,560

Standard errors clustered at the market level. *p<0.1; **p<0.05; ***p<0.01

Finally, I use the $L = 20$ estimated market-category fixed effects as the only market characteristic ($\gamma^M_{l(m)}$), which stay constant over time.

6.2 Second Stage: Structural Parameters

The estimates for the structural parameters can be found in Table 12. Column (1) shows the results using a broad definition of strategic acquisitions by considering all major acquisitions conducted by a strategic acquirer, using in the first stage column (2) from Table 10. All parameters have the expected sign. In particular, the competitive effect is significantly negative, and the effect of a strategic acquisiton is negative, albeit not significant. The returns from being acquired or doing an IPO in the future are both positive and significant, indicating that a higher expected acquisition or IPO in the future makes entry more profitable. Moreover, the market category fixed effects, which are supposed to account for unobserved heterogeneity in profitability or market size, are successively becoming larger.

Column (2) employs a more narrow way to define strategic acquirers by using all major acquisitions by New Tech or GAFAM firms, and employing column (2) of Table 11 in the first stage. Again, parameters have the expected sign. The strategic acquistion effect now becomes marginally significant, albeit only at the 10% level.

Interpretation. The estimate for α^{acq} essentially measures an entrepreneur's valuation for being more likely to be acquired at a given price measured in millions of dollars. One can therefore 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

Table 12: Estimates of structural parameters.

	(1)	(2)
Entry costs, κ	-3.008^{***}	-2.978^{***}
	(0.139)	(0.138)
log(# of competitors), γ^N	-0.246^{***}	-0.251^{***}
	(0.010)	(0.011)
Cumsum of strategic acq of competitor **by Enterprise Software acquirer**, γ^A	-0.011	
	(0.015)	
Cumsum of strategic acq of competitor **by GAFAM or New Tech**, γ^A		-0.068^{*}
		(0.038)
Own IPO in future, α^{ipo}	0.005^{***}	0.006^{***}
	(0.001)	(0.001)
Own acquisition in future, α^{acq}	0.038^{***}	0.038^{***}
	(0.003)	(0.003)
Market category 2, γ_2^M (5th-10th perc)	0.321^{***}	0.325^{***}
	(0.024)	(0.024)
Market category 3, γ_3^M (10th-15th perc)	0.392^{***}	0.397^{***}
	(0.025)	(0.025)
...	...	...
Market category 19, γ_{19}^M (90th-95thth perc)	1.140^{***}	1.156^{***}
	(0.046)	(0.046)
Market category 20, γ_{20}^M (95th-100th perc)	1.298^{***}	1.316^{***}
	(0.050)	(0.050)
Log-likelihood	-10619.51	-10613.52
Observations	10,560	10,560

Note: *p<0.1; **p<0.05; ***p<0.01

sunk costs of entry parameter is approximately equal to US$78 million . This is less than the lifetime amount of funding that successfully exiting, later-stage enterprise software startups obtain, according to *Crunchbase* data. Further, I find that the lifetime costs of having one additional competitor in the market are equal to US$6.8 million . Moving up from the least to the most profitable market, in terms of the 20 market-category fixed effects, is worth US$322 million , which emphasizes the importance of market fixed effects. Moving up from the 50th to the 55th quantile is worth US$12.8 million .

It is noteworthy that the prospect of being acquired is not valued very highly compared to the other parameters, and that a lot of value depends on the market-category effects. As mentioned above, this could result from the fact that entrepreneurs in fact likely receive only a fraction of the acquisition price, or of the valuation when going public, respectively. If one was to account for this, the estimates for γ^A could likely rise 5- to 20-fold. Moreover, this finding could indicate that entrepreneurs may place a high value on competing in a market, and do not rely on being bought out. It could also possibly reflect the highly probabilistic nature of being acquired in a given market and risk-aversion on the part of entrepreneurs.

It is not clear what the main driving force is behind the estimated parameters. For instance, prior literature has established the presence of "IPO peer effects", which could explain the positive coefficient of α^{ipo} (Aghamolla & Thakor, 2021). Similarly, the positive α^{acq} be due to the entry-for-buyout effect, but might also be partly driven by a hearding effect (Conti, Guzman, & Rabi, 2021) or an acquisition probability effect (Song & Walkling, 2000).

6.3 Counterfactual Simulations

6.3.1 Procedure

One of the purposes of the model is to answer the question: how would entry evolve 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, $\hat{\gamma}_A$. As explained below, I currently do not solve for the equilibrium that equates agents' actions with agents' beliefs for computational reasons.

I study two counterfactual changes in the prevailing antitrust regime. In the first scenario, the competition authority blocks only major strategic startup acquisitions.[44] In the second scenario, the competition authority blocks all startup acquisitions altogether. In each scenario, I assume that the policy change takes place in the first quarter of 2014, i.e. the first period of observation of my data.

To conduct the simulation, I take the starting values of the state variables 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:

1. Take $x_{m,2014Q1}$ from the data.

[44] This reflects a recommendation by, for instance, 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".

2. Adjust the transition probabilities according to the counterfactual that one is interested in: for instance, for the counterfactual in which no acquisitions are possible, set the probability of a future buyout to 0. Based on this, forward-simulate the state variables, drawing 200 paths for 100 time periods into the future.

3. Using the estimated parameters from Table 12, column (2), 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^0_{ijt}, ϵ^1_{ijt} from a type-1 extreme value distribution.

5. Given the value of entering and the drawn cost shocks, compute the number of actual entrants (i.e. the number of potential entrants for which the value of entering is higher than the value of staying out).

6. Compute and simulate what the counterfactual state variables will be in the next period.

7. Repeat steps 2 to 6 until the last period of observation.

For the forward-simulation in step 2, I use the original policy function and transition probabilities. I thereby assume that startups hold onto their original beliefs of how state variables will evolve over time. 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 infeasible.[45]

6.3.2 How would entry evolve under counterfactual merger policy regimes? – Results

I begin by examining the effects on entry and on the number of competitors in the average market. Table 13 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. This results in a very slight increase in entry and in competition in the average market.

I then simulate the counterfactual in which all acquisitions are blocked. Given the current values of the parameter estimates, in the average market, firms *prefer* competing on the market forever, rather than being acquired. This leads to the finding exhibited in the second row of Table 13: entry rates and the number of competitors increase in the counterfactual. In reality, however, it may be unlikely that firms competed forever in a situation in which acquisitions are not possible at all. Instead, there might be a substantial risk of profits going to zero, as there would be no opportunities to find VC funding due to the lack in exit opportunities.

I therefore introduce a rate at which firms may obtain a negative shock that leads profits to go to 0 in the counterfactual with no acquisitions, akin to a bankruptcy rate. The results are displayed in rows

[45] In future iterations of the paper, I plan to either fully solve this dynamic problem in a small subset of markets. An alternative would be to consider an approximation based on Aguirregabiria and Ho (2012).

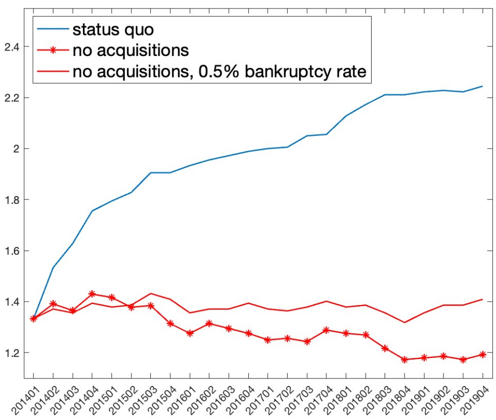
Counterfactual	Change in entry		Change in # of competitors	
	in numbers	in percent	in numbers	in percent
Blocking only New Tech & GAFAM acquisitions:				
· Effect on average market	0.002	0.44%	0.05	0.24%
· Effect on market affected by strategic acquisition	0.04	4.12%	0.56	1.36%
Blocking all acquisitions; startups earn profits forever in counterfactual:				
· Effect on average market	0.03	5.09%	0.36	1.85%
Blocking all acquisitions; 0.25% chance of profits going to 0 per quarter:				
· Effect on average market	-0.02	-4.18%	-0.35	-1.78%
Blocking all acquisitions; 0.5% chance of profits going to 0 per quarter:				
· Effect on average market	-0.05	-10.73%	-0.79	-4.03%

Table 13: Change in the mean number and percent of entrants, and in competitors, in counterfactual scenarios compared to the baseline.

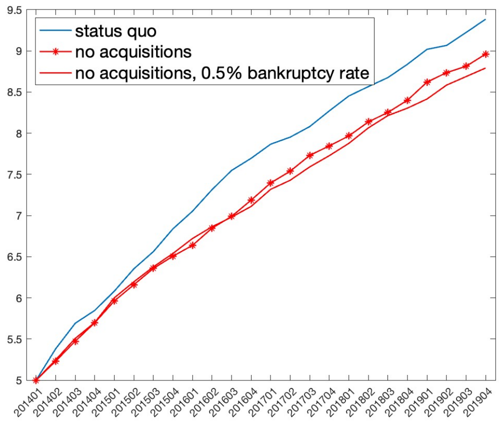
3 and 4. If firms have a 0.25% increased probability of having profits go down to 0 in every quarter in the counterfactual with no acquisitions will lead to a reduction in the number of entrants as well as in the number of competitors.[46] In currently ongoing work, I will verify to make sure these assumed rate of bankruptcies could be supported by scientific literature in empirical finance. I carry out fifteen simulations of each type, and take the average.

As the data contain over 400 markets, I can explore how the effect of blocking startup acquisitions varies across markets of different types. In particular, by way of the market-category effects, the structural model essentially groups markets according to their unobserved market size or inherent profitability. Figure 5 shows that effects do vary for markets of different profitability. For low-profitability markets – panels (a) and (b) – the number of firms decreases in the counterfactual, especially in later time periods. In contrast, entry tends to increase in markets with a very high inherent profitability, as in those markets, staying on the market – as opposed to being acquired – is very profitable. My finding of a strong drop in entry if all mergers were blocked appears to be plausible: Fons-Rosen et al. (2023) find that, if startup acquisitions in the entire US economy were blocked, the startup rate would decline by 14.9%. Cabral (2023) calibrates a model of innovation for the tech industry, and similarly 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". I intend to explore the heterogeneity and its plausibility further in future work.

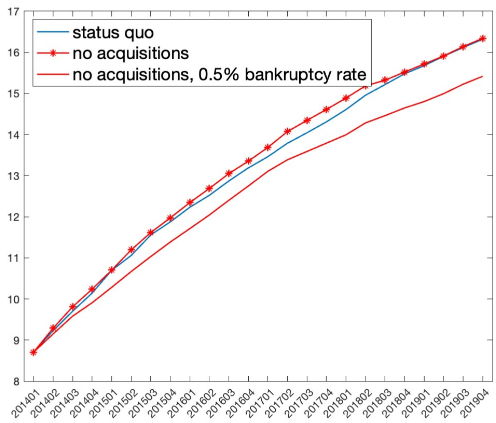
[46] In the *Crunchbase* data, the actual quarterly bankruptcy rate for enterprise software startups is around 1.2%.



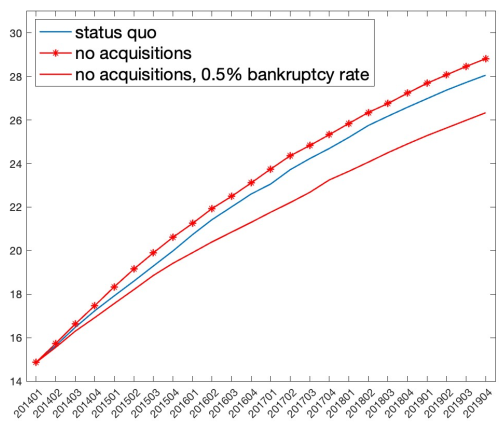
(a) Markets at 5th percentile of profitability



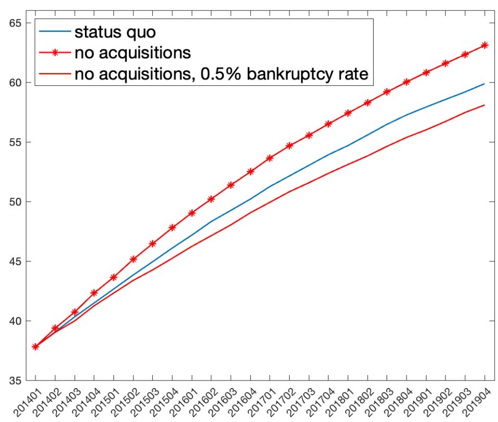
(b) Markets at 25th percentile of profitability



(c) Markets at 50th percentile of profitability



(d) Markets at 75th percentile of profitability



(e) Markets at 95th percentile of profitability

Figure 5: Heterogeneity in the effect of blocking startup acquisitions on the number of competitors, across markets of different unobserved profitability.

7 Discussion

7.1 Limitations of market definitions

The market definitions that I employ are more granular than standard industry classification systems used in previous literature, and thereby allow to make progress on our understanding of the effects of startup acquisitions in software markets. At the same time, these new product-level market definitions are subject to some of the same caveats that more 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 commonly arises in software, where markets can be complementary. Nor can the market definitions capture the distinction of markets for technology, as opposed to product markets (see Gans and Stern (2003)). 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.[47] 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. 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. The market-category effects that I employ can control for this to some extent, as the estimation essentially only uses variation within the given profitability quantile a given market is in. The assumption is therefore that, conditional on those market-category effects that capture the profitability of a given market, the extent of startup acquisitions is as good as random.

The market structure parameter, γ^A, is identified from variation in the number of entrants around the time of a major acquisition by a strategic acquirer both between and within markets. For strategic acquirers, the consideration of *which market* to acquire in is possibly endogenous to observed and unobserved market characteristics. However, there is a random element in the decision of *which of the startups in a given market* is ultimately purchased, *by whom*, and *at what time*. The match value between a target firm and an acquirer is affected by characteristics such as travel distance, network, or whether the

[47] See Aridor (2022), who estimates consumer substitution patterns across social media with the help of a field experiment.

two firms happen to share the same technology stack, which are exogenous to *new startups'* entry decisions. Anecdotally, startups frequently turn down offers they obtain, seemingly for reasons exogenous to market or firm characteristics.[48] It therefore seems plausible that potential entrants cannot anticipate a acquisition of a future competitor by a strategic acquirer, which means that short-run declines in entry after a merger announcements should be driven by the acquisition. In a similar vein, contrasting financial with strategic acquirers around the event of the merger announcement, akin to the event study above, may be as close as one can get to identifying any potential entry-deterring effect of major strategic buyouts.

Endogenizing acquisitions, as is done in some prior research (e.g., Cortes et al. (2022), Igami and Uetake (2020), Stahl (2011)), is not feasible in my setting due to computational and conceptual challenges.[49]

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? My data collection effort allows to make progress on this question in the context of startup acquisitions in the software industry. Merger policy in software markets is being fiercely debated in many jurisdictions, but our understanding of the motives as well as the implications of these mergers for competition and innovation is extremely limited.

I provide new data and descriptive evidence of the likely effects of the acquisitions of VC-funded startups in the enterprise software industry. I build and estimate a model of startup entry decisions that fleshes out, in a stylized way, an entry-for-buyout effect that fosters entry, and an effect via market structure that deters entry. I find that an overall ban of all startup acquisitions would decrease entry by 8-20% in markets that have a low baseline profitability. Nonetheless, acquisitions conducted by strategic acquirers appear to deter entry. If these acquisitions were banned, entry might be increased. These findings are highly relevant to the ongoing policy debates regarding startup acquisitions in technology sectors. More broadly, my results can contribute to the debate on the relationship between market structure and innovation, going back to Schumpeter (1942) and Arrow (1962).

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 enter, but also that firms are willing to enter and *remain independent* upon successful entry. Recent literature has provided evidence that startups wanting

[48]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 05/10/2023). An interview I conducted with a startup co-founder who shall remain unnamed revealed that their company received offers from three of the GAFAM firms, but eventually sold to another large digital services company.

[49]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: the motives that are driving acquisitions here seem to be very heterogeneous, and any attempt of writing down a stylized model would not capture those accurately enough. 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.

to be publicly listed might face barriers (Ederer & Pellegrino, 2023). Firms' decisions to agree to a buyout, as opposed to continued operation, is likely a function of startup age, funding, the number and types of alternative acquirers, the costs and risks associated with an IPO, and further determinants of startups' outside option. Future research could study what affects firms' willingness to remain independent in software markets, possibly with the help of 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, unless one is willing to make very strong assumptions, the lack of demand data precludes me from making any strong conclusions regarding welfare implications. In this respect, my findings invite a number of follow-up questions, such as: how much does new product entry 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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A Anecdotal evidence

A.1 Entry-for-buyout effect

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

In a blog post titled "The FTC versus tech M&A", Benedict Evans 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?"[50]

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

I transcribed the following quote from an interview by *Tech Off*, a podcast by *Les Echos Entrepreneurs*, with *Clustree* founder Bénédicte de Raphélis Soissan. She had previously successfully sold her startup to Cornerstone. In one part of the interview, she is being asked what the key points are to recognize very early-on when starting a startup business. Translated into English:

> "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."[51]

A.1.3 Trade-off: raising a new funding round vs. selling out

This article on a blog of Silicon Valley Bank highlights the trade-off start-ups may face between staying independent and raising a new funding round, vs. selling out. It also highlights the various random factors that can affect this trade-off for individual entrepreneurs: https://www.svb.com/startup-insights/startup-strategy/types-startup-exit-strategy/ (accessed 11/07/2024).

A.1.4 Incubators are asking entrepreneurs early-on to think about potential acquirers

According to Drew Houston's application to be admitted to the startup incubator program by *Y Combinator*, one of the questions contained in the initial applicant survey was:

[50] See https://web.archive.org/web/20221027140238/https://www.ben-evans.com/benedictevans/2022/8/1/within-and-tech-mampa (accessed 07/04/2023).

[51] 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."* Source: see minute 51.50 ff. of the podcast available on https://business.lesechos.fr/entrepreneurs/communaute/0603458127497-podcast-benedicte-de-raphelis-soissan-fondatrice-de-clustree-338661.php (accessed 07/04/2023).

"Which companies would be most likely to buy you?"[52]

This question reflects that, for a startup to receive any VC funding and be successful, it is key to think about potential acquirers very early on.

A.2 Kill zone effect

A.2.1 Jason Roberts, founder of Preezo, 2010

In "How I Screwed Up My Google Acquisition", the founder talks about his attempt at selling his startup *Preezo* 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 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."[53]

B How can acquisitions deter entry? - Summary of theoretical literature

Through which economic mechanisms can an acquisition in technology markets prevent entry? The theoretical literature has put forward several economic channels that seem applicable to the setting considered in this paper. The practice of strategic tying is one such 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 et al. (2024) considers the incentives to build digital ecosystems, i.e., to create firms that offer a wide range of online services. The model builds on the premise that firms can employ "cross-market leveraging" by steering consumers from one market into another market, for

[52] See https://web.archive.org/web/20230817171520/https://www.businessinsider.com/dropbox-y-combinator-application-from-2007-by-drew-houston-2013-9?r=US&IR=T (accessed 17/08/2023).

[53] See https://web.archive.org/web/20220728220203/http://www.codusoperandi.com/posts/how-i-screwed-up-my-google-acquisition (accessed 07/04/2023).

instance through default effects of online 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 directly applicable to this paper's context.

Motivated by the acquisitions in digital markets, the 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 et al. (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 therefore 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.

C Supplementary information on data creation

C.1 Cleaning and construction of firm-event panel data using *Crunchbase*

Crunchbase comprises over a million public, private, as well as firms that existed in the past but have been closed. Companies may be located all over the world and may span all sectors of the economy, but people who have worked for the VC industry mentioned to me that *Crunchbase*'s coverage may be most accurate for firms located in North America and Europe. Information on *Crunchbase* are sourced using Machine Learning, an in-house data team, a venture program, and via crowdsourcing.

The *Crunchbase* data was obtained in a format that requires some handling of the data in order to make it useful for economic analyses. First, *Crunchbase* contains "organizations", which comprises companies, but also other institutions like schools; I therefore exclude the latter. I then create a "firm-event panel" in which each observation corresponds to a certain "event" that was happening in a given company's lifetime, as well as its characteristics. I obtain the following events from *Crunchbase*: *founded, getting funding, investment, being acquired, acquiring, IPO, inactive, closed*. In addition, I create the event "inactive" based on prior literature as the date five years after any kind of relevant event of a given private, non-acquired company.[54] From such a dataset, one can easily create quarterly data of, for instance, the number of acquisitions per quarter, or the number or volume of funding rounds.

I moreover create the parent-subsidiary structure for all firms. I consider parents up to two levels up of a given focal company, which is sufficient in all cases in my data.

[54] I have found prior literature that codes companies that did not receive venture capital within 3, 5, or 7 years as inactive.

C.2 Definitions of "startup" and "Venture Capital funding round"

Venture Capital 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*. I thus exclude, for instance, Post IPO funding rounds, Private Equity, or Secondary Market investment.

(Pre-exit) Startup: Any private company that has raised at least one Venture Capital funding round (i.e. prior to any recorded event of the type *acquisition, IPO, closed* or *inactive*).

I focus on startups, as startups have been found to be particularly innovative and disruptive. Startup acquisitions account for approximately 44% of all acquisitions observed in the matched data. This fact is reflected in my data showing that products supplied by VC-funded startups have more reviews, even when employing a range of controls for company characteristics and age (see Appendix F, Table 18).

As pointed out in the text, *Crunchbase* defines acquisitions as majority takeovers, which may mean majority investments. This is very reasonable, as a majority investment allows startup founders and early investors to cash out, and transfers ownership and control into new hands[55].

C.3 Motivation for seeking data from *Capterra*

I here motivate in greater detail why I cannot rely on existing industry classifications alone, providing a motivation for web-scraping additional data from *Capterra*. First, the labels provided on *Crunchbase* are broad: as of 2021, fewer than 800 labels were used to describe the entire economy, which is not sufficient to determine which companies actually compete against each other.[56] Many of the labels are specific to an *industry*, but not to a *market* (e.g. the label "enterprise software" could in principle capture markets as distant as enterprise resource management and video advertising). Second, the labels given by *Crunchbase* vary on the firm level. However, many firms are multi-product firms. Amazon for instance is famously an e-commerce platform, a logistics company, and offers cloud computing services. Distinguishing which companies compete with each other in a given market requires a *product-level* definition of competitors. Third, the aim of this research is to study privately held startups. This prevents me from using standard industry classifications that are available for public firms only, or from using 10-K reports to distinguish competitors as Hoberg and Phillips (2016) pioneered. Fourth, from *Crunchbase* alone, it is not always clear whether a given company is actually still active in producing a given product. Using *Capterra* data allows me to focus on companies that are actually active.

Capterra confirmed to me that categories and text are accurate. According to the company, new products are being placed into a single category when they are introduced on the website, upon which

[55]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. Another example is from the press statement from Francisco Partners regarding their majority investment of LiveU: "Francisco Partners, a global technology-focused private equity firm, together with co-investor IGP Capital, have acquired LiveU from its existing shareholders to accelerate further the company's global expansion.", see `/web/20221105112118/https://www.franciscopartners.com/news/liveu-announces-majority-investment-from-francisco-partners-to-accelerate-growth`, accessed 05/11/2022.

[56]If one used these labels as markets, one would end up with over 1,300 firms per "market", which is unreasonably many. Note also that *Crunchbase*'s main purpose is not the precise categorization of startups into markets or areas of activity, but rather the documentation of startups and their funding round events.

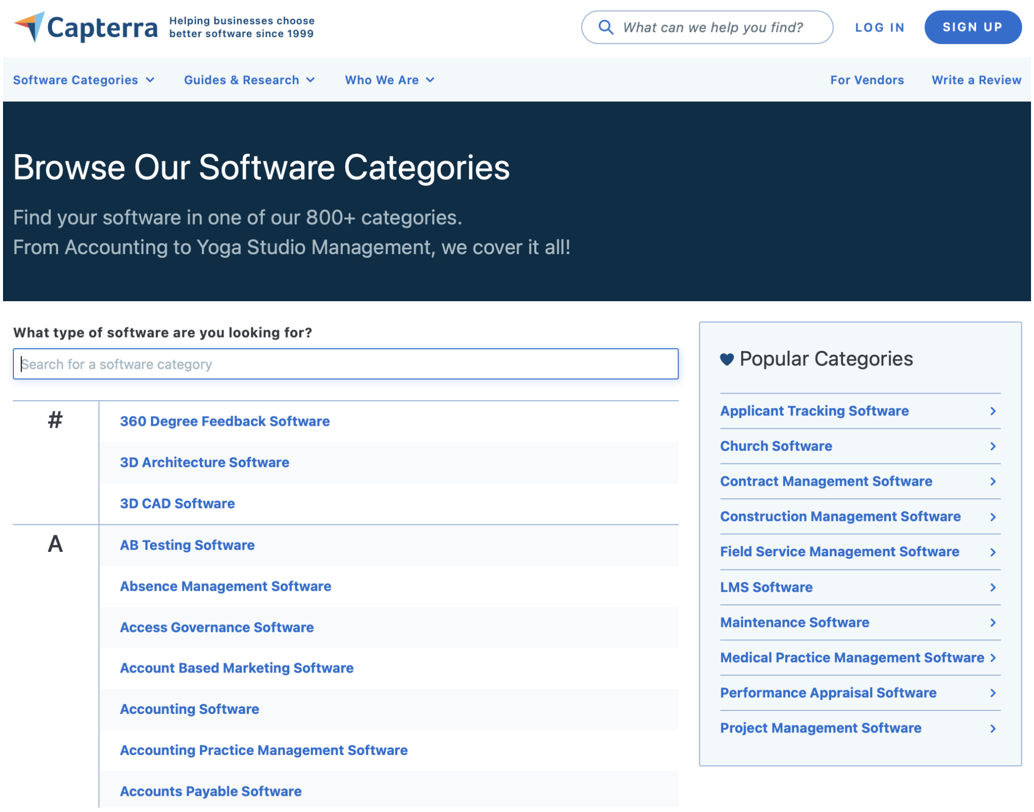


Figure 6: *Capterra*'s categories page

companies can request to be added to further categories. A dedicated catalog team will then review the request and approve the product if the additional category seems suitable. Figure 6 shows a screen shot of *Capterra*'s list of over 800 product categories which consumers view upon visiting the website.

Note that prior research on the market for mobile applications has made use of the fact that app categories are meaningful for defining competitors (e.g., Affeldt and Kesler (2021b), Ershov (2023), Janssen, Kesler, Kummer, and Waldfogel (2022), or Yin, Davis, and Muzyrya (2014)). I essentially proceed in a similar way, although I cannot rely on the categories alone, as a product can be assigned to multiple categories in the case of *Capterra*.

C.4 Web-scraping *Capterra*

I first web-scrape the list of categories available on *Capterra* (see Figure 6). 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 that process, I find that in some instances, a single product can have multiple URLs (and thus 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 finally obtain approximately 70,000 unique product-level observations.

Aside from the data described in Section 2.2.2, 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. I decide to not include pricing information as it is likely not very meaningful for the following reasons: first, prices for enterprise software may be negotiated at the company-level. Increasingly, enterprise software providers are moreover distributed under a freemium model in which users pay nothing at first, but can then subscribe for upgrading storage space or unlocking more features for instance (see https://techcrunch.com/2020/12/01/bottom-up-saas-a-framework-for-mapping-pricing-to-customer-value/ or https://www.acquired.fm/episodes/the-zoom-ipo-with-santi-subotovsky for anecdotal evidence).

C.5 Merging *Capterra* products to *Crunchbase* companies

I first use company URL and name to match products on *Capterra* to their producing firms on *Crunchbase*.[57] Panel A in Figure 7 gives a few examples of products matched to companies by URL and name.

However, in cases where the product originated with a startup, but is now provided by the acquirer, the above matching algorithm will associate the product to its acquirer and current owner, not to its *originating* company. To trace products back to the startups that may have been the originators of a given product that was then acquired, I make use of the fact that young startups typically provide a single product whose name is the same as the company's name. Therefore, whenever a given product's producing firm (as indicated on *Capterra*) has previously acquired a company that shares any similarity with a given *product*'s name, I assume that it is the *acquired* firm that initially entered the market with this product; see panel B in Figure 7.

C.6 Capterra data: Gauging coverage and checking for potential sample selection

Coverage & quality of Capterra data. *Capterra* is owned by *Gartner*, a large public consulting and technological research company. Reviews and ratings are pooled across the *Gartner Digital Markets network*, which comprises *Capterra* as well as two other subsidiary websites (*GetApp* and *Software Advice*). Information on reviews and ratings on *Capterra* seem to be accurate, representative, and of high quality based on comparison's with *Capterra*'s competitors. *Capterra*'s 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). *Capterra* was available in over 30 countries and at least seven languages. 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 ("Waybackmachine"), I found at least anecdotally that products whose discontinuation was publicly announced were removed earlier from the *Capterra* website than from *G2*.

[57] I first extract all firm URLs that are unique in both *Crunchbase* and *Capterra*, and match those products to firms based solely by URL. For the remaining firms with non-unique URLs on either *Crunchbase* or *Capterra*, I then employ a fuzzy matching algorithm to match the remaining firms: both their URLs must be equal, and additionally, firm names must at least share some similarity. Finally, somewhat less than 1% of all products are matched manually by looking up the company.

Product Name on Capterra	Name of Producing Company (from Capterra)	Matched to Crunchbase Company	Matched how?
A			
Jira	Atlassian	Atlassian	URL & company name
Adobe Acrobat Reader DC	Adobe	Adobe	URL & company name
ClickUp	ClickUp	ClickUp	URL & company name
Box	Box	Box	URL & company name
Safari	Apple	Apple	URL & company name
B			
AWS Cloud9	Amazon Web Services	Cloud9 IDE	Amazon acquired the company Cloud9 IDE
Widevine DRM	Google	Widevine	Google acquired the company Widevine
Yammer	Microsoft	Yammer	Microsoft acquired the company Yammer

Figure 7: Example of how existing products on *Capterra* were matched to firms on *Crunchbase*. Products in panel A were matched by company URL and name. Products in panel B were matched to the target that was acquired by producing firm in the past based on name similarity.

Including "shut-down acquisitions". As noted above, the product-level data obtained by *Capterra* is cross-sectional in nature, covering enterprise software products available in June and July of 2021. I therefore 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 distinguish acquired startups into enterprise software related (e.g., *Zenter*, *Sparrow*, or *LiveLoop*) and not enterprise software related by looking up information on each of those companies on the 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 words that should or should not be contained in those variables. Testing these criteria on the initially manually classified sample, the criteria have an accuracy of 81%, a false positive rate of 17%, and a false negative rate of 19%. A lot of the false positive cases are edge cases where the classification is unclear.

I focus on 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 5,034 companies that have been acquired by enterprise software companies in the past and are also tagged with enterprise software related terms. I term those additional companies "shut-down acquisitions".

Checking for potential sample selection issues. After including the above shut-down acquisitions, any additional survival bias stemming from firms that previously exited is likely not problematic, and possibly even wanted, as it allows to disregard likely irrelevant, "dying" competitors. As the focus of

Table 14: Companies with enterprise software related tags and keywords on *Crunchbase* that are not part of *Capterra*. The below percentages are approximate and are recovered using both systematic investigations, as well as an additional manual investigation.

Likely reason why firm is not included in sample	% of companies
closed or inactive before 2021	31.5
important variables not available; hence likely inactive / not relevant	18.6
acquired by non-enterprise software and discontinued	14.8
likely not in enterprise software	14.1
founded very recently	10.6
located in China, Japan, or Korea (systematically under-represented on *Capterra*)	7.8
arguably should have been part of sample	2.6

this paper is on firm entry (as opposed to closures), and as the data collection took place soon after the end of the sample period, I am likely capturing all actually relevant and actually viable entrants and competitors. I nevertheless investigate potential selection issues further. I therefore compare the sample of firms used with the set of companies on *Crunchbase* that satisfy the abovementioned selection criteria, and would hence be classified as "enterprise software related" but not on *Capterra*. I find that this set of companies is twice as large as the sample used. At the same time, however, this set of company contains only 60% of the currently included sample, and hence excludes a large part of active and relevant enterprise software firms such as multi-product firms like Facebook or Apple.

I conduct manual and systematic analyses of the likely enterprise software related companies that are not part of my sample, in order to investigate whether those firms possibly should have been included. As shown in Table 14, I find that approximately 32% of these companies have likely been shut down as of 2021, and another 19% have missing data in usually well-covered variables (such as industry or category) and are thus likely not major competitors, nor very active. Upon closer investigations, 14% of companies seem to actually be active in other industries (such as consulting, venture capital, business development, or actually provide add-ons to existing products), albeit being tagged with enterprise software related terms. All in all, I find that for only between two and three percent of these companies, one may argue that they should have been included into my sample. These companies are missing from *Capterra* for unknown reasons. However, this selection will likely be random across markets, and will likely not affect major competitors.

Geographic reach. As of 2021, *Capterra* was available in many Western European languages as well as in Japanese. Accordingly, I find European and North American companies to be somewhat over-represented on *Capterra*, and companies from East Asian countries and Russia to be under-represented.[58] I do not believe this to be problematic, as the products developed by companies in, e.g., East Asia might indeed not be available in English or other Western European languages, and might thus not be easily substitutable with the products covered by *Capterra*.

[58]It is known that *Crunchbase* is already mostly covering European and North American companies better that, but my analysis shows that *Capterra* is even more centered on North America and European companies. Even though *Capterra* is available in Japanese, Japanese firms are not very represented on *Capterra*.

C.7 Building a dictionary and tagging products with keywords

Each product on *Capterra* can be associated to *more* than one category.[59] This precludes me from using the *Capterra* categories directly as market definitions. In order to place products into *unique* and *disjoint* markets, I essentially need to reduce the dimensionality of the categories. Aside from the category names, I "tag" products with further meaningful keywords whenever those appear in the products' descriptive text.

I first pre-process category names by replacing acronyms in the category name (e.g. "Search Engine Optimization" instead of "SEO"), and by creating bi-grams (e.g., by replacing "photo editing" by "photo-editing"). Moreover, I add a small number of further meaningful terms to that dictionary. I then "tag" each product with the respective keywords whenever they occur either in the category name, or in its descriptive text. Acquired companies whose products were shut down (and for which *Capterra* categories or product description are thus not available) are tagged with the respective keywords from the same dictionary whenever they occur in these companies' *Crunchbase* industry tag or descriptive text. For instance, if a given company on *Crunchbase* is described as providing spreadsheet software, this company's product will be associated with the term "spreadsheet".

C.8 K-means clustering

I employ a k-means clustering algorithm to partition products into disjoint sets. For a given number of clusters k, k-means clustering divides observations into groups in a way that minimizes the within-cluster variation summed over all k clusters. Within-cluster variation is defined to be the squared Euclidean distance.

Further clustering algorithms exist, but so far have resulted in less intuitive outcomes in my setting. In particular, using HDBSCAN yielded clusters that are less aligned with *Capterra*'s initial product categories, which might be a meaningful benchmark. Evaluating outcomes of a certain clustering outcome does in fact not seem to be straightforward. See Grimmer and King (2011) for how to evaluate the outcome of a clustering algorithm, and see Delgado, Porter, and Stern (2016), who evaluate different methods for detecting regional industry clusters. I intend to explore this issue more thoroughly in future work.

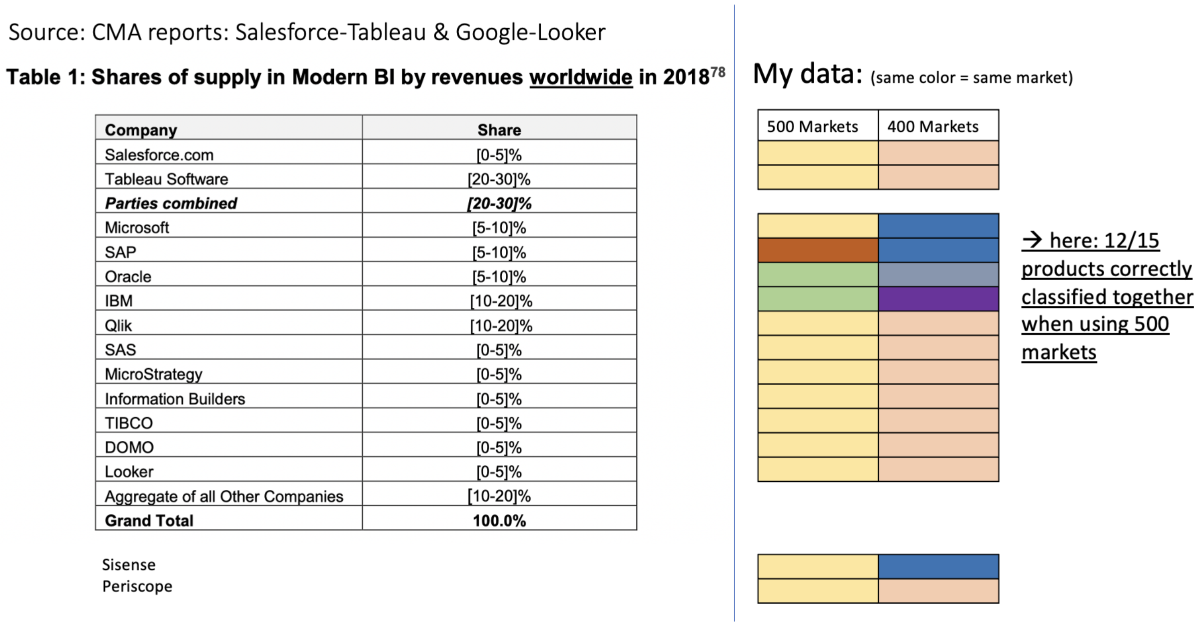
C.9 Validation of Market Definition

C.9.1 Using market definitions from recent merger decisions in the domain of enterprise software

In Figure 8, I conduct a validation of the market definitions by comparing my markets to markets distinguished by the UK Competition and Markets Authority in their decisions with respect to the Salesforce-Tableau merger, and the Google-Looker merger (see here: `bit.ly/3XhIE2T` and here: `bit.ly/3iemS0N`, both accessed 15/03/2022). I find that, when grouping products into 500 markets,

[59] The average number of categories per product, for instance, is 1.9, the median is one. 29 products are associated to over 30 categories.

twelve out of the 15 products (80%) are categorized as substitutes and thus into the same market. When grouping products into 400 markets, ten products are classified as substitutes.



Company	Share
Salesforce.com	[0-5]%
Tableau Software	[20-30]%
Parties combined	***[20-30]%***
Microsoft	[5-10]%
SAP	[5-10]%
Oracle	[5-10]%
IBM	[10-20]%
Qlik	[10-20]%
SAS	[0-5]%
MicroStrategy	[0-5]%
Information Builders	[0-5]%
TIBCO	[0-5]%
DOMO	[0-5]%
Looker	[0-5]%
Aggregate of all Other Companies	[10-20]%
Grand Total	**100.0%**

Figure 8: Validation of market definition.

C.9.2 Using known firms

Below is a list of products that are clustered together in the same market, as well as the three most commonly occurring keywords of products in those markets (after excluding the terms "software" and "management"):

- {filesharing, syncing, file}: Dropbox for Business, Box, Google Drive, OneDrive, etc.
- {presentation, presentations, tool}: PowerPoint, Google Slides, Slidebean, Pitch, etc.
- {development, application, build}: Github, Gitlab, Bitbucket, etc.
- {browser, internet, email}: Google Chrome, Firefox, Safari, Microsoft Edge, Yandex Browser, Tor Browser, etc.
- {customer, service, call}: Kustomer, Zendesk, Freshdesk, Hiver, Salesforce Service Cloud, etc.

C.10 Size of Enterprise Software Industry

These computations are based on full *Crunchbase* data (instead of only *Crunchbase* firms that are matched to *Capterra*), and thus separate of the main part of the paper. I compare enterprise software, and biotechnology / 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 look at only relevant VC funding rounds, with VC funding rounds defined as in C.2. 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. Looking at all investments (not only VC investments), the enterprise software industry has received US$319, whereas the pharmaceutical and biotechnology industry has received US$278. (Note, however, that it is possible that R&D in pharmaceuticals and biotechnology is less likely to be VC funded.)

C.11 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 C.11.1), and successful *targets* active in enterprise software predominantly exit via acquisition (Section C.11.2). 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.

C.11.1 The most important acquirers of startups of any industry are software firms

Table 15 shows the top twenty acquiring firms of VC-funded startups in 2005-2020.[60] For each acquirer, I sum up both the number of acquired firms, as well as the transaction prices.[61] Looking at the names of

[60] 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.

[61] 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.

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 15: Largest acquirers of VC-funded startups of any industry (first exits only, excluding LBOs and management buyouts), in count (left) and transaction volume (right), 2005-2020. Companies active in digital technology or software in **bold**. Acquisition prices are missing in 82% of observations, most likely for smaller acquisitions and startups in financial distress ("fire sales", see Kerr et al. (2014)). I consider acquired startups worldwide, but startups located in North America or Europe are most likely over-represented on *Crunchbase*.

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. Even relatively young and smaller companies like Groupon, Dropbox, or Twitter, are among the top 20 acquirers of VC-funded startups *of any industry*. 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.

C.11.2 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 failure rates are remarkably similar (55%) for startups active in both industries[62], I find that 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 dif-

[62] This rate is in line with empirical finance literature: Kerr et al. (2014) find that 55% of startups that received VC funding were terminated at a loss.

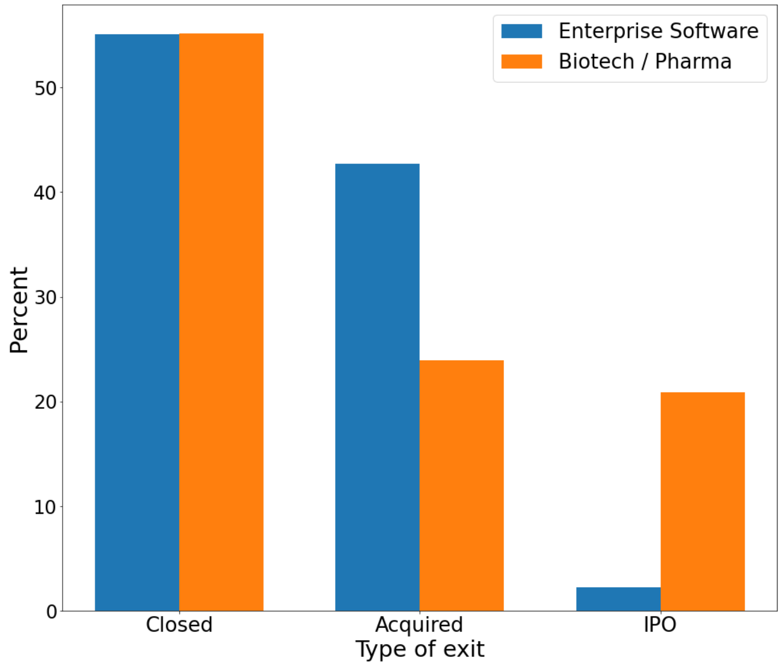


Figure 9: Types of exits of startups in biotechnology & pharmaceuticals, and enterprise software, in percent. I consider US-based startups founded after 2001 and exiting in 2005-2020. Details on the industry definition can be found in Appendix C.10.

ferent 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.

D Further Details on Different Acquirer Types

The three types of acquiring companies – enterprise software, financial, and other – not only vary by industry sector, but also in terms of other characteristics. Enterprise software acquirers are more likely to once have been VC-funded themselves (68%), tend to be somewhat younger than financial or other acquirers, and tend to be located in the US and California. Industry outsider firms are relatively more likely to be foreign to the target compared to the other groups. Financial companies tend to be much smaller than acquirers of the other types in terms of employment size, and are less likely to be public companies. I found that for only 35% of acquisitions, the acquirer is a public company as of 2021.

Table 16 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 **??** and **??**) at exit.

Panel A: "Broad" groups of acquirers (exhaustive)

Acquirer type	Number of funding rounds (mean)	Volume of funding (million USD, median)	% funding volume is not available
Enterprise Software	2.7	7.4	12.0
Financial	2.6	10.0	12.0
Other Industries	2.8	8.5	14.9
Panel B: Looking at non-exhaustive groups of enterprise software acquirers, and IPOs			
GAFAM	2.7	10.0	9.6
New tech	2.9	10.8	12.5
Old tech	3.3	25.2	10.5
Pre-exit	2.5	3.4	14.6
IPO	4.5	101.0	4.1

Table 16: Number and volume of VC funding rounds at exits of VC-funded startups, 2012-2020. Excludes leveraged buyouts or management buyouts.

E Many Acquired Products are Discontinued After the Acquisition: Further Anecdotal Evidence

Acquihires. 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. In contrast, for products kept alive, only 0.7% of acquisitions are recorded as an acqui-hire.

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 alive, I can compile further descriptives using the web-scraped product-level data. I first look at 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 are always single-product. Next, I look at the number of reviews of products acquired and continued, which could be an indication for demand. Table 17 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.

Panel A:

Acquirer type	Number of reviews (median)	Number of reviews (mean)
Enterprise Software	2.0	152.5
Financial	1.0	44.8
Other Industries	1.0	48.8
Panel B: Looking at a subset of Enterprise Software acquirer groups:		
GAFAM	19.0	1234.5
New tech	8.0	26.5
Old tech	2.0	40.5
Pre-exit	2.0	13.0
IPO	12.0	572.4

Table 17: Number of reviews, VC-funded startups with continued products only, 2012-2020. For multi-product firms, I sum the reviews of all products supplied by a given firm.

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

Reviews could be interpreted as a proxy for product demand, or for product quality. In Table 18, 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. Note that both regressions use cross-sectional data only.

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). In general, however, there seem to be a lot of other factors explaining the number of reviews, as indicated by the low adjusted R^2.

Table 18: Regression using cross-sectional data: what explains product reviews?

	Dependent variable:			
	Product-level data: num_reviews		Company-level data: mean_reviews	
	(1)	(2)	(3)	(4)
# of VC funding rounds received by producing company	9.996**		10.167**	
	(4.119)		(4.496)	
1{Any VC funding round received by producing company}		12.035		25.460***
		(9.499)		(8.329)
as.factor(status)closed	−37.845***	−36.730***	−44.914***	−46.426***
	(10.975)	(11.478)	(11.161)	(11.612)
as.factor(status)inactive	−6.695	−11.255	−17.029	−24.692**
	(9.719)	(10.452)	(10.714)	(11.449)
as.factor(status)ipo	124.192***	126.652***	9.465	11.629
	(39.476)	(39.487)	(32.137)	(32.110)
as.factor(status)operating	−5.109	−0.711	−21.051	−18.699
	(11.793)	(11.765)	(12.923)	(12.678)
as.factor(employee_count)10000+	311.316***	317.951***	150.189***	160.931***
	(66.689)	(66.293)	(49.833)	(50.204)
as.factor(employee_count)1001-5000	185.764***	199.116***	255.708***	271.787***
	(40.302)	(43.357)	(70.471)	(75.298)
as.factor(employee_count)101-250	14.577	26.337***	22.658	34.902***
	(11.466)	(10.049)	(13.821)	(11.710)
as.factor(employee_count)11-50	−2.108	1.727	0.649	4.299*
	(2.944)	(2.498)	(3.045)	(2.445)
as.factor(employee_count)251-500	22.710***	34.788***	41.584***	55.727***
	(8.668)	(9.023)	(10.657)	(10.951)
as.factor(employee_count)5001-10000	89.000**	97.722***	102.069**	111.804**
	(36.779)	(37.013)	(51.939)	(51.964)
as.factor(employee_count)501-1000	102.530***	114.908***	129.627***	143.098***
	(27.788)	(28.096)	(33.180)	(34.255)
as.factor(employee_count)51-100	3.110	11.495***	6.789	14.910***
	(4.860)	(3.862)	(5.055)	(3.573)
as.factor(employee_count)unknown	24.615***	28.426***	17.991***	25.327***
	(7.214)	(7.771)	(5.864)	(6.506)
Company year-of-birth FE	✓	✓	✓	✓
Observations	20,432	20,432	16,374	16,374
Adjusted R^2	0.031	0.030	0.018	0.016

Standard errors are heteroskedasticity-robust. *p<0.1; **p<0.05; ***p<0.01

G Robustness: Event Studies

Table 19: Event study like in Table 6, 4 quarters, 2012-2020, but Poisson model instead of linear model.

	Dependent variable:				
	Number of entrants in market m, quarter t				
	(1)	(2)	(3)	(4)	(5)
Major acq by enterpr softw company	−0.097* (0.058)				
Major acq by public enterpr software softw		−0.126* (0.068)			
Major acq by GAFAM or 'New Tech'			−0.306*** (0.111)		
Major acq by company in other industry				−0.116 (0.081)	
Major acq by financial company					0.116 (0.132)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Observations	17,064	17,064	17,064	17,064	17,064
Log Likelihood	−15,983.270	−15,982.910	−15,980.500	−15,983.920	−15,984.630
Akaike Inf. Crit.	32,986.550	32,985.820	32,981.010	32,987.850	32,989.270
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 20: Event study like in Table 6, 4 quarters, 2012-2020, but using all acquisitions above a transaction value of 50US$ million as events.

	Dependent variable:				
	Number of entrants in market m, quarter t				
	(1)	(2)	(3)	(4)	(5)
Major acq by enterpr softw company	−0.216* (0.113)				
Major acq by public enterpr software softw		−0.282** (0.122)			
Major acq by GAFAM or 'New Tech'			−0.361*** (0.093)		
Major acq by company in other industry				−0.098 (0.060)	
Major acq by financial company					−0.090 (0.127)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.299	0.299	0.3	0.299	0.299
Observations	17,064	17,064	17,064	17,064	17,064
SEs clustered on market level.					*p<0.1; **p<0.05; ***p<0.01

Table 21: Testing for anticipation effects: are events preceded by more, or less entry? Market-quarter panel, 2012-2020.

	Dependent variable:				
	Number of entrants in market m, quarter t (Sample mean: 0.65)				
	Strategic acquirer			Financial acquirer	
	(1)	(2)	(3)	(4)	(5)
Major acq by enterprise software company	-0.089				
(89 acquisitions)	(0.075)				
Major acq by public enterprise software company		-0.136^{**}			
(59 acquisitions)		(0.064)			
Major acq by GAFAM or 'New Tech'			0.103		
(21 acquisitions)			(0.179)		
Major acq by company not in enterpr softw (incl. financial)				0.038	
(40 acquisitions)				(0.105)	
Major acq by financial company					0.006
(13 acquisitions)					(0.149)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.299	0.299	0.299	0.299	0.299
Observations	16,590	16,590	16,590	16,590	16,590

Standard errors in parentheses, clustered at market level. *p<0.1; **p<0.05; ***p<0.01

Table 22: Standard diff-in-diff, using events as in Table 6, 2012-2020.

	Dependent variable:				
	Number of entrants in market m, quarter t				
	(1)	(2)	(3)	(4)	(5)
Major acq by enterpr softw company	-0.173^{**}				
	(0.075)				
Major acq by public enterpr software softw		-0.144			
		(0.089)			
Major acq by GAFAM or 'New Tech'			-0.343^{***}		
			(0.112)		
Major acq by company in other industry				-0.161^{*}	
				(0.091)	
Major acq by financial company					-0.129
					(0.105)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.3	0.3	0.3	0.299	0.299
Observations	17,064	17,064	17,064	17,064	17,064

SEs clustered on market level. *p<0.1; **p<0.05; ***p<0.01

Table 23: Same event study as in main text (Table 6), using event window of 4 quarters, but this time using data from 2014-2019.

	Dependent variable:				
	Number of entrants in market m, quarter t				
	(1)	(2)	(3)	(4)	(5)
Major acq by enterpr softw company	−0.123				
	(0.075)				
Major acq by public enterpr software softw		−0.152			
		(0.093)			
Major acq by GAFAM or 'New Tech'			-0.539^{***}		
			(0.140)		
Major acq by company in other industry				−0.050	
				(0.107)	
Major acq by financial company					0.174
					(0.155)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.304	0.304	0.305	0.304	0.304
Observations	11,376	11,376	11,376	11,376	11,376
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 24: Event window: 5 quarters. Market-quarter panel, 2012-2020.

	Dependent variable:				
	Number of entrants in market m, quarter t				
	(1)	(2)	(3)	(4)	(5)
Major acq by enterpr softw company	−0.088				
	(0.067)				
Major acq by public enterpr software softw		-0.138^{*}			
		(0.078)			
Major acq by GAFAM or 'New Tech'			-0.407^{***}		
			(0.139)		
Major acq by company in other industry				−0.079	
				(0.077)	
Major acq by financial company					−0.064
					(0.141)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.299	0.299	0.3	0.299	0.299
Observations	17,064	17,064	17,064	17,064	17,064
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 25: Event window: 3 quarters. Market-quarter panel, 2012-2020.

	Dependent variable:				
	Number of entrants in market m, quarter t				
	(1)	(2)	(3)	(4)	(5)
Major acq by enterpr softw company	−0.093				
	(0.072)				
Major acq by public enterpr software softw		−0.114			
		(0.097)			
Major acq by GAFAM or 'New Tech'			-0.328^{**}		
			(0.151)		
Major acq by company in other industry				−0.100	
				(0.085)	
Major acq by financial company					−0.023
					(0.190)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.299	0.299	0.3	0.299	0.299
Observations	17,064	17,064	17,064	17,064	17,064

SEs clustered on market level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

H Details on Market-Category Effects

As written in the main text, 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), but the more likely one will face an issue regarding the incidental parameters problem. Further, more groups imply that the fixed effects will absorb more of the variation in p_m^{ipo} and p_m^{acq} in the second stage. In order to strike a balance between those effects, I choose to group markets into 20 categories.

As a 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, e.g. markets tagged with the keywords "church / accounting / membership / donation", "club / membership / fitness / business", "catering / event / business / food", or "call / predictive / dialer / call-center". In contrast, markets with the highest estimated market-category effect seem to be active in broader, more growing markets, for instance in markets tagged with the keywords "artificial-intelligence / platform / customer / business", "app / development / application / building", as well as markets related to business intelligence, CRM, and marketing.

I Alternative Model Specification

The model covered in the main text contains $\boldsymbol{x}_{mt} = \{N_{mt}, A^{\text{strat}}_{mt}, l(m)\}$ as a vector of state variables. Here, I consider instead an alternative version of the model with $\boldsymbol{x}_{mt} = \{N_{mt}, A^{\text{strat in } t-K}_{mt}, l(m)\}$ as state variables. $A^{\text{strat in } t-K}_{mt}$ mirrors the event study indicator variables employed in Section 4, and is equal to 1 in the event of a strategic acquisition in the past K quarters, and 0 otherwise.

I set $K = 4$, as in the reduced-form regressions in Section 4. The first-stage results are displayed in Tables 26 and 27. The coefficients of the strategic acquisiiton affect increase somewhat in magnitude, as the variable is now a dummy (instead of the cumulative number), and remains mostly insignficiant. There is essentially no change in the fit of the first-stage regression model.

The second stage results are displayed in Table 28. Judging from the log-likelihood, the fit of the model is somewhat worse compared to the main results in the text, and the coefficients of γ^A are insignificant in both specifications.

Table 26: First stage, using a broad definition of "strategic" acquirers, and a moving average indicator variable with window length 4 quarters to capture strategic acquisition effect. Standard errors are clustered at the market level. In column (4), they are computed using block bootstrapping with 5,000 bootstraps to account for the estimated market-category fixed effect.

	Dependent variable:				
	Number of entrants in market m, quarter t				
			Poisson		
	(1)	(2)	(3)	(4)	(5)
# of competitors	0.022***	−0.163***	−0.118***	−0.066***	−0.161***
	(0.001)	(0.015)	(0.017)	(0.012)	(0.015)
Major Enterprise Software acquisition pre-4Q	−0.056	−0.002	0.050	−0.021	−0.007
	(0.069)	(0.067)	(0.079)	(0.078)	(0.067)
1{quarter=2}					−0.126***
					(0.020)
1{quarter=3}					−0.151***
					(0.019)
1{quarter=4}					−0.212***
					(0.019)
Market FE		✓	✓		✓
20 market-category FE				✓	
Adjusted R^2	0.11	0.34		0.24	0.35
Log Likelihood			−9,813.634		
Akaike Inf. Crit.			20,511.270		
Observations	10,560	10,560	10,560	10,560	10,560
Standard errors clustered at market level.					*p<0.1; **p<0.05; ***p<0.01

Table 27: First stage, using a narrower definition of "strategic" acquirers, and a moving average indicator variable with window length 4 quarters to capture strategic acquisition effect. Standard errors are clustered at the market level. In column (4), they are computed using block bootstrapping with 5,000 bootstraps to account for the estimated market-category fixed effect.

	Dependent variable:				
	Number of entrants in market m, quarter t				
			Poisson		
	(1)	(2)	(3)	(4)	(5)
# of competitors	0.022***	−0.162***	−0.117***	−0.066***	−0.161***
	(0.001)	(0.015)	(0.017)	(0.012)	(0.015)
Major New Tech or GAFAM acquisition pre-4Q	−0.311*	−0.205	−0.195	−0.178	−0.203
	(0.174)	(0.162)	(0.176)	(0.210)	(0.163)
1{quarter=2}					−0.125***
					(0.020)
1{quarter=3}					−0.151***
					(0.019)
1{quarter=4}					−0.212***
					(0.019)
Market FE		✓	✓		✓
20 market-category FE				✓	
Adjusted R^2	0.11	0.34		0.24	0.35
Log Likelihood			−9,812.992		
Akaike Inf. Crit.			20,509.980		
Observations	10,560	10,560	10,560	10,560	10,560
Standard errors clustered at the market level.					*p<0.1; **p<0.05; ***p<0.01

Table 28: Estimates of structural parameters, this time using $A_{mt}^{\text{strat in } t-K}$ as state variable with K=4.

	(1)	(2)
Entry costs, κ	-2.957^{***}	-2.984^{***}
	(0.137)	(0.138)
log(# of competitors), γ^N	-0.248^{***}	-0.248^{***}
	(0.011)	(0.011)
Strategic acq of competitor **by Enterprise Software acquirer**, γ^A	-0.032	
(Dummy indicating major such acquisition in past 4 quarters)	(0.027)	
Strategic acq of competitor **by GAFAM or New Tech**, γ^A		-0.085
(Dummy indicating major such acquisition in past 4 quarters)		(0.053)
Own IPO in future, α^{ipo}	0.006^{***}	0.005^{***}
	(0.001)	(0.001)
Own acquisition in future, α^{acq}	0.037^{***}	0.038^{***}
	(0.003)	(0.003)
Market category 2, γ_2^M (5th-10th perc)	0.319^{***}	0.320^{***}
	(0.024)	(0.024)
Market category 3, γ_3^M (10th-15th perc)	0.390^{***}	0.392^{***}
	(0.025)	(0.025)
...	...	...
Market category 19, γ_{19}^M (90th-95thth perc)	1.142^{***}	1.143^{***}
	(0.046)	(0.046)
Market category 20, γ_{20}^M (95th-100th perc)	1.301^{***}	1.301^{***}
	(0.050)	(0.050)
Log-likelihood	-10631.63	-10617.22
Observations: 440 markets, 24 quarters	10,560	10,560
Note:		*p<0.1; **p<0.05; ***p<0.01