Entry and Acquisitions in Software Markets*

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Abstract

How do acquisitions of young, innovative, venture capital funded firms (startups) affect the incentives of new firms to enter a market? I create a new dataset by merging web-scraped product-level data on enterprise software with data on firms' entry and acquisition decisions. The data produce new facts on software acquisitions, highlighting the heterogeneous motivations of acquirers. I build and estimate a dynamic model that endogenizes startups' entry decisions in the face of these acquisitions. In the model, acquisitions can affect returns to entry (1) via market structure, and (2) by providing an entry-for-buyout incentive to potential entrants. I find that, whereas overall startup acquisitions can incentivize new firms to enter, certain types of acquisitions – those conducted by established industry players and targeting more mature startups – tend to be followed by less entry. Preliminary results from counterfactual simulations suggest that if competition authorities were to block all startup acquisitions, entry would fall in some markets. A case-by-case merger analysis may thus be favorable for sustained startup entry.

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

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

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1 Introduction

Over the past two decades, companies active in digital technology and software – most famously, dominant incumbents such as Alphabet and Microsoft, but also much smaller players like Dropbox or HubSpot – have acquired thousands of young, innovative companies. How do such acquisitions affect the returns to entry into a given market? New product entry constitutes the main dimension of competition in software industries. Often, new entrants into these markets are venture capital funded, innovative, young firms, which I refer to as *startups*.

On one hand, acquisitions provide an entry-for-buyout incentive if the returns of being acquired are higher than the returns of competing on the market (Cabral, 2018, Hege & Hennessy, 2010, Mermelstein, Nocke, Satterthwaite, & Whinston, 2020, Motta & Shelegia, 2021, Phillips & Zhdanov, 2013, Rasmusen, 1988). In the software industry, over 90% of startups that successfully "exit" from the private market are acquired by other firms, as opposed to listing on public stock markets.[1] Survey results suggest that being acquired is a major goal for startup entrepreneurs.[2] This suggests that regularly occurring startup acquisitions in a given market can encourage entry.

On the other hand, an acquisition can affect market structure and the competitive environment that potential entrants are facing. This change in market structure can affect the returns to entry either positively or negatively. In some situations, acquisitions could deter new startups from entering, as these will be facing a competitor that is able to capture a larger share of demand. This may create a "kill zone" in a given market (Kamepalli, Rajan, & Zingales, 2021, Motta & Shelegia, 2021). In other instances, the target's product may be vertically integrated and become unavailable to previous customers.This would reduce the number of products competing in that market, and follow-on entrants will face a less competitive environment. This may *increase* the returns to entry (Stigler, 1950).

I answer this research question by (1) collecting and assembling new data; (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.

I construct a new dataset by web-scraping product-level data from *Capterra*, a vertical search engine

[1] Author's computation, using *Crunchbase* data on enterprise software startups with headquarter in the USA and exiting in 2005-2020. In contrast, only somewhat more than 50% of startups in Biotech or Pharmaceuticals exit via acquisition. See Appendix A.7.

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

for enterprise software.[3] Answering the research question requires to accurately define *markets*, i.e. sets of competing companies. With the help of product descriptions and categories available from the website, I segment products into clusters of likely substitutes using text-as-data methods. I merge these narrow, product-level market definitions with information on firms' histories of acquisitions stemming from *Crunchbase*.

The data produce novel, policy-relevant descriptive facts about startup acquisitions in software markets. 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. These firms presumably buy startups for purposes that are linked to the startup's R&D capabilities, the functionalities of its product, or its human capital, for instance. On the opposite end of the spectrum, financial companies, such as private equity firms, acquire companies mainly to generate financial returns before re-selling the company again.

Presumably, both financial and strategic acquirers may generate an entry-for-buyout incentive, whereas only acquisitions conducted by strategic acquirers can affect market structure. 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.

While these reduced-form regressions can shed light on short-run effects of an acquisition that are transmitted via the market structure, they cannot inform about the presence of the more long-run entry-for-buyout effect. I therefore build a simple structural dynamic model of startup entry that accounts for both channels of effect. In this model, firms obtain payoffs in the event of a change in ownership, i.e. an initial public offering (IPO), or an acquisition. When deciding whether to enter a given market, potential entrants on the one hand take into account the current and expected future market structure. Market structure is determined by the number of competitors, as well as by major, strategic acquisitions. On the other hand, potential entrants also form beliefs about the likelihood with which they may be acquired in the future. The events of being acquired or going public are modelled as exogenous, stochastic shocks that may arrive upon the startup with varying frequency across markets. Using a revealed preference approach, I estimate the parameters quantifying the importance of each of these channels for spurring or deterring entry.

[3] I thank the parent company *Gartner* for granting me the official permission to web-scrape the *Capterra* website.

The estimated model reveals that firms are more inclined to enter into markets with a higher rate of startup acquisitions. Moreover, as seen in the reduced-form regressions, certain types of acquisitions – those conducted by major industry incumbents and targeting more mature startups – may deter entry. The overall effects from banning all or a subset of acquisitions is determined by the magnitudes of both channels. Based on preliminary counterfactual simulations, I find that startup entry may decline at least in some markets if all startup acquisitions were blocked. In contrast, blocking only mergers conducted by large, strategic acquirers would slightly increase entry. All in all, this suggests that competition authorities should continue reviewing mergers on a case-by-case basis.

Both my descriptive and 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 (see Wollmann (2019) for a study of these types of acquisitions). The sheer number of these types of transactions has caught the attention of antitrust practitioners and academics worldwide. My data show that *Alphabet*, for instance, has acquired about one company every week in the years of 2010 to 2015. 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).

This paper is also linked to the important question of how innovation is affected by market structure, going back to Schumpeter (1942) and Arrow (1962). Moreover, entry dynamics in software markets are still poorly understood. As these markets are bringing vast welfare gains in the years to come, understanding the frictions that entering startups face is economically important.

This paper has two main contributions to the literature. The first contribution is the creation of a new dataset that reveals novel facts on startup acquisitions in software markets. 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, but establish findings on the effects of startup acquisitions conducted by any kind of firm, including financial firms. In fact, one strength of my analysis is the distinction between different types of acquirers who pursue different motives and who should affect entry in different ways. I am nevertheless able to track acquisitions at the *product* level, and to define markets on a more granular level, compared to previous literature (G. Z. Jin, Leccese, & Wagman, 2022a).

The second contribution lies in new results on entry dynamics in the face of acquisitions, which I obtain with the help of a structural model of startup entry. Previous literature uses reduced-form regressions to find out how GAFAM acquisitions and measures of investment or entry correlate (Bauer & Prado, 2021, G. Z. Jin et al., 2022a, Kamepalli et al., 2021, Koski, Kässi, & Braesemann, 2020). These reduced-form regressions, however, cannot account for the different channels of effect that are associated with acquisitions. The model I set up explicitly accounts for the two channels and allows to quantify each. It moreover allows to simulate how entry would evolve under counterfactual antitrust regimes. I estimate the model using a two-step procedure, following literature on the estimation of dynamic discrete games (e.g. Hotz and Miller (1993), Aguirregabiria and Mira (2007), Bajari, Benkard, and Levin (2007)).

The paper is organized as follows. I cover the data construction in Section 2, and extensive descriptive analyses in Section 3. Section 4 contains reduced-form analysis providing suggestive evidence for the differential effects of different types of acquisitions. Section 5 introduces the model and covers its estimation. Section 6 covers the results, and is going to cover the counterfactual experiment in a future version of the paper. Section 7 discusses findings and assumptions. Section 8 draws a conclusion and suggests topics for future research.

Related Literature

Empirical findings on acquisitions by GAFAM and other firms. Motivated by the high number of acquisitions of technology companies in recent years, a body of research has tried to shed light on the motivations of acquiring firms and potential effects of these mergers. One strand of this literature studies exclusively deals conducted by the five GAFAM firms, emphasizing the very young age of the targets in these transactions. This research is somewhat divided as to whether GAFAM acquisitions strength the GAFAM's existing market segments (Gautier & Lamesch, 2021), or whether acquisitions are focused on adjacent, complementary markets (Argentesi et al., 2021, G. Z. Jin et al., 2022a). A subset of these papers explore the effect of acquisitions on the amount of venture capital raised thereafter by companies in the same market segment as the acquired company, employing difference-in-difference designs. Bauer and Prado (2021) find *more* VC funding in the quarters and markets after an acquisition takes place. This is in contrast to the other papers: Koski et al. (2020) find that a higher cumulative number of acquisitions in a given market is associated with *reduced* entry and lower VC funding. Kamepalli et al. (2021), who focus on twenty major acquisitions of consumer-facing platforms by Facebook and Google, equally find a *decrease* in VC funding following an acquisition by the GAFAM, thereby providing suggestive evidence for the presence of a "kill zone" in certain technology areas. Studying 50 mobile applications that were affected by GAFAM acquisitions and using more granular data, Affeldt and Kesler (2021a) find that half of the acquired apps were shut down post-acquisition. Affeldt and Kesler (2021b) uncover that in an acquired app's market, entry declines, and competitors innovate less. Concerning the motives of acquisitions in tech more broadly, Ng and Stuart (2021) find high turnover rates of "acqui-hired" employees, casting some doubt on the idea that technology companies acquire startups mostly for hiring purposes. On the policy side, Lemley and McCreary (2020) suggests changes in laws to make IPOs a more attractive exit route for startups, and emphasizes a potential entry-for-buyout effect.

My descriptive findings add to these bodies of literature by comparing the GAFAM firms' acquisitions and their effects to other acquirers. This has only been done by G. Z. Jin et al. (2022a), but unlike those authors, I can follow acquisitions at the product-level, enabling me to have precise market definitions. G. Z. Jin, Leccese, and Wagman (2022b) extend this analysis to all North American public firms, finding that acquisitions take place in adjacent markets. This goes along with my finding that the vast majority of mergers are not horizontal and that many acquirers are industry outsiders.

Theoretical literature on mergers and innovation in technology markets and beyond. An emergent theoretical literature has investigated the likely effects of startup acquisitions on innovation and competition. A number of papers emphasize the idea that the numerous acquisitions of highly innovative startups by large incumbents may affect both the extent and the direction in which startups choose to innovate (Bryan & Hovenkamp, 2020, Cabral, 2018, Callander & Matouschek, 2020, Dijk, Moraga-Gonzàlez, & Motchenkova, 2021, Katz, 2021, Letina, Schmutzler, & Seibel, 2021, Motta & Shelegia, 2021). Kamepalli et al. (2021) focus on B2C tech products and argue that kill zones can occur as "techies" do not adopt entrants' products, anticipating that products will be shut down upon acquisition. Cunningham, Ederer, and Ma (2021) show that acquirers may have incentives to acquire nascent companies in order to shut down their nascent products, thereby removing a future competitor, and show empirically that this phenomenon is a reality in the pharmaceutical industry. Fumagalli, Motta, and Tarantino (2022) analyzes to under which conditions acquirers tend to shelve, or develop, an acquired product. They discover a bright side of startup acquisitions: under some conditions, the acquirer is able to fund and develop projects that would otherwise never reach the market (due to financial constraints and asymmetric information).

My paper is also broadly related to literature on mergers or market structure and innovation, both using theory (Hollenbeck, 2020, Jullien & Lefouili, 2018, Mermelstein et al., 2020, Nocke & Whinston, 2010) as well as empirical methods (Haucap, Rasch, & Stiebale, 2019, Igami & Uetake, 2020, Poege, 2022, Watzinger, Fackler, Nagler, & Schnitzer, 2020).

Competitive effects of IPO, acquisition, patenting, and entry. Using data that spans many industries, 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. Aghamolla and Thakor (2021) show that a firm's IPO can positively affect a competitor's firms likelihood to equally do an IPO. Song and Walkling (2000) show that a company's acquisition leads to increasing returns of this company's rivals, as it increases the probability that these rivals will be targets themselves. Conti, Guzman, and Rabi (2021) find a similar effect using data on Israeli startup acquisitions, highlighting the channel of increased prominence. This paper sheds 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.

Literature on entry and dynamic games. I model entrepreneurs' entry decisions as dynamic strategic interactions in a setting with incomplete information. To estimate the parameters governing agents' decisions, I employ methods proposed in the literature on dynamic games (Aguirregabiria & Mira, 2007, Bajari et al., 2007), and employ forward simulation techniques used in Hotz, Miller, Sanders, and Smith (1994).

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 acquiring the highest *number* of startups worldwide are all active in software, as highlighted in 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 have 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.[4] Studying entry into this industry is therefore economically relevant in its own right.

I consider entry by *startups*, which are young, risky, very innovative, 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 essential for guaranteeing competition *for* the market. More broadly, startups play an important role for innovation and industry dynamics in the economy. In the past, startups have re-defined 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

[4] 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%.

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.[5] Both of these events are generally considered a success, and may yield a high return to investors and founders.[6]

2.2 Data

I construct a panel dataset of companies using the data portal *Crunchbase*. I merge this company data to cross-sectional information on enterprise software products that I web-scraped from the platform *Capterra*.

The resulting dataset is a panel of products. Each observation is an "event" of a given product's company – such as founding date, funding round, or acquisition – with a date at which the event took place. The data is aggregated to a market-quarter panel for the reduced-form analyses and structural model.

2.2.1 Firm-level Panel: *Crunchbase*

I obtained access to data on *Crunchbase*, a data portal that tracks financial information on public and private companies, in particular VC-funded firms. *Crunchbase* records companies' founding dates, all 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). It associates each company to at least one of over 40 "industry groups" (e.g. Advertising, Consumer Electronics, Financial Services), and over 700 "industries" which are subgroups of an industry group (e.g. Ad Network, Drones, Consumer Lending). The industries can be thought of as labels, as a company can be associated to any number of industries associated to any industry groups. Each company profile has two bodies of descriptive text describing the company.

[5]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).

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

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.[7] I then define "startups" as companies that have received at least one such VC-type investment.

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.[8] I then construct a panel of company events.

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

Whereas the *Crunchbase* dataset does contain information on a startup's industry in the form of labels and descriptive text, a more careful look at companies that have an industry tag in common reveals that the tags are not very accurate in determining which companies actually compete against each other in a given market. This is due to the fact that, first, the tags may be specific to an *industry*, but not to a *market* (e.g. the tag "Enterprise Software" could in principle capture markets as remote as enterprise resource management, and video advertising).[9] 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. In order to delineate which companies compete with each other in a given market, a *product-level* definition of competition is needed. 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.

To obtain more accurate, product-level information, I web-scrape new data from *Capterra*, a vertical search engine for enterprise software.[10] The platform is designed to assist customers with comparing and finding suitable enterprise software, and is one of the market leaders among platforms offering this service. The website classifies each enterprise software product into one or more of 821 narrow categories – for example, "Audio Editing Software", "Conference Software" or "Spreadsheet Software".

[7] 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.

[8] 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.

[9] *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.

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

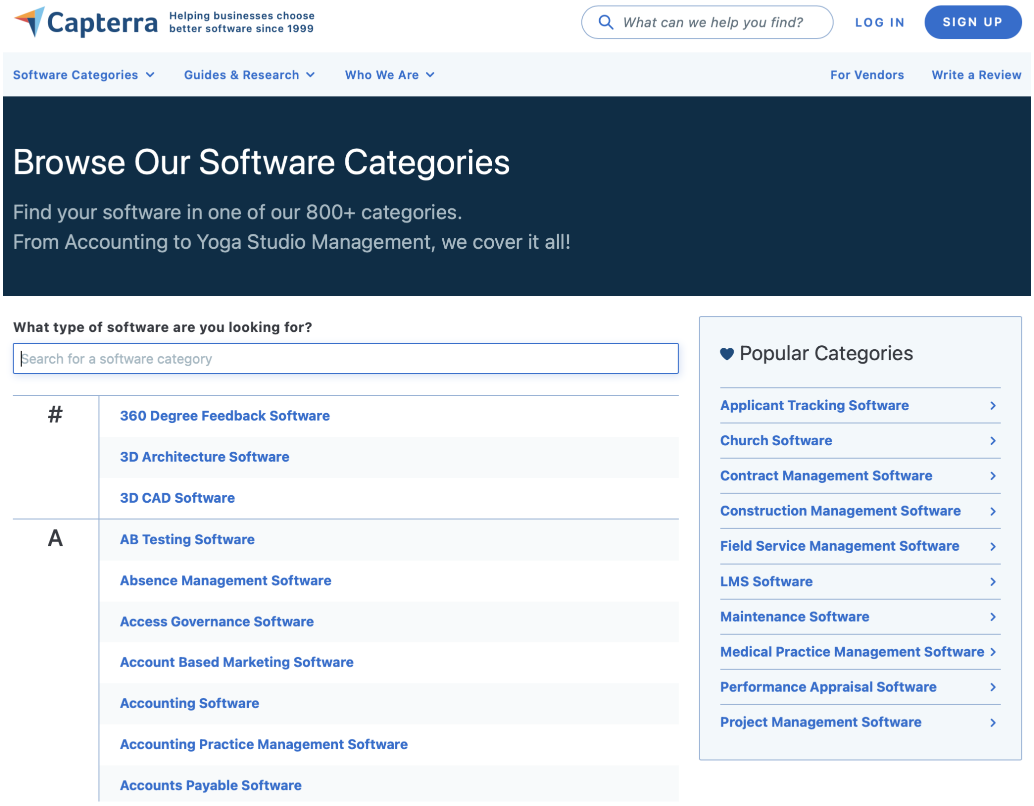


Figure 1: *Capterra*'s categories page

It provides descriptive text, information on the producing company, as well as user reviews and ratings for each product (see Figure 1 and 2).[11] The range of products covered on *Capterra* is exhaustive and very up-to-date.[12]

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.[13]

All in all, I make use of the *Capterra* data for the following purposes: (1) to cluster products into

[11] 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*).

[12] 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*.

[13] 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.

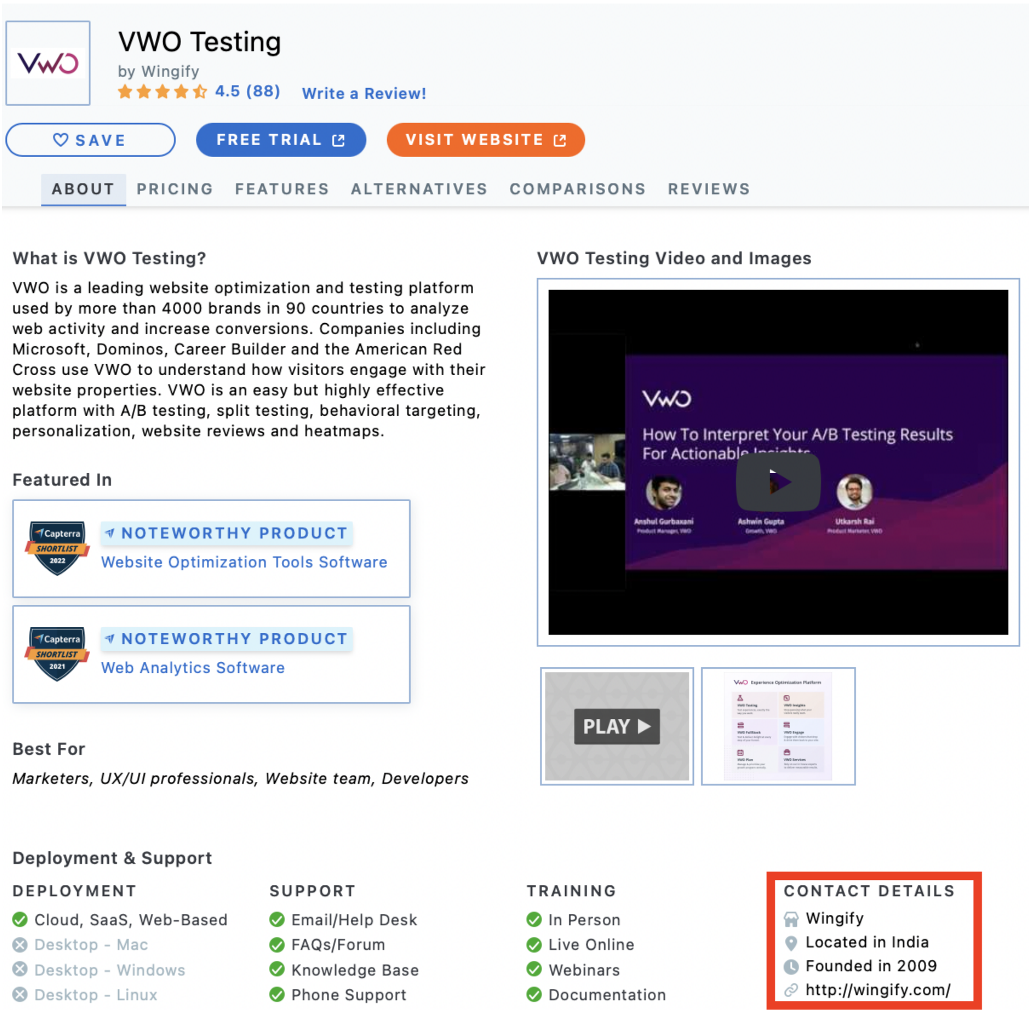


Figure 2: Example of product page on *Capterra*. The red frame highlights the company information (in particular, name and URL) available for all products on *Capterra*.

groups of substitutable products, with the help of a machine learning model (see Section 2.2.3); and (2) to find out which enterprise software startups' products are actually active and available as of July 2021.

2.2.3 Matching *Capterra* to *Crunchbase* data

I match products on *Capterra* to their producing 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.[14] 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*.[15] 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 independent markets of substitutable products by using text-as-data methods (Gentzkow, Kelly, & Taddy, 2019). Each product on *Capterra* is associated with a body of text, stemming from the category name(s), and the product description. As a given product may be associated to more than one category, one cannot distinguish independent markets of products by using the categories themselves alone.

The textual information on *Capterra* can be viewed as meaningful information on a product's functionalities, in the sense that companies present in the same (or similar) categories should be more substitutable:

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

[15] 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.

Capterra's purpose is to guide consumers searching for specific enterprise software products. The company therefore has an incentive to accurately categorize products.[16]

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, respectively) 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 pre-trained word vector stemming from *GloVe*, an unsupervised learning algorithm for obtaining vector representations for words (Pennington, Socher, & Manning, 2014).[17] 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 will be located close to each other. For each product, I then take the average of all its vectors of the category names, so that each product will be associated to 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 categories are linguistically close – will be 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 defintions 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).[18]

Table 1 shows basic descriptives 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 public firms, showing that we would miss a lot if we focused on public firms only, which some literature does due to data constraints. Table 2 displays descriptives on the market-quarter panel. It becomes clear that the data tend to be right skewed.

[16] *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.

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

[18] The 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.

	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
# pre-event firms	4.396	4.926	1	3	6
# VC-funded, pre-exit startups	15.362	15.377	5	10	20
# acquired & alive startups	1.547	2.149	0	1	2
# public firms	3.777	3.721	1	3	5
# startups entering	0.651	1.033	0	0	1
# startup acquisitions	0.161	0.542	0	0	0
# startup IPOs	0.020	0.141	0	0	0
Median price, startup acquisitions	395.153	945.820	40	130	360
Median valuation, startup IPOs	3,774.739	13,875.350	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$.

3 Stylized Facts

This section lays out empirical facts that motivate the research question, guide the modelling assumptions, and build towards the model-based results.

In this section, I distinguish 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 non-horizontal (Section 3.4).

3.1 Distinguishing 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.[19] 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.[20]
  - Examples: The We Company; Verizon; Dentsu International; Samsung Electronics; Ericsson.

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

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

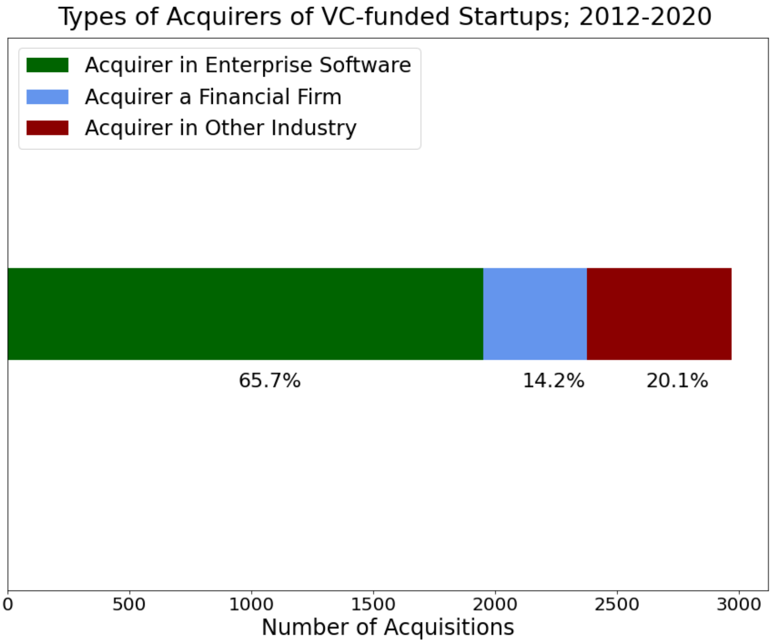


Figure 3: Types of acquirers for first-time acquisitions ("exits") of VC-funded startups worldwide in the domain of enterprise software, for acquisitions occurring between 2012 and 2020. These descriptives are on the company, as opposed to on the product, level. I exclude acquisitions of the types LBO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

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. Note that these sets of companies may switch categories as they grow: for instance, Dropbox acquisitons are contained in the category *pre-exit* for the years in which Dropbox had not exited yet, and is 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

Acquirer type (# 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 (168 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.)

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 in Table 4. Looking at Panel A, what is noteworthy is that Enterprise Software firms are much more likely to acquire VC-funded, pre-exit startups than the other types of firms. Financial firms, in contrast, are predominantly engaged in acquiring private firms that have not received VC funding. Panel B shows a result that may be particularly interesting from a policy perspective: comparing the different subgroups of Enterprise Software acquirers, the acquisition strategy that the GAFAM pursue is closest to New Tech firms. For both groups of firms, the share of VC-funded pre-exit companies among all targets is very high. Similarly, the share of targets that are very young companies that have no prior funding historyis also very high. The pattern is similar for pre-exit firms, except that these are somewhat more active in acquiring non-VC funded firms. In contrast, Old Tech firms acquire very rarely the very young companies with no prior funding rounds. Instead, they are more likely to acquire not VC-funded firms,

Panel A:					*(in %)*
Acquirer type	<3 years old and no VC funding (yet)	VC-funded, pre-exit ("startup")	VC-funded, post exit	Not VC-funded	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 a subset of Enterprise Software acquirer types:					
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	9.4	51.8	4.7	31.6	100

Table 4: Which types of companies do different types of acquirers buy? I use data from 2014-2019. I exclude leveraged buyouts and management buyouts, but otherwise place no restriction on the type of company acquired.

or post-exit firms. This finding raises some questions, as the Old Tech firms tend to dominate markets in a similar fashion as the GAFAM, but apparently pursue an acquisition strategy that is very different from the GAFAM.

For the remainder of this section, I look at 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 the following characteristics: acquisition prices (Table 5), age at acquisition (Table 6), funding (Table 7), and valuations (Table 8).[21] I observe the following pattern: Enterprise Software firms tend to acquire firms at lower prices, that are younger, have received less VC funding in million US$, and have a lower valuation, 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 the highest price, high age, large amount of funding, and high valuations. Therefore, startups acquired by Old Tech firms tend to be quite mature, and their acquisition pattern is slightly more similar to that of financial firms. The GAFAM and New Tech, in contrast, acquire VC-funded startups at lower prices, a much lower age, that have received less funding and lower valuations. For GAFAM firms in particular, the acquired firms tend to be of a very low maturity. For pre-exit firms, whereas the age of acquired startups is about as high as for GAFAM and New Tech firms, the acquisition prices either often missing or very low, and acquired firms have received few funding rounds and a low valuation. This points to the possibility that pre-exit firms might tend to acquire mainly financially distressed startups (Kerr, Nanda, & Rhodes-Kropf, 2014).

[21] 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:

	Acquisition price (million USD, median)	Percent acquisition price not observed
Enterprise Software	120.0	81.0
Financial	150.0	88.4
Other Industries	100.0	79.9
Panel B: Looking at a subset of Enterprise Software acquirer types:		
GAFAM	164.0	78.2
New tech	152.5	60.7
Old tech	400.0	74.2
Pre-exit	15.8	95.8

Table 5: Acquisition prices at exits of VC-funded startups, 2012-2020. Excludes leveraged buyouts or management buyouts.

Panel A:

	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 a subset of Enterprise Software acquirer types, 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.

Table 9 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 tends to be particularly low for GAFAM and New Tech acquirers. In contrast, acquisitions by financial and Other Industry 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

Panel A:

	Number of funding rounds (mean)	Volume of funding (million USD, median)	Percent funding volume not observed
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 a subset of Enterprise Software acquirer types, 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 7: Number and volume of VC funding rounds at exits of VC-funded startups, 2012-2020. Excludes leveraged buyouts or management buyouts.

Panel A:

Acquirer type	Valuation at exit (million USD; median)	Percent NA
Enterprise Software	25.0	94.6
Financial	59.0	95.5
Other Industries	26.2	93.4
Panel B: Looking at a subset of Enterprise Software acquirer types, and IPOs:		
GAFAM	49.8	90.4
New tech	263.0	92.9
Old tech	476.0	92.6
Pre-exit	4.4	94.3
IPO	1000.0	69.1

Table 8: Valuation at exits of VC-funded startups, 2012-2020. I use the latest available post-money valuation at the time of exit. Excludes leveraged buyouts or management buyouts.

Panel A:

Acquirer type	Number of years since last funding round (mean)
Enterprise Software	2.7
Financial	3.5
Other Industries	3.3
Panel B: Looking at a subset of Enterprise Software acquirer types, and IPOs:	
GAFAM	1.8
New tech	1.8
Old tech	2.4
Pre-exit	2.4
IPO	2.2

Table 9: Time (in years) since last funding round at time of exits of VC-funded startups, 2012-2020. Excludes leveraged buyouts or management buyouts.

Panel A:		
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 a subset of Enterprise Software acquirer groups:		
Old tech	72.1%	137
New tech	64.9%	109
GAFAM	80.8%	126
Pre-exit	66.8%	432

Table 10: Discontinuations of products post-acquisition, for different types of acquirers, and for startups acquired in 2012-2020.

company's lifetime is 8 (5 for Industry Outsider firms). 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 – 53% – of acquisitions, the product has been discontinued under the same brand name after the acquisition, as of 2021. These numbers are in alignment 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 findings show that this carries over to other acquirers active in the software industry, and seems to be a widespread phenomenon in software.

Shut-down rates vary depending on the acquiring firm. Table 10 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 11). Moreover, the median firm tends to be acquired at less than 75% of

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

the price of companies whose products were kept alive.[22]

Looking only at 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 acccording to my definition), the aggregate shutdown rate is even higher, amounting to 75%. Given that the acquired and discontinued companies were seemingly less mature suggest that many of the shut down 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.

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 12 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, 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.

3.4 Most Acquisitions Are Non-Horizontal

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

[22]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.

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 12: 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.

market definitions, I find that only 8% of all acquisitions of VC-funded startups in 2012-2020 can be classified as being horizontal.[23]

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 being less likely to be a serious threat to a major incumbent like Google. Second, the finding that most acquisitions are non-horizontal makes them being killer acquisitions less likely. Anecdotally, it seems that most acquisitions could instead be classified as being either vertical, or conglomerate.

Moreover, as Table 10 shows, shut-downs 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, pre-exit startups or "new" tech firms account for a much larger share of discontinued startups than the GAFAM. Instead,

[23] 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 extent to which the acquirer supplies enterprise products.

there is anecdotal evidence that acquired products are sometimes integrated into the acquirer's existing produt as an additional feature or functionality, or otherwise to improve the existing product.[24] Some of the transactions seem to be so-called acqui-hires in which the acquired startup's employees are paid to become part of the acquiring company.[25] This is somewhat different for private equity or 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.[26] I have also found cases in which the product was re-branded. However, any re-branding seems to have gone along with a number of changes to the original product.[27]

The difference in the age profile of acquired startups between Enterprise Software and financial firms is in line with the fact that financial firms acquire tested products, as presumably these firms are interested in obtaining cashflows. In contrast, Enterprise Software firms might be interested in acquiring even startups whose products do *not* yet have a customer base. Software creation is very modular. 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 product 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, different acquirers differ in important ways in their respective motivations for acquiring startups. Moreover, one may argue that only certain types of acquirers have the capabilities and 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

[24] For instance, according to news reports, this may have been the case with Amazon's acquisition of the data warehousing company Amiato, see https://techcrunch.com/2015/04/20/amazons-aws-acquired-amiato/; Google's acquisition of app performance startup Pulse.io, see https://venturebeat.com/2015/05/28/google-acquires-mobile-app-performance-startup-pulse-io/; or Upskill's acquisition of Pristine, see https://www.prnewswire.com/news-releases/augmented-reality-industry-leader-upskill-acquires-pristine-300453872.html (both accessed 07/08/2022).

[25] Examples are Dropbox-Verst, Google-Bebop, Apple-Union Bay Networks, Twitter-tenXer, or Box-Wagon. In 3% of startup shutdown-acquisitions, the *Crunchbase* data in fact notes that the acquisition is an "acqui-hire". I believe the actual number of acqui-hires to be rather higher. Especially in cases in which the acquirer announced the shut-down at the time of the acquisition, the acquisition seems to have often been an acqui-hire.

[26] One example is the alternative data company *7Park Data*, which was acquired by *Vista Equity Partners* and later folded into *Apptio*, another one of *Vista Equity Partners*'s portfolio firms. Another example is *SCIO Health Analytics*, which was acquired by the holding group *ExlService Holdings* and is now part of its product *EXL Health*.

[27] An example is the acquisition of Acompli, a mobile email and productivity app, by Microsoft. The product was rebranded as Outlook Mobile a month after the acquisition, see e.g. https://www.theverge.com/2015/1/29/7936081/microsoft-outlook-app-ios-android-features (accessed 07/08/2022).

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.

This is in contrast with the intentions and capabilities of acquirers in financial and other industries. Financial acquirers are typically transitional owners of the acquired firms. They may be focused on generating cashflows in the medium term by changing a companies' management, with the intention to later re-sell the company. For acquirers active in other industries, acquisitions in enterprise software may often be vertical integrations of software products, or portfolio acquisitions, which should both not fundamentally affect market structure and competition. Therefore, I pose the following hypothesis:

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

I attempt to shed light on this hypothesis by setting up an event study framework. I use quarter-market panel data ranging from 2012-2020, and study this hypothesis using the following linear models:

$$\text{num\_entrants}_{mt} = \beta^{acq}\mathbf{1}\{\text{acquisition of type } \mathrm{g}_{[t-\tau,t],m}\} + \lambda_m + \gamma_t + \epsilon_{mt} \tag{1}$$

num_entrants$_{mt}$ denotes the number of VC-funded startups entering in a given market m at quarter t.Type g an be either a of a financial acquirer, or a strategic acquirer. τ is the event window, which I set to 4 in my preferred specification. The coefficient of interests is therefore β^{acq}. λ_m and γ_t denote market and time fixed effects, and ϵ_{mt} is an econometric error term.

I define "entry" events as being a firm that receives its first VC funding round in my data. The firm will thereafter be considered a startup.[28]

Acquisitions are plentiful in the data, and tend to be clustered in certain markets and periods. Moreover, acquisitions of very small firms whose products were integrated post-acquisition might be less likely to have a measurable effect on entry via market structure. For the event study, I thus use large acquisitions (transaction price above 100US$ million) of VC-funded startups that have not exited

[28] According to this definition, a pre-event firm with no prior funding but that has had a "founding" event has not "entered" the market yet.

yet and whose product were kept alive as events.[29] 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.

Table 13 shows 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 portfolio acquirer. The results provide suggestive support for the hypothesis. Major startup acquisitions by strategic acquirers – both by wide as well as more narrow definitions – tend to be followed by a decline in entry. In contrast, this pattern seems somewhat less prevalent for financial acquirers.

I perform a placebo test by asking: Are acquisitions of these different acquirers *preceded* by a decline, or by an increase, in entry? Table 14 suggests that only major acquisitions by public enterprise software companies may be preceded by a significant drop in entry.

Table 13: 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 (89 acquisitions)	-0.112^{*} (0.059)				
Major acq by public enterprise software company (59 acquisitions)		-0.158^{**} (0.075)			
Major acq by GAFAM or 'New Tech' (21 acquisitions)			-0.401^{***} (0.135)		
Major acq by company not in enterpr softw (incl. financial) (40 acquisitions)				-0.101 (0.072)	
Major acq by financial company (13 acquisitions)					0.032 (0.119)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.299	0.299	0.3	0.299	0.299
Observations	17,064	17,064	17,064	17,064	17,064

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

Instead of conducting an event study, Table 15 repeats the regression, this time using the cumulative sum of acquisitions of a certain type in a certain market as an explanatory variable. Again, we find that

[29] 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.

Table 14: Placebo: 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		

entry is higher in markets that have been subject to many acquisitions by acquirers active in enterprise software.

Table 15: 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	−0.142***				
(ranges from 0 to 4)	(0.053)				
Major acq by public enterprise software company		−0.133**			
(ranges from 0 to 4)		(0.065)			
Major acq by GAFAM or 'New Tech'			−0.297***		
(ranges from 0 to 2)			(0.085)		
Major acq by company not in enterpr softw (incl. financial)				−0.141*	
(ranges from 0 to 2)				(0.072)	
Major acq by financial company					−0.129
(ranges from 0 to 1)					(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		

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 with a lot of entry. This goes against my findings in Tables 13 and 14, 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. However, with the exception of Enterprise Software acquisitions which becomes insignificant at the 10% level, the results hold when studying the time period of 2014-2019, which is the time period under study in the model. The results moreover 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. Finally, I conduct the event study, but using a different control group, again with similar findings. See Appendix E for these robustness checks and a further placebo test.

These reduced-form regressions offer suggestive support for short-run negative effects of a strategic acquisition, 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., 2022a, Kamepalli et al., 2021, Koski et al., 2020).[30] However, any reduced-form approach can only shed light on short-run effect of an acquisition that is transmitted through the resulting change in market structure. As I pointed out, acquisitions can affect entry not only through market structure. Instead, the prospect of being target oneself can also stimulate new entry. 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 startups that decide whether or not to enter into a given market.

[30]This literature has focused on GAFAM firms only. With the exception of Affeldt and Kesler (2021b), they have focused on broader industries. They have moreover used other data and employed alternative, in some cases less precise ways to distinguish markets.

When deciding whether to enter, these startups take into account market characteristics and their evolution in the future. In particular, startups keep track of whether or not a major strategic acquisition that may reduce profits has occurred or is likely to occur in the future. Moreover, startups form expectations over the market-specific likelihood of being acquired, or going public, in the future, which yield a lump-sum return to the startup. All acquisitions and IPOs are assumed exogenous in this model.[31]

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.[32] The potential entrants are homogeneous, except for a private cost shock that each agent draws from a distribution. In each period, all potential entrants simultaneously decide whether to enter the market or not, so as to maximize their expected profits.

If a potential entrant decides to not enter the market, there will be no future chance of entry and it stays out forever.[33]

If a firm decides to enter, it competes against all other firms present on the market. In each period, all active firms earn flow profits. These flow profits depend on a set of state variables that are common knowledge, $\boldsymbol{x}_{mt}$. Moreover, in every period following the entry decision, companies can be acquired, or can be listed on the public stock market. These 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.

[31] Endogenizing acquisitions would pose serious computational challenges: the data contain thousands of potential acquirers that at each moment may decide whether to or not to acquire another firm.

[32] 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.

[33] 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 dynamic: agents are forward-looking, and they incur the sunk costs of entry only once.

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 shock that a potential entrant i obtains as ϵ_{imt}, the expected payoff of entry writes as follows:

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

Here, $\pi(\boldsymbol{x}_{mt};\boldsymbol{\gamma})$ denote the flow profits that the firm obtains in each period, which depend on the state variables and a vector of parameters. κ^e is a parameter denoting the sunk cost of entry, which the potential entrant incurs only once when entering. The expression after the discount factor $\beta \in (0,1)$ denotes the 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^{acq}_m and p^{ipo}_m, 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 react to exit opportunities in their given market. If the firm is not acquired nor listed on the stock market, which occurs with probability $(1 - p^{acq}_m - p^{ipo}_m)$, 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 or any measure of demand, for the ten thousands of firms observed in my dataset.[34] Therefore, I employ a reduced-form approach and model firm profits in the fashion of Bresnahan and Reiss (1991), which has been widely applied in structural models endogenizing firms' discrete actions (e.g. 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. By relating a firms' entry decisions to state variables that, according to economic theory, should influence firm profits, one can estimate to what extent firms' discrete entry decisions depend on these state variables.

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

Thus, the vector of state variables $\boldsymbol{x}_{mt} = \{N_{mt}, A_{mt}^{\text{strat in }\tau}, M_m\}$ consists of variables that are relevant to firms' profits. N_{mt} captures the number of competitors on market m at time t. It is thus an endogenous state variable that evolves according to firms' entry decisions, as well as to an exogenous component[35]. The other state variables evolve exogenously. First, in a very similar way as in the event studies in Section 4, the state variable $A_{mt}^{\text{strat in }\tau}$ is an indicator variable that is equal to 1 in the event of a strategic acquisition in the past τ quarters, and 0 otherwise. M_m denote market effects that control for a market's size or profitability, and will be covered in detail in Section 6.1.

Without loss of generality, the payoff of staying out is normalized to zero plus an econometric error term, $U_{imt}^0 = \epsilon_{imt}^0$. I assume that ϵ_{imt}^0 and ϵ_{imt}^1 are independently and identically distributed according to a type-I extreme value distribution. These shocks are privately observed by firms, but unobserved by the econometrician.

5.2 Estimation

I employ a two-step estimation method to retrieve the structural parameters of the model. 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 has been used in the estimation of dynamic games (e.g. Aguirregabiria and Mira (2007), Bajari et al. (2007)), and is based on techniques developed in the dynamic discrete choice literature (Hotz & Miller, 1993, Hotz et al., 1994).

In a first step, I use the data to flexibly estimate reduced-form regressions (policy functions) that map potential entrants' actions into the state space. 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

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

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).

5.3 Parameterization and Implementation

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

$$\pi(\boldsymbol{x_{mt}};\boldsymbol{\gamma}) = \gamma_1 \log(N_{mt}) \quad + \quad \gamma_2 \mathbf{1}\{A_{mt}^{\text{strat in }\tau}\} \quad + \quad \boldsymbol{\gamma}_3 M_m$$

I set $\tau = 4$, as in the reduced-form regressions in Section 4, so that the variable $A_{mt}^{\text{strat in }\tau}$ 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. One can expect γ_1 to be negative, γ_2 to be negative as well (based on the reduced-form results in Section 4), and $\boldsymbol{\gamma}_3$ to be a vector of positive coefficients. $\boldsymbol{\gamma}_3$ can be interpreted as reflecting baseline profits that can be earned in a given market. These baseline profits are then reduced depending on the number of competitors N_{mt}, and depending on whether or not a major strategic acquisition has taken place in the previous quarters, $A_{mt}^{\text{strat in }\tau}$.

The key parameters of the model are therefore γ_2 and α^{acq}. γ_2 measures the extent to which a major strategic acquisition may depress, or increase, 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.[36] 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 the entry model predicts to enter in

[36] I thus exclude companies whose products in a given market do not have any review. This is supported by the higher fit in the first stage, indicating that products wihtout any reviews might constitute a competitive fringe.

each period. In contrast, D^{exog}_{exit} and D^{exog}_{entry} 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. For instance, a firm may be acquired and shut down (which leads to a reduction in the number of competitors by 1); or a firm that is not VC-funded enters and goes public (which leads to an increase in the number of competitors by 1). I model them as as random variables that follow a Bernoulli distribution with parameters p^{exog}_{exit} and p^{exog}_{entry}, respectively. These parameters can be estimated using the data. The extent to which D^{exog}_{exit} and D^{exog}_{entry} matter (or are needed at all), i.e. the magnitude of p^{exog}_{exit} and p^{exog}_{entry} in the data, depends on how one defines the number of competitors, N_{mt}, in the first place.[37]

I employ both, a "broad" and a "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 $A^{\text{strat in }\tau}_{mt}$, 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.[38] 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. 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. [39]

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.[40]

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.

[37] This implies that 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 promille 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.

[38] 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".

[39] I explored the idea of making R^{acq} and R^{ipo} dependent on the state space. However, reduced-form regressions showed essentially no indication that these vary a lot depending on the state space. Therefore, this approach would not change the results.

[40] 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: Reduced-form Results

The results for the first stage can be found in Table 16, using a "broad" definition of strategic acquirers, and Table 17, 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 16. 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.[41]

Finally, I employ market fixed effects along with quarter fixed effects in column (5) to control for seasonal effects which are present in the data. I again recover similar results; seemingly, the negative

[41] 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). Furthermore, 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 markets tagged with the keywords "artificial-intelligence / platform / customer / business", "app / development / application / building", as well as business intelligence, CRM, and marketing.

strategic effect is not driven by any seasonal effect.

Table 16: First stage, using a broad definition of "strategic" acquirers. Competitors include only companies whose product have at least one review on *Capterra* and can be of the following types: startups, public firms, pre-event very young firms, and acquired & continued startup firms, and private firms.

	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)	(0.004)	(0.015)
Major Enterprise Software acquisition pre-4Q	−0.056	−0.002	0.050	−0.021	−0.007
	(0.069)	(0.067)	(0.079)	(0.066)	(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		
Standard errors clustered at market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 17: First stage, using a narrower definition of "strategic" acquirers. Here, competitors include: startups, public firms, pre-event very young firms, and acquired & continued startup firms.

	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)	(0.004)	(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)	(0.137)	(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		
Standard errors clustered at the market level.			*p<0.1; **p<0.05; ***p<0.01		

Using any of these policy functions, and using estimates of the parameters p^{exog}_{exit} and p^{exog}_{entry} which I take from the data ($\hat{p}^{exog}_{\text{exit}} = 0.061$ and $\hat{p}^{exog}_{\text{entry}} = 0.0076$), 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 $A^{\text{strat in }\tau}_{mt}$, I estimate the empirical frequency with which a strategic acquisition occurs. I then forward-simulate occurrences of major strategic acquisitions by drawing from a Bernoulli distribution each period, and construct the forward simulated flow of $A^{\text{strat in }\tau}_{mt}$ 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.

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 18. 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 16 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 17 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 17 in the first stage. Clearly, the counterintuitive result propagates into the second stage of the estimation, making it seem as if more competitors attracted more entry.

Table 18: Estimates of structural parameters.

	(1)	(2)	no market / category FEs (neither in 1st nor in 2nd stage) (3)
Entry costs, κ^e	-2.9573^{***}	-2.9835^{***}	-4.0915^{***}
	(0.1371)	(0.1382)	(0.0588)
log(# of competitors), γ_1	-0.2481^{***}	-0.2476^{***}	0.0640^{***}
	(0.0107)	(0.0105)	(0.0019)
Strategic acq of competitor **by Enterprise Software acquirer**, γ_2	-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_2		-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 (5th-10th perc)	0.3192^{***}	0.3203^{***}	
	(0.0240)	(0.0239)	
Market category 3 (10th-15th perc)	0.3903^{***}	0.3922^{***}	
	(0.0252)	(0.0251)	
...	...	...	
Market category 19 (90th-95thth perc)	1.1415^{***}	1.1425^{***}	
	(0.0463)	(0.0458)	
Market category 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

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^e 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 Counterfactuals

One of the main purposes of the model is to seek an answer to the question: how would entry evolve if acquisitions by certain types of acquirers were blocked by competition authorities? The ultimate effect will depend on the respective magnitudes of the estimated parameters for the entry-for-buyout effect, α^{acq}, and the estimated market-structure effect of acquisitions, γ_2.

To conduct the simulation, I assume that the change in the antitrust regime occurs in the first quarter of 2014, i.e. the first period of observation in my data. I take the starting values of the state variables to be their respective values in this first period. I then simulate the entry decisions of N^{pe} potential entrants in this period, compute the state variables for the next period, and iterate until the end of the sample period. To elaborate, I start with the first quarter of 2014, which I call year 0, and carry out the following steps:

1. Take x_{m0} from the data.
2. Forward-simulate the state variables, again drawing 200 paths for 100 time periods into the future. Adjust the state variables 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.
3. Using the estimated parameters from Table 18, 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 calculated value of entering and the cost shock draws, compute the number of actual entrants in this counterfactual.

6. Simulate what the counterfactual state variables will be in period the next period, period 1.

7. Repeat steps 1 to 6 until the last period of observation.

For the forward-simulation in step 2, I use the original policy function and transition probabilities. This assumes that startups retain their original beliefs about the evolution of state variables in future periods. This is a simplification and can be viewed as an approximation to the truth. If I was to account for the fact that startups' beliefs about the evolution of the state space adjust, I would have to solve for a fixed point that equals startups' beliefs to observed actions in the counterfactual world. This is computationally infeasible, given the high number of observed markets.[42]

6.3.1 Results for the average market

I first look at the effects on entry and on the number of competitors in the average market. The results are displayed in Table 19. I first simulate the counterfactual in which only strategic acquisitions are blocked. As a result, one observes 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 displayed in the second row of Table 19: 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.[43] In currently ongoing work, I will verify to make sure these assumed rate of bankruptcies could be supported by scientific literature in empirical finance.

[42]In future iterations of the paper, I plan to fully solve this dynamic problem in a small subset of markets.

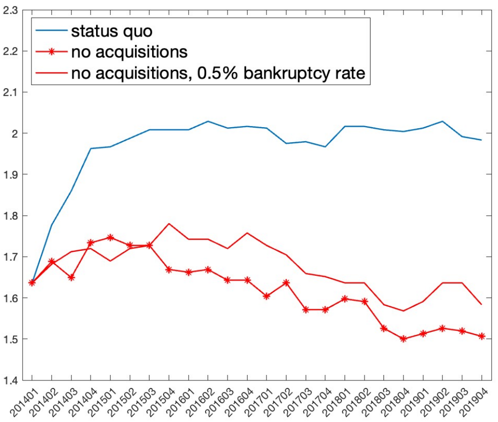
[43]Using *Crunchbase* data, I find that the actual quarterly bankruptcy rate for enterprise software startups is around 1.2%.

Counterfactual	Change in Entry in numbers	in percent	Change in # of Competitors in numbers	in percent
Blocking only strategic acquisitions	0.001	0.122%	0.022	0.111%
Blocking all acquisitions; startups earn profits forever in counterfactual	0.025	5.476%	0.369	1.849%
Blocking all acquisitions; 0.25% chance of profits going to 0 per quarter	-0.012	-2.539%	-0.207	-1.040%
Blocking all acquisitions; 0.5% chance of profits going to 0 per quarter	-0.047	-10.110%	-0.747	-3.746%

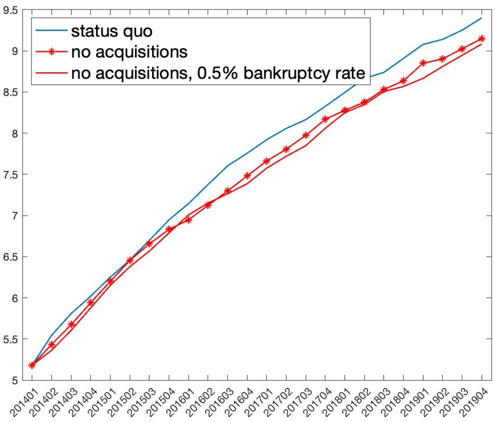
Table 19: Change in the mean number and percent of entrants, and in competitors, in counterfactual scenarios compared to the baseline.

6.3.2 Results for markets of different market size

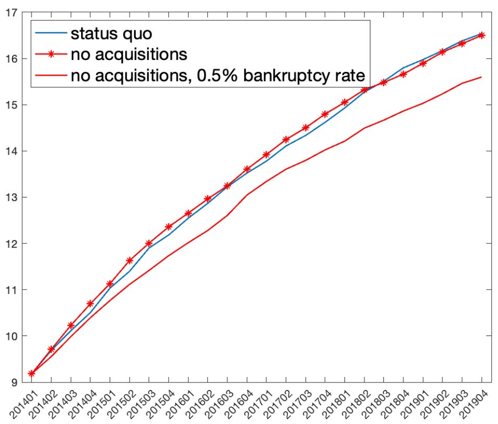
As I observe over 400 markets, I can explore how the effect of blocking startup acquisitions varies across markets of different types. In particular, by way of the market-category effects, the structural model essentially groups markets according to their unobserved market size or inherent profitability. Figure 4 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.



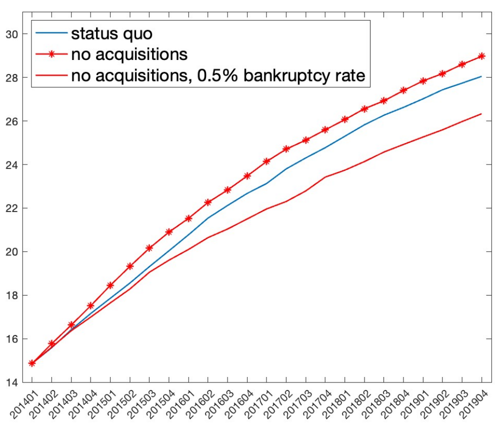
(a) 5th percentile of market profitability



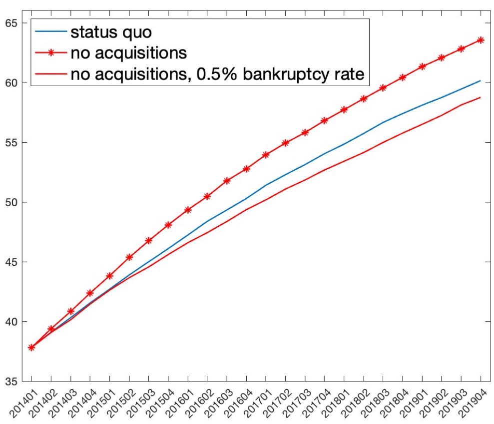
(b) 25th percentile of market profitability



(c) 50th percentile of market profitability



(d) 75th percentile of market profitability



(e) 95th percentile of market profitability

Figure 4: Heterogeneity in the effect of blocking startup acquisitions on the number of competitors, across markets of different unobserved profitability.

7 Discussion

The very granular market definitions that I employ allow to make progress on the research question, as they do not suffer from the drawbacks of the more crude, but more standard industry classification systems that vary on the firm, as opposed to on the product or functionality level. Nevertheless, there are of course aspects of competition that these market definitions do not capture. For instance, startups may pivot, and develop from complementary into a substitutable product. A possible interdependence between markets, which could arise from interoperability between different software systems, or consumer inertia, cannot be captured either. Nor can the market definitions capture the distinction of markets for technology as opposed to product markets cannot be captured by my market definitions. However, note that these caveats are shared by essentially all static market definitions.

Overall, the question of how to accurately define markets for software are frontier research questions by themselves.[44] The discussion highlights the need for future research on how to characterize demand for software, and competition between nascent software products. I plan to conduct a number of robustness checks, for instance by varying the number of markets created.

A further caveat is that the model assumes acquisitions and IPOs to be exogenously occurring events. In fact, one can argue that there is a random element in acquisitions, as acquisitions are essentially matches between an acquirer and a target. Endogenizing acquisitions, like prior research has done (e.g. Igami and Uetake (2020)), is infeasible in my setting due to the fact I am not looking at only one market, so that there are thousands of potential acquirers. In future iterations of this project, I plan to provide robustness checks with respect to this assumption.

8 Conclusion

This paper is related to a question that is of an enormous importance for economic welfare and policy: how to incentivize the production of knowledge? In particular, the paper informs the debate on the relationship between market structure and innovation, going back to Arrow (1962) and Schumpeter (1942).

I analyze and quantify two channels through which acquisitions in a given market can affect innovative entry. The two channels that the model fleshes out – an entry-for-buyout effect, and an effect via market

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

structure – are presumably especially prevalent in software markets where entering firms are risky, innovative, VC-funded businesses. I find that an overall ban of all startup acquisitions would decrease entry in some markets. Noneless, there are certain types of acquisitions that may deter entry.

The new data I collect produces stylized facts that inform the policy debate regarding startup acquisitions in technology sectors. In particular, startup acquisitions are conducted by heterogeneous types of acquirers. A high share of startup acquisitions in software are conducted by firms that are VC-funded startups themselves, whereas only few of these acqusitions are conducted by the "big tech" firms that have been subject to attention by regulators. The pattern of acquisitions conducted by the latter – Meta, Microsoft, Apple, Amazon, and Alphabet – closely resembles that of other recently founded, but by now relatively large, technology firms such as Salesforce or Dropbox.

The paper highlights several avenues for future research. One possible extension of the model would endogenize firms' decisions of whether and how to exit, depending on age and characteristics that determine startups' outside option. A further extension would incorporate the data on startups' funding rounds, and possibly endogenize the decision to obtain an additional round of VC funding; or potentially use VC funding as a measure of product maturity or innovativeness.

Moreover, while the paper's strength is its ability to take into account an entire industry sector, 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 is welfare affected by the shut-down of some products? From a welfare perspective, is there too much, or too little entry into these markets? – I leave these questions for future research.

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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.[45] 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.

Crunchbase defines acquisitions as majority takeovers by *Crunchbase*.

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.

Startup: Any company that has raised at least one Venture Capital funding round.

Pre-exit startup: Any startup 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

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

acquisitions account for approximately 44% of all acquisitions observed in the matched data. This fact is reflected in my data showing that products supplied by VC-funded startups have more reviews, even when employing a range of controls for company characteristics and age (see Appendix D, Table 21).

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 clean the data by first defining 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. In the end, I obtain approximately 70,000 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*.[46] Panel A in Figure 5 gives a few examples of products matched to companies by URL and name.

However, in cases where the product originated with a startup, but is now provided by the acquirer, the above matching algorithm will associate the product to its acquirer and current owner, not to its *originating* company. To trace products back to the startups that may have been the originators of a given product that was then acquired, I make use of the fact that young startups typically provide a single product whose name is the same as the company's name. Therefore, whenever a given product's producing firm (as indicated on *Capterra*) has previously acquired a company that shares any similarity with a given *product*'s name, I assume that it is the *acquired* firm that initially entered the market with this product; see panel B in Figure 5.

[46] 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 5: 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.

A.5 Building a dictionary and tagging products with keywords

As each product can be associated to *more* than one keyword[47], one needs to reduce the dimensionality of the categories so that each product will be grouped along with other products into a *unique* market.

I moreover need to clean the category names in some instances to make them useful. For example, 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 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

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

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

In Figure 6, 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.

A future version of this paper will contain further validation checks with respect to the market definitions.

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

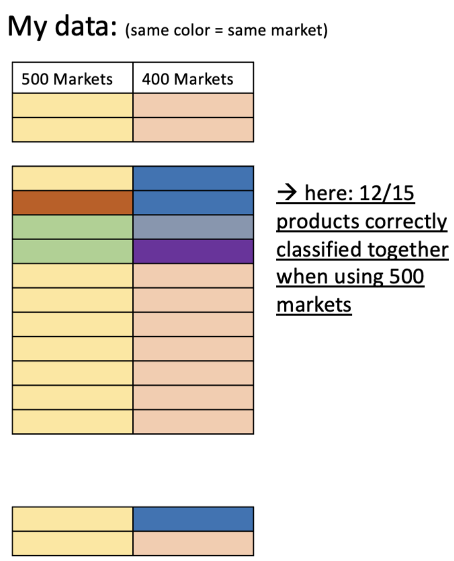

Figure 6: Validation of market definition.

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 Terms of Numbers, the Largest Acquirers of Startups of Any Industry are Software Firms

Table 20 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.[48] 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 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.

[48]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 20: 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*.

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[49], I find that out of all successfully exiting startups in enterprise software, 95% exit by acquisition. Comparing this to the biotechnology and pharmaceutical industry, the common exit routes are strikingly different: here, 53% of successful startups exit by acquisition. The finding highlights once again that industry dynamics might be fundamentally different across industries (due to different production technologies etc.), which motivates to study entry and acquisitions within enterprise software.

[49] 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.

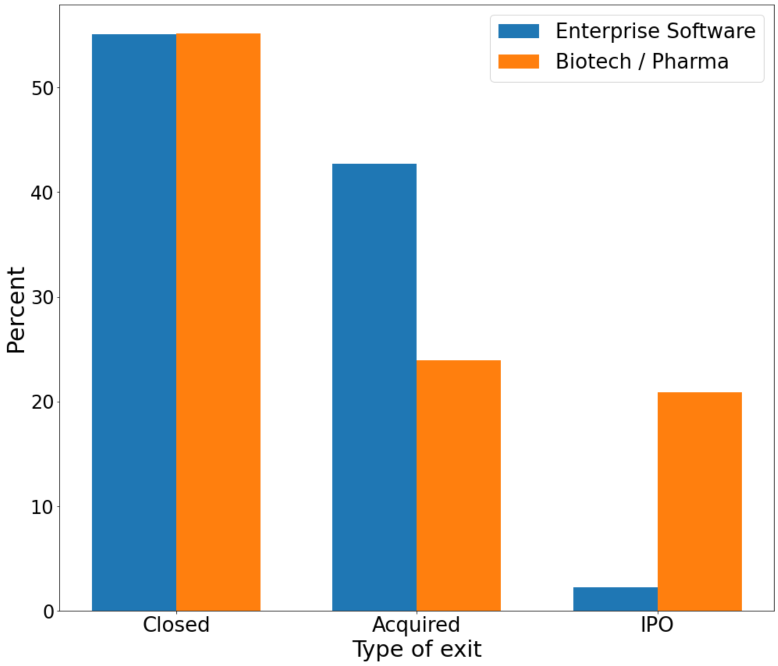

Figure 7: Types of exits of startups in biotechnology & pharmaceuticals, and enterprise software, in percent. I consider US-based startups founded after 2001 and exiting in 2005-2020. Details on the industry definition can be found in Appendix A.8.

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 Acquirers Are of Different Types: Further Details

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.

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).

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

In Table 21, 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 21: 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 22: Same event study as in main text (Table 13), but as control group, use only markets in which *any* major acquisition 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*				
	(0.062)				
Major acq by public enterprise software company		−0.159**			
		(0.072)			
Major acq by GAFAM or 'New Tech'			−0.383***		
			(0.138)		
Major acq by company not in enterpr softw (incl. financial)				−0.078	
				(0.074)	
Major acq by financial company					0.110
					(0.129)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Adjusted R^2	0.252	0.252	0.253	0.251	0.251
Observations	3,420	3,420	3,420	3,420	3,420
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 23: Same event study as in main text (Table 13), using event window of 4 quarters, but this time using data from 2014-2019.

	Dependent variable:				
	entry_fdstage_count				
	(1)	(2)	(3)	(4)	(5)
acqrer_on_capterra_medmajor_count_ma	−0.123				
	(0.075)				
alltech_medmajor_count_ma		−0.340**			
		(0.147)			
newtech_gafam_medmajor_count_ma			−0.539***		
			(0.140)		
finance_offcapt_medmajor_count_ma				−0.050	
				(0.107)	
financeacq_medmajor_count_ma					0.174
					(0.155)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Observations	11,376	11,376	11,376	11,376	11,376
Adjusted R^2	−0.045	−0.045	−0.044	−0.046	−0.046
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 24: Placebo, event window: 4 quarters. Market-quarterly panel, 2014-2019.

	Dependent variable:				
	entry_fdstage_count				
	(1)	(2)	(3)	(4)	(5)
acqrer_on_capterra_medmajor_count_ma	0.002				
	(0.111)				
alltech_medmajor_count_ma		0.296			
		(0.193)			
newtech_gafam_medmajor_count_ma			−0.178		
			(0.290)		
finance_offcapt_medmajor_count_ma				0.351	
				(0.438)	
financeacq_medmajor_count_ma					−0.197
					(0.454)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Observations	11,376	11,376	11,376	11,376	11,376
Adjusted R^2	−0.046	−0.046	−0.046	−0.046	−0.046
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 25: Event window: 5 quarters. Market-quarter panel, 2012-2020.

	Dependent variable:				
	entry_fdstage_count				
	(1)	(2)	(3)	(4)	(5)
acqrer_on_capterra_medmajor_count_ma	−0.088				
	(0.067)				
alltech_medmajor_count_ma		−0.351***			
		(0.111)			
newtech_gafam_medmajor_count_ma			−0.360***		
			(0.135)		
finance_offcapt_medmajor_count_ma				−0.079	
				(0.077)	
financeacq_medmajor_count_ma					−0.064
					(0.141)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Observations	17,064	17,064	17,064	17,064	17,064
Adjusted R^2	−0.031	−0.030	−0.030	−0.031	−0.031
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 26: Event window: 3 quarters. Market-quarter panel, 2012-2020.

	Dependent variable:				
	entry_fdstage_count				
	(1)	(2)	(3)	(4)	(5)
acqrer_on_capterra_medmajor_count_ma	−0.093				
	(0.072)				
alltech_medmajor_count_ma		−0.254*			
		(0.140)			
newtech_gafam_medmajor_count_ma			−0.328**		
			(0.151)		
finance_offcapt_medmajor_count_ma				−0.100	
				(0.085)	
financeacq_medmajor_count_ma					−0.023
					(0.190)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Observations	17,064	17,064	17,064	17,064	17,064
Adjusted R^2	−0.031	−0.030	−0.030	−0.031	−0.031
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		

Table 27: Event window : 4 quarters. Market-quarter panel, 2012-2020. Here, I am considering acquisitions of a transaction value of above 50US$ million (as opposed to 100US$ million).

	Dependent variable:				
	entry_fdstage_count				
	(1)	(2)	(3)	(4)	(5)
acqrer_on_capterra_smaller_count_ma (105 acquisitions)	−0.114**				
	(0.056)				
alltech_smaller_count_ma (46 acquisitions)		−0.263***			
		(0.096)			
newtech_gafam_smaller_count_ma (29 acquisitions)			−0.361***		
			(0.093)		
financeacq_portfolio_smaller_count_ma (55 acquisitions)				−0.098	
				(0.060)	
financeacq_smaller_count_ma (39 acquisitions)					−0.090
					(0.127)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Observations	17,064	17,064	17,064	17,064	17,064
Adjusted R^2	−0.030	−0.030	−0.030	−0.031	−0.031
SEs clustered on market level.			*p<0.1; **p<0.05; ***p<0.01		