Entry and Acquisitions in Software Markets*

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Abstract

How do acquisitions of young, innovative, venture capital funded firms (startups) affect entry incentives of new firms? I create a new dataset by merging web-scraped product-level data on enterprise software with data on firms' M&A activities. I find suggestive evidence that the effect of acquisitions on entry may depend on the type of the acquirer. In particular, acquirers may be firms active in the same industry, or industry outsiders, such as financial firms. I develop a structural model of startups' entry decisions. 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 evidence of a positive entry-for-buyout incentive and a negative market structure effect. My preliminary results from counterfactual simulations suggest that if competition authorities were to block all startup acquisitions, entry would fall.

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 Google 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, the type of 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 being listing on public stock markets.[1] Survey results suggest that being acquired is a main goal for many startup entrepreneurs.[2] This suggests that a continuous flow of startup acquisitions in a given market can encourage entry.

On the other hand, an acquisition affects 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 creates a "kill zone" in a given market (Kamepalli, Rajan, & Zingales, 2021, Motta & Shelegia, 2021). In other instances, the target's product may be made unavailable to previous customers (Fumagalli, Motta, & Tarantino, 2022). 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).

To answer this research question, I assemble a new dataset. I web-scrape product-level data from *Capterra*, a vertical search engine for enterprise software. Using product descriptions and categories as data, I segment products into clusters of likely substitutable products using text-as-data techniques. These narrow market definitions are combined with information on firms' histories of acquisitions from *Crunchbase*.

[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 software in Biotech or Pharmaceuticals exit via acquisition. See Section 3.1.

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

The data produce novel, policy-relevant descriptive facts about startup acquisitions in software markets. I distinguish between different types of acquirers that likely are driven by different motives. Acquirers active in the same industry are called "strategic" acquirers, following literature in finance (Hege, Lovo, Slovin, & Sushka, 2018). These firms presumably buy startups for purposes that are linked to the startup's capabilities, its product functionalities, or its employees, for instance. On the opposite end of the spectrum, financial companies, such as private equity firms, acquire companies mainly to generate financial returns.

Both financial and strategic acquirers may generate an entry-for-buyout incentive, whereas market structure is mainly affected by strategic acquirers. 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 long-run entry-for-buyout effect. In the second part of the paper, I build a structural dynamic model of startup entry that accounts for both channels of effect. As opposed to other models of entry employed in the literature, potential entrants obtain payoffs in the event of a change in ownership, which may be an initial public offering (IPO), or an acquisition. When deciding whether to enter a given market, potential entrants thus take into account both the current and expected market structure, but also form beliefs about the likelihood with which they may be acquired in the future. The model can thus account for an entry-for-buyout incentive, and one can estimate the parameter quantifying the importance of this effect.

I estimate the model using a two-step procedure (e.g. Hotz and Miller (1993), Aguirregabiria and Mira (2007), Bajari, Benkard, and Levin (2007)). The parameter estimates that I obtain indicate that the profitability of entry indeed depends not only on market structure, which is affected by recent strategic acquisitions, but is also positively affected by the prospect of an acquisition. Preliminary results from counterfactual simulations suggest a drop in entry following a ban of all acquisitions.

This paper has two main contributions. 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 findings (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 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. To my knowledge, in the industrial organization literature, only G. Z. Jin, Leccese, and Wagman (2022a) has compared different acquirer types. In contrast to (G. Z. Jin et al., 2022a), however, I am able to track acquisitions at the product-level. This also allows me to employ new market definitions that allow to very accurately define "competitors", without reliance on standard industry classifications which would be too broad to be useful in my case.

The second contribution lies in new results on entry dynamics in the face of acquisitions, which I obtain thanks to the structural model of startup entry. In contrast, previous literature uses reduced-form regressions to find out how GAFAM acquisitions and follow-on funding rounds (potentially a measure of startup 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 them. It moreover allows to explore how entry would evolve under counterfactual antitrust regimes.

My 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 target firms are small, albeit highly innovative and potentially disruptive, startups. The sheer number of such transactions has caught the attention of antitrust practitioners and academics worldwide. My data show that *Alphabet*, for instance, has acquired about one company every month 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).

Finally, 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 therefore equally meaningful.

The paper is organized in three parts:

- Part I will cover the data construction in Section 2, and extensive descriptive analyses in Section 3.
- Part II contains reduced-form analysis providing suggestive evidence for the differential effects of different types of acquisitions.
- Part III will cover the model and its estimation: 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 draws a conclusion and suggests topics for future research.

Literature

Empirical findings on acquisitions by GAFAM and other firms. A body of research has compiled descriptive evidence on the acquisitions conducted solely by the GAFAM firms. It classifies the GAFAM's acquisitions, emphasizes the very young age of the targets in these transactions, and tries to shed light on the motives for these numerous acquisitions. On the one hand, this research finds that the GAFAM tend to acquire in adjacent, complementary markets (Argentesi et al., 2021, G. Z. Jin et al., 2022a). In contrast, Gautier and Lamesch (2021) state that most acquisitions occur seemingly to strengthen the GAFAM's existing market segments, and could be thought of as a substitute to in-house R&D. Concerning the motives of these acquisitions, 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.

Some 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) address the problem of endogeneity by using a two-way fixed effects and a difference-in-differences with propensity score matching, and 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) employ a difference-in-difference strategy and 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. Affeldt and Kesler (2021a) study 50 GAFAM acquisitions of businesses that supply mobile applications, and find that half of the acquired apps were shut down post-acquisition. In Affeldt and Kesler (2021b), the authors find that in an acquired app's market, entry declines, and competitors innovate less. With my descriptive findings, I add to these bodies of literature by comparing the GAFAM firms' acquisitions and their effects to other acquirers, which has only been done by G. Z. Jin et al. (2022a). Moreover, I develop a precise way to distinguish markets that covers a vast industry.

Compared to the above papers focusing solely on the GAFAM firms, G. Z. Jin et al. (2022a) is closer to the approach I chose, as they compare acquisitions by the GAFAM to acquisitions by other top acquirers. They highlight the role of private equity acquirers, and find that other top acquirers tend to acquire in more similar categories as the GAFAM over time. G. Z. Jin, Leccese, and Wagman (2022b) extend this analysis to all North American public firms, finding that acquisitions take place in adjacent markets. I contribute to these findings by using new, very narrow market definitions based on the actual products that companies produce, and by being able to look at acquisitions by private firms.

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 et al. (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).

This 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).

On the policy side, Lemley and McCreary (2020) suggests changes in laws to make IPOs a more attractive exit route for startups.

Competitive effects of IPO, acquisition, or success of competitor. 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. Finally, this paper sheds new light on startups' commercialization strategies and how innovation is generated in an industry, as highlighted in Gans and Stern (2003).

Literature on entry and dynamic games. I combine methods of dynamic games employed in the empirical industrial organization literature (Aguirregabiria & Mira, 2007, Bajari et al., 2007) with a model of software startups' entry decisions. This model reflects the very specific objectives that software startups are pursuing. In particular, as opposed to most industrial organization literature on firm entry which presumes that firms enter a market in order to compete and earn returns, I take the perspective of an entrepreneur deciding whether or not to enter. These entrepreneurs not only enter a market to gain revenues, but also benefit from a transfer in ownership, namely from being acquired, or from going public on the stock market.

Part I

2 Setting, Data, and Market Definitions

2.1 Setting: Startup Entry in Enterprise Software

I study firm entry in the *enterprise software* industry, where the acquisition of young startups is particularly pronounced. Software products consist of programming code, are usually distributed at zero marginal costs, but may require substantial fixed cost. By *enterprise software*, I am referring to any software product that can 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 B). Enterprise software is likely to bring along important welfare gains in the years to come, as software enables the adoption of digital technology in enterprises, such as cloud computing or analytics, which can substantially reduce costs or increase efficiency. 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%. Studying entry into this industry is therefore relevant in its own right.

I consider entry by *startups*, which are young, risky, very innovative, privately held companies. In networked industries, the thread 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. As the startup grows larger and its product more mature, these funding rounds become successively larger, too.[3] VCs are financial intermediaries specialized in providing funding, as well as advice, to these highly risky, but potentially high-growth firms in exchange for an equity stake. VC investors manage closed-ended funds, which implies that after a period of 7-10 years, these investors try to divest. In this so-called "exit" event, the startup might either be listed on a public stock exchange and thus become a public company, or may be sold to another firm.[4] Both of these events are generally considered a success, as they may yield a high return to investors and founders.[5]

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 from *Crunchbase*, a data portal that tracks financial information on companies, and covers especially events of 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

[3] Early-stage rounds such as seed rounds have a size of 10,000 to 2 million US dollars; Series A or B rounds range in the order of one to 30 million US dollars, according to Crunchbase (2022).

[4] More recently, some startups are staying private for longer. In those cases, early investors sell their shares to investors specialized on later-stage companies (so-called crossover investors).

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

any number of industries associated to any industry groups. Each company profile has two bodies of descriptive text describing the company.

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.[6] 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.[7] I then construct the 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, and even though previous literature has used these labels (e.g. Koski et al. (2020)), 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).[8] 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.[9] The platform is designed to assist customers with comparing

[6] 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.

[7] 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.

[8] *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.

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

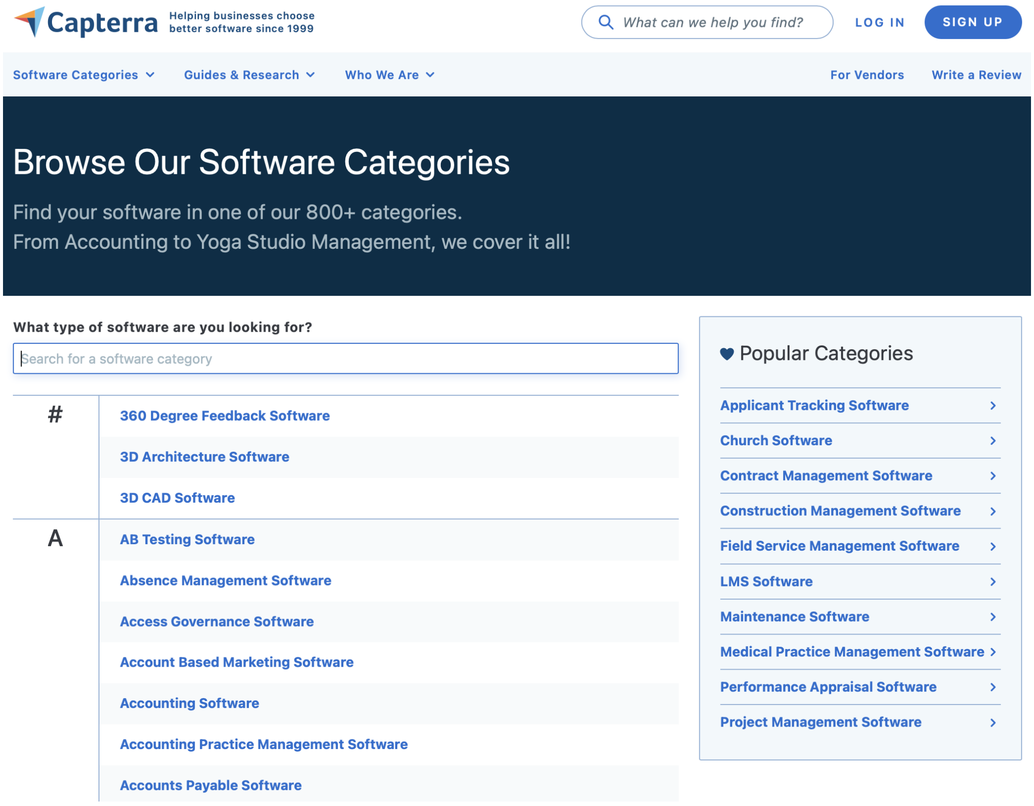

Figure 1: *Capterra*'s categories page

and finding suitable enterprise software, and is one 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". It provides descriptive text, information on the producing company, as well as user reviews and ratings for each product (see Figure 1 and 2).[10] The range of products covered on *Capterra* is exhaustive and very up-to-date.[11]

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. I download and save the following information from each product page: the product name; company name; a text describing the product; a text describing the intended audience for the given product; pricing information; company headquarter location; company's web domain; the year in which the company was founded; the cumulative number of user reviews of the

[10] 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*).

[11] 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*.

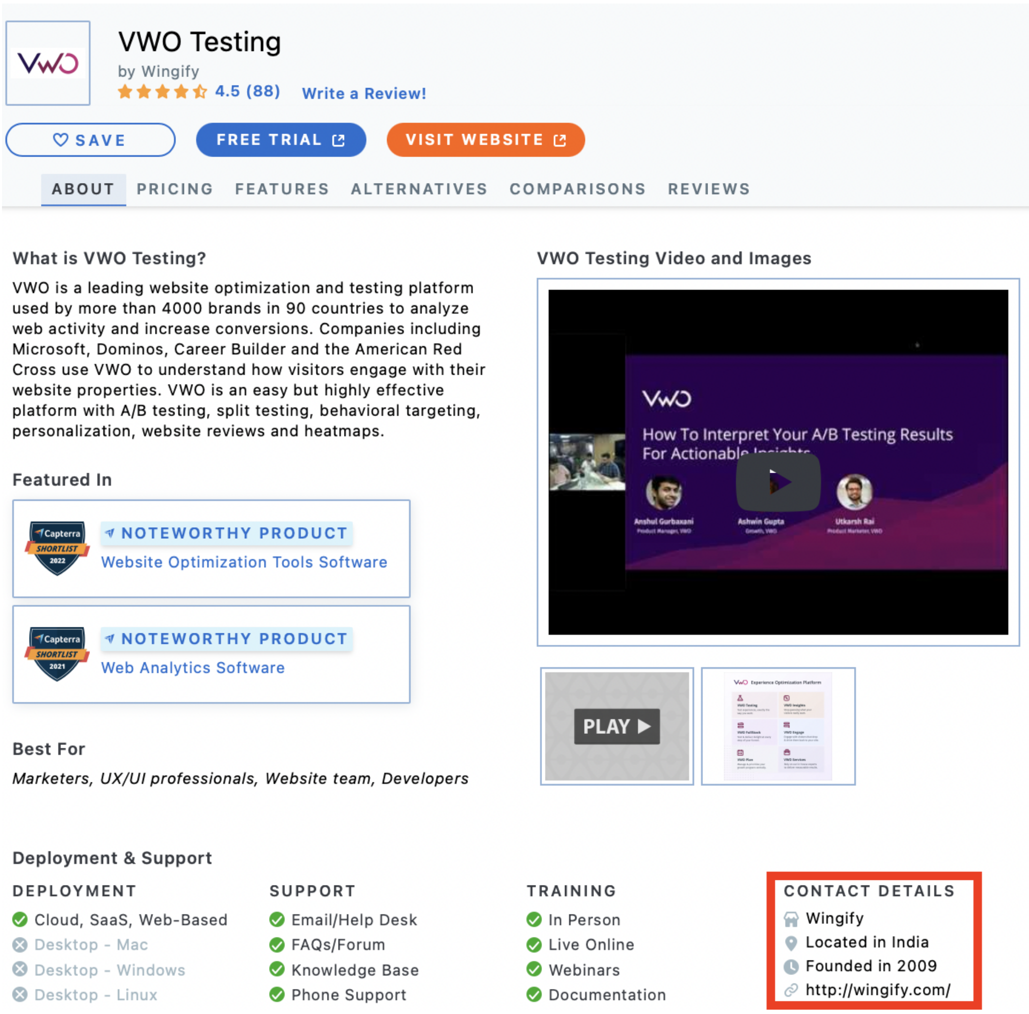

Figure 2: Example of product page on *Capterra*. The red frame highlights the company information (in particular, name and URL) available for all products on *Capterra*.

given product at the time of scraping; and the user rating. I also record time and date of each instance of scraping.[12]

All in all, I make use of the *Capterra* data for the following purposes: (1) to find out which enterprise software startups' products are actually active and available as of July 2021; and (2) to cluster products into groups of substitutable products, with the help of a machine learning model (see Section 2.2.3).[13]

2.2.3 Matching *Capterra* to *Crunchbase* data

I carefully 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. For products that were acquired by another firm in the past and thus have the acquirer's URL and name, I make sure to match them to the originating firm. Details of the matching procedure are provided in Appendix A.4. I end up merging 71% of all we-bscraped 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 accurary of my matching procedure procedure.

Next, I leverage the fact that the *Crunchbase* data contain both, enterprise software companies with existing products on *Capterra*, but also enterprise software companies which were acquired and whose products were subsequently shut down. From the non-matched firms in the *Crunchbase* data, I select firms that must be 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*.[14] 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.

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

[13]In a future iteration of the project, I may employ the cross-sectional measures of demand and quality that are available in the form of the number of user reviews and an average rating.

[14]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.

2.3 Defining Markets

To conduct this research, one needs to define independent markets of substitutable products. I do so by using text-as-data methods (Gentzkow, Kelly, & Taddy, 2019). Each product on *Capterra* is associated with a body of text: the category name, 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 *Capterra* category names, however, can be viewed as meaningful information on a product's functionalities, so that companies present in the same (or similar) categories should be more substitutable: *Capterra*'s purpose is to guide consumers searching for specific enterprise software products. The company therefore has an incentive to accurately categorize products.[15] Moreover, if consumers use websites such as *Capterra*, products within the same category tend to enter consumers' choice set together, which should make them more substitutable.

I build a dictionary of meaningful keywords by using all *category names* (e.g. "filesharing" for "Filesharing Software"), as well as additional keywords that are frequently occurring in *Capterra*'s product description.[16] 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".

I next associate each product on *Capterra* (or each company for shutdown-acquisitions, respectively) to a unique market. I follow the approach taken by Decarolis and Rovigatti (2021): I first match each *category name* – 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 way, each category term will be placed at a certain location inside a 300-dimensional vector space. Synonyms and terms that are linguistically close to each other will be

[15] *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.

[16] I 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. Details can be found in Appendix A.5.

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

Number of markets	474
Number of products	24,327
· Percent of products alive	83.9%
Number of companies	20,271
· Percent of companies ever VC-funded in 2012-20	65.4%
· Percent of companies ever public in 2012-20	4.6%
Number of acquisitions	6,064
· Percent startup acquisitions	42.8%
Number of IPOs	375
· Percent of startups going public	54.7%

Table 1: Basic descriptives, after cleaning markets that I view as outliers, 2012-2020. I exclude LBOs and management buyouts from the acquisitions.

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. Therefore, 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 which one wants to end up with. As guidance, I use the silhouette score, 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.

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

	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, 2012-2020. (Prices and valuations in million US$.)

3 Stylized Facts

The purpose of this section is to lay out empirical facts that motivate the research question and guide the modelling assumptions. The main focus is on the acquisitions of startups: Startups are defined as firms that have received at least one VC investment in the past. Acquisitions are defined as majority takeovers by *Crunchbase*. Startup acquisitions account for approximately 44% of all acquisitions observed in the matched data.

I focus on startups, as startups have been found to be particularly innovative and disruptive. 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 E, Table 19).

I begin with a bird's eye view by discovering general patterns of startup acquisitions across industries in Section 3.1, and then zoom into the enterprise software market by focusing on the matched dataset from Section 3.2 onwards.

3.1 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.

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 3: 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*.

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

Table 3 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.[19] 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. However, software firms tend to acquire companies at lower prices, but more of them, compared to companies active in finance or pharmaceuticals.

[19]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.

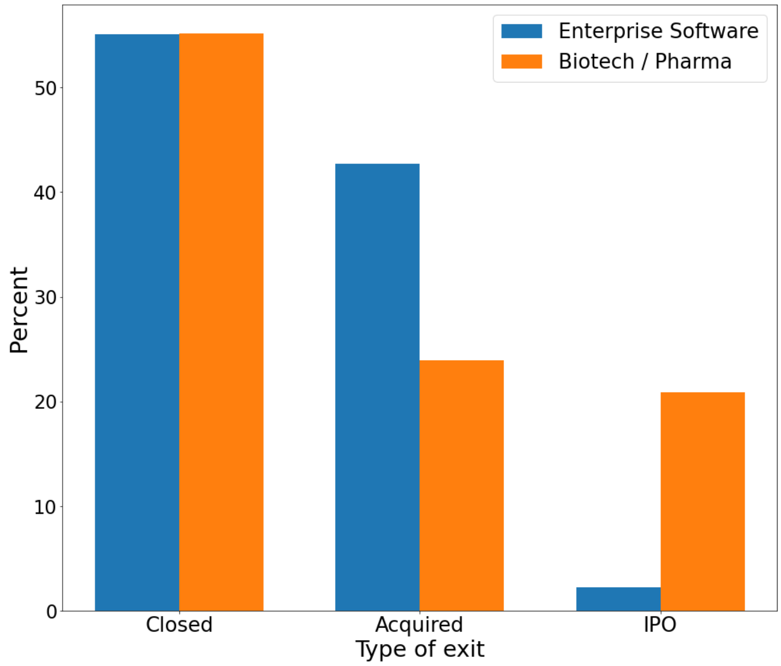

Figure 3: Types of exits of startups in biotechnology & pharmaceuticals, and enterprise software, in percent. I consider US-based startups founded after 2001 and exiting in 2005-2020. Details on the industry definition can be found in Appendix B.

3.1.2 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[20], 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.

[20]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.

3.2 Acquirers Are of Different Types

From now on, I turn to the matched dataset and compile descriptive facts that relate to enterprise software startups only, for the period of 2014-2019. In the data, I identify three main types of acquirers that acquire enterprise software startups.

- *Companies on Capterra*: 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.
- *Companies off Capterra*: these companies do not have existing products on *Capterra*, and are thus mainly active in other industries.[21]
  - Using *Crunchbase*'s industry tags, I find that over half of off-Capterra acquirers are active in seemingly related industries, 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 off-Capterra acquirers is scattered across seemingly less related industry branches, such as transportation, consumer products, e-commerce or biotech.
  - Examples: The We Company; Verizon; Dentsu International; Samsung Electronics; Ericsson.
- *Financial companies*: I identify these companies as active in finance, based on *Crunchbase* information.[22] Among these are private equity firms.
  - Examples: Vista Equity Partners; TransUnion; Thoma Bravo.

The fractions of these three main acquirer types are displayed in Figure 4. Over 60% of acquisitions of exiting startups are conducted by firms that have an existing software product on *Capterra*. 21% of acquisitions are carried out by financial firms, and 15% are carried out by firms with no own, existing product on *Capterra*. Further characteristics on these three types of acquirers can be found in Appendix C.

To be able to shed light on how sub-groups of different on-Capterra acquirers behave, I divide on-Capterra acquirers into further (non-exhaustive) sub-groups, detailed in Table 4. The goal of distinguishing these sub-groups is to analyze different sets of companies that, based on anecdotal evidence, are

[21] Among these are also holding companies, which do not produce software products themselves, but acquire them and hold them in a portfolio.

[22] I use *Crunchbase*'s inudstry tags, as well as *Crunchbase*'s data on investor types.

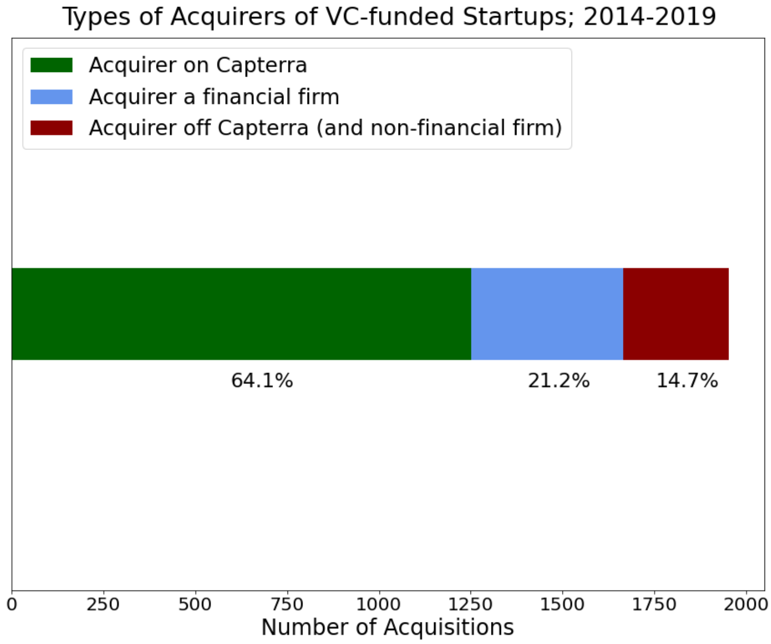

Figure 4: Types of acquirers for first-time acquisitions ("exits") of VC-funded startups worldwide in the domain of enterprise software, for acquisitions occurring between 2014 and 2019. These descriptives are on the company, as opposed to on the product, level. I exclude acquisitions of the types LBO or management buyout.

similar in growth trajectories, innovative strategy, and age. Companies within the groups GAFAM, Old Tech and New Tech conducted each roughly 100 startup acquisitions in the years of 2014-2019, whereas pre-exit firms account for over 400 startup acquisitions.

3.3 The Different Acquirer Types Acquire Different Sets of Companies

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

I first look at a more aggregate pattern and find out how prevalent target firms are *VC-funded startups*, versus other companies, for each of these acquirer types. The answer is detailed in Table 5. Looking at Panel A, what is noteworthy is that on-Capterra 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 not-VC funded, but private firms. Panel B shows a particularly interesting result: comparing the different subgroups of on-Capterra acquirers, it becomes clear that the strategy that the GAFAM pursue is closest to New Tech firms. Both groups acquire heavily VC-funded pre-exit companies, and are

Acquirer type (# startup acq)	Description	Examples
GAFAM (105)	Google (Alphabet), Apple, Facebook (Meta), Amazon, Microsoft and their subsidiaries.	GAFAM, LinkedIn, AWS, GitHub.
Old tech (103)	Public companies founded prior to 1995 with over 10,000 employees.	Cisco, Oracle, VMware, SAP, Dell EMC, HP Enterprises, IBM, Adobe.
New tech (98)	Companies founded 1995 or later that started off as VC-funded companies[23] but that have exited.	Salesforce, Palo Alto Networks, Workday, Servicenow.
Pre-exit (437)	VC-funded startups acquiring at a time at which they have not exited yet.	Sprinklr, Freshworks, Ignite Technologies, Dropbox, DataRobot, Stripe, Hootsuite.

Table 4: Definitions of subgroups of on-Capterra 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 2014-2019.

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
On Capterra	6.4	48.9	3.6	38.7	100
Financial	2.9	29.1	5.0	62.1	100
Off Capterra	4.4	36.7	4.6	53.3	100
Panel B: Looking at a subset of on-Capterra 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 5: 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.

also engaged with very young companies that have no prior funding history. Pre-exit firms are similar, but somewhat more active acquiring non-VC funded firms. In contrast, Old Tech firms acquire very rarely the very young companies with no prior funding rounds, but are more likely to acquire not VC-funded firms, or post-exit firms. This finding raises 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.

I next look at acquired VC-funded startups only. I compare the maturity of startups at the time acquisition by different types of acquirers. In particular, I look at acquisition prices (Table 6), age at acquisition (Table 7), funding rounds (Table 8), and valuations (Table 9). The pattern I observe is as follows: on-Capterra 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. What is most

Panel A:		
	Acquisition price (million USD, median)	Percent acquisition price not observed
On Capterra	107.5	81.5
Financial	117.0	89.9
Off Capterra	100.0	81.1
Panel B: Looking at a subset of on-Capterra acquirer types:		
GAFAM	150.0	81.9
New tech	173.0	56.1
Old tech	400.0	72.8
Pre-exit	16.0	95.0

Table 6: Acquisition prices at exits of VC-funded startups, 2014-2019. Excludes leveraged buyouts or management buyouts.

striking, however, is that there seems to be substantial heteroegneity between the sub-groups of on-Capterra 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 et al., 2014).

Table 10 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 off-Capterra 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.

Finally, many acquirers are "serial acquirers". For on-Capterra and financial firms, the median number

Panel A:

	Age (median # of years since founding date)	Age (median # of years since first funding round)
On Capterra	6.5	4.5
Financial	10.0	5.1
Off Capterra	6.8	5.0
Panel B: Looking at a subset of on-Capterra acquirer types, and IPOs:		
GAFAM	4.2	3.3
New tech	5.0	3.8
Old tech	7.4	5.2
Pre-exit	5.4	3.8
IPO	10.6	7.7

Table 7: Age at exits of VC-funded startups, 2014-2019. Excludes leveraged buyouts or management buyouts.

Panel A:

	Number of funding rounds (mean)	Volume of funding (million USD, median)	Percent funding volume not observed
On Capterra	2.7	7.2	11.8
Financial	2.4	10.0	11.9
Off Capterra	2.8	7.6	14.6
Panel B: Looking at a subset of on-Capterra acquirer types, and IPOs:			
GAFAM	2.6	8.6	11.4
New tech	3.0	12.0	11.2
Old tech	3.6	32.8	8.7
Pre-exit	2.5	4.0	15.9
IPO	4.7	116.4	3.5

Table 8: Number and volume of VC funding rounds at exits of VC-funded startups, 2014-2019. Excludes leveraged buyouts or management buyouts.

Panel A:

Acquirer type	Valuation at exit (million USD; median)	Percent NA
On Capterra	25.0	93.9
Financial	60.7	96.5
Off Capterra	16.3	93.3
Panel B: Looking at a subset of on-Capterra acquirer types, and IPOs:		
GAFAM	31.3	90.5
New tech	241.0	92.9
Old tech	1000.0	89.3
Pre-exit	4.4	94.4
IPO	1000.0	66.0

Table 9: Valuation at exits of VC-funded startups, 2014-2019. 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)
On Capterra	2.7
Financial	3.5
Off Capterra	3.3
Panel B: Looking at a subset of on-Capterra acquirer types, and IPOs:	
GAFAM	1.8
New tech	1.9
Old tech	2.2
Pre-exit	2.4
IPO	1.8

Table 10: Time (in years) since last funding round at time of exits of VC-funded startups, 2014-2019. Excludes leveraged buyouts or management buyouts.

of acquisitions of any industry during the company's lifetime is 8 (5 for off-Capterra firms). This mirrors David (2021), who emphasizes that serial acquisitions are a ubiquitous feature in the economy.

3.4 Many Acquired Products are Discontinued After the Acquisition

As explained in Section 2.2.3, the data I created can shed light on companies that were acquired in the past, but whose products are not available any more under the same brand name. Looking at acquisitions of VC-funded, enterprise software related startups in 2014-2019, 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 seem to be a widespread phenomenon in software.

Shut-down rates vary considerably different depending on the acquiring firm. Table 11 shows that shutdowns are especially prevalent for acquirers that are software firms themselves; these companies discontinue the acquired product in 65% of all acquisitions. Financial firms, in contrast, discontinue the acquired products in only 30% of all acquisitions.

The acquired companies whose products are shut down tend to be nearly two years younger, and the median firm tends to be acquired at roughly 60% the price of companies whose products were kept alive (Table 12).[24] Looking only at companies that were acquired at an age of less than 3 years and that

[24]Prices are missing in 85% of shut-down acquisitions, and in 80% of continued acquisitions. As presumably low prices are

Panel A:

Acquirer Type	Discontinuations, **percent**	Discontinuations, **count**
On Capterra	64.6%	817
Financial	29.7%	85
Off Capterra	35.3%	147
All acquirers	53.3%	1049

Panel B: Looking at a subset of on-Capterra acquirer groups:

Old tech	60.2%	62
New tech	61.2%	60
GAFAM	81.0%	85
Pre-exit	67.8%	305

Table 11: Discontinuations of products post-acquisition, for different types of acquirers.

	Products discontinued	Products kept alive
Age: years since founding date (median)	5.9	7.8
Age: years since 1st funding round (median)	4.1	5.3
Price in US$ million (median)	80.0	136.8

Table 12: Heterogeneity in age at acquisition and in transaction price, for startups whose products were either discontinued (left), or kept alive (right).

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 71%. 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 not a fully developed product. Appendix D 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 per acquired firm. I find that those startups that exited via IPO or via an acquisition by a financial acquirer have 1.7 and 1.4 products on average, whereas companies exiting by GAFAM or pre-exit firms are always single-product. Next, I look at the number of reviews of acquired and continued, which could be an indication for demand. Table 13 reveals that products acquired by the GAFAM, and even more products whose companies exited by going public, tend to have more reviews. These numbers should however be regarded in the light that the GAFAM are 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; nor is it clear whether acquired firms were perhaps multi-product before the acquisition

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)
On Capterra	2.0	113.5
Financial	2.0	56.3
Off Capterra	1.0	36.1
Panel B: Looking at a subset of on-Capterra acquirer groups:		
GAFAM	9.5	859.4
New tech	2.5	37.6
Old tech	2.0	35.4
Pre-exit	2.0	10.5
IPO	16.5	784.5

Table 13: Number of reviews, VC-funded startups with continued products only, 2014-2019. For multi-product firms, I sum the reviews of all products supplied by a given firm.

took place or not. However, these findings might indicate that firms like the GAFAM are less likely to hold a portfolio of brands. GAFAM tend to either acquire successful products, or manage to reach a vast customer base with these acquired products.

3.5 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 market as of 2021. According to this definition and using the above narrow market definitions, I find that only 8.2% of all acquisitions of VC-funded startups in 2014-2019 can be classified as being horizontal.[25]

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.

3.6 Discussion

What are the motives behind the shutdown-acquisitions that I find? Whereas product shut-downs could in principle consist of so-called killer acquisitions (Cunningham et al., 2021), in this setting, such acquisitions are possibly less likely to concern the majority of these shut-downs. First, the acquired firms are often very young and possibly have not even raised a single funding round, thereby being less likely

[25] 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.

to be a serious thread 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 11 shows, shut-downs are prevalent among companies that with much less market power than Google and the likes – even startups that have not exited yet and that are very young acquire and shut products down in 60% 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, 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.[26] 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.[27] This is somewhat different for private equity or financial acquirers, where anecdotally it seems that these firms more often merge two companies in their portfolios, or rebrand their products, rather than entirely shutting them down or acqui-hiring them.[28] I have also found cases in which the product was re-branded; however, this seems to have gone along with a number of changes to the original product.[29]

The difference in maturities of acquired startups between on-Capterra and financial firms suggests that financial firms acquire mature, tested products, as presumably these firms are interested in obtaining cashflows. In contrast, on-Capterra firms might be interested in acquiring even startups whose products do *not* yet have a customer base. Software is highly modular, so products that are in principle functioning, or that were created by a capable team, might be an interesting target for on-Capterra firms even if they failed to attract demand, for some reason. This might be very different in the pharmaceutical market, and may thus be the reason for the difference in acquisition patterns observed in Section 3.1.

All in all, the previous subsections highlighted that VC-funded startups are acquired by different types

[26]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).

[27]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.

[28]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*.

[29]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).

of acquirers. The data also show that these different acquirer types target firms at different maturities. Given that these different types of acquirers acquire different sets of firms highlights that presumably, the companies follow different motivations. These different acquirer motivations in turn may affect entry to different extents.

In particular, one can distinguish two groups of firms, as literature in finance has done (e.g. Hege et al. (2018)):

Financial acquirers (and possibly portfolio or off-Capterra acquirers) are typically transitional owners of firms they acquired who view the acquisition first and foremost as a financial investment (Hege et al., 2018). These firms are mostly interested in cash flows and relatively stable and growing returns. They are likely not interested in the product, the team of founders, the innovative capabilities of the startup itself. As the descriptives show, these types of acquirers are moreover less to change the acquired products in major ways, aside from managerial practices.

On the other end, there are **strategic acquirers**, which acquire in order to enter a market new market with a new product, acquire a new product feature, or sourcing new innovation. These types of acquirers take a more long-run perspective. They are less interested in cashflows, but may be interested in innovative capabilities, technology, or product functionalities. These types of acuqirers may try to leverage existing market power into the market of the acquired firm. These acquirers have capabilities to make the acquired products a much stronger competitor through complementarities, for example with their existing product portfolio or customer base. One could consider this group to consist of the GAFAM, but also any of the other on-Capterra acquirers.

Part II

4 Reduced-form Evidence on Acquisitions and Entry

Section 3.6 pointed out that financial and strategic acquirers differ in important ways in their respective motivations for acquiring companies. Importantly, acquisitions of either type of acquirer are considered a success by VC investors and entrepreneurs. Therefore, both types of acquisitions can be thought to have the potential to positively affect entry in the long-run via an entry-for-buyout incentive.

However, only strategic acquirers might have the capabilities to deter follow-on entry, as only those may possess strong complementary assets, resources, or market power that could fundamentally influence the acquired product's capabilities to compete in a given market. Therefore, I set up the following hypothesis:

- **Hypothesis**: In the short run, acquisitions conducted by a strategic acquirer may decrease of entry into a given market. This effect is absent for acquisitions undertaken by a financial acquirers.

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

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

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.[30]

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

[30] 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.

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 yet and whose product were kept alive as events.[31] 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 on-Capterra acquirers; more narrow definitions consider subsets of these. Similarly, the broadest definition of financial acquirers considers both financial as well as off-Capterra firms.

Table 14 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. 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 15 suggests that, if anything, financial acquisitions are preceded by a drop in entry.

Table 14: Event study: acquisitions and entry patterns, using an event window of 4 quarters. Market-quarter panel, 2012-2020.

	Dependent variable:				
	Number of entrants				
	Strategic acquirer			Financial acquirer	
	(1)	(2)	(3)	(4)	(5)
Acquirer on Capterra (89 acquisitions)	-0.112^{*} (0.059)				
Old Tech or New Tech or GAFAM (27 acquisitions)		-0.337^{***} (0.110)			
New Tech or GAFAM (21 acquisitions)			-0.401^{**} (0.135)		
Financial or Off-Capterra (40 acquisitions)				-0.101 (0.072)	
Financial (13 acquisitions)					0.032 (0.119)
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

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

[31] 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 15: Placebo: are events preceded by more, or less entry? Market-quarter panel, 2012-2020.

	Dependent variable:				
	Number of entrants				
	Strategic acquirer			Financial acquirer	
	(1)	(2)	(3)	(4)	(5)
Acquirer on Capterra	−0.098				
(89 acquisitions)	(0.123)				
Old Tech or New Tech or GAFAM		0.242			
(27 acquisitions)		(0.224)			
New Tech or GAFAM			−0.019		
(21 acquisitions)			(0.298)		
Financial or Off-Capterra				0.025	
(40 acquisitions)				(0.263)	
Financial					−0.318*
(13 acquisitions)					(0.187)
Market FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Observations	17,064	17,064	17,064	17,064	17,064
Adjusted R^2	−0.031	−0.031	−0.031	−0.030	−0.031

Standard errors 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 3.6, 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 14 and 15, 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 On-Capterra 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. See Appendix F for these robustness checks and a further placebo test.

These event studies 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).[32] 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.

[32] 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.

Part III

5 Dynamic Model of Entry

5.1 Setup

Time is discrete and infinite. 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 startup in a given product market, and this flow of entrepreneurs with ideas is exogenous and constant over time.[33] The potential entrants are homogeneous, except for a private cost shock which each agent draws from a distribution. The potential entrants then simultaneously decide whether to enter the market or not, so as to maximize their expected profits.

Once the potential entrants have entered, they compete against each other as well as other firms already present on the market. In each period, they 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, in the model the firm stops earning flow profits, and instead earns a single lump-sum return. I model acquisitions and IPOs as stochastic shocks that arrive upon companies on the market. If no acquisition or IPO arrives, the firm will just stay on the market and continue earning flow profits.

If a potential entrant decides to not enter the market, it stays out forever. Thus, staying out is a terminal action, as there will be no future chance of entry.[34]

The timing within each period is as follows:

1. Firms already on the market may be acquired, or do an IPO.

2. The potential entrants receive and observe their 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

[33]Other models of firm entry have fixed these potential entrants in a similar way, e.g. Perez-Saiz (2015) or Igami (2017).

[34]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.

(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 payoff of entry writes as follows:

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

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 $\mathbb{E}[V_{t+1}(\boldsymbol{x_{mt+1}};\boldsymbol{\gamma})|\boldsymbol{x_{mt}}]$.

The payoff of staying out is normalized to zero plus an econometric error term, $U^0_{imt} = \epsilon^0_{imt}$. I assume that ϵ^0_{imt} and ϵ^1_{imt} are independently and identically distributed according to a type-I extreme value distribution, and observed by firms, but unobserved by the econometrician.

Whereas my dataset covers ten thousands of firms, I do not observe firms' profits, nor demand or any measure of demand.[35] Therefore, I use 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 the extent of competition and other state variables, one can estimate to what extent firms' discrete choices of whether to enter or not depend on these state variables.

The vector of state variables $\boldsymbol{x_{mt}} = \{N_{mt}, A^{\text{strat in }\tau}_{mt}, M_m\}$ consists of variables that are relevant to firms'

[35] 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.

profits. N_{mt} is an endogenous state variable that evolves depending on firms' entry decisions. It captures the number of competitors on market m at time t. 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. Finally, M_m denote market effects that control for a market's size or profitability, and will be covered in detail in Section 6.1.

5.2 Estimation

I employ a two-step estimation method to retrieve the structural parameters of the model. This approach allows to circumvent the need to solve a dynamic game 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, Miller, Sanders, & Smith, 1994).

In the 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 and characterizes agents' actions given the state space, and describe how the state space evolves.

Given these policy functions and transition probabilities, one can forward-simulate the state space. One can simulate S paths of each state variable sufficiently far into the future, until discounting renders the the payoffs of any additional periods insignificant. Taking the average across these paths yields the expected payoffs of each discrete choice, given a set of parameter values. The intuition behind this procedure is that agents' choices incorporate the beliefs about the future (Arcidiacono & Ellickson, 2011).

The second step estimates the structural parameters by imposing optimality on the agents' choices that are observed in the data. Given 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.

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 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.[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 each period. In contrast, D_{exit}^{exog} and D_{entry}^{exog} are *exogenous* entry and exit variables that are included to match the data, as companies may leave or be added to N_{mt} in ways not modelled. For instance, may can 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_{exit}^{exog} and p_{entry}^{exog}, respectively. These parameters can be estimated using the data. The extent to which D_{exit}^{exog} and

[36] I thus exclude private, operating companies, for instance.

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 on-Capterra acquirers, whereas the narrow definition accounts for a subset of on-Capterra 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. In particular, I 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. [38]

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 ten.[39]

6 Results

I use market-quarterly data to estimate the model. After excluding a few outlier markets, I end up covering 450 markets in the years of 2014-2019 (24 periods), yielding 10,800 observations..

6.1 First Stage: Reduced-form Results

The results for the first stage can be found in Table 16, using a "broad" definition 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

[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] 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.

[39] 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).

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 on-Capterra 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.[40]

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 strategic effect is not driven by any seasonal effect.

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 ($\hat{p}^{exog}_{\text{exit}} = 0.0222$ and $\hat{p}^{exog}_{\text{entry}} = 0.0125$), 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

[40] 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.

Table 16: First stage, using a broad definition of "strategic" acquirers. Here, competitors include: startups, public firms, pre-event very young firms, and acquired & continued startup firms.

	Dependent variable:				
	# startups entering in market m, quarter t				
	panel linear		*Poisson*	*OLS*	*panel linear*
	(1)	(2)	(3)	(4)	(5)
# of competitors	0.024***	−0.026***	−0.018***	−0.018***	−0.024***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.004)
Major on-Capterra acquisition pre-4Q	−0.140*	−0.062	−0.051	−0.104	−0.068
	(0.078)	(0.080)	(0.080)	(0.067)	(0.080)
1{quarter=2}					−0.145***
					(0.025)
1{quarter=3}					−0.169***
					(0.023)
1{quarter=4}					−0.235***
					(0.024)
Market FE		✓	✓		✓
20 market-category FE				✓	
Observations	10,800	10,800	10,800	10,800	10,800
Adjusted R^2 (overall)	0.189			0.276	
Adjusted R^2 (within)		−0.024			−0.014
Log Likelihood			−10,601.330		
Akaike Inf. Crit.			22,106.650		

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

construct the forward simulated flow of $A_{mt}^{\text{strat in }\tau}$ 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 braod 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 an expected acquisition or IPO in the future makes entry more profitable. Moreover, the market category fixed effects, which are supposed to account for

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:				
	entry_fdstage_count				
	panel linear		*Poisson*	*OLS*	*panel linear*
	(1)	(2)	(3)	(4)	(5)
# of competitors	0.024***	−0.026***	−0.017***	−0.018***	−0.024***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.004)
Major New Tech or GAFAM acquisition pre-4Q	−0.564***	−0.351**	−0.302*	−0.348***	−0.354**
	(0.152)	(0.165)	(0.170)	(0.126)	(0.164)
1{quarter=2}					−0.145***
					(0.025)
1{quarter=3}					−0.169***
					(0.023)
1{quarter=4}					−0.235***
					(0.024)
Market FE		✓	✓		✓
20 market-category FE				✓	
Observations	10,800	10,800	10,800	10,800	10,800
Adjusted R^2 (overal)	0.190			0.277	
Adjusted R^2 (within)		−0.023			−0.013
Log Likelihood			−10,598.820		
Akaike Inf. Crit.			22,101.630		
Standard errors clustered at the market level.				*p<0.1; **p<0.05; ***p<0.01	

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 value of a future IPO is slightly larger and more significant, and the strategic acquistion effect becomes 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.

The parameter estimates allow to express firms' sunk costs in terms of "acquisition 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 161 million US$. This may seem like a lot. However, it roughly corresponds to the lifetime amount of funding that successfully exiting, later stage startups obtain. Further, I find that the lifetime costs of having one additional competitor in the market are equal to 2.8 million US$. Moving up from the least to the most profitable market, in terms of the 20 market-category fixed effects, is worth 304 million US$, which emphasizes the importance of market fixed effects. Moving up from the 9th to the 10th quantile is worth 4.7 million US$.

Table 18: Estimates of structural parameters.

	(1)	(2)	no market / category FEs (neither in 1st nor in 2nd stage) (3)
Entry costs, κ^e	-3.0694^{***}	-3.0846^{***}	-5.9963^{***}
	(0.1873)	(0.1875)	(0.0967)
log(# of competitors), γ_1	-0.0990^{***}	-0.0984^{***}	0.0998^{***}
	(0.0072)	(0.0072)	(0.0019)
Strategic acq of competitor **by on-Capterra acquirer**, γ_2 (Dummy indicating major such acquisition in past 4 quarters)	-0.0299		
	(0.0237)		
Strategic acq of competitor **by GAFAM or New Tech**, γ_2 (Dummy indicating major such acquisition in past 4 quarters)		-0.1276^{***}	-0.1380^{***}
		(0.0449)	(0.0444)
Own IPO in future, α^{ipo}	0.0027^{**}	0.0030^{***}	0.0014
	(0.0009)	(0.0009)	(0.0029)
Own acquisition in future, α^{acq}	0.0191^{***}	0.0197^{***}	-0.0007
	(0.0028)	(0.0028)	(0.0089)
Market category 2 (5th-10th perc)	0.0871^{***}	0.0870^{***}	
	(0.0191)	(0.0191)	
Market category 3 (10th-15th perc)	0.1403^{***}	0.1386^{***}	
	(0.0184)	(0.0184)	
...	...	...	
Market category 19 (90th-95thth perc)	0.5731^{***}	0.5721^{***}	
	(0.0241)	(0.0241)	
Market category 20 (95th-100th perc)	0.6486^{***}	0.6469^{***}	
	(0.0259)	(0.0259)	
Observations: 450 markets, 24 quarters	10,800	10,800	10,800
Log-likelihood	$-10,708$	$-10,709$	$-11,368$

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

6.3 Counterfactuals *(in progress)*

I next seek to answer the question: how would entry evolve if acquisitions by certain types of acquirers were blocked more often? The ultimate effect depends 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.

I conduct the simulatation by taking all state variables at the 2014 values, and then simulating how entry would evolve if acquisitions were not possible.

Preliminary results suggest a slight decline in entry following the blocking of all acquisitions. The effect depends on what startups' outside options are when they are not acquired: if they remain and compete on the market, the drop in entry does not seem so strong.

6.4 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 that industry classification systems that are crude and that vary on the firm, as opposed to on the product or functionality level, suffer from. Nevertheless, there are aspects of competition that these market definitions do and do not capture. Startup pivoting; the development from complementary products into substitutable products; interdependence between markets; the importance of interoperability; or the distinction of markets for technology as opposed to product markets cannot be captured by my market definitions.

The question of how to accurately define markets for software are frontier research questions by themselves. 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 robustness checks, for instance by varying the number of markets.

7 Conclusion

The paper highlights several avenues for future research. One extension of the model would be to endogenize firms' decisions of whether or how to exit, depending on age and other characteristics.

A further fruitful avenue of future research would be to collect information on product entry not only by startups as I do in this paper, but also product entry by multi-product firms, or even on product expansion and development. My data precludes me from pursuing this objective, as with web-scraped data I am unable to observe the date of product availability. Such data would enable to obtain measues on the *direction* of innovation, and could also inform whether incumbents might use acquisitions as a mode of market entry (see Perez-Saiz (2015)). The anticipation of an acquisition could well influence the direction of innovation, as anecdotal evidence from startups' pivoting behavior shows, and as theory literature has emphasized (Dijk et al., 2021, Motta & Shelegia, 2021). It would also be interesting to see whether incumbents expand the scope of their products over time, as recent literature has suggested that acquisitions and investments may help firms expand into adjacent markets (G. Z. Jin et al., 2022b, Zhang, 2022).

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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.[41] From such a dataset, one can easily create quarterly data of, for instance, the number of acquisitions per quarter, or the number or volume of funding rounds.

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

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

Venture Capital funding round: Any funding round of the following type: *Angel, Pre-Seed, Seed, Series A to Series J, Unknown Series, Corporate Round, Convertible Note, Undisclosed*. I thus exclude, for instance, Post IPO funding rounds, Private Equity, or Secondary Market investment.

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*.

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

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*.[42] 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.

A.5 Building a dictionary and tagging products with keywords

As each product can be associated to *more* than one keyword[43], one needs to reduce the dimensionality of the categories so that each product will be grouped along with other products into a *unique* market.

[42] 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.

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

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.6 Validation of market definition

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

In Figure 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

My data: (same color = same market)

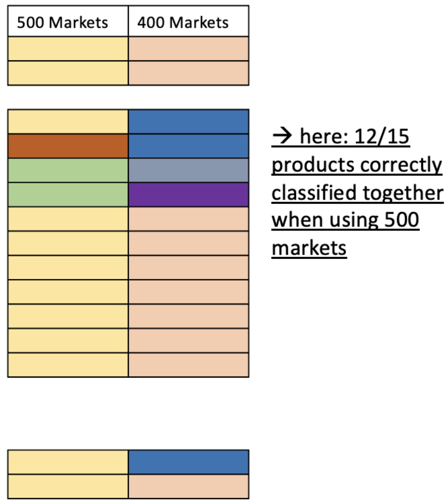

Figure 6: Validation of market definition.

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.

B 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.)

C Acquirers Are of Different Types: Further Details

The three types of acquiring companies – on-Capterra, off-Capterra, and financial – not only vary by industry sector, but also in terms of other characteristics. For instance, on-Capterra acquirers are more likely to once have been VC-funded themselves (68%), tend to be somewhat younger than financial or off-Capterra firms, and tend to be located in the US and California. Off-Capterra 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.

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

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).

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

In Table 19, 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 19: 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

F Robustness: Event Studies

Table 20: Same event study as in main text, 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)
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 21: 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)
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 22: 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)
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 23: 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)
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 24: 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	-0.114^{**}				
(105 acquisitions)	(0.056)				
alltech_smaller_count_ma		-0.263^{***}			
(46 acquisitions)		(0.096)			
newtech_gafam_smaller_count_ma			-0.361^{***}		
(29 acquisitions)			(0.093)		
financeacq_portfolio_smaller_count_ma				-0.098	
(55 acquisitions)				(0.060)	
financeacq_smaller_count_ma					-0.090
(39 acquisitions)					(0.127)
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. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$