Entry and Acquisitions in Software Markets*

Luise Eisfeld†

November 11, 2022

Job Market Paper

Click here for latest version.

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 findings indicate 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 results 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

*I am grateful to Alexandre de Cornière, Daniel Ershov, and Bruno Jullien for their continued support and invaluable guidance while writing my thesis. I thank Patrick Coen, Pierre Dubois, Olivier de Groote, Florian Ederer, Ulrich Hege, Marc Rysman, and Timothy Simcoe for their thoughtful comments at different stages of the project. I thank Walter Ferrarese and Yingkang Xie for serving as discussants of this paper. The paper also benefited from comments I received when presenting at the Technology & Policy Research Initiative Seminar, the Boston University Economics Department, the Questrom School of Business, the Toulouse School of Economics, the Trans-Atlantic Doctoral Conference, EARIE, and the Jornadas de Economía Industrial. I thank *Crunchbase* (www.crunchbase.com) for granting me research access to their data, and I thank *Gartner* for agreeing to make their website available for scientific purposes. All errors are mine.

†PhD Candidate, Toulouse School of Economics (TSE). E-mail: luise.eisfeld@tse-fr.eu

1 Introduction

Companies active in digital 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? New, innovative entrants are thought to be a main competitive force in software markets, and able to discipline dominant incumbents (e.g. Crémer, de Montjoye, and Schweitzer (2019), Scott Morton, Jullien, Katz, and Kimmelman (2019)).

On the one hand, acquisitions provide an entry-for-buyout incentive if the returns from being acquired are higher than the returns from competing (Cabral, 2018, Mermelstein, Nocke, Satterthwaite, & Whinston, 2020, Phillips & Zhdanov, 2013, Rasmusen, 1988). In software markets, over 90% of successful, venture-backed startups are acquired by other firms, as opposed to being listed on public stock markets.[1] Survey results indicate that acquisitions are a major goal for startup founders.[2] This suggests that regular startup acquisitions in a given market can reward innovation efforts and encourage entry.

On the other hand, an acquisition can affect market structure and the competitive environment that new entrants are facing. In some situations, an acquired company benefits from the acquirer's market power, or its complementary assets. The acquired product is then able to capture a larger share of demand in the market. This *decreases* returns to entry for potential entrants, converting the market to a so-called "kill zone" in which entry is deterred (Denicolò & Polo, 2021, Kamepalli, Rajan, & Zingales, 2021, Motta & Shelegia, 2021).

I study startups' entry incentives in the face of acquisitions (1) by collecting and assembling new data that enables to identify competing firms; (2) by producing new, policy-relevant facts on startup acquisitions in software markets; and (3) by building and estimating a dynamic structural model of startup entry.

Answering the research question requires to accurately define *markets*: 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 by web-scraping product-level data from *Capterra*, a vertical search

[1] 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 A.7.2.

[2] The survey results are not public but will be made public in a forthcoming working paper by Stephen Michael Impink.

engine for enterprise software.[3] 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 markets at the *product* level. I merge these product data with information on firms' entry and acquisition decisions stemming from *Crunchbase*, a database that records M&As and VC investments of firms worldwide.

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 dominant incumbents – in particular, on the so-called GAFAM[4]. However, I find that other firms, in particular young, VC-funded but by now large companies, display a similar pattern of acquisitions.

I distinguish between different types of acquirers along the dimensions of industry incumbency and measures of age. These acquirer types are likely driven by different motives. I call acquirers that, like the target, are active in enterprise software, "strategic" acquirers. I argue that strategic acquirers are the most likely to possess the capabilites and the incentives to bolster up an acquired firm's product, either via synergies or via market power, in a way that will deter follow-on entry. In contrast, industry outsiders tend to acquire enterprise software startups to vertically integrate new tools, and do not have incentives to affect a market niche's development in the long run. Financial acquirers like private equity firms tend to be transitional owners, and acquire in order to generate financial returns.

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, acquirers tend to be followed by a decrease in new entry.

Studying how acquisitions affect startup entry requires to analyze and quantify both any entry-deterring effect that is transmitted via market structure, as well as the more long-run entry-for-buyout effect. This is only possible within a structural model of startup entry that accounts for both channels of effect. I thus set up a dynamic model in discrete time. In each period and in each market, a new set

[3] I thank the parent company *Gartner* for granting me the official permission to web-scrape the *Capterra* website.
[4] This acronym refers to the firms *Google (Alphabet)*, *Amazon*, *Facebook (Meta)*, *Apple*, and *Microsoft*.

of forward-looking potential entrants considers whether to enter the market.[5] Firms that have entered 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 that affected the market in the past. In future periods, firms may moreover be acquired or listed on the public stock market. Whenever this transition in ownership occurs, firms earn a single lump-sum return, and stop earning flow profits. These events are modeled as stochastic shocks that arrive upon the startup with varying frequencies across markets, and are assumed exogenous conditional on 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 which a change in ownership – being acquired, or going public – occurs. Using a revealed preference approach and a two-step estimation method (e.g. Aguirregabiria and Mira (2007)), I estimate the parameters quantifying the importance of each of these channels for spurring or deterring entry.

The parameter estimates reveal that in markets in which firms are acquired at a higher frequency, startups are more inclined to enter. 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 believe 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 my descriptive and my model-based findings are of first-order importance from an antitrust perspective. The types of acquisitions that are the focus of this paper rarely meet merger notification thresholds, as targets are small firms, albeit highly innovative and potentially disruptive ones (also see Wollmann (2019)). The sheer number of these types of transactions has caught the attention of antitrust

[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.

practitioners and academics worldwide.[6] At the same time, software is an industry where entry is highly valuable, as strong network effects often lead markets to "tip". 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 (Federal Trade Commission, 2021).

By studying innovative entry, this paper is linked to the long-running question of how firms' innovation incentives is 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 poorly documented and understood. As these markets are bringing vast welfare gains in the years to come, understanding any frictions that entering startups face is economically important.

Related 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 component. I am able to produce new facts thanks to a dataset that I created and a novel method for developing market definitions. In contrast to previous empirical literature (Affeldt & Kesler, 2021a, 2021b, Argentesi et al., 2021, Gautier & Lamesch, 2021), I do not restrict the focus on the analysis of GAFAM acquisitions. Instead, I establish findings on the effects of startup acquisitions conducted by any kind of firm, including financial firms, which to my knowledge has only been done by G. Z. Jin, Leccese, and Wagman (2022). In fact, one strength of my approach is the distinction between several acquirer types who pursue different motives that should affect entry incentives in different ways. Whereas much literature in empirical industrial organization tends to focus on few firms, my dataset is therefore extensive, covering an entire industry branch and tens of thousands of enterprises. Nevertheless, I am able to follow acquisitions at the *product* level, and to define markets on a more granular level compared to earlier work (G. Z. Jin et al., 2022, Vaziri, 2022). I thus characterize the effects of acquisitions employing an approach that to my knowledge has only been used in the context of the pharmaceutical industry, where project-level data is abundant (Cunningham, Ederer, & Ma, 2021).

The second contribution is a model that allows to disentangle and to quantify two channels through which acquisitions can affect returns to entry. Previous empirical literature focuses on only one of

[6]The firm *Alphabet*, for instance, has acquired about one company every week from 2010 to 2015.

these channels. Bauer and Prado (2021), G. Z. Jin et al. (2022), Kamepalli et al. (2021), Koski, Kässi, and Braesemann (2020) employ reduced-form regressions to study how GAFAM acquisitions correlate with measures of investment or entry. X. Wang (2018) and Warg (2021) find that startups "cater" to potential acquirers by investing into adjacent technology areas that may be useful for potential acquirers, which may be viewed as evidence for an entry-for-buyout effect. The effect of blocking acquisitions on entry, however, depends on both effects. A linear regression cannot account for different channels of effect that are associated with acquisitions. The model I set up explicitly quantifies the two channels, which allows to simulate how entry would evolve under counterfactual antitrust regimes. The most related work that models (among other decisions) entry decisions within a dynamic structural model is Igami (2017) and Igami and Uetake (2020). However, both papers model study a very different industry, have different data, and analyze the decisions firms take in a single market.

Prior theoretical research has pointed out a potential entry-deterring effect of acquisitions. The theory of bundling (Whinston, 1990) suggests that companies may leverage market power from one market into another, and thus foreclose rivals. Motivated by the acquisitions in digital markets, the model proposed by Denicolò and Polo (2021), a cumulative number of acquisitions can entrench a dominant position of an incumbent, leading to market power and less entry, even in the presence of an entry-for-buyout effect. Motta and Shelegia (2021) do not directly speak to a possibly entry-deterring effect of acquisitions, but study the interaction of incumbents' aggressive behavior and acquisitions. In their model, entrants expect aggressive behavior by the incumbent in the form of imitation, and therefore produce a complement instead of a substitute to the incumbent's product. Even in anticipation of possibly being bought out, entrants may stay away from directly challenging the incumbent. As acquisitions by large strategic buyers are often akin to market entry by the buyer, one might expect this "kill zone" effect in anticipation of imitation to take place upon an acquisition in a given market. Kamepalli et al. (2021) study a setting with network effects and consumer switching costs. In their model, consumers anticipate that startups' products will be acquired and integrated into the acquirer's product. To avoid switching costs, consumers are therefore reluctant to try out a new product, which leads to low adoption and low demand of the startups' products, and subsequently to a lack of willingness to fund new entrants.[7]

[7]Further literature has outlined 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). 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, 2021, Fumagalli, Motta, & Tarantino, 2022, Gilbert & Katz, 2022, Guéron & Lee, 2022, Hege & Hennessy, 2010, Katz, 2021, Lemley & McCreary, 2020, Letina, Schmutzler, & Seibel, 2021, Motta & Peitz, 2021).

I model entrepreneurs' entry decisions as dynamic strategic interactions with incomplete information. Methodologically, my paper leans on the dynamic discrete game literature (Aguirregabiria & Mira, 2007, Bajari, Benkard, & Levin, 2007) and employs forward simulation techniques used in Hotz, Miller, Sanders, and Smith (1994). A main difference to most dynamic models is that in my setting, in each period, there is a new set of agents deciding whether to enter or not. Each agent therefore only takes a single decision once.[8]

This paper is also related to findings in the finance literature on the effects of startup exits. Some of these are reflected in my model-based results (Aghamolla & Thakor, 2021, Conti, Guzman, & Rabi, 2021, Song & Walkling, 2000). I also shed new light on startups' commercialization strategies, as highlighted in Gans and Stern (2003), and is related to the concept of divided technological leadership emphasized by Bresnahan and Greenstein (1999). Also studying the enterprise software industry, Cockburn and MacGarvie (2011) study the relationship between patenting and entry into a market.

More broadly, the paper contributes to literature on market structure (including mergers and breakups) and innovation. This literature has either used theoretical modeling and simulation techniques (Hollenbeck, 2020, Jullien & Lefouili, 2018, Mermelstein et al., 2020, Nocke & Whinston, 2010), or empirical methods (Haucap, Rasch, & Stiebale, 2019, Igami & Uetake, 2020, Poege, 2022, Watzinger, Fackler, Nagler, & Schnitzer, 2020) to reveal how market structure affects firms' innovation incentives.

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 simulation. 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 firm entry in the *enterprise software* industry. Startup acquisitions in this industry are especially prevalent when compared to other innovative industries, such as pharmaceuticals. In fact, the companies

[8]Nevertheless, agents incur a sunk cost upon entering, are forward-looking, and agents' payoffs depend on state variables that evolve according to their decisions, which renders the model dynamic.

acquiring the highest *number* of startups worldwide are all active in software (see Appendix A.7).

I define as enterprise software any software product that can be used in a business environment. This definition captures both, products that are targeted specifically to business clients (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). The enterprise software industry is large and growing: between 2005 and 2020, enterprise software startups received more venture capital (VC) funding than all startups belonging to the biotechnology and pharmaceuticals industry (see Appendix A.8). 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.[9] Studying entry into this industry is therefore economically relevant in its own right.

I consider entry by *startups*, which are young, risky, very innovative, VC-backed, privately held companies. In industries with network effects where markets may "tip" in favor of a large incumbent, the threat of entry by these young firms is deemed essential for guaranteeing competition *for* the market (Furman, Coyle, Fletcher, Marsden, & McAuley, 2019). More broadly, startups play an important role for innovation and industry dynamics in the economy. In the past, startups have redefined markets and out-competed large incumbents in some industries. Startups tend to bring forward higher quality and more novel innovation than established companies (Schnitzer & Watzinger, 2022), and have at times contributed to economic welfare in very meaningful ways, most recently with the development of Covid-19 vaccines.

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. In this so-called "exit" event, the startup may either be listed on a public stock exchange and thus become a public company. Alternatively, and much more commonly, the startup may be sold to another firm.[10] Both of these events are generally considered a success, and may yield a high return to

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

[10] See Appendix A.7.2 for exit rates of startups active in enterprise software, and biotech or pharma. More recently, some startups have been able to stay private for longer. In those cases, early investors sell their shares to investors specialized on later-stage companies (so-called crossover investors).

investors and founders.[11]

2.2 Data

The study of entry incentives in the face of acquisition requires data on companies' entry and acquisition decisions in clearly defined markets. I obtain information on entry and acquisition decisions from the data portal *Crunchbase*. As *Crunchbase* does not contain enough information to distinguish sets of competing firms (i.e. markets), 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 me to use text-as-data methods to classify products into distinct markets. It also enables me 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. It comprises nearly 500 markets and contains variables indicating the number of entrants, types and number of acquisitions, and so on.

2.2.1 Firm-level Panel: *Crunchbase*

I obtained access to data on *Crunchbase*, a data portal that tracks financial information on over a million public and private companies, in particular VC-funded firms. *Crunchbase* records companies' founding dates, funding rounds, acquisitions, investments into other companies, initial public offerings (IPOs), and closures of over a million companies worldwide. Unlike other financial databases, having received a VC investment is not a pre-condition for being present on this database. The database 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).

As *Crunchbase* contains both, venture capital and other types of investments (such as private equity), 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.[12] I then define "startups" as companies that have received at least one such VC-type investment. I further define a startup's "entry"

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

[12] 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 A.2 for details.

event as the first VC-funding round for a firm in my data.[13] *Crunchbase* itself defines acquisitions as majority takeovers.

Using the observations of all acquisitions in a company's lifetime, I reconstruct the parent-subsidiary structure of up to two levels of all firms over time.[14] I then construct a panel of company events.

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, these labels are relatively broad – as there are fewer than 800 labels describing the entire economy – and not very useful for determining which companies actually compete against each other in a given market.[15] 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 remote 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. The distinction of which companies compete with each other in a given market requires a *product-level* definition of competitors. Moreover, I intend to consider both public and private firms, which prevents me from using standard industry classifications that are available for public firms only. Lastly, it is not clear from *Crunchbase* which companies are actually still active and producing any product at all.

I web-scrape a platform called *Capterra* in order to obtain more accurate, product-level information.[16] *Capterra* is a vertical search engine for enterprise software, and is thus designed to assist customers with comparing and finding suitable enterprise software. It is one of the market leaders among platforms offering this service, and offers us a natural structure that can be used for identifying competing products. The website classifies enterprise software products into one or more 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

[13] 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.

[14] This allows to associate acquisitions that were undertaken by e.g. LinkedIn after its acquisition by Alphabet as a GAFAM-acquisition. In general, the partent-subsidiary structure can go above two tiers; however, this is rare on *Crunchbase* and does not occur for the sample of firms considered.

[15] 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.

[16] *Capterra* is owned by *Gartner*, a large public consulting and technological research company. I thank *Gartner* for allowing me to scrape this website.

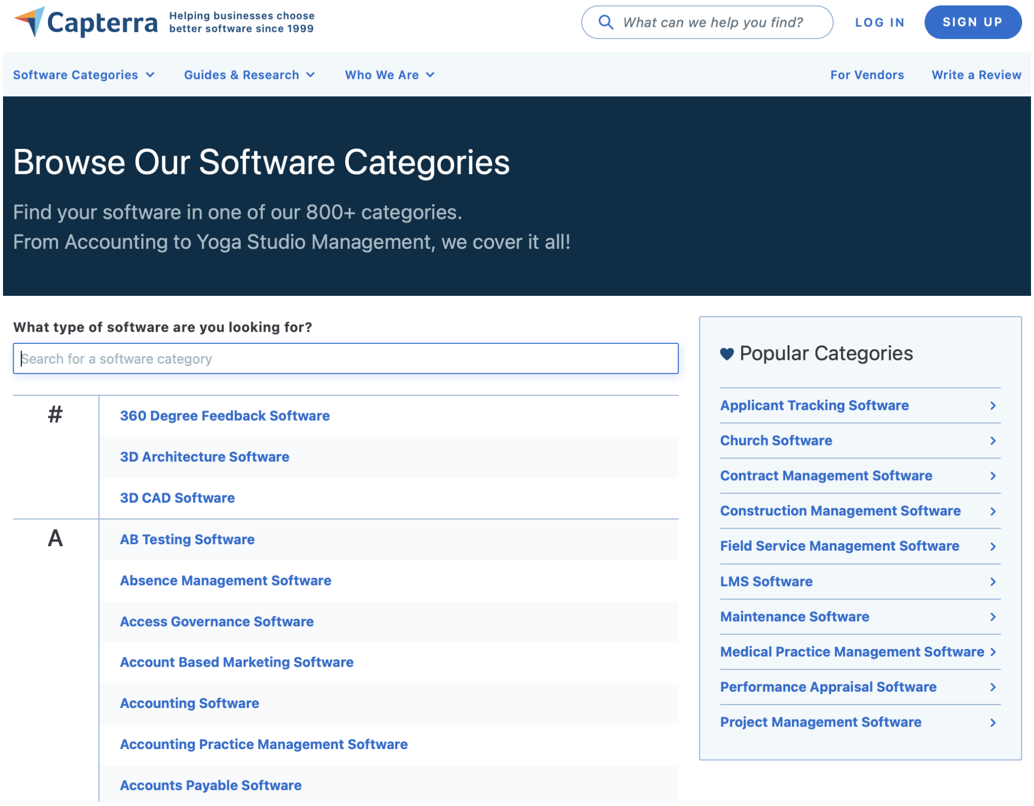


Figure 1: *Capterra*'s categories page

product (see Figure 1 and 2).[17] The range of enterprise software products covered on *Capterra* is exhaustive and very up-to-date.[18]

From *Capterra*'s product listings pages, I obtain 72,986 links to product pages on *Capterra*, which I query one-by-one in June and July of 2021. From each product page download and save all information available. In particular, I record product and company names; the categories a product is assigned to; the company's web domain; a text describing the product; and the user rating and the cumulative number of user reviews.[19]

All in all, I make use of the *Capterra* data for the following purposes: first, for clustering products into groups of substitutable products, with the help of a machine learning model (see Section 2.2.3). Second, it

[17]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*).

[18]Based on comparisons with its competitors, information on reviews and ratings seem accurate and representative. *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), and it is available in over 30 countries and at least seven languages. Looking at individual products, the relative number of reviews - an indicator of demand - seemed comparable between *G2* and *Capterra*. Using the Internet Archive ("Waybackmachine"), I found at least anecdotally that products that were discontinued were removed earlier from the *Capterra* website than from *G2*.

[19]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. See Appendix A.3 for details on the web-scraping process.

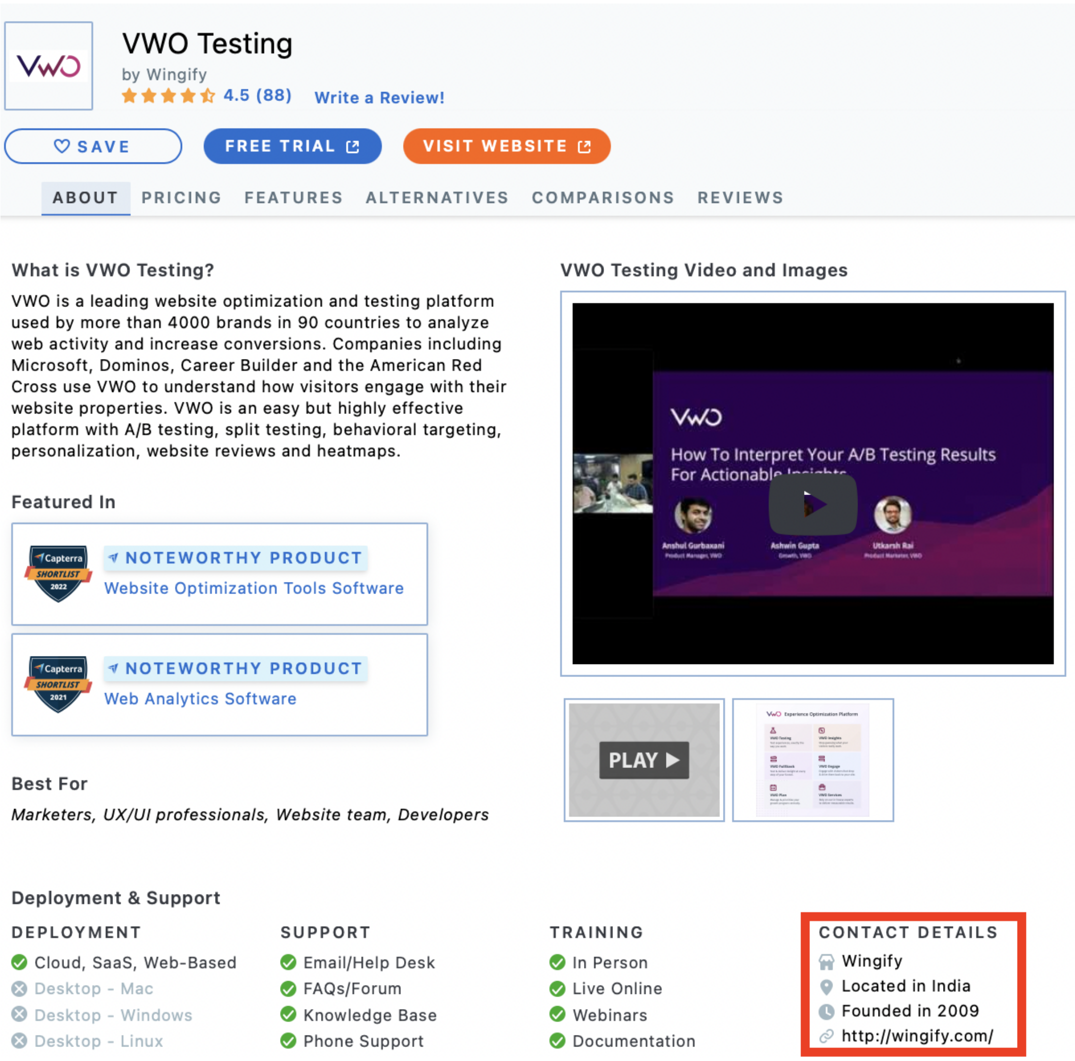


Figure 2: Example of product page on *Capterra*. The red frame highlights the company information (in particular, name and URL) available for all products on *Capterra*.

allows me to find out 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 market shares. When estimating the model, this allows me to differentiate companies that are actually "relevant" competitors that act strategically in a given market, and which ones should be considered a 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, as shown in the red frame in Figure 2. As there are products that were acquired by another firm in the past and thus have the acquirer's URL and name, I make sure to match these products to the originating firm, instead of the acquirer.[20] I end up merging 71% of all web-scraped products, and 96% of products with over 100 reviews, to firms on *Crunchbase*. Almost all of the remaining non-matched products do not have many reviews, and thus must be insignificant competitors that do not play a major role in this market. Manual checks confirm a very high accuracy of this matching procedure.

From the non-matched firms in the *Crunchbase* data, I moreover include firms in my sample that are enterprise software related based on its descriptive text, industry group and industry variable, *and* that were acquired by a firm that was matched and thus owns a product on *Capterra*.[21] For this subset of acquired, enterprise software related companies, I conclude that their products must have been discontinued under the original name at some point after the acquisition took place.

The final dataset contains 46,186 currently existing products and their respective companies' events, as well as the events of 5,034 enterprise software companies that were acquired and whose products are not existing under the same name on *Capterra* any more.

2.3 Defining Markets

I create markets of substitutable products by using text-as-data methods.[22] Each product on *Capterra* is associated with a body of text, stemming from one or more category names, and the product description.[23] The textual information on *Capterra* can be viewed as meaningful information on a product's

[20]Details of the matching procedure are provided in Appendix A.4.

[21]I thus do not include enterprise software companies that stayed independent and do not have a product on *Capterra*, although one could retrieve information on these firms. I first identify a set of enterprise software related companies by manual selection, based on which I develop an algorithm that selects enterprise software firms based on *Crunchbase*'s categories.

[22]See Gentzkow, Kelly, and Taddy (2019) for a review on these methods.

[23]As a given product may be associated to more than one category, one cannot create disjoint sets of products by using categories alone.

functionalities, in the sense that companies present in the same (or similar) categories should be more substitutable: *Capterra*'s purpose is to guide consumers searching for specific enterprise software products. The company therefore has an incentive to accurately categorize products.[24]

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 A.5.

To cluster all products on *Capterra* (or each company for shutdown acquisitions) into disjoint markets, 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).[25] This will 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 vectors of the category names so that each product ois associated with a single vector. Next, I cluster products (based on their respective locations in the vector space) into distinct markets using a k-means clustering algorithm. Products whose vectors are located close to each other, and thus, whose attached keywords are close in meaning, are grouped together.

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 A.6).[26]

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 – 65% – are indeed VC-funded. In contrast, only 4.6% of producing companies are (at any point in the observation period) public firms, showing that a lot of relevant entry behavior would be missed if one were to focus on only public firms.

[24] *Capterra* confirmed this to me by explaining that new products are in a single category when they are introduced on the website, upon which companies can request to be added to further categories. A dedicated catalog team will then review the request and approve the product if the category seems suitable.

[25] The word vectors were trained on Common Crawl.

[26] Market definitions in principle allow for distance metrics between markets. The current version of this paper does not make use of this.

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 exclude LBOs and management buyouts from the acquisitions.

Table 2 exhibits descriptives on the market-quarter panel. It becomes clear that the data tend to be right skewed.

	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	395.2	945.8	40	130	360
Startup IPOs: valuation	3,774.7	13,875.4	352	885.4	2,165.2

Table 2: Descriptives using market-quarter panel, comprising 474 markets (after dropping markets that I view as outliers), 2012-2020. Prices and valuations in million US$. 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 therefore do not consider these as startup firms.

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. The different acquirer types acquire different types of targets, reflecting their heterogeneous motives (Section 3.2).

2. Many acquired products are discontinued (Section 3.3).

3. Most acquisitions are nonhorizontal (Section 3.4).

3.1 Different Types of Acquirers

I identify three main types of acquirers.

- *Companies in Enterprise Software*: these companies have existing products on *Capterra* that do not stem from a previous acquisition, and are thus active producers of enterprise software.
  - Examples: the so-called GAFAM; Cisco; Oracle; Salesforce; VMware.
- *Financial companies*: I identify these companies as active in finance, based on *Crunchbase* information.[27] Among these are private equity firms.
  - 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 industries.[28]
  - Examples: The We Company; Verizon; Dentsu International; Samsung Electronics; Ericsson.

The fractions 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 B.

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 those have been the focus of attention by competition policy practitioners, and are deemed to be especially dominant in many markets. These 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

[27] 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").

[28] 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 less related industry sectors, such as transportation, consumer products, e-commerce, or biotech.

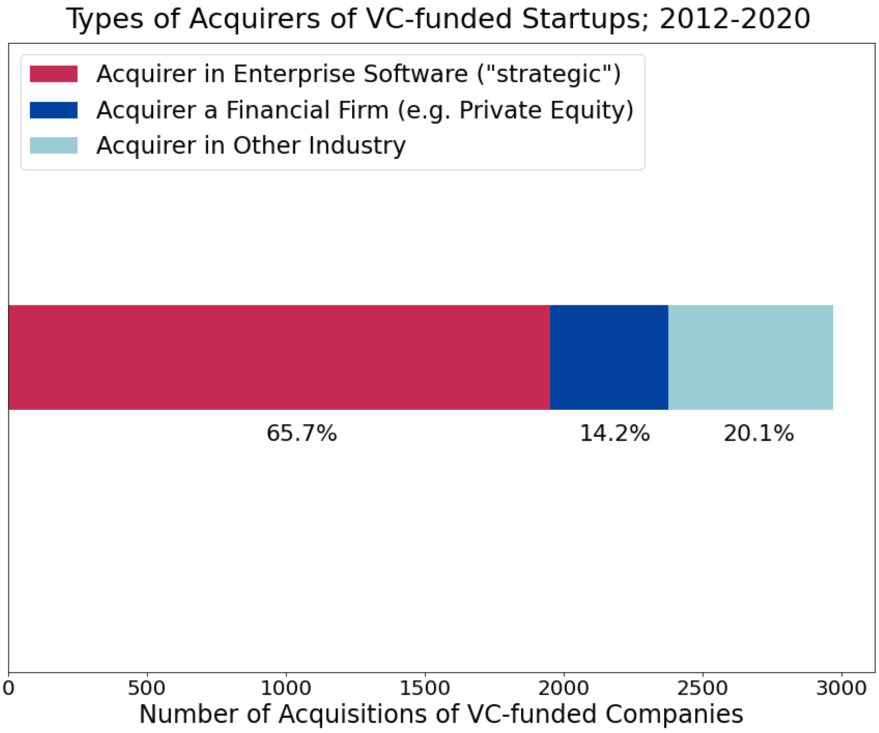


Figure 3: Types of acquirers for first-time acquisitions ("exits") of VC-funded startups worldwide in the domain of enterprise software, for acquisitions occurring between 2012 and 2020. The total number of such acquisitions is 2,973. These numbers are on the company (as opposed to product) level. I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

Acquirer type (# of startup acq)	Description	Examples
GAFAM (156 acq)	Google (Alphabet), Apple, Facebook (Meta), Amazon, Microsoft and their subsidiaries.	GAFAM, 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 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.)

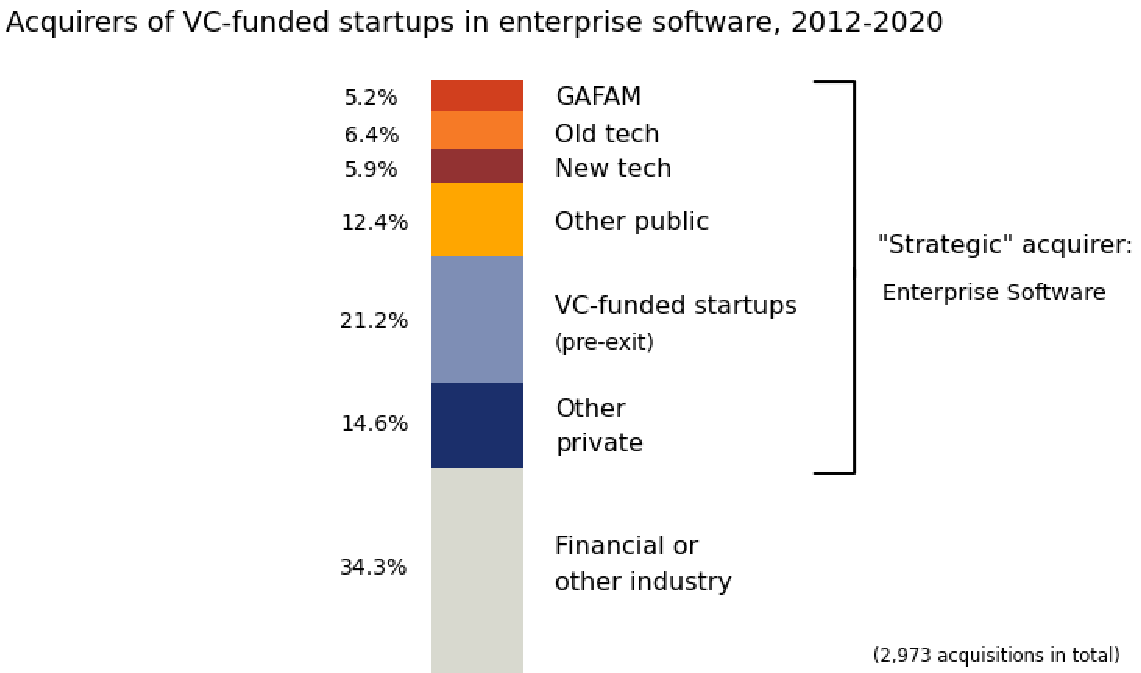


Figure 4: Subgroups of acquirers for first-time acquisitions ("exits") of VC-funded startups worldwide in the domain of enterprise software, for acquisitions occurring between 2012 and 2020. As in Figure 3, the total number of such acquisitions is 2,973; the numbers are on the company (as opposed to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

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 Different Acquirer Types Acquire Different Sets of Targets

Next, I turn to the question: for each of these different sets of acquirers, what are the likely motives for acquiring? I try to reveal acquirers' motives by studying the characteristics of the acquired companies for each of these acquirer types.

I start with a more aggregate pattern, and find out to what extent target firms are *VC-funded startups*, as opposed to other, non VC-funded companies, for each of these acquirer types. The numbers are detailed

Panel A: "Broad" groups of acquirers (exhaustive) *(in %)*

Acquirer type	≤3y old and no VC funding (yet)	VC-funded, pre-exit ("startup")	VC-funded, post exit	Not VC-funded (and >3y old)	Total
Enterprise Software	6.4	48.9	3.6	38.7	100
Financial	2.9	29.1	5.0	62.1	100
Other Industries	4.4	36.7	4.6	53.3	100
Panel B: Looking at non-exhaustive groups of enterprise software acquirers					
GAFAM	9.8	72.0	2.8	12.6	100
New tech	5.5	76.4	4.7	11.8	100
Old tech	1.9	63.6	8.4	20.7	100
Pre-exit (VC-funded)	9.4	51.8	4.7	31.6	100

Table 4: Which types of companies are acquired by different types of acquirers? I use data from 2012-2020. I exclude leveraged buyouts and management buyouts, but otherwise place no restriction on the type of company acquired.

in Table 4. Looking at Panel A, what is noteworthy is that roughly half (48.9%) of targets acquired by enterprise software firms are VC-funded, pre-exit startups. This number is much lower for financial firms (29.1%) or firms in other industries (36.7%), which both tend to acquire non-VC-funded firms. Panel B shows a result that is particularly interesting from a policy perspective. Comparing the different subgroups of enterprise software acquirers, the pattern of firms acquired by the GAFAM is closest to New Tech firms. For both groups of firms, the share of targets that are VC-funded is very high, amounting to more than 70%. Similarly, the share of targets that are very young companies that have no prior funding history is also very high. Old Tech and pre-exit firms tend to be more active acquiring firms that are non-VC funded. Moreover, Old Tech firms very rarely acquire very young companies with no prior funding history. All in all, whereas the Old Tech firms tend to dominate markets in a similar fashion as the GAFAM, they apparently pursue an acquisition strategy that is quite different from the GAFAM.

For the remainder of this section, I consider only acquisitions in which the target was a VC-funded startup. I first compare the maturity of startups at the time of acquisition by different types of acquirers. In particular, I consider acquisition price and valuation (Table 5) and age (Table 6) at exit.[29] I observe the following pattern: enterprise software firms tend to acquire firms that are younger, and at lower prices and at lower valuations, compared to financial acquirers. Moreover, we observe a striking amount of heterogeneity between the sub-groups of enterprise software firms. Notably, Old Tech firms tend to acquire at a higher age, at the highest price, and high valuations. The same pattern is observed when looking at the amount of funding a startup has received at exit (see Appendix B, Table 18). Startups

[29]One caveat of prices and valuations is that this amount is very often missing; most likely particularly at the low end. I therefore also report the percent of observations in which the price or valuation variables are not available.

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

Acquirer type	**Acquisition price** (million USD; median)	**Valuation at exit** (million USD; median)	% acquisition price is not available	% valuation is not available
Enterprise Software	120.0	25.0	81.0	94.6
Financial	150.0	59.0	88.4	95.5
Other Industries	100.0	26.2	79.9	93.4
Panel B: Looking at non-exhaustive groups of enterprise software acquirers				
GAFAM	164.0	49.8	78.2	90.4
New tech	152.5	263.0	60.7	92.9
Old tech	400.0	476.0	74.2	92.6
Pre-exit	15.8	4.4	95.8	94.3
At IPO	-	-	1000.0	69.1

Table 5: Acquisition prices and valuations at exits of VC-funded startups (left columns) , as well as the percent of observations in which valuation or acquisition price are not available (right columns). 2012-2020. Excludes leveraged buyouts or management buyouts.

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

Acquirer type	Age (median # of years since founding date)	Age (median # of years since first funding round)
Enterprise Software	6.6	4.5
Financial	9.8	5.5
Other Industries	7.2	5.2
Panel B: Looking at non-exhaustive groups of enterprise software acquirers, and IPOs		
GAFAM	4.6	3.4
New tech	4.9	3.7
Old tech	7.3	5.1
Pre-exit	5.6	3.8
IPO	10.6	7.7

Table 6: Age at exits of VC-funded startups, 2012-2020. Excludes leveraged buyouts or management buyouts.

acquired by Old Tech firms thus tend to be quite mature, and the Old Tech's acquisition pattern somewhat resembles that of financial firms. In contrast, the New Tech firms, but in particular the GAFAM, acquire VC-funded startups at lower prices, lower valuations, and at a much lower age. For pre-exit firms, the acquisition pattern instead points to the possibility that pre-exit firms might tend to acquire mainly financially distressed startups, as acquisition prices are either missing or very low (Kerr, Nanda, & Rhodes-Kropf, 2014).

Table 7 looks at the average time span between the last funding round raised, and the date of acquisition, for the different types of acquirers. The rationale for doing so is that startups that have very recently raised new capital should not face strong financial constraints. These firms may have relatively higher bargaining power and presumably do not get sold due to a fire sale. This time span

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

Acquirer type	Number of years since last funding round (mean)
Enterprise Software	2.7
Financial	3.5
Other Industries	3.3

Panel B: Non-exhaustive group of enterprise software acquirers, and IPOs

GAFAM	1.8
New tech	1.8
Old tech	2.4
Pre-exit	2.4
IPO	2.2

Table 7: Time (in years) since last funding round at time of exits of VC-funded startups, 2012-2020. Excludes leveraged buyouts or management buyouts.

tends to be particularly low for GAFAM and New Tech acquirers. In contrast, acquisitions by financial and other acquirers happen nearly twice as long after the latest funding round. As acquisitions are negotiated between startups and acquirers, this could reflect entrepreneurs' preferences for selling to one of the GAFAM, as opposed to other firms, thereby indicating GAFAM's strong bargaining power. These numbers could also be a sign that GAFAM tend to acqurie pre-emptively, or have better information on the quality of the startups, compared to other acquirers.

A final finding concerning all acquirer types is that many acquirers are serial acquirers. For enterprise software and financial firms, the median number of acquisitions of any industry during the company's lifetime is 8 (5 for companies in other industries). This mirrors David (2021), who emphasizes that serial acquisitions are a ubiquitous feature in the economy.

3.3 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 has been discontinued under the same brand name 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. Gautier and Lamesch (2021) find that the GAFAM shut down the companies in 60% of all cases. My results show

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: Looking at non-exhaustive groups of enterprise software acquirers

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

Table 8: Discontinuations of products post-acquisition, for different types of acquirers, and for startups acquired in 2012-2020.

	Products discontinued	Products kept alive
Age: years since founding date (median)	6.2	7.8
Age: years since 1st funding round (median)	4.0	5.2
Price in US$ million (median)	100.0	136.8

Table 9: Heterogeneity in age at acquisition and in transaction price, for startups whose products were either discontinued (left), or kept alive (right).

that this carries over to other acquirers active in the software industry, and seems to be a widespread phenomenon in software.

Shutdown rates vary depending on the acquiring firm. Table 8 shows that shutdowns are especially prevalent for acquirers that are enterprise software firms themselves; these companies discontinue the acquired product in 67% of all acquisitions. Financial firms, in contrast, discontinue the acquired products 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 9), and acquired at 75% of the price, compared to continued products[30]. 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 (and are thus not considered startups based on my definition). All of this suggests 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 C contains further details on these acquisitions.

[30]Not in Table. Prices are missing in 83% of shut-down acquisitions, and in 77% of continued acquisitions. As presumably low prices are missing more often (Kerr et al., 2014), the difference in median acquisition prices might therefore well be even higher.

3.4 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, I find that only 8% of all acquisitions of VC-funded startups in 2012-2020 can be classified as horizontal.[31]

However, note that 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.

3.5 Discussion

What are the motives behind the shutdown acquisitions that I find? Whereas product shutdowns could in principle indicate so-called killer acquisitions (Cunningham et al., 2021), I do not believe these types of acquisitions to be very prevalent in this setting. First, the acquired firms are often very young and sometimes have not even raised a single funding round. Thereby, they are less 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. Anecdotally, it seems that most acquisitions could instead be classified as either vertical, or conglomerate type.

Moreover, as Table 8 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. In terms of numbers, preexit startups or "new" tech firms account for a much larger share of discontinued startups than the GAFAM. Instead, there is anecdotal evidence that acquired products are sometimes integrated into the acquirer's existing product as an additional feature or functionality, or otherwise to improve the existing product.[32] Some of the transactions seem to be so-called acqui-hires in which the acquired startup's employees are paid to

[31] I also find variation in the number of horizontal mergers across different acquirer types. However, this variation is not very insightful, as it correlates by construction with the number of enterprise products supplied by the acquirer.

[32] 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 (both accessed 07/08/2022).

become part of the acquiring company.[33] This is somewhat different for financial acquirers. Anecdotally, it seems that these firms more often merge two companies in their portfolios, rather than entirely shutting them down or acqui-hiring them.[34] 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.[35]

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. Software is modular and can be built on top of one another. 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, for instance. This aspect is very different in the pharmaceutical market and may thus be the reason for the difference in acquisition patterns observed in Appendix A.7.

4 Reduced-form Evidence on Acquisitions and Entry

As pointed out in Section 3, acquirer types most likely differ in important ways in their respective motives when acquiring startups. Moreover, one may 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. In particular, only firms active in the same industry of enterprise software – which I call *strategic* – may possess complementary assets, resources, or market power that could fundamentally influence the acquired product's capabilities to compete in a given market. These types of acquirers may also have a strong incentive to fundamentally affect competition in their favor following the acquisition in a given market, as they may acquire to enter new markets, or to build a software ecosystem. These potential entry-deterring effects may be stronger if the acquirer is more dominant (e.g. Denicolò and Polo (2021), Kamepalli et al. (2021), Motta and Shelegia (2021)), or larger and thus more likely to possess resources to create a

[33]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.

[34]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*.

[35]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).

synergistic value.

This contrasts with the intentions and capabilities of acquirers in financial and other industries. Many the financial acquirers that I observe are private equity investors. These are typically transitional owners of the acquired firms, and tend to be 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.[36] An acquisition by a non-enterprise software acquirer therefore is a transition in the ownership of a startup that should however not fundamentally affect market structure and competition in a way that deters follow-on entry.[37] 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 dominant. 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:

$$num\_entrants_{m,t} = \beta \sum_{\tau=0}^{K} acquisition_{m,t-\tau} + \delta_m + \lambda_t + \epsilon_{m,t} \tag{1}$$

$num\_entrants_{m,t}$ 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. δ_m and λ_t denote market and quarter fixed effects, and $\epsilon_{m,t}$ is an econometric error term.

Any entry-deterring effects should be more likely to display when the acquired startup is more valuable, and whenever the startup's product has been kept alive after the acquisition. I therefore study acquisitions of VC-funded, private startups at a transaction price above 100US$ million, and focus

[36] examples may be *Valsoft* or *Ropers Technologies*.

[37] 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.

only on acquisitions in which the product has not been discontinued.[38] 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.[39]

Table 10 displays the 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.

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 11 suggests that only major acquisitions by public enterprise software companies may be preceded by a significant drop in entry.

One concern might be that "treated" markets, i.e. markets in which a large acquisition at any point, might be different in terms of observables or unobservables compared with markets in which no such acquisition occurred. In Table 12, I perform the event study using only markets in which *any* major acquisition occurred. Even in this study, which has a much smaller sample size, the coefficients retain the sign.

Instead of conducting an event study, Table 23 in Appendix E repeats the regression, this time using the cumulative sum of acquisitions of a certain type in a certain market as an explanatory variable. Again, entry is higher in markets that have been subject to many acquisitions by acquirers active in enterprise software; however, we also observe a significant decline in entry subsequently to financial or other-industry acquisitions.[40]

[38]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, the indicator just remains 1.

[39]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*.

[40]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 10: 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	
	(1)	(2)	(3)	(4)	(5)
Major acq by enterprise software company	−0.112*				
(89 acquisitions)	(0.059)				
Major acq by public enterprise software company		−0.158**			
(59 acquisitions)		(0.075)			
Major acq by GAFAM or 'New Tech'			−0.401***		
(21 acquisitions)			(0.135)		
Major acq by company not in enterpr softw (incl. financial)				−0.101	
(40 acquisitions)				(0.072)	
Major acq by financial company					0.032
(13 acquisitions)					(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
SEs clustered on market level.					*p<0.1; **p<0.05; ***p<0.01

Table 11: 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
SEs clustered on market level.					*p<0.1; **p<0.05; ***p<0.01

Table 12: Same event study as in main text (Table 10), 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				
	(1)	(2)	(3)	(4)	(5)
Major acq by enterprise software company	-0.108^{*}				
(89 acquisitions)	(0.062)				
Major acq by public enterprise software company		-0.159^{**}			
(59 acquisitions)		(0.072)			
Major acq by GAFAM or 'New Tech'			-0.383^{***}		
(21 acquisitions)			(0.138)		
Major acq by company not in enterpr softw (incl. financial)				-0.078	
(40 acquisitions)				(0.074)	
Major acq by financial company					0.110
(13 acquisitions)					(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

SEs clustered on 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 3.5, 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 a lot of entry. This goes against my findings in Tables 10 and 11, which both show that strategic acquisitions are not preceded by more entry, and even tend to be succeeded by a fall in entry.

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. 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 E 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 diff-in-diff.

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"(Affeldt & Kesler, 2021b, Bauer & Prado, 2021, G. Z. Jin et al., 2022, Kamepalli et al., 2021, Koski et al., 2020).[41] However, 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 whose parameters I can estimate. The economic agents in this model are potential entrants deciding whether or not to enter into a given market. I model potential entrants' decisions as a dynamic discrete game with imperfect information. The model leans on prior literature (Aguirregabiria & Mira, 2007, Bajari et al., 2007), but is different to the extent that agents only take a decision once in their lifetime. Acquisitions and IPOs are assumed exogenous in this model conditionally on twenty market-category effects that control for unobserved variables in the 440 markets.[42]

5.1 Setup

Time is discrete and infinite. We consider a finite number of independent markets. In every period and in every market, there is an exogenously given, fixed set of potential entrants. One can think of this set of potential entrants as representing entrepreneurs having ideas for a new product in a given market. This flow of entrepreneurs with ideas is exogenous and constant over time.[43] In each period, all potential entrants simultaneously decide whether to enter the market or not, so as to maximize their expected

[41] This literature looks at effects of acquisitions conducted by the GAFAM firms only. With the exception of Affeldt and Kesler (2021b) who look at 50 acquisitions conducted by the GAFAM in the mobile app market, the papers focus on many industries and employs alternative, firm-level (and thus possibly less precise) market definitions.

[42] Endogenizing acquisitions would pose challenges: the data contain thousands of potential acquirers that at each moment may decide whether to or not to acquire another firm. It is not clear how to write down a model that explains who acquires whom, given the scarce data available to researchers.

[43] 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.

profits. The potential entrants are homogeneous, except for a private cost shock that each agent draws from a distribution.

If a potential entrant decides to not enter the market, there will be no future chance of entry and it stays out forever.[44]

If a firm decides to enter, it competes against other firms present on the market. In each period, all active firms earn flow profits. These flow profits depend on a vector of state variables that are common knowledge, $\boldsymbol{x}_{mt}$. These state variables are aspects of market structure that are likely to influence firm profits, such as the number of competitors, and whether or not a competitor has been acquired by a major strategic acquirer (see below).

In every period following the entry decision, companies either continue to compete, or can "exit" by being target in an acquisition, or 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 arrives in a given period, the firm will stay on the market and continue earning flow profits.

The timing within each period is as follows:

1. Firms currently active on the market may be acquired, or do an IPO.
2. All potential entrants receive privately observed cost shocks and simultaneously decide: {enter, stay out}, so as to maximize their expected profits.
3. All companies on the market, including the new entrants but excluding those that left the market (via IPO or acquisition), earn flow profits that depend on a vector of state variables.

Denoting the cost shocks that a potential entrant i obtains as $\boldsymbol{\epsilon}_{imt} = \{\epsilon^0_{imt}, \epsilon^1_{imt}\}$, the expected payoff of entry writes as follows:

$$U^1_{imt} = \pi(\boldsymbol{x}_{mt};\boldsymbol{\gamma}) - \kappa + \epsilon^1_{imt} + \beta\left[\alpha^{ipo}\left(p^{ipo}_m \cdot R^{ipo}\right) + \alpha^{acq}\left(p^{acq}_m \cdot R^{acq}\right) + (1 - p^{ipo}_m - p^{acq}_m)\cdot\mathbb{E}[V_{t+1}(\boldsymbol{x}_{mt+1};\boldsymbol{\gamma})|\boldsymbol{x}_{mt}]\right] \tag{2}$$

$\pi(\boldsymbol{x}_{mt};\boldsymbol{\gamma})$ denote the flow profits that the firm obtains in each period, which depend on the state variables

[44] A difference with respect to most other dynamic discrete choice models is that in this model, entrants do not take actions repeatedly in every time period. This is natural in this setting, as the only decision firms take in this model is entry. Nevertheless, the model is a dynamic model: agents are forward-looking, and they incur the sunk costs of entry only once.

and a vector of parameters. κ is a parameter denoting the sunk cost of entry, which the potential entrant incurs only once upon entering. The expression after the discount factor $\beta \in (0,1)$ denotes expected payoffs in future periods. As stated above, in every period, the firm may make an exit in the form of an acquisition or an IPO at probabilities p_m^{acq} and p_m^{ipo}, yielding returns (either acquisition price, or firm value) R^{acq} or R^{ipo}, respectively. 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 occurs with probability $(1 - p_m^{acq} - p_m^{ipo})$, the firm continues to earn flow profits in that period. In the next period, any of the same set of events – {acquisition; IPO; continue} – may occur, and so on. I express this expected value of being present on the market from period $t+1$ onwards with $\mathbb{E}[V_{t+1}(\boldsymbol{x}_{mt+1}; \boldsymbol{\gamma})|\boldsymbol{x}_{mt}]$.

I do not observe firms' profits, nor demand, for the tens of thousands of firms observed in my dataset.[45] Therefore, I employ a semi-structural approach: instead of modelling demand and profits directly, I treat flow profits as a latent variable, as has been done in 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 then 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.

Thus, the vector of state variables that are common knowledge, $\boldsymbol{x}_{mt} = \{N_{mt}, A_{mt}^{\text{strat in } t-K}, \boldsymbol{M}_m\}$, consists of variables that are relevant to firms' profits. N_{mt} denotes the number of competitors on market m at time t, and measures the attractiveness. It is thus an endogenous state variable that evolves according to firms' entry decisions, as well as to an exogenous component[46]. The state variable $A_{mt}^{\text{strat in } t-K}$ mirrors the event study indicator variables employed in Section 4. This indicator variable is equal to 1 in the event of a strategic acquisition in the past K quarters, and 0 otherwise, and evolves exogenously. Intuitively, $A_{mt}^{\text{strat in } t-K}$ captures heuristically that a major strategic acquisition of a competitor may affect competition in the market.[47] $\boldsymbol{M}_m$ is a vector of binary variables that are constant over time and only vary

[45] I do observe the number reviews which may be indicative of demand. However, I observe these only as a single cross-section, and only for products not discontinued before 2021.

[46] This is required to rationalize the data; see Section 5.3.

[47] Previous research has modelled firms as heterogeneous agents. This 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. In Igami and Uetake (2020), a merger between firms implies that As I do not and cannot model firm productivity or

by market. These dummies are *market-category* effects that can be interpreted as measuring some baseline attractiveness of a given market. They control for a market's unobserved size or profitability, and its construction is covered in Section 6.1.

Without loss of generality, the payoff of staying out is normalized to zero plus an econometric error term, $U^0_{imt} = \epsilon^0_{imt}$. I assume that ϵ^0_{imt} and ϵ^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.

5.2 Estimation

In order to estimate the parameters of the dynamic discrete game, I employ a two-step estimation method (e.g. Aguirregabiria and Mira (2007), Bajari et al. (2007)). This approach circumvents the need to solve a dynamic discrete game in over 400 independent markets, which would make the estimation computationally infeasible. The method is essentially an extension of Hotz and Miller (1993)'s Conditional Choice Probability estimator, and deals with the problem of multiple equilibria.

In a first step, I use the data to flexibly estimate reduced-form regressions (policy functions) that map the state space into potential entrants' actions. Transition probabilities of the state variables that evolve exogenously are estimated nonparametrically from the data. This first step is essentially model-free. Policy functions characterize agents' actions given the state space, and transition probabilities describe how the state space evolves.

Given the policy functions and transition probabilities, one can forward-simulate the state space. 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.

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 can set up the likelihood function. Maximizing the likelihood function yields the estimates of the structural parameters that are the most likely to have generated the data. The intuition behind this procedure is that agents' choices incorporate the beliefs about the future (Arcidiacono & Ellickson, 2011).

firm characteristics, I use a dummy variable to capture that the acquisition affects comeption in the market.

5.3 Parameterization and Implementation

Each decision period is one quarter. I parameterize flow profits as follows:

$$\pi(\boldsymbol{x_{mt}};\boldsymbol{\gamma}) = \gamma_N \log(N_{mt}) \quad + \quad \gamma_A A_{mt}^{\text{strat in } t-K} \quad + \quad \boldsymbol{\gamma}_M' \boldsymbol{M}_m$$

I set $K = 4$, as in the reduced-form regressions in Section 4, so that the variable $A_{mt}^{\text{strat in } t-K}$ is equal to 1 in the quarter in which a major strategic acquisition has taken place in market m, as well as in the four following quarters. 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, γ_A to be negative as well (based on the reduced-form results in Section 4), and $\boldsymbol{\gamma}_M$ to be a vector of positive coefficients. $\boldsymbol{\gamma}_M$ can be interpreted as reflecting baseline profits that can be earned in a given market. These baseline profits are becoming smaller in the number of competitors N_{mt}, and if a major strategic acquisition has taken place in the previous quarters, $A_{mt}^{\text{strat in } t-K}$.

The key parameters of the model are therefore γ_A and α^{acq}. γ_A measures the extent to which a major strategic acquisition may depress entry. α^{acq}, in contrast, 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 1 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; and private firms.[48] The law of motion of N_{mt} writes as follows:

$$N_{mt} = N_{mt-1} + \text{num\_entrants}_{mt} - D_{\text{exit}}^{exog} + D_{\text{entry}}^{exog} \tag{3}$$

num_entrants$_{mt}$ denotes the endogenous number of entrants that enter in period t. In contrast, D_{exit}^{exog} and D_{entry}^{exog} are *exogenous* entry and exit variables that are included to match the data, as companies may leave or be added to N_{mt} in ways not modelled.[49] I model them as as random variables that follow a

[48] I thus exclude companies whose products in a given market do not have any review. I moreover exclude non-VC-funded private companies that have been acquired, 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 wihtout any reviews might constitute a competitive fringe. At the same time, changing this definition of competitors somewhat does not greatly affect final results.

[49] 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).

Bernoulli distribution with parameters p^{exog}_{exit} and p^{exog}_{entry}, respectively. I estimate these parameters in a first step using a frequency estimator.[50]

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 $A^{\text{strat in } t-K}_{mt}$, 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.[51] 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. [52] 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.[53]

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.

[50] In the forward simulation, it may theoretically be possible that the simulated number of competitors in the future reaches a value below 0. I found that this is the case in far less than one per mille of simulated observations, and would only far in the future (where due to discounting it would hardly matter). I set these forward-simulated observations equal to 0.5 in case it does occur.

[51] This is the case in particular for buyouts by Private Equity firms. Anecdotally, see Chopra (2018)'s article in the online newspaper 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".

[52] 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.

[53] 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).

6.1 First Stage: Startups' Entry Decisions

The results for the first stage can be found in Table 13, using a "broad" definition of strategic acquirers, and Table 14, 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), Y. Wang (2022)), and stems from unobserved market-specific factors that are not controlled for. In this context, market size and profitability would both lead to more competitors present on the market being correlated with more entry. To control for these unobserved factors, I estimate the model using market fixed effects in column (2). Reassuringly, the coefficient on the number of competitors becomes negative. The coefficient on major Enterprise Software acquisitions is negative, although insignificant when using the broad definition in Table 13. 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 variation of market fixed effects, which the literature has called market-category effects (Collard-Wexler, 2013, Y. Wang, 2022). These types of fixed effects equivalently control for unobserved heterogeneity of markets. I follow Y. Wang (2022) and Lin (2015), and first estimate the model with fixed effects in column (2). From the estimated market fixed effects, I construct 20 quantiles. 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 dummies based on these *groups*, as opposed to a dummy based on the market (as would be the case for market fixed effects). Just like market fixed effects, the group-level dummies control for unobserved heterogeneity between markets that is persistent over time. Column (4) shows that this procedure yields similar results.[54]

Finally, I employ market fixed effects along with quarter fixed effects in column (5) to control for

[54] I have estimated the regression employing fewer or more groups; it seems that using 20 groups is just sufficient. The more groups I use, the closer the estimates to the results in column (2), but the more likely one will face an issue regarding the incidental parameters problem, and the more one will possibly absorb too much of the variation in p_m^{ipo} and p_m^{acq} in the second stage. 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.

seasonal effects which are present in the data. I again recover similar results; seemingly, the negative strategic effect is not driven by any seasonal effect.

Table 13: First stage, using a broad definition of "strategic" acquirers. Standard errors are clustered at the market level, and computed using block bootstrapping with 5,000 bootstraps in column (4) 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				✓	
Observations	10,560	10,560	10,560	10,560	10,560
Adjusted R^2	0.11	0.34		0.24	0.35
Log Likelihood			−9,813.634		
Akaike Inf. Crit.			20,511.270		

*p<0.1; **p<0.05; ***p<0.01

Using any of these policy functions, and using frequency estimates of the parameters p_{exit}^{exog} and p_{entry}^{exog} ($\hat{p}_{\text{exit}}^{exog} = 0.061$ and $\hat{p}_{\text{entry}}^{exog} = 0.0076$), I can use the law of motion in equation 3 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 $A_{mt}^{\text{strat in } t-K}$, 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 $A_{mt}^{\text{strat in } t-K}$ so that the variable is equal to 1 in the four quarters following a strategic acquisition, and in the quarter in which the event takes place.

Finally, I use the estimated group-level dummies as the only market characteristic (denoted M_m above), which stay constant over time.

Table 14: First stage, using a narrower definition of "strategic" acquirers. Standard errors are clustered at the market level, and computed using block bootstrapping with 5,000 bootstraps in column (4) 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)	(0.206)	(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				✓	
Observations	10,560	10,560	10,560	10,560	10,560
Adjusted R^2	0.11	0.34		0.24	0.35
Log Likelihood			−9,812.992		
Akaike Inf. Crit.			20,509.980		

*p<0.1; **p<0.05; ***p<0.01

6.2 Second Stage: Model-based Results

As the discount factor is not identified in these types of models, I follow prior literature by setting $\beta = 0.9$ (e.g. Igami and Uetake (2020)). The estimates of the structural model can be found in Table 15. Column (1) shows the results using a broad definition of strategic acquisitions by considering all major acquisitions conducted by a strategic acquirer, using column (2) from Table 13 in the first stage. 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 higher.

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 14 in the first stage. Again, parameters have the expected sign. The strategic acquistion effect now becomes marginally significant as well.

Finally, column (3) does not control in any way for heterogeneity in unobserved market profitability, and uses the "wrong" results of column (1) of Table 14 in the first stage. Clearly, the counterintuitive

Table 15: Estimates of structural parameters.

	(1)	(2)	no market / category FEs (neither in 1st nor in 2nd stage) (3)
Entry costs, κ	-2.9573^{***}	-2.9835^{***}	-4.0915^{***}
	(0.1371)	(0.1382)	(0.0588)
log(# of competitors), γ_N	-0.2481^{***}	-0.2476^{***}	0.0640^{***}
	(0.0107)	(0.0105)	(0.0019)
Strategic acq of competitor **by Enterprise Software acquirer**, γ_A	-0.0325		-0.0001
(Dummy indicating major such acquisition in past 4 quarters)	(0.0265)		(0.0260)
Strategic acq of competitor **by GAFAM or New Tech**, γ_A		-0.0852^{*}	
(Dummy indicating major such acquisition in past 4 quarters)		(0.0525)	
Own IPO in future, α^{ipo}	0.0056^{***}	0.0052^{***}	0.0014^{*}
	(0.0009)	(0.0010)	(0.0008)
Own acquisition in future, α^{acq}	0.0373^{***}	0.0382^{***}	0.0147^{***}
	(0.0032)	(0.0032)	(0.0025)
Market category 2, γ_M^2 (5th-10th perc)	0.3192^{***}	0.3203^{***}	
	(0.0240)	(0.0239)	
Market category 3, γ_M^3 (10th-15th perc)	0.3903^{***}	0.3922^{***}	
	(0.0252)	(0.0251)	
...	...	...	
Market category 19, γ_M^{19} (90th-95thth perc)	1.1415^{***}	1.1425^{***}	
	(0.0463)	(0.0458)	
Market category 20, γ_M^{20} (95th-100th perc)	1.3010^{***}	1.3013^{***}	
	(0.0502)	(0.0497)	
Observations: 440 markets, 24 quarters	10,560	10,560	10,560
Log-likelihood	$-10{,}631.6$	$-10{,}617.2$	$-11{,}580.8$

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

result propagates into the second stage of the estimation, making it seem as if more competitors attracted more entry.

The parameter estimate for being acquired essentially measures a startup's valuation for being more likely to be acquired in millions of dollars. This allows to express firms' sunk costs in terms of these expected dollars by dividing the estimate of the paramter κ by the estimate of the parameter α^{acq}. I find that the sunk cost of entry parameter is approximately equal to 80 million US$. This is less than the lifetime amount of funding that successfully exiting, later-stage enterprise software startups obtain, according to *Crunchbase* data. Further, I find that the lifetime costs of having one additional competitor in the market are equal to 6.8 million US$. Moving up from the least to the most profitable market, in terms of the 20 market-category fixed effects, is worth 322 million US$, which emphasizes the importance of market fixed effects. Moving up from the 50th to the 55th quantile is worth 12.8 million US$.

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. The counterfactual scenario I compute can thus be interpreted as an initial impulse response by potential entrants, as

I study two counterfactual changes in the prevailing antitrust regime. In the first scenario, the competition authority blocks only major strategic startup acquisitions. 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.

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 15, column (2), and the forward-simulated state variables, compute the expected discounted value of entering.

4. For each potential entrant, draw independent 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.[55]

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 16 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

[55] 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 in numbers	in percent	Change in # of competitors 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 16: Change in the mean number and percent of entrants, and in competitors, in counterfactual scenarios compared to the baseline.

strategic acquisitions are blocked. This results in a very slight increase in entry and in competition in the average market.

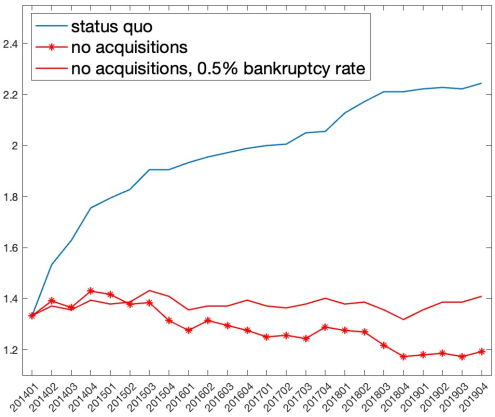
I then simulate the counterfactual in which all acquisitions are blocked. Given the current values of the parameter estimates, in the average market, firms *prefer* competing on the market forever, rather than being acquired. This leads to the finding exhibited in the second row of Table 16: entry rates 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 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.[56] In currently ongoing work, I will verify to make sure these assumed rate of bankruptcies could be supported by scientific literature in empirical finance.

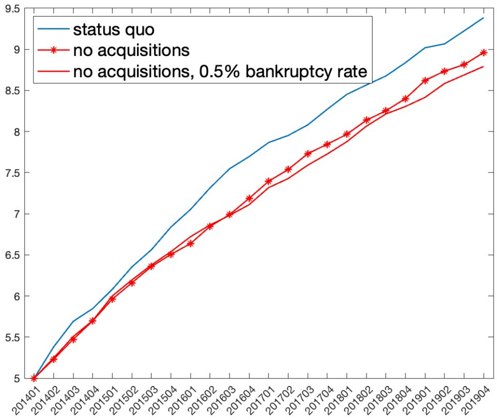
I carry out fifteen simulations of each type, and take the average.

[56]Using *Crunchbase* data, I find that the actual quarterly bankruptcy rate for enterprise software startups is around 1.2%.

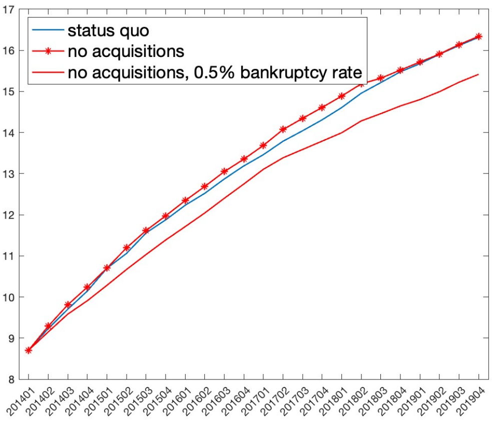
As the data contain over 400 markets, I can explore how the effect of blocking startup acquisitions varies across markets of different types. In particular, by way of the market-category effects, the structural model essentially groups markets according to their unobserved market size or inherent profitability. 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. I intend to explore this heterogeneity and its plausibility further in future work.



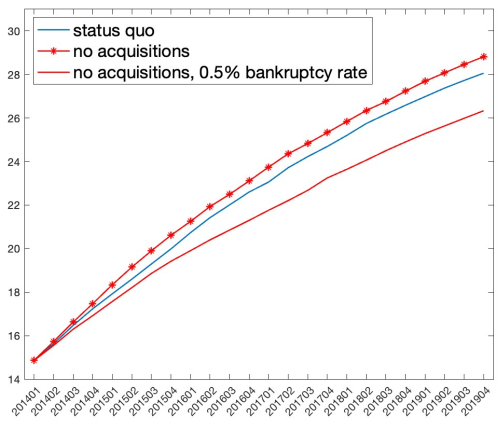
(a) Markets at 5th percentile of profitability



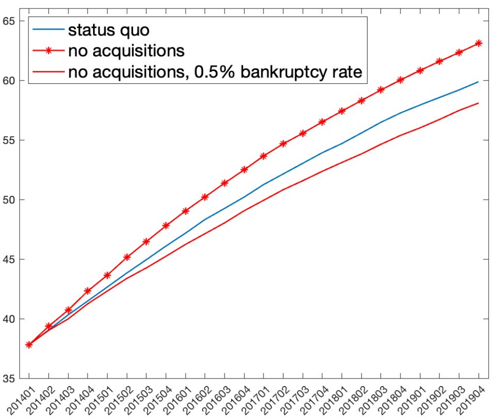
(b) Markets at 25th percentile of profitability



(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 regarding 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. However, these new product-level market definitions is subject to some of the same caveats that more standard firm-level taxonomies suffer from. In software, startups sometimes 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 could arise from the bundling of products or the provision software ecosystems. 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. Crémer et al. (2019), Furman 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.[57] This discussion highlights the need for future empirical advances in characterizing demand for software and competition between nascent software products. I am in the process of conducting a number of robustness checks, for instance by varying the number of markets created. In future work, I plan to work with proximity measures between different markets.

7.2 Endogeneity of acquisitions

I estimate the model parameters under the assumption that acquisitions are exogenous. Realistically, however, the decision to acquire another firm is driven by a multitude of considerations, including expectations about the market and the target company. In my model, I can control for some market-level unobservables that might contribute to a higher frequency of startup acquisitions in one market versus another one. Moreover, my event study leverage the fact that financial acquirers acquire for different reasons than strategic acquirers. One can moreover argue for a random element in who acquires whom at what time. This suggests that my results are nevertheless meaningful.

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

To elaborate, I first turn to potential endogeneity concerns regarding the entry-for-buyout parameter. Each market observed 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^{acq}), and observed startup entry. One concern might be that both acquisitions and entry behavior are being driven by an unobserved variable, such as technological advances leading to a rise in demand and an increase in entry.[58] On the other hand, this may also have induced acquisitions to take place, as companies may have found it profitable to buy and integrate software producers. 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. In future iterations of this project, I hope to employ an instrumental variable strategy to provide causal evidence for the existence of this channel.[59]

The market structure parameter is identified by variation in the number of entrants around the time of a major acquisition by a strategic acquirer both between and within markets. As pointed out earlier, for same-industry acquirers, the motive of an acquisition is often to integrate a product or a product feature into the acquirers' existing product portfolio, or to enter a market. For these firms, the acquisition decision is therefore driven by higher expected profits when expanding into a certain complementary direction in the product space. Thus, the consideration of *which market* to acquire in is possibly endogenous to certain observed and unobserved market characteristics. However, there is a random element in *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 language, travel distance, whether the two firms happen to share the same technology stack, or sympathy, 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.[60] Overall, contrasting financial with strategic acquirers around the event of the merger announcement, akin to an event study – as done in the reduced form – may be as close as one can get to finding out about any potential entry-deterring effect of major strategic buyouts.

[58]For instance, the ubiquitous collection of data requires all companies in the economy to collect and analyze consumer data in order to remain competitive. As a result, demand has risen for data analytics, data management, or dashboard software, for instance. This may on one hand have induced new startups to enter.

[59]Potential instruments are regulations that made acquisitions in a given market more burdensome. I found anecdotal evidence that in the European Union, the General Data Protection Regulation (GDPR) may have had such an effect.

[60]Snap, for instance, received an offer to be acquired by Google and Facebook, but eventually remained independent. A startup co-founder who shall remain unnamed told me that their company received offers from three of the GAFAM firms, but eventually sold to another large software company.

Endogenizing acquisitions, as is done in some prior research (e.g. Igami and Uetake (2020)), is not feasible in my setting due to computational and conceptual challenges.[61]

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 these incentives? My data collection effort allows me to make progress on this question in the context of startup acquisitions in the software industry. Merger policy in software markets is being hotly debated in many jurisdictions, but our understanding about the motives and implications of these mergers is extremely limited. More broadly, my results can inform the debate on the relationship between market structure and innovation, going back to Schumpeter (1942) and Arrow (1962).

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 two channels: an entry-for-buyout effect, and an effect via market structure. I find that an overall ban of all startup acquisitions would decrease entry by 8-20% in markets that have a low baseline profitability. Noneless, acquisitions conducted by strategic acquirers appear to deter entry. If these acquisitions were banned, entry may be increased. These findings are highly relevant to the ongoing policy debates regarding startup acquisitions in technology sectors.

The data I collected and the evidence I have found 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. 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 work 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.

Moreover, in future work I would like to exploit the distance metrics between markets which I can

[61] First, there would be thousands of potential acquirers, as I study over 400 markets at once. Second, it would be extremely difficult – or even impossible – to write down a model that accurately describes acquiring firms' decision making. This is possible in Igami and Uetake (2020) as products are homogeneous and as firms are described by a single profitability parameter that is plausibly very influential for merger decisions.

obtain using the text-as-data methods. This would yield further evidence on the extent to which different types of acquirers buy startups in (dis)similar market niches.

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.

References

Affeldt, P., & Kesler, R. (2021a). Big Tech Acquisitions - Towards Empirical Evidence. *Journal of European Competition Law and Practice*, *12*(6), 471–478. doi: 10.1093/jeclap/lpab025

Affeldt, P., & Kesler, R. (2021b). Competitors' Reactions to Big Tech Acquisitions: Evidence from Mobile Apps. *Working Paper*.

Aghamolla, C., & Thakor, R. T. (2021). IPO peer effects. *Journal of Financial Economics*. doi: 10.1016/j.jfineco.2021.05.055

Aguirregabiria, V., & Ho, C. Y. (2012). A dynamic oligopoly game of the US airline industry: Estimation and policy experiments. *Journal of Econometrics*, *168*(1), 156–173. Retrieved from http://dx.doi.org/10.1016/j.jeconom.2011.09.013 doi: 10.1016/j.jeconom.2011.09.013

Aguirregabiria, V., & Mira, P. (2007). Sequential Estimation of Dynamic Discrete Games. *Econometrica*, *75*(1), 1–53. Retrieved from https://doi.org/10.1111/j.1468-0262.2007.00731.x doi: https://doi.org/10.1111/j.1468-0262.2007.00731.x

Arcidiacono, P., & Ellickson, P. B. (2011). Practical Methods for Estimation of Dynamic Discrete Choice Models. *Annual Review of Economics*, *3*(1), 363–394. Retrieved from https://doi.org/10.1146/annurev-economics-111809-125038 doi: 10.1146/annurev-economics-111809-125038

Argentesi, E., Buccirossi, P., Calvano, E., Duso, T., Marrazzo, A., & Nava, S. (2021). Merger Policy in Digital Markets: An Ex Post Assessment. *Journal of Competition Law and Economics*, *17*(1), 95–140. doi: 10.1093/joclec/nhaa020

Aridor, G. (2022). Drivers of Digital Attention: Evidence from a Social Media Experiment. *Working Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4069567

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. *The rate and direction of inventive activity: Economic and social factors*, 609–626.

Bajari, P., Benkard, C. L., & Levin, J. (2007). Estimating Dynamic Models of Imperfect Competition. *Econometrica*, *75*(5), 1331–1370. Retrieved from https://doi.org/10.1111/j.1468-0262.2007.00796.x doi: https://doi.org/10.1111/j.1468-0262.2007.00796.x

Bauer, J. M., & Prado, T. S. (2021). Effects of Big Tech Acquisitions on Start-up Funding and Innovation. *Working Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3787127&download=yes

Berman, R., & Israeli, A. (n.d.). The Value of Descriptive Analytics: Evidence from Online Retailers. *Marketing Science*.

Bresnahan, T. F., & Greenstein, S. (1999, sep). Technological Competition and the Structure of the Computer Industry. *The Journal of Industrial Economics*, *47*(1), 1–40. Retrieved from http://www.jstor.org/stable/117505

Bresnahan, T. F., & Reiss, P. C. (1991). Entry and Competition in Concentrated Markets. *Journal of Political Economy*, *99*(5), 977–1009.

Bryan, K. A., & Hovenkamp, E. (2020). Antitrust Limits on Startup Acquisitions. *Review of Industrial Organization*, *56*(4), 615–636. doi: 10.1007/s11151-020-09751-5

Cabral, L. (2018). Standing on the Shoulders of Dwarfs: Dominant Firms and Innovation Incentives. *CEPR Discussion Paper*. Retrieved from http://luiscabral.net/economics/workingpapers/innovation201808.pdf

Cabral, L. (2021). Merger policy in digital industries. *Information Economics and Policy*, *54*. doi: 10.1016/j.infoecopol.2020.100866

Callander, S., & Matouschek, N. (2020). The Novelty of Innovation: Competition, Disruption, and Antitrust Policy. *Working Paper*. Retrieved from https://sjc.people.stanford.edu/sites/g/files/sbiybj4051/f/innovation_13october2020.pdf

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. Retrieved from https://doi.org/10.1016/j.jeconom.2020.12.001 doi: 10.1016/j.jeconom.2020.12.001

Chopra, A. (2018). Private equity buyouts have become viable exit options — even for early-stage startups. *TechCrunch*, *28 Decembe*. Retrieved from https://web.archive.org/web/20210615140407/https://techcrunch.com/2018/12/28/private-equity-buyouts-have-become-viable-exit-options-even-for-early-stage-startups/

Cockburn, I. M., & MacGarvie, M. J. (2011, sep). Entry and Patenting in the Software Industry. *Management Science*, *57*(5), 915–933. Retrieved from http://www.jstor.org/stable/25835748

Collard-Wexler, A. (2013). Demand Fluctuations in the Ready-Mix Concrete Industry. *Econometrica*, *81*(3), 1003–1037. Retrieved from https://doi.org/10.3982/ECTA6877 doi: https://doi.org/10.3982/ECTA6877

Conti, A., Guzman, J., & Rabi, R. (2021). Herding in the Market for Startup Acquisitions.

Crémer, J., de Montjoye, Y.-A., & Schweitzer, H. (2019). Competition Policy for the Digital Era. *Final Report for the Commission Directorate-General for Competition*.

Crunchbase. (2022, feb). *Glossary of Funding Types.* Retrieved 2022-03-12, from https://support.crunchbase.com/hc/en-us/articles/115010458467-Glossary-of-Funding-Types

Cunningham, C., Ederer, F., & Ma, S. (2021). Killer Acquisitions. *Journal of Political Economy*, *129*(3), 649–702.

David, J. M. (2021). The Aggregate Implications of Mergers and Acquisitions. *The Review of Economic Studies*, *88*(4), 1796–1830. doi: 10.1093/restud/rdaa077

Decarolis, F., & Rovigatti, G. (2021, oct). From Mad Men to Maths Men: Concentration and Buyer Power in Online Advertising. *American Economic Review*, *111*(10), 3299–3327. doi: 10.1257/AER.20190811

Denicolò, V., & Polo, M. (2021). Acquisitions, innovation and the entrenchment of monopoly. *Working Paper*. Retrieved from https://deliverypdf.ssrn.com/delivery.php?ID=68710106700810202401701800407608009009605505804702304303109100410908610702908803112

Dijk, E., Moraga-Gonzàlez, J. L., & Motchenkova, E. (2021). How Do Start-up Acquisitions Affect the Direction of Innovation? *Working Paper*.

Federal Trade Commission. (2021). *FTC Staff Presents Report on Nearly a Decade of Unreported Acquisitions by the Biggest Technology Companies.* Retrieved from https://www.ftc.gov/news-events/press-releases/2021/09/ftc-report-on-unreported-acquisitions-by-biggest-tech-companies

Fumagalli, C., Motta, M., & Tarantino, E. (2022). Shelving or Developing? Acquisition of Potential Competitors. *Working Paper*.

Furman, J., Coyle, D., Fletcher, A., Marsden, P., & McAuley, D. (2019). Un-locking digital competition. Report of the Digital Competition Expert Panel.

Gans, J. S., & Stern, S. (2003). The product market and the market for "ideas": Commercialization strategies for technology entrepreneurs. *Research Policy*, *32*(2), 333–350. doi: 10.1016/S0048-7333(02)00103-8

Gautier, A., & Lamesch, J. (2021). Mergers in the digital economy. *Information Economics and Policy*, *54*, 1–34. doi: 10.1016/j.infoecopol.2020.100890

Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as Data. *Journal of Economic Literature*, *57*(3), 535–574. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jel.20181020 doi: 10.1257/jel.20181020

Gilbert, R. J., & Katz, M. L. (2022). Dynamic merger policy and pre-merger product choice by an entrant. *International Journal of Industrial Organization*, *81*. Retrieved from https://doi.org/10.1016/j.ijindorg.2021.102812 doi: 10.1016/j.ijindorg.2021.102812

Gompers, P., & Lerner, J. (2001). The venture capital revolution. *Journal of Economic Perspectives*, *15*(2), 145–168. doi: 10.1257/jep.15.2.145

Guéron, Y., & Lee, J. (2022). Innovation Learning, and Killer Acquisitions. *Working Paper*.

Haucap, J., Rasch, A., & Stiebale, J. (2019). How mergers affect innovation: Theory and evidence. *International Journal of Industrial Organization*, *63*, 283–325. Retrieved from https://doi.org/10.1016/j.ijindorg.2018.10.003 doi: 10.1016/j.ijindorg.2018.10.003

Hege, U., & Hennessy, C. (2010, jul). Acquisition Values and Optimal Financial (In)Flexibility. *The Review of Financial Studies*, *23*(7), 2865–2899. Retrieved from https://doi.org/10.1093/rfs/hhq017 doi: 10.1093/rfs/hhq017

Hollenbeck, B. (2020). Horizontal mergers and innovation in concentrated industries. *Quantitative Marketing and Economics*, *18*(1), 1–37. doi: 10.1007/s11129-019-09218-2

Hotz, V. J., & Miller, R. A. (1993). Conditional Choice Probabilities and the Estimation of Dynamic Models. *The Review of Economic Studies*, *60*(3), 497–529. Retrieved from http://www.jstor.org/stable/2298122 doi: 10.2307/2298122

Hotz, V. J., Miller, R. A., Sanders, S., & Smith, J. (1994). A simulation estimator for dynamic models of discrete choice. *The Review of Economic Studies*, *61*(2), 265–289.

Igami, M. (2017). Estimating the innovator's dilemma: Structural analysis of creative destruction in the hard disk drive industry, 1981–1998. *Journal of Political Economy*, *125*(3), 798–847. doi: 10.1086/691524

Igami, M., & Uetake, K. (2020). Mergers, Innovation, and Entry-Exit Dynamics: Consolidation of the Hard Disk Drive Industry, 1996-2016. *Review of Economic Studies*, *87*(6), 2672–2702. doi: 10.1093/restud/rdz044

Igami, M., & Yang, N. (2016). Unobserved heterogeneity in dynamic games: Cannibalization and preemptive entry of hamburger chains in Canada. *Quantitative Economics*, *7*(2), 483–521. Retrieved from https://doi.org/10.3982/QE478 doi: https://doi.org/10.3982/QE478

Jin, G. Z., Leccese, M., & Wagman, L. (2022). How Do Top Acquirers Compare in Technology Mergers? New Evidence from an S&P Taxonomy. *Working Paper*. doi: 10.2139/ssrn.4010491

Jin, Z. (2019). How do Large Companies Affect Entrepreneurship: Evidence From Amazon's HQ2 Search. *Working Paper*.

Jullien, B., & Lefouili, Y. (2018). Horizontal mergers and innovation. *Journal of Competition Law and Economics*, *14*(3), 364–392. doi: 10.1093/joclec/nhy010

Kamepalli, S. K., Rajan, R. G., & Zingales, L. (2021). Kill Zone. *Working Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3555915 doi: 10.2139/ssrn.3555915

Katz, M. L. (2021). Big Tech mergers: Innovation, competition for the market, and the acquisition of emerging competitors. *Information Economics and Policy*, *54*. Retrieved from https://doi.org/10.1016/j.infoecopol.2020.100883 doi: 10.1016/j.infoecopol.2020.100883

Kerr, W. R., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as Experimentation. *Journal of Economic Perspectives*, *28*(3), 25–48. Retrieved from https://www.aeaweb.org/articles?id=10.1257/jep.28.3.25 doi: 10.1257/jep.28.3.25

Koski, H., Kässi, O., & Braesemann, F. (2020, jul). *Killers on the Road of Emerging Start-ups – Implications for Market Entry and Venture Capital Financing* (ETLA Working Papers No. 81). The Research Institute of the Finnish Economy. Retrieved from https://ideas.repec.org/p/rif/wpaper/81.html

Lemley, M. A., & McCreary, A. (2020). Exit Strategy. *Working Paper*.

Letina, I., Schmutzler, A., & Seibel, R. (2021). Killer Acquisitions and Beyond: Policy Effects on Innovation Strategies. *Working Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3673150 doi: 10.2139/ssrn.3673150

Lin, H. (2015). Quality Choice and Market Structure: A Dynamic Analysis of Nursing Home Oligopolies. *International Economic Review*, *56*(4), 1261–1290. Retrieved from https://doi.org/10.1111/iere.12137 doi: https://doi.org/10.1111/iere.12137

Mazzeo, M. J. (2002). Product Choice and Oligopoly Market Structure. *The RAND Journal of Economics*, *33*(2), 221–242. Retrieved from http://www.jstor.org/stable/3087431 doi: 10.2307/

3087431

Mermelstein, B., Nocke, V., Satterthwaite, M. A., & Whinston, M. D. (2020). Internal versus external growth in industries with scale economies: A computational model of optimal merger policy. *Journal of Political Economy*, *128*(1), 301–341.

Motta, M., & Peitz, M. (2021). Big tech mergers. *Information Economics and Policy*, *54*. Retrieved from https://doi.org/10.1016/j.infoecopol.2020.100868 doi: 10.1016/j.infoecopol.2020.100868

Motta, M., & Shelegia, S. (2021). The "kill zone": Copying, acquisition and start-ups' direction of innovation. *Working Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3846285

Nocke, V., & Whinston, M. D. (2010). Dynamic merger review. *Journal of Political Economy*, *118*(6), 1201–1251. doi: 10.1086/658161

Pennington, J., Socher, R., & Manning, C. D. (2014). GloVe: Global Vectors for Word Representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (emnlp).* Retrieved from http://nlp.

Perez-Saiz, H. (2015). Building new plants or entering by acquisition? Firm heterogeneity and entry barriers in the U.S. cement industry. *The RAND Journal of Economics*, *46*(3), 625–649. Retrieved from https://doi.org/10.1111/1756-2171.12100 doi: https://doi.org/10.1111/1756-2171.12100

Phillips, G. M., & Zhdanov, A. (2013). R&D and the Incentives from Merger and Acquisition Activity. *The Review of Financial Studies*, *26*(1), 34–78. Retrieved from https://doi.org/10.1093/rfs/hhs109 doi: 10.1093/rfs/hhs109

Poege, F. (2022). Competition and Innovation: The Breakup of IG Farben. *Working Paper*. Retrieved from https://www.felixpoege.eu/assets/publications/2021IGFarben/research_paper.pdf

Rasmusen, E. (1988). Entry for Buyout. *Journal of Industrial Economics*, *36*(3), 281–299.

Schnitzer, M., & Watzinger, M. (2022). Measuring the Spillovers of Venture Capital. *The Review of Economics and Statistics*, *104*(2), 276–292. Retrieved from https://doi.org/10.1162/rest_a_00937 doi: 10.1162/rest_a_00937

Schumpeter, J. A. (1942). Capitalism, Socialism and Democracy. *New York NY: Harper & Brothers*.

Scott Morton, F., Jullien, B., Katz, R., & Kimmelman, G. (2019). Committee for the Study of Digital Platforms Market Structure and Antitrust Subcommittee Subcommittee. *Stigler Center for the Study of the Economy and the State*.

Seim, K. (2006). An empirical model of firm entry with endogenous product-type choices. *RAND Journal of Economics*, *37*(3), 619–640. doi: 10.1111/j.1756-2171.2006.tb00034.x

Song, M. H., & Walkling, R. A. (2000). Abnormal returns to rivals of acquisition targets: A test of the 'acquisition probability hypothesis'. *Journal of Financial Economics*, *55*(2), 143–171. doi: 10.1016/S0304-405X(99)00048-3

Vaziri, M. (2022). Antitrust Law and Business Dynamism. *2243 Cambridge Working Papers in Economics*. Retrieved from https://www.econ.cam.ac.uk/research-files/repec/cam/pdf/cwpe2243.pdf

Wang, X. (2018). Catering Innovation: Entrepreneurship and the Acquisition Market. *Working Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3247274 doi: 10.2139/ssrn.3247274

Wang, Y. (2022). Competition and Multilevel Technology Adoption: A Dynamic Analysis of Electronic Medical Records Adoption in U.S. Hospitals. *International Economic Review*, *63*(3), 1357–1395. Retrieved from https://doi.org/10.1111/iere.12586 doi: https://doi.org/10.1111/iere.12586

Warg, K. (2021). The Acquisition Option and Startup Innovations. *Working Paper*. Retrieved from https://katarinawarg.com/wp-content/uploads/2021/12/Katarina-Warg-The-Acquisition-Option-and-Startup-Innovations.pdf

Watzinger, M., Fackler, T. A., Nagler, M., & Schnitzer, M. (2020). How Antitrust Enforcement Can Spur Innovation: Bell Labs and the 1956 Consent Decree. *American Economic Journal: Economic Policy*, *12*(4), 328–359. Retrieved from https://www.aeaweb.org/articles?id=10.1257/pol.20190086 doi: 10.1257/pol.20190086

Whinston, M. D. (1990, nov). Tying, Foreclosure, and Exclusion. *The American Economic Review*, *80*(4), 837–859. Retrieved from http://www.jstor.org/stable/2006711

Wollmann, T. G. (2019). Stealth Consolidation: Evidence from an Amendment to the Hart-Scott-Rodino

Act. *American Economic Review: Insights*, *1*(1), 77–94. Retrieved from https://www.aeaweb.org/articles?id=10.1257/aeri.20180137 doi: 10.1257/aeri.20180137

Yu, S. (2020). How do accelerators impact the performance of high-technology ventures? *Management Science*, *66*(2), 530–552. doi: 10.1287/mnsc.2018.3256

A Supplementary information on data creation

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

Crunchbase comprises the profiles of more than a million firms worldwide, and documents all important company events. Information found on *Crunchbase* are sourced using Machine Learning, an in-house data team, a venture program, and via crowdsourcing. Public, private, as well as firms that existed in the past but have been closed, located all over the world and spanning all sectors of the economy, are present on *Crunchbase*. 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.

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.[62] 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.

A.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

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

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 D, Table 20).

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[63].

A.3 Web-scraping *Capterra*

I first web-scrape the list of categories available on *Capterra* (see Figure 1). For each category, I then query the listings page, which I fully expand to obtain a list of all the products that are associated with that given category. For each product in that list, I download the hyperlink that directs to the specific product page (see Figure 2). 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 it can be active in. I finally obtain approximately 70,000 unique product-level observations.

A.4 Merging *Capterra* products to *Crunchbase* companies

I first use company URL and name to match products on *Capterra* to their producing firms on *Crunchbase*.[64] Panel A in Figure 6 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

[63] 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.

[64] 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 6: 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.

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 6.

A.5 Building a dictionary and tagging products with keywords

Each product on *Capterra* can be associated to *more* than one category.[65] 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 the category names, I "tag" products with further meaningful keywords whenever those appear in the products' descriptive text.

I first clean some category names. I replace some acronyms in the category name (e.g. "Search Enginge Optimization" instead of "SEO"), and I create 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

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

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".

A.6 Validation of market definition

A.6.1 Validation using market definitions used in recent merger decisions in the domain of enterprise software

In Figure 7, 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: https://assets.publishing.service.gov.uk/media/5dfa5c69e5274a670091be1a/Publication_version_-_Decision_-_Salesforce-Tableau_.pdf and here: https://assets.publishing.service.gov.uk/media/5e6f8119e90e070ac9b21 Google_Looker_decision-.pdf, both accessed 15/03/2022). I find that, when grouping products into 500 markets, 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.

Source: CMA reports: Salesforce-Tableau & Google-Looker

Table 1: Shares of supply in Modern BI by revenues worldwide in 2018[78]

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%**

Sisense
Periscope

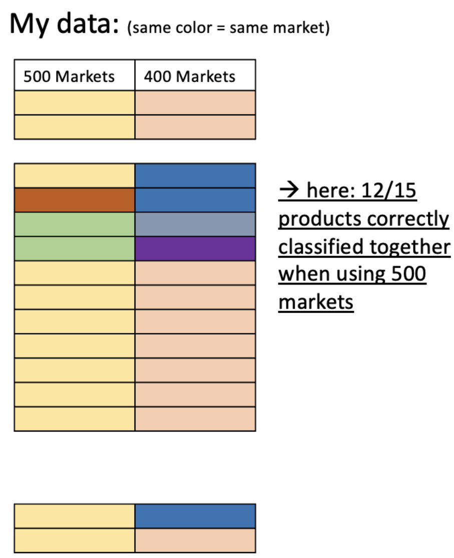


Figure 7: Validation of market definition.

A.6.2 Validation 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
- {presentation, presentations, tool}: PowerPoint, Google Slides, Slidebean, Pitch, etc.
- {development, application, build}: Github, Gitlab, Bitbucket
- {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.

A.7 In Software Markets, Startup Acquisitions are Especially Prevalent

I first document the high prevalence of startup acquisitions in the software industry compared to other industries. This finding suggests that the motives for these numerous startup acquisitions may be specific to the software industry, and provides a motivation for conducting the study *within* this industry. Instead of using the matched dataset that covers only enterprise software, in this subsection I exceptionally use the entire *Crunchbase* database.

A.7.1 In count, the largest acquirers of startups of any industry are software firms

Table 17 shows the top twenty acquiring firms of VC-funded startups, without placing any restriction on the type of industry or geographic location of acquirer or target firm. I use data for the years of 2005-2020. For each acquirer, I sum up both the number of acquired firms, as well as the transaction prices. I take into account acquisitions conducted by subsidiaries of the parent firm.[66] Looking at the names of the top 20 acquirers in terms of the number of acquired firms (left column), what is striking is that most of the listed companies are producers of software. The GAFAM are among the top 10 acquiring firms, but many other digital technology firms are very active in startup acquisitions as well. Even relatively young

[66] This means: I take into account acquisitions conducted by Flipkart after Walmart purchased a majority stake in that company, 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 17: 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*.

and smaller companies like Groupon, Dropbox, or Twitter, are among the top 20 acquirers of VC-funded startups. 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.

A.7.2 Startups in software are much more likely to exit via acquisition than startups in other industries

Next, I turn from acquirers to potential targets by comparing how startups in different industries "exit" the private financial market. As mentioned 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[67], I find that out of all successfully exiting startups in enterprise software, 95% exit by acquisition. Comparing this to the biotechnology and

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

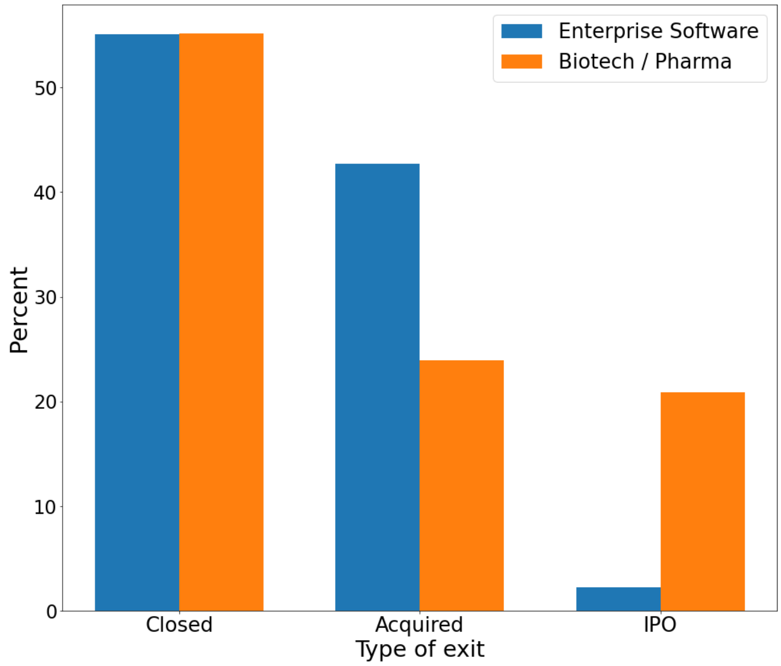


Figure 8: Types of exits of startups in biotechnology & pharmaceuticals, and enterprise software, in percent. I consider US-based startups founded after 2001 and exiting in 2005-2020. Details on the industry definition can be found in Appendix A.8.

pharmaceutical industry, the common exit routes are strikingly different: here, 53% of successful startups exit by acquisition. The finding highlights once again that industry dynamics might be fundamentally different across industries (due to different production technologies etc.), which motivates to study entry and acquisitions within enterprise software.

A.8 Size of Enterprise Software Industry

These computations are based on *Crunchbase* data only, and separate of the remainder of the paper. I compare enterprise software and biotechnology / pharmaceuticals as both software and biotechnology / pharmaceutical startups are thought to be captured especially well on *Crunchbase*. As *Crunchbase* does not specifically distinguish industries, I define these industries as indicated below.

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 A.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.)

B Further Details on Different Acquirer Types

The three types of acquiring companies – Enterprise Software, Industry Outsider, and financial – not only vary by industry sector, but also in terms of other characteristics. For instance, Enterprise Software acquirers are more likely to once have been VC-funded themselves (68%), tend to be somewhat younger than financial or Industry Outsider firms, 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 in only 35% of acquisitions is the acquirer a public company as of 2021.

Table 18 shows the pattern of funding rounds received by different startups at the time of exit, which closely mirrors the patterns observed for startup age, price and valuation (Tables 5 and 6) 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 18: Number and volume of VC funding rounds at exits of VC-funded startups, 2012-2020. Excludes leveraged buyouts or management buyouts.

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

Acquihires. Some acquisitions on *Crunchbase* are tagged with an acquisition type that is other than "acquisition". I find that 2.6% of acquisitions of startups in which the product is coded as *shut down* are acquihire. In contrast, for products kept alive, only 0.7% of acquisitions are coded as an acquihire.

Timing. As to the timing of the shut-down, anecdotally there are 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 the startups acquired and kept alive, I can compile 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 2 and 1.4 products on average, 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 19 reveals that products acquired by the GAFAM tend to have many more reviews. These numbers should however be regarded in the light that the GAFAM are also especially likely to discontinue products. Moreover, it is not clear whether high number in reviews means that the acquisition has boosted demand for these products, or whether these products were successful previously. However,

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 19: 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.

these findings might indicate that firms like the GAFAM are less likely to hold a portfolio of brands. GAFAM tend to either acquire the successful products, or manage to reach a vast customer base with these acquired products.

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

In Table 20, 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: both regressions use cross-sectional data.

Reviews can be interpreted as a proxy for product demand. 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, the number of reviews are difficult to explain using the data – the R^2 is very low.

Table 20: 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

E Robustness: Event Studies

Table 21: Event study like in Table 10, 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 22: Event study like in Table 10, 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 23: 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)				
	(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 24: Standard diff-in-diff, using events as in Table 10, 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 25: Same event study as in main text (Table 10), 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 26: 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 27: 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		