NBER WORKING PAPER SERIES

HOW DO TOP ACQUIRERS COMPARE IN TECHNOLOGY MERGERS? NEW EVIDENCE FROM AN S&P TAXONOMY

Ginger Zhe Jin
Mario Leccese
Liad Wagman

Working Paper 29642
http://www.nber.org/papers/w29642

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2022, Revised November 2022

We are grateful to S&P for providing access to the data and to our home universities for financial support. George Mason University has provided financial support for our presentation of this paper at its 2022 Research Roundtable on Capitalism & the Rule of Law. We thank Editor Yossi Spiegel, two anonymous referees, Martin Peitz, Yann Delaprez, Oezlem Bedre-Defolie, Kathrine Rockett, James Copper, Christopher Yoo, and participants at the 2021 CRESSE conference, the 2022 George Mason Roundtable, the 2022 Hal White Antitrust Conference, and the 2022 NBER conference on Megafirms and the Post-COVID Economy for constructive comments. Jin was on academic leave to work full time at the US Federal Trade Commission in 2015-2017 and at Amazon in 2019-2020. This project started after both leaves. She has provided consulting services to one firm in this study, and is a current consultant to another. She also holds more than $10,000 in stock in one firm in the sample. None of these firms nor any government agency has any financial or non-financial relationship with this research project. The content, analyses and views expressed herein are those of the authors and do not relate to any institution or organization with whom the authors are affiliated. All rights reserved. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

How Do Top Acquirers Compare in Technology Mergers? New Evidence from an S&P Taxonomy Ginger Zhe Jin, Mario Leccese, and Liad Wagman
NBER Working Paper No. 29642
January 2022, Revised November 2022
JEL No. G34,L40,O33,O38

ABSTRACT

Some argue that large platforms, such as Alphabet/Google, Amazon, Apple, Facebook and Microsoft (or GAFAM), are unusual in their number, pace and concentration of technology mergers, with the potential to harm market competition. Using a unique taxonomy developed by S&P Global Market Intelligence, we compare the M&A activities of GAFAM to other top acquirers from 2010 to 2020. We find: (i) GAFAM completed more tech acquisitions per firm than other groups of top acquirers, and acquired younger and more consumer-facing firms on average. (ii) The top 25 private equity firms outpaced GAFAM in tech acquisitions per firm since 2018. (iii) GAFAM acquisitions are less concentrated across tech categories than other top acquirer groups, due, in part, to an "acquire-adjacent-and-then-expand" strategy. (iv) Over time, more and more GAFAM and other top acquirers acquire in the same categories.(v) No evidence suggesting that a GAFAM acquisition in a category, compared to similar categories without GAFAM acquisitions, is correlated with a slowdown in the number of new acquirers acquiring in that category. Overall, we find that technology acquisitions do not shield GAFAM from competition, at least not from other GAFAM members or other firms that acquire in the same categories.

Ginger Zhe Jin
University of Maryland
Department of Economics
College Park, MD 20742-7211
and NBER
ginger@umd.edu

Mario Leccese
University of Maryland
Department of Economics
Tydings Hall
7343 Preinkert Dr.
College Park, MD 20742
United States
leccese@umd.edu

Liad Wagman
Illinois Institute of Technology
565 W Adams St, Suite 412
Chicago, IL 60661
lwagman@stuart.iit.edu

1 Introduction

Recently, concerns have been raised about the mergers and acquisitions (M&A) activities of large incumbent firms, especially if the target firm is a small nascent competitor or produces complementary inputs. In theory, an acquirer could shut down innovations of the target firm (so-called "killer acquisitions," Cunningham et al., 2021), extend its existing market power to another market via acquisition and thereby discourage new innovative entrants in this market (creating a "kill zone," Kamepalli et al., 2020), or reduce competitor access to complementary assets ("raising rival's costs," Salop and Scheffman, 1983; Ordover, Saloner and Salop, 1990). Regardless of the mechanism, these theories share the concern that acquisitions of innovative targets could curb innovation, preempt future competition, and reinforce the acquirer's market position.

Broadly, these concerns could apply to M&A in all sectors, but the recent debates have highlighted them in technology. Much of the spotlight has been concentrated on the five leading technology platforms, namely Alphabet (Google), Apple, Facebook, Amazon, and Microsoft — known as GAFAM. Collectively, the five companies acquired hundreds of firms in recent years, raising the concern among government agencies and scholars that their M&A practices may be unusual in pace, volume and concentration. For example, scholars have argued that the nature of digital platforms — namely the indirect network effects between multiple sides of a platform — may have motivated incumbents like GAFAM to acquire nascent firms, especially if the target is an emerging competitor or collects complementary user data, allowing the incumbent to better monetize the data on the other sides of the platform (Motta and Peitz, 2021). It is also of potential concern that these motives would generate a systematic M&A pattern that is difficult to identify in each single acquisition, which has the potential to harm market competition in the long run (Scott Morton and Dinielli 2020a, 2020b).[1]

[1]This concern is also raised by the Final Report of the Stigler Committee on Digital Platforms (September 2019), available at `https://www.chicagobooth.edu/research/stigler/news-and-media/committee-on-digital-platforms-final-report`.

In conjunction, antitrust enforcers around the globe have expressed interest in the topic. For instance, the UK's Unlocking Digital Competition Report (March 2019) states that "Over the last 10 years, the 5 largest firms have made over 400 acquisitions globally" and that "this pace is not slowing, with close to 250 acquisitions in the last 5 years."[2] The US Congress issued a 2020 Majority Staff Report on Investigation of Competition in Digital Markets, similarly stating that GAFAM "acquired hundreds of companies just in the last ten years."[3] In September 2021, the US Federal Trade Commission released a staff report describing 600+ acquisitions completed by the five GAFAM firms between 2010 and 2019, including those not reported to the US antitrust agencies under the Hart-Scott-Rodino Act.[4] Similar interest in GAFAM acquisitions was expressed in Australia[5], France[6] and the European Commission.[7]

Recent legislative bills and proposals that relate to M&A activity have also been specifically targeted at GAFAM. For example, the proposed House of Representatives' H.R. 3826, called the Platform Competition and Opportunity Act, would restrict "covered platforms" from acquiring competitors or potential competitors.[8] Covered platforms are defined as those

[2] "Unlocking Digital Competition: Report of the Digital Competition Expert Panel," led by Jason Furman, available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf (accessed on 10/11/2021). The consulting firm LEAR, advising the UK's Competition and Markets Authority, in the 2019 report "Ex-post Assessment of Merger Control Decisions in Digital Markets" (henceforth, the 2019 LEAR report), available at https://www.learlab.com/publication/ex-post-assessment-of-merger-control-decisions-in-digital-markets/ (accessed on 10/11/2021), similarly identified 168 acquisitions by Google, 60 by Amazon, and 71 by Facebook.

[3] "Investigation of Competition in Digital Markets: Majority Staff Report and Recommendations, Subcommittee on Antitrust, Commercial and Administrative Law of the Committee on Judiciary," available at https://judiciary.house.gov/uploadedfiles/competition_in_digital_markets.pdf?utm_campaign=4493-519, accessed on 10/11/2021.

[4] "Non-HSR Reported Acquisitions by Select Technology Platforms, 2010-2019: An FTC Study," available at https://www.ftc.gov/reports/non-hsr-reported-acquisitions-select-technology-platforms-2010-2019-ftc-study,accessedon10/11/2021.

[5] The Australian Competition & Consumer Commission's Digital Platforms Inquiry (July, 2019) similarly states that "Several of the digital platforms relevant to this Inquiry have also benefited from an increasing degree of horizontal and vertical integration, acquiring multiple businesses." (available at https://www.accc.gov.au/publications/digital-platforms-inquiry-final-report,accessed10/11/2021.

[6] The French Competition Authority's Opinion on the Online Advertising Sector (March, 2018) states that "Since the early 2000s, Google has acquired around 200 companies in various technology sectors."

[7] A report to the European Commission, "Competition Policy for the Digital Era," prepared by Jacques Crémer, Yves-Alexandre de Montjoye and Heike Schweitzer in 2019, devotes a chapter to the debate about "acquisitions by dominant platforms of small startups with a quick growing user base and significant competition potential." (available at https://ec.europa.eu/competition/publications/reports/kd0419345enn.pdf, accessed on 10/11/2021.

[8] https://www.congress.gov/bill/117th-congress/house-bill/3826

that (i) have at least 50 million U.S.-based monthly active users or at least 100,000 U.S.-based monthly active business users, (ii) have net annual sales or a market capitalization greater than $600 billion, and (iii) are critical trading partners for the sale or provision of any product or service offered on or directly related to the platform. Such criteria entail that only GAFAM firms, as of the time of the legislative proposal, would be impacted by the bill.

Outside the U.S., the European Union's Digital Markets Act (DMA) provides certain presumptions for a company to be designated as "gatekeeper." Those presumptions, in large part, relate to size: (i) an EU-wide turnover of at least EUR 7.5 billion in each of the last three financial years, or (ii) a market capitalization of at least EUR 75 billion in the last financial year, and (iii) at least 45 million monthly active end-users and at least 10,000 business users in the EU for at least one core platform service in the last financial year.[9] With the exception of Verizon Wireless, through its acquisition of Yahoo, the five GAFAM firms were the only five firms that qualified as gatekeepers under the different iterations of and proposals for the DMA's numerical thresholds for gatekeepers.[10] Under the DMA, a gatekeeper must inform the EU Commission of any intended acquisition of a company that provides services in the digital sector, irrespective of whether the transaction triggers a merger filing requirement at the EU or Member State level. The EU Commission may then initiate merger control proceedings, even if the relevant filing thresholds are not met. Moreover, the EU Commission, should it determine that a gatekeeper engaged in systematic non-compliance, may altogether prohibit a gatekeeper firm from acquisitions in the digital sector for a period of time it deems proportionate to the non-compliance.

Despite the intense attention from regulators and policymakers, most of the supporting evidence focuses on the M&A history of GAFAM firms, *without* comparing them to other top acquirers or the overall trends of technology M&A. Such a comparison is difficult to make because the existing literature does not have a good method to classify acquired

[9] https://oeil.secure.europarl.europa.eu/oeil/popups/ficheprocedure.do?lang=en&reference=2020/0374(COD)

[10] https://www.bruegel.org/blog-post/which-platforms-will-be-caught-digital-markets-act-gatekeeper-dilemma.

technology firms into detailed industry categories and subcategories. The commonly used North American Industry Classification System (NAICS), for instance, is limited, because even when using the most specific (6-digit) NAICS code, a large number of the acquired technology entities tend to fall under "Software Publishers" or "Internet Service Providers" (Werden and Froeb, 2018). As a result, researchers have so far adopted industry categorizations that are either ad-hoc, and/or specific to the relatively small sample of transactions under consideration (see, e.g., the 2019 LEAR report, Gautier and Lamesch 2021)[11], or lack a taxonomy with a structured hierarchy (e.g., as in the 2020 House Majority Staff Report), making it difficult to cohesively evaluate whether acquisitions fall in adjacent or unrelated industries. As a result, the comparisons between GAFAM's acquisitions relative to other leading technology acquirers have been limited.

In this paper, we aim to shed light on the pace, volume and concentration of GAFAM acquisitions relative to acquisitions by other top acquirers, including major technology companies and private equity firms. To do so, we use a dataset from S&P Global Market Intelligence that specifically tracks technology acquisitions and categorizes all associated firms into a hierarchical taxonomy. More specifically, besides GAFAM, we identify three groups of companies that have been or have the potential to be top acquirers of technology companies. The first group includes the 25 top-ranked companies that appear in Forbes's 2019 ranking of Top 100 Digital Companies, excluding GAFAM. The second group includes the 25 largest private equity firms ranked by Private Equity International as of December, 2020. The third group includes another 25 firms that have the highest number of acquisitions in our S&P dataset but do not appear in any of the other groups of top acquirers. We put more emphasis on the firms ranked high on these lists, because the ongoing legislative and policy debates use firm size to define the thresholds of applicability. A test of whether such thresholds are correctly chosen naturally entails a comparison between firms around the size thresholds.

We show that, on the one hand, GAFAM has completed a greater number of tech acquisi-

[11] Gautier and Lamesch (2021) examine and categorize 175 acquisitions by GAFAM during 2015-2017, according to whether the target firm's products are offered to advertisers, businesses, consumers, merchants, content editors, and platform products (mainly hardware and operating systems).

tions per firm than the other groups of top acquirers, and on average, GAFAM does acquire younger and more business-to-consumers (B2C) firms but they are not necessarily firms whose products are more data-intensive. On the other hand, on a per-firm basis, the top 25 private equity firms have outpaced GAFAM in tech acquisitions since 2018. Combining all acquisitions from 2010 to 2020, GAFAM acquisitions are significantly less concentrated across categories than any of the top acquirer groups we considered. This is achieved by GAFAM first acquiring targets in adjacent categories and then expanding around them.

While it may be argued that acquisitions by GAFAM firms, as the larger incumbents, could amount to claiming competitive turf in the target firms' categories, and could consequently deter entry by potential competitors, our findings suggest otherwise. Specifically, we do not find evidence suggesting that GAFAM entry via acquisitions in categories, in comparison to similar categories in which GAFAM has not yet acquired, are correlated with any slowdown in the number of new acquirers acquiring in the same categories after the initial acquisitions by GAFAM. In addition, it has been argued that the largest platforms are increasingly encroaching on each other's turfs.[12] Our findings confirm that, over time, more members of GAFAM acquire in the same categories, and other top acquirers also acquire in the same categories as GAFAM.

Admittedly, the categories defined by the S&P taxonomy do not necessarily align with antitrust market definitions. That said, observing different acquirers entering the same business area via M&A still informs the debate about potential and/or nascent competition that *may* happen in antitrust markets in or related to that business area. Our findings suggest that potential competition in the same category could arise from different firms that acquire ventures in that category. Empirically, at least in the period and categories we study, technology acquisition does not shield GAFAM from potential competition that may arise from other GAFAM members or other firms acquiring in the same industry categories.

We also acknowledge that the aforementioned legislative efforts may be driven not only by

[12]See, for instance, the following news article. Source: `https://www.nytimes.com/interactive/2019/11/13/magazine/internet-platform.html`, accessed on 10/25/2021.

GAFAM's M&A activities, but also the nature of platform business, market power concerns, and antitrust histories of specific firms. Our descriptive evidence focuses on M&A only, and thus does not speak to other reasons that could justify the proposed legislative or policy changes. We aim for this paper to be one of the first data-driven efforts to aid policymakers in better understanding the similarities and differences between GAFAM and other acquirers, and to better target legislation to address problematic behavior.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the S&P data, including the advantages of the S&P taxonomy over other classifications in the literature, and our definition of top acquirers. Section 4 provides a brief summary of M&A activities of GAFAM and other groups of top acquirers. Section 5 documents how GAFAM and other top acquirers differ in their concentration of M&A, and how they expand M&A activities over time. Section 6 documents the extent to which top acquirers acquire in the same categories, as well as the degree of acquisitions overlap within and across groups of top acquirers. Section 7 concludes with what this descriptive paper can and cannot say about competition, M&A and innovation, and directions for researchers to dive into other important questions in this area.

2 Related Literature

Like all M&As, large incumbent acquisitions of startup firms could be anti-competitive or improve economic efficiency. What is special about acquisitions of startups is that entrepreneurs may seek to found — and investors may seek to finance — companies that incumbents will acquire (Rasmusen 1988, Lemley and McCreary, 2019). The incentive of entry for buyout complicates the potential consequences of M&A on innovation and competition.[13]

On the anti-competitive side, researchers have investigated at least three possibilities.

[13]It has long been argued that institutions, such as the patent system, create opportunities for incumbents to maintain market power by taking pre-emptive actions, including research and development (R&D) and acquisitions (Gilbert and Newberry, 1982). For a recent survey of theoretical works on the effects of mergers on innovation, see Calvano and Polo (2020). For other relevant theoretical works in the literature on antitrust in innovative markets see Aghion et al. (2005), Segal and Whinston (2007), and Cabral (2018).

First, an incumbent firm may preemptively prevent future competitors by acquiring innovative targets for the sole purpose of discontinuing their products. This practice is called "killer acquisition." Cunningham et al. (2021) examine biotechnology acquisitions of potential competitor pharmaceutical drugs. They find that molecules acquired by an incumbent with an overlapping drug are 23.4% less likely to be developed compared to those acquired by non-overlapping incumbents, and that 5.3%-7.4% of all acquisitions in their sample are killer acquisitions. As for digital M&As, Gautier and Lamesch (2021) examine 175 acquisitions by GAFAM during 2015-2017. They find that a substantial portion of acquired products and services are no longer supplied, maintained or upgraded under their original brand names, though such "discontinuation" does not necessarily "kill" the acquired products.

Second, incumbents may dissuade others from using the products and services of nascent competitors, because the nascent firms may find it hard to compete against a large incumbent that already offers similar products and services (organically or via M&A). Kamepalli et al. (2020) name this practice as creating a "kill zone." In particular, they argue that, in a setting with network externalities where customers face switching costs, the prospect of an acquisition by an incumbent platform may reduce the incentives of early adopters to adopt the entrance's product or service, which further reduces prospective payoffs to new entrants. This may create a "kill zone" where startups are not pursued by investors for potential funding. To support their argument, Kamepalli et al. (2020) showcase an empirical example of changes in venture investment in startups after major acquisitions by Facebook and Google.

Unlike the above two possibilities, which focus on direct or potential competition between the acquirer and the target, anti-competitive concerns could arise in vertical acquisitions. If the target provides complementary inputs, the acquirer may foreclose or raise rivals' costs of accessing the target's products and services (Salop and Scheffman 1983; Ordover, Saloner and Salop 1990). Bryan and Hovenkamp (2020) consider this possibility in a model that incorporates entrepreneurs' choice to enter a market in the hope of an incumbent buyout. In particular, they use a differentiated oligopoly model to show that imposing no limits on startup acquisitions may entail market inefficiencies.[14] They argue that leading incumbents make acquisitions in part to keep lagging competitors from catching up technologically, and this incentive may pivot entrepreneurs towards inventions that improve the leading incumbent's technology rather than those that help laggard incumbents catch up.[15] Once the leading incumbent establishes a sufficient gap between itself and laggard incumbents, its willingness to pay for new technologies plummets, which may in turn dry up entrepreneurs' and investors' incentives to invest in further innovations.

Empirically, Chipty (2001) shows that vertical integration between programming and distribution in the cable television industry can provide the merged entity with the incentive to exclude rivals in the downstream market. The concerns regarding market foreclosure and raising rivals' costs may also be greater in the presence of network effects. Argentesi et al. (2021) evaluate, retrospectively, Facebook's acquisition of Instagram, and discuss how it prompted a reduction in Instagram's interoperability with other networks by making it harder to repost photos on other social networks.

In addition, a universal anti-competitive concern relates to the merger notification regime, where the merging parties may not need to notify antitrust enforcers before the transaction's consummation if the deal falls below certain thresholds.[16] As shown in Wollmann (2019), lack of antitrust scrutiny may encourage small but potentially anti-competitive M&A deals.[17] This may be of concern for startup acquisitions in the technology sector, because the M&A notification regime in the US has a specific exemption in the reporting thresholds for non-manufacturing firms — a characterization that is readily applicable to digital products and

[14] The inefficiencies may arise in both entry for buyout strategies as well as in new technology development decisions. For example, the choice of incumbent to which founders sell their firms may be inefficient, the choice of technology that entrepreneurs develop may be inefficient, and/or the amount invested in the development of new technologies may be inefficient.

[15] Researchers have examined acquisitions as a cause of widening productivity gaps between market leaders and laggards; see, e.g., Andrews et al. (2015) and Baily and Montalbano (2016).

[16] `https://www.federalregister.gov/documents/2021/02/02/2021-02110/revised-jurisdictional-thresholds-for-section-7a-of-the-clayton-act`.

[17] Wollmann (2019) shows that acquisitions of smaller firms by incumbents became much more common when the Hart-Scott-Rodino Act was modified in 2001 to exempt mid-sized firms from pre-merger notifications. Mergers outside the purview of the Act resulted in a combined concentration of activity adding up to 30% of the total change in four-firm revenue concentration over 1994-2011, suggesting that, in aggregate, these acquisitions are important for market structure.

services.[18] Moreover, many digital startups tend to develop a strong customer base first and then monetize. As a result, some of the target firms may not meet the reporting thresholds as far as annual revenues or total assets, even if the transaction value of the M&A is relatively large.

All the above put emphasis on the potential anti-competitive nature of startup acquisitions. For completeness, we also recognize some counter arguments in favor of such acquisitions on the grounds of efficiency: for example, entrepreneurs may view M&A as a successful exit, so that the prospect of acquisition by an incumbent firm would encourage more startup innovations in the future; acquirers could accelerate the growth of the target firm, especially if they have complementary resources or have accumulated expertise in a related area; startup acquisition could help the incumbent acquirer to adopt new technology faster and become more efficient; and an efficient incumbent acquiring a startup in a new area might increase competition and efficiency in that area. These efficiency reasons may explain why the existing laws in the US and many other countries allow below-threshold M&As to consummate without ex ante antitrust scrutiny.

Relatedly, Mermelstein et al. (2020) study the evolution of industries where firms can improve their efficiency through mergers, and investment by new firms may take the form of entry for buyout. They show that an optimal dynamic merger policy may significantly diverge from a static regulation of mergers. Letina, Schmutzler, and Seibel (2021) develop an analytical framework, showing how prohibiting acquisitions can reduce innovation.

Some empirical research has demonstrated the potential efficiency of M&A in digital markets. Gautier and Lamesch (2021), utilizing data on 175 GAFAM acquisitions in 2015-2017, argue that GAFAM firms primarily utilize acquisitions as a substitute for in-house R&D. Prado and Bauer (2022) use a dataset of more than thirty-two thousand venture-capital deals reported worldwide from 2010 to 2020. They find a positive effect of GAFAM's

[18] For non-manufacturing firms, for transactions above $50M and below $200M (as adjusted, reflecting a range of $92M to $368M in 2021, respectively), the maximum threshold for not reporting a transaction based on the target entity's sales increases from $10M to $100M (as adjusted, reflecting $18.4M and $184M in 2020, respectively). See, e.g. `https://www.ftc.gov/sites/default/files/attachments/permerger-introductory-guides/guide2.pdf`.

startup acquisitions on venture investment in startups in similar industry categories, in contrast to the "kill zone" argument.

Finally, a separate strand of literature highlights the indirect network effects between multiple sides of a digital platform, and argues that such indirect network effects could have motivated platform incumbents like GAFAM to acquire nascent firms. For example, using a simple theoretical framework, Motta and Peitz (2021) identify six scenarios where a large platform's acquisitions of startups may be anti-competitive. At the same time, they recognize that the indirect network effects on digital platforms can also generate extra efficiencies, because larger platforms in concentrated markets may enable more positive network effects and bring benefits to consumers.

Our paper is complementary to these works and helps inform recent debates by (i) contrasting technology acquisitions activities in the categories where GAFAM did and did not acquire target entities; (ii) examining whether the pace, volume, concentration, and other features (such as target age, data reliance, and whether it is consumer facing) of GAFAM acquisitions are unique relative to other top acquirers; (iii) demonstrating whether GAFAM is more likely to acquire in its core, adjacent, or unrelated categories; and (iv) determining how, over time, the categories of tech acquisition overlap within GAFAM and across top acquirers.

The aim of this descriptive paper is to compare the M&A patterns between GAFAM and other acquirers, not to test any specific antitrust theory. The latter would entail data on ventures that are not yet targets of acquisitions, and on measures of patents, initial public offering (IPO), and other venture or market outcomes. That being said, our empirical findings may shed light on the potential competition of GAFAM and other acquirers if they engage in M&A activities in the same category, no matter which theory motivates these acquisitions. Our findings that increasingly more members of GAFAM acquire in the same categories, and that the categorical overlap between GAFAM and other top acquirers has increased over time, do not support the stylized concern that the presence of GAFAM in a category through acquisition may deter all potential competition in that category. It also suggests that GAFAM is not unique in tech acquisitions: many other incumbents are active in acquiring startups in the same categories. Hence, the evaluation of policies regarding antitrust reform in M&As, should policymakers deem they are needed, may omit important considerations if they are confined to GAFAM firms. Given the ongoing debates about competition and M&A, we argue that a better understanding of the relevant data, such as the summaries and correlations reported in this paper, is a crucial step.

Moreover, the technology taxonomy we utilize allows us to distinguish whether acquired firms operate in the same, adjacent or unrelated categories as the incumbent acquirer. As detailed below in Section 3, this is a significant improvement from the classifications used by previous research. Though the categories defined by S&P in this taxonomy are different from the classical market definitions in antitrust, such business proximity is likely correlated with the incumbents' ability to expand their market power or apply their expertise beyond their original core businesses. Our results that pertain to business proximity can help policymakers better link empirical M&A patterns to the potential pro- or anti-competitive effects of M&A in the technology sector. In short, we offer a deep dive into the S&P data, which will likely be useful to other researchers interested in studying technology M&As, given that this dataset presently offers the highest level of detail when it comes to the classification of this significant portion of the technology space.

3 Data

We use data from a database maintained and operated by Standard and Poor's Global Market Intelligence called 451 Research (henceforth, S&P). The data tracks majority acquisitions of technology companies since the early 2000s, focusing on information, communication and energy technologies (ICET). This means the dataset covers majority (control) acquisitions, where the acquirer obtains more than 50% of the voting shares of the target. The database is updated on a daily basis and has been widely used by investors and analysts in the financial industry, but we were told that the entries before 2010 may be less comprehensive due to insufficient or imprecise information. In light of this, our analysis focuses on acquisitions consummated between January 1, 2010 and December 31, 2020.

We cross-checked this database with the Worldwide Mergers, Acquisitions, and Alliances Databases produced by Refinitiv's SDC. The SDC data is by definition broader than S&P's as it also tracks non-tech targets and includes minority acquisitions. After merging the two data sets, we find that the S&P data is more comprehensive as far as majority tech acquisitions. In particular, we define tech industries using the industry sector of the targets — which corresponds to 4-digit NAICS codes — as provided in the SDC data.[19] Within this broad definition of tech industries, we find that, out of the transactions in the SDC data that could not be matched with the S&P data, less than 10% are majority acquisitions. In contrast, roughly half of the observations in the S&P data remained unmatched with SDC, and their distribution across technology categories is roughly the same as that of the original S&P data. These suggest that the partial overlap between the two datasets is primarily driven by missing values in the SDC data, rather than a lack of coverage by S&P.

S&P classifies the acquiring and acquired companies into a hierarchical technology taxonomy with 4 levels, with level-1 being the broadest (resembling an industry, such as "Application Software" and "Internet Content and Commerce," in some cases similar to 4-digit NAICS codes such as 5112 and 5191) and level-4 being the narrowest (resembling a technology business vertical, such as "Benefit and Payroll Management" and "Video-on-demand Servers"). All level-1 "parent" categories have level-2 "children" categories, but not all level-2 categories have further children levels.

In total, there are about two dozen level-1 categories and two hundred level-2 categories, yielding an average of about nine level-2 categories per level-1 parent. We refer to two level-2 categories as "adjacent" if they share the same level-1 parent category.

Each firm in the database is assigned a primary category, representing the firm's core business, which, in the taxonomy, includes a level-1, a level-2, and, if available, level-3 and level-4 classifications. Firms may also be assigned one or more secondary categories

[19]A mapping of the categories in the S&P data to NAICS codes was provided by S&P.

(organized analogously in the taxonomy). The database provides the location of each firm's headquarters, whether a firm is publicly traded, a consummation date for each acquisition, and the founding dates for the firms tracked (available in 87.64% of the transactions for the acquired firms and 94.80% for the acquiring firms). This allows us to compute the age of most target firms as of the time of the consummation of their acquisition.[20]

We have three reasons to believe that the S&P taxonomy is more systematic, more reliable, and more detailed than alternative taxonomies that other researchers have used to study technology mergers. For example, Gautier and Lamesch (2021) manually identify six different user groups associated with GAFAM firms and match each GAFAM target to one of these segments. Similarly, Argentesi et al. (2019, 2021) use a self-made taxonomy which classifies the products of the targets acquired by Google, Facebook and Amazon into markets, with no coverage on other acquirers. Both these taxonomies are self-made, for academic usage only, and cover a very small subset of the ICET space and of the companies acquiring in this area. In comparison, the S&P classification is much more comprehensive, covers the entire ICET space, and provides a systematic classification made by third-party professionals which is widely-used for financial analysis. According to an internal statistic reported by S&P, more than 85% of tech bankers who advise on more than 10 deals per year rely heavily on this dataset for their trend and valuation analysis.

Moreover, Jin et al. (2022) show the reliability of the S&P taxonomy by comparing the cosine similarities of the business descriptions of a random sample of technology targets. These business descriptions are available through Crunchbase, a dataset that tracks investment rounds in technology ventures and is independent of S&P. The exercise confirms that targets within the same S&P category are more similar than targets across categories, for both level-1 and level-2 categories.

Lastly, the taxonomy in Prado and Bauer (2022) is the most similar to ours, it relies on the portion of CB Insights—another database that tracks technology M&As—that covers the

[20]The databases also provides the number of employees a firm has and the transaction sizes in dollars, though these are sparsely populated.

sectors of "Internet" and "Mobile telecommunications." A comparison of the two taxonomies suggests that the S&P taxonomy proffers a finer partition of the technology space. In particular, we find that GAFAM, combined, spread their acquisitions across 17 level-1s and 100 level-2s between 2010 and 2020 in the S&P data, whereas Prado and Bauer (2022) report that in the same period, in the data that CB Insights made available to them, GAFAM concentrated their acquisitions in only 4 "industries"—which are comparable to S&P level-1s—and 82 "subindustries"—which are comparable to S&P level-2s.

Besides GAFAM, we identify three groups of companies that have been or have the potential to be top acquirers in the technology sector. The first group, referred to as "Top 25 Tech," includes the 25 top-ranked companies that appear in Forbes's 2019 ranking of Top 100 Digital Companies, excluding GAFAM.[21] The second group, referred to as "Top 25 PE," includes the 25 largest private equity firms ranked by Private Equity International as of December, 2020.[22] The third group, referred to as "Top 25 S&P," includes another 25 firms that have the highest number of acquisitions in the S&P database but do not appear in any of the other groups of top acquirers.[23] Our comparisons place more emphasis on firms listed high on these rankings. That is because the sized-based thresholds in the proposed or enacted legislative bills distinguish among acquirers based on such thresholds. In the econometric analysis of which acquirer tends to conduct M&A in a business category following a GAFAM acquisition in the same category (Section 6), we utilize the full sample of acquirers.

Table 1 lists the identity of each top acquirer in Top 25 Tech, Top 25 PE, and Top 25 S&P, from rank 1 to rank 25. As expected, many firms in Top 25 Tech are well known media, telecommunication and technology companies; some of them are based in the US (e.g., AT&T, Verizon, Intel, IBM, Cisco, Walt Disney), while others are headquartered in Asia (e.g., Samsung, Alibaba, Softbank), Europe (e.g., Deutsche Telekom) and Latin

[21]Source: `https://www.forbes.com/top-digital-companies/list/`. Each GAFAM firm is on this Top-100 list.

[22]Source: `https://www.privateequityinternational.com/database/#/pei-300`, accessed December 11, 2020; see, also, `https://www.mekkographics.com/25-largest-private-equity-firms/`.

[23]To check the robustness of our results, we also compare GAFAM with the 5 most acquisitive companies in the S&P database, including top tech and private equity firms. We find that our results continue to hold and are even stronger with respect to some dimensions.

America (America Movil). Because Forbes's ranking focuses on top digital companies, it covers a range of industries including telecommunication, semiconductor, computer software, consumer electronics, e-commerce, entertainment, and consulting. In comparison, all firms in Top 25 PE are private equity firms, and those in Top 25 S&P could be private equity firms (e.g. Marlin Equity Partners) or firms that provide products and services in computer software (e.g. Salesforce, Yahoo), media (Thomson Reuters), hardware (Ericsson), consumer electronics (Siemens), and communication (Publicis Groupe).

To facilitate meaningful comparisons, we keep all group definitions fixed over time, but recognize the possibility that some firms in our top acquirer groups may become a target later in our study period. For example, Yahoo was acquired by Verizon in 2017, but Yahoo had acquired many firms before this acquisition. In this case, the Verizon purchase of Yahoo is counted as Verizon's acquisition, while Yahoo's acquisitions only include the deals that Yahoo completed before it was acquired by Verizon. Most firms in our top acquirer groups are independent and active as of today.

Henceforth, we compare five groups of acquirers — namely, GAFAM, Top 25 Tech, Top 25 PE, Top 25 S&P, and a grouping of all other firms that have completed any acquisition in the S&P database (referred to as "All Other"). The 80 firms in the first four groups are also henceforth referred to as top acquirers.

Table 1: List of Top Acquirers in Each Group (Excluding GAFAM)

Rank	Top 25 Tech	Top 25 PE	Top 25 S&P
1	Samsung	The Blackstone Group	Constellation Software
2	AT&T	The Carlyle Group	WPP plc
3	Verizon	KKR & Co.	TA Associates
4	China Mobile	TPG Capital	J2 Global
5	Walt Disney	Warburg Pincus	Marlin Equity Partners
6	Alibaba	Neuberger Berman	Providence Equity
7	Intel	CVC Capital Partners	HG Capital
8	Softbank	EQT Partners	The Riverside Company
9	IBM	Advent International	Abry Partners
10	Tencent	Vista Equity Partners	Genstar capital
11	Nippon Telegraph	Leonard Green & Partners	Apax Partners
12	Cisco	Cinven	Dentsu
13	Oracle	Bain Capital	H.I.G. Capital
14	Deutsche Telekom	Apollo Global Management	GTCR
15	Taiwan Semiconductor	Thoma Bravo	Trimble
16	KDDI	Insight Partners	Hexagon
17	SAP	Blackrock	New Mountain Capital
18	Telefónica	General Atlantic	Battery Ventures
19	América Móvil	Permira	Publicis Groupe
20	Hon Hai Precision	Brookfield Asset Management	Salesforce.com
21	Dell	EnCap	Audax Group
22	Orange	Francisco Partners	GI partners
23	China Telecom	Platinum Equity	EMC
24	SK Hynix	Hillhouse Capital Group	Deloitte
25	Accenture	Partners Group	Yahoo

Notes: The table lists the companies in each of the top acquirers groups considered. The top 25 tech list is taken from the top 100 digital companies of Forbes as of 2019. The list of the top 25 PE firms comes from Private Equity International as of 2020, and ranks the top 25 PE firms based on five years funds raised. The top 25 S&P comes directly from our dataset and includes the 25 firms with the highest number of acquisitions but that are not in any of the other groups considered.

4 M&A Activity of Top Acquirers

In this section, we compare the technology M&A activities of the five groups of acquirers. Motivated by the recent literature, we examine whether GAFAM has completed more acquisitions than other acquirers, and whether the targets of GAFAM and other groups of acquirers differ in their nascency, reliance on data, and orientation towards offering products and services consumers as opposed to businesses.

To measure the nascency of a target, we compute the age of the target at the time of acquisition by comparing its founding date and the acquisition's consummation date. Because different technology categories may naturally differ in terms of business growth, and may thus tend to attract acquisitions at different firm age ranges, we also normalize the target age by dividing it over the average target age within the same level-1 category. For example, a normalized age of 0.8 means that the absolute age of the target is 20% lower than the average age of all targets in the corresponding level-1 category.

For each transaction, the S&P data includes a categorical variable that describes the "primary audience" of the target involved as "general," "consumer," or "business."[24] Whenever the target's primary audience is "consumer," we tag the target as consumer-facing (B2C). To judge whether a target heavily relies on data ("data-intensive") — as we do not directly observe a variable reporting this in our dataset — we search for keywords in the S&P descriptions of the target. If a target's description includes "data," "statistics," "location-based services," "AI," "social media" or "e-commerce," we tag the target as data-intensive. The correlation between these two dummies is weakly negative (-0.1), as potentially both business-to-business (B2B) and B2C firms can be data-intensive.

As a first step, we examine whether Google/Alphabet, Amazon, Facebook/Meta, Apple, and Microsoft display similarities in their M&A activity, thus justifying the shared special attention that competition authorities have paid to GAFAM acquisitions. To that end, the first five columns of Table 2 show that while the five GAFAM firms display some differences, they also display certain features that distinguish them from acquirers in the other groups. In particular, while Google/Alphabet completed almost twice as many acquisitions as the second-largest GAFAM acquirer in the sample (Microsoft), all five GAFAM firms are relatively large acquirers: for example, with the exception of Amazon, they are all larger than the average acquirer in any of the other top groups. Moreover, all five GAFAM firms tend to acquire relatively many B2C and younger targets, although this holds true to a some-

[24]The information is unavailable only for 36 transactions, while for only 289 transactions the target's primary audience is recorded as "professional."

what lesser extent for Microsoft. In addition, zooming into individual top acquirers in our sample, we find that even if there are companies that are comparable or more acquisitive than GAFAM firms (these include, but are not limited to, Constellation Software, J2 Global, Cisco, Accenture, Oracle, and KKR), they tend to acquirer fewer consumer-oriented and/or older firms.

Next, Table 2 directly compares the M&A activity of the five groups of acquirers. Although many concerns have been raised regarding the acquisitiveness of tech giants, together, the 80 acquirers in our top groups only account for 14.24% of the total number of tech acquisitions between 2010 and 2020. This suggests that the relatively high M&A activity in the tech space is driven by all kinds of acquirers, not just the top ones. Still, on average, each firm in the four groups of top acquirers has completed 72 more acquisitions than any other acquirer we observe in the data between 2010 and 2020. This is consistent with Jin et al. (2022), a companion study in which we merge the S&P data with data on all firms listed in the North American stock exchanges. That study finds that only 13.1% of public firms engage in tech M&A, , although such acquisitions are widespread across sectors of the economy, and that larger and older firms are more likely to acquire tech companies.

Table 2 also highlights important differences across the groups of top acquirers. On a per-firm basis, GAFAM has completed a greater number of acquisitions than any other top acquirer. More specifically, on average, each member of GAFAM has almost three times the acquisitions of a top 25 tech company. The other two groups, Top 25 PE and Top 25 S&P, are somewhere in between.

However, the picture looks rather different if we study the pace of acquisitions across the groups. Figure 1 shows that after reaching its peak in 2014, GAFAM experienced a slowdown in its annual count of tech acquisitions. On a per-firm basis, the Top 25 PE firms have outpaced GAFAM since 2018, and the Top 25 S&P firms have exceeded GAFAM in 2018 and 2020. This similarity is noteworthy, given the wide range of industries, countries and types of firms covered by our top acquirer groupings.

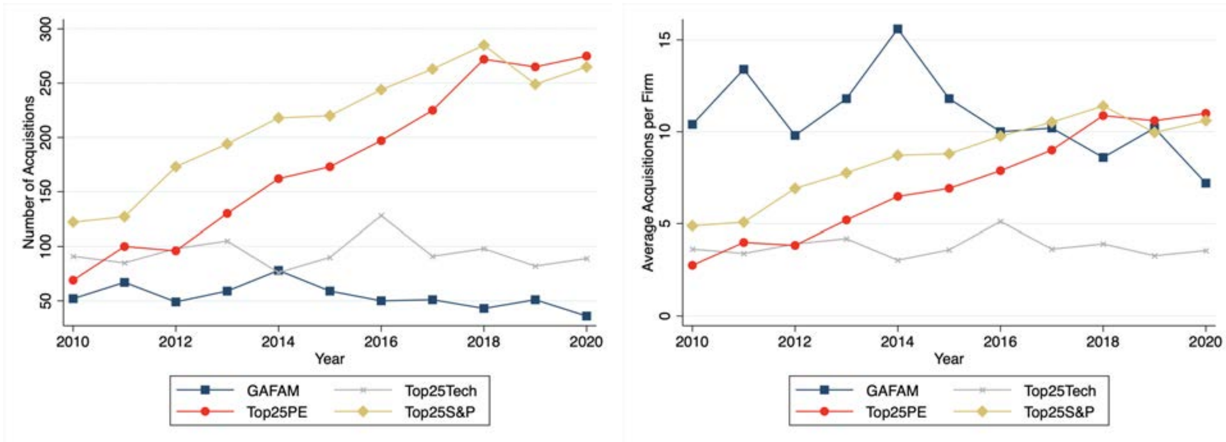
Another concern of the M&A pattern of GAFAM is the alleged tendency to acquire

Table 2: Summary of Top Acquirers' M&A Activity

	Google	Amazon	Facebook	Apple	Microsoft	GAFAM	Top 25 Tech	Top 25 PE	Top 25 S&P	All Other
Number of Acquisitions	215	66	99	100	115	595	1,033	1,964	2,360	35,844
Average Acquisitions per Firm	.	.	.	.	.	119.00	41.32	78.56	94.40	2.31
Percent of Data-intensive Targets	19.53%	22.73%	17.17%	27.00%	27.83%	22.35%	25.60%	22.20%	24.15%	17.97%
Percent of B2C Targets	27.91%	30.30%	33.33%	27.00%	15.65%	26.55%	8.37%	3.05%	3.18%	11.28%
Average Value of the Deal (M$)	900.66	411.68	3,826.17	1,005.61	2,678.34	1,548.73	1,685.65	927.27	493.85	297.94
Average Employees of Targets	618.15	427.60	20.32	387.88	1,788.24	736.92	1,183.24	1,735.25	463.55	627.85
Average Target Age (Years)	8.92	6.76	6.76	7.41	10.42	8.36	13.16	18.82	17.01	15.03
Normalized Average Target Age	0.73	0.51	0.51	0.52	0.85	0.66	0.85	1.27	1.15	0.98

Notes: The table describes the acquisitiveness of GAFAM and other groups of top acquirers, as well as some relevant features of the transactions: the average value of the transactions in millions of $, the average number of employees of the targets, the average age of the targets, and the average age of the targets normalized by the average age of targets within each level 1 category.

Figure 1: Pace of Acquisitions across Groups



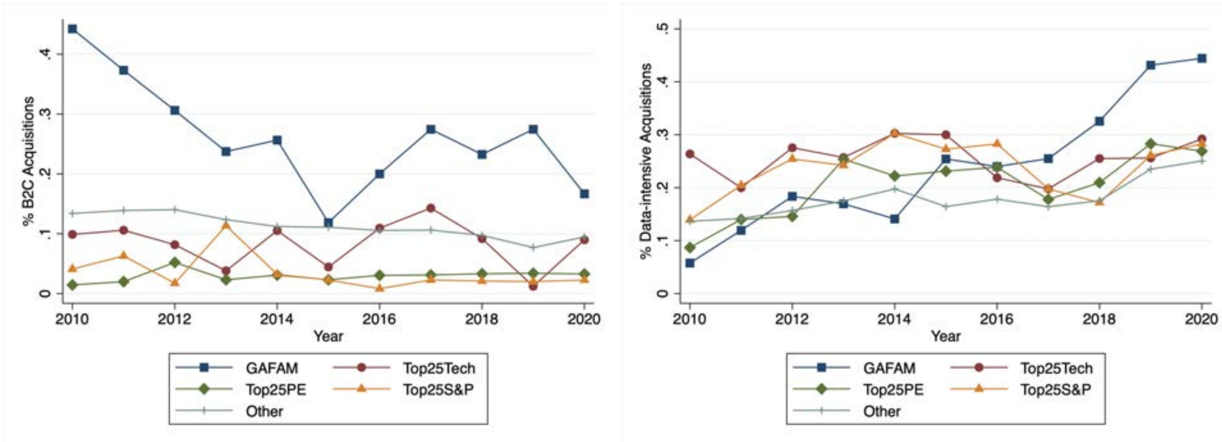
Notes: The left figure plots the total number of acquisitions completed by each group over the 11 years of the sample. As this does not account for the fact that GAFAM is a smaller group (as it only includes five companies) compared to 25 in the other top groups, the right figure plots the pattern of the average number of acquisitions per firm within each group between 2010 and 2020.

nascent targets. To assess this dimension, we compare the group-wide average age of the targets, as well as the normalized age relative to the average age of targets within the same level-1 category. As shown in Table 2, both measures suggest that GAFAM does acquire younger firms on average.

To further verify the age pattern, we regress the age of the target on a full set of dummies for each group of top acquirers, controlling for level-1 fixed effects, year fixed effects, the location of the target, and whether the target is publicly traded in a stock exchange. Results suggest that, compared to the firms acquired by any non-top acquirer, those acquired by GAFAM are significantly younger by more than four years on average. In comparison, the average target age of the Top 25 Tech group is less than three years younger than that of non-top acquirers. Top 25 PE and Top 25 S&P tend to acquire significantly older firms than non-top acquirers.[25] Furthermore, we test whether GAFAM acquires younger firms within each level-1 category. Out of the 17 level-1s in which GAFAM completed at least one acquisition, only in six cases — specifically, "Semiconductors," "Infrastructure management," "Internet content & commerce," "Communication services," "Energy & power," and "Enterprise Networking" — does GAFAM not have the lowest average target age among all

[25]See Table A.2 in the Appendix for the details of this regression analysis.

Figure 2: Pace of Acquisitions of B2C and Data-Intensive Targets across Groups



Notes: The left figure plots the percentage of B2C targets acquired by each group over the 11 years of the sample. The right figure plots the percentage of data-intensive targets acquired by each group over the 11 years of the sample.

groups. Only in one case is GAFAM the group that has the highest average age of targets ("Enterprise Networking").

The fact that GAFAM tends to acquire younger targets is consistent with the concern of "killer acquisitions" and the potential difficulty in merger reviews. As highlighted by the 2019 LEAR report, "[...] This may be problematic to the extent that there are considerable difficulties in understanding the competitive implications of acquiring a young firm, as at that stage in their life cycle their evolution is still uncertain and it is therefore very difficult to determine if the target will grow to become a significant competitive force." However, acquiring a target at a younger age does not necessarily imply an anti-competitive motive or anti-competitive outcomes. In the killer acquisition theory, for a target to be a real threat to an incumbent, it must have introduced a valuable product or service that has a significant overlap with the incumbent's business, and the acquiring incumbent must offer a price that exceeds the expected payoff of the target should it remain independent. This logic implies that killer acquisitions should be characterized by large transaction prices.

Unfortunately, most (73%) acquisitions of technology firms included in the S&P database (and Refinitiv SDC M&A database) have missing values on the dollar value of the deals. Conditional on those that have non-missing values, Table 2 shows that the average value of the GAFAM deals is higher than that of Top 25 PE and Top 25 S&P, but lower than that of Top 25 Tech. In comparison, conditional on non-missing values, which leaves only 24% of the observations, the average employment of the target in GAFAM deals is higher than that of Top 25 S&P, but lower than Top 25 Tech and Top 25 PE. Age of the target is a rather noisy proxy of deal value — their correlation is merely 0.12 in our sample. The correlation between the employment of the target and the deal value is higher (0.40), but missing values are also common for employment.[26] In short, GAFAM tends to acquire younger targets, but not necessarily have a higher deal value or greater employment at the target firm on average.

Table 2 further reports the percent of target firms that are B2C or data-intensive, for the five groups of acquirers. On average, GAFAM targets are more likely to be B2C than any other groups, and this difference is statistically significant at 95% confidence. The other top acquirers, instead, tend to acquire less B2C companies than non-top acquirers. The left panel of Figure 2 shows that GAFAM's focus towards B2C targets decreased between 2010 and 2015, although the percentage of B2C firms acquired remained higher than that of any other acquirer group in each year. In contrast, the percentage of GAFAM targets that are data-intensive is statistically similar to that of Top 25 Tech, Top 25 PE and Top 25 S&P; and all these four groups have a significantly higher percentage of data-intensive targets than the group of All Other. Although this may suggest that the frenzy towards data is common among all groups of top acquirers, the trend displayed in the right panel of Figure 2 highlights how GAFAM has been the only group of top acquirers with an increasing percentage of data-intensive targets acquired between 2010 and 2020.

Finally, as our S&P data provides information on the primary revenue model of each firm that appears in the dataset, we study the correlation between the acquisition of a B2C target and an acquirer's revenue model being based on advertising.[27] We find a positive correlation (+0.22), which is consistent with the view that firms that monetize through advertising tend

[26]Correlations are reported in Table A.1 in the Appendix.

[27]In particular, S&P classifies under a certain model (e.g., "Product sales") firms whose revenues only come from the sales of products, while firms whose revenues comes from more than one source—for example, advertising and product sales—are grouped together in a residual category.

to place higher values on consumer data, and by extension also on consumer-facing rather than business-facing target firms (Scott Morton and Dinielli, 2020b).

5 Concentration and Expansion

In this section, we study how the four groups of top acquirers concentrate or expand their acquisitions across categories in the S&P taxonomy. Of particular interest is the intersection or lack thereof between the acquirers' core businesses and the categories of their acquired firms.

According to the killer acquisition theory, for a nascent target to impose a real threat to the incumbent, its products and services must have a significant overlap with the incumbent's core business. Unfortunately, the S&P data does not include product-specific information and thus we cannot perform a formal test of market overlap. As an alternative, we use S&P level-1 and level-2 categories as a crude proxy for the potential overlap between two firms or between two transactions. The killer acquisition theory implies that the targets should belong to the same or an immediately adjacent category as the acquirer.

As a start, we test whether GAFAM acquisitions are more or less concentrated than those of other top acquirers as of the end of our sample (2020). In particular, for each acquirer in the sample, we know its total number of acquisitions from 2010 to 2020, as well as its acquisitions in each particular category. To understand how each acquirer spreads its acquisitions across categories, we apply the classical formula of Herfindahl-Hirschman Index (HHI) to the count of acquisitions. We focus on the count, in part because missing values in the S&P data prevent us from computing the dollar or employment share of acquisitions in an acquirer's M&A portfolio, and in part because many of the policy reports referenced earlier focus on the absolute counts of acquisitions by specific acquirers. Specifically, we define an acquirer-level count-based acquisition HHI as:

$$\mathrm{HHI}_i = \sum_{j \in \mathcal{J}} \left(\frac{q_{ij}}{q_i} \times 100 \right)^2, \tag{1}$$

where $\mathcal{J}$ is the set of level 1 or level 2 categories, q_{ij} is the number of acquisitions completed by firm i in category j between 2010 and 2020, and q_i is the total number of acquisitions completed by firm i between 2010 and 2020. We aggregate this measure by averaging across firms of the same group.

Table 3 summarizes the average HHI (per acquirer, as of 2020), for the five groups of acquirers. With the exception of GAFAM, Top 25 Tech, Top 25 PE and Top 25 S&P are all similar in the concentration of acquisitions across level-1 or level-2 categories. The M&A activity of All Other acquirers is rather concentrated, because most of them completed few acquisitions between 2010 and 2020. GAFAM acquisitions are significantly less concentrated across categories, and its gap to any other group increases if we use level-2 rather than level-1 categories to compute the HHI. This suggests that GAFAM spreads its acquisitions not only across but also within each level-1 category.

To further study this, we zoom into the five level-1 categories where GAFAM completed the highest number of acquisitions between 2010 and 2020, and compute the HHI across level-2s within each of those level-1s. As shown in the last panel of Table 3, GAFAM acquisitions are still less concentrated than any of the top acquirer groups, within each of the five level-1s except for "Infrastructure Management" where GAFAM's HHI is similar to that of Top 25 S&P.

Since our HHI measure depends on the relative number of acquisitions completed by each individual firm in a grouping, the group average can be inflated by acquirers with few deals. To address that, Table A.4 reports that our results are robust when we focus on a subsample that only includes acquirers with at least ten acquisitions. As a further robustness check, we use an alternative statistical measure of the extent to which acquirers disperse their acquisitions across different categories, utilizing the Shannon entropy measure (Shannon, 1948), and obtain analogous results.[28] In particular, we compute the Shannon entropy of acquirer i as $E_i = -\sum_{j \in \mathcal{J}} (\frac{q_{ij}}{q_i}) \log \left((\frac{q_{ij}}{q_i}) \right)$, which implies that the measure is higher for

[28]Shannon entropy, which is widely used in information science, has also been used in the economics literature. For example, the measure has been used as an index of product variety (Straathof, 2007), and as a measure of app users' level of multitasking (DeVaro et al., 2018).

acquirers whose acquisitions are uniformly spread over a larger number of categories than those who are uniformly spread over a smaller number of categories. In addition, both our HHI and Shannon entropy measures have the appealing property of not being affected by the number of acquisitions. To see this, note that they remain unchanged when all acquisitions in each category double.

This analysis is relevant for ongoing antitrust debates in two ways. First, we acknowledge that level-2 categories are likely different from the typical market definitions concerning relevant antitrust markets. That being said, if the level-2 categorization is not too far from the antitrust market definition, or if firms within the same level-2 category face less difficulty entering the relevant antitrust market, then the lesser concentration of GAFAM acquisitions may alleviate some of the concern out of the large number of GAFAM acquisitions, as the increase in the acquirer's market power may have been limited within each level-2 category. Second, GAFAM's widespread acquisitions may signal a desire to expand beyond their core businesses. This could be pro-competitive if they represent GAFAM's entry into new areas of competition, or anti-competitive if they end up dissuading other entrants (as described in the "kill zone" theory) or making it more difficult for other competitors to access complementary inputs (as described in the foreclosure or raising-the-rival's-cost theory).

Table 3 describes how an acquirer concentrates or spreads their acquisitions up to 2020 across S&P categories. However, the table does not specify how distant the acquisitions are from the acquirer's core business, nor does it tell us how each acquirer completes the series of acquisitions over time.

To answer these questions, we first define whether the target operates in the acquirer's core business. For each acquirer in our data, we know its primary category (level-1 and level-2) at the beginning of the sample. For instance, this is "Internet content & commerce (level-1) / Social networking & collaboration (level-2)" for Facebook, or "Mobility (level-1) / Mobile devices (level-2)" for Apple. Combining this with the categorization of the target, we define the acquirer and the target as "unrelated," if the level-1 category of the target is different from that of the acquirer. For example, any acquisition completed by Apple

Table 3: GAFAM and other groups concentration (HHI) across Level-1s, Level-2s, and across Level-2s within Top GAFAM Level-1s

	Level-1s			
	mean	sd	min	max
GAFAM	1,530.28	92.64	1,390.67	1,625.12
Top 25 Tech	3,257.51	2,521.99	1,093.75	10,000.00
Top 25 PE	2,693.75	1,757.98	1,088.39	10,000.00
Top 25 S&P	3,277.79	1,765.54	1,368.15	7,997.63
Other	8,640.07	2,394.55	1,005.92	10,000.00

	Level-2s			
	mean	sd	min	max
GAFAM	455.27	107.60	336.38	609.12
Top 25 Tech	1,700.09	2,128.85	453.65	10,000.00
Top 25 PE	1,451.70	1,966.04	389.18	10,000.00
Top 25 S&P	1,512.10	1,571.16	311.91	6,406.49
Other	8,142.79	2,861.36	498.61	10,000.00

	Within Top Level-1s			
	GAFAM	Top 25 Tech	Top 25 PE	Top 25 S&P
Application Software	1,517.32	3,871.53	4,139.19	3,498.38
Information Management	4,300.81	6,621.31	6,489.98	6,568.01
Infrastructure Management	5,786.37	7,149.41	6,224.09	5,733.12
Mobility	5,346.39	6,978.89	6,559.34	6,809.32
Systems	3,323.30	7,878.28	6,197.92	6,737.47

Notes: For each group, concentration is measured through the average HHI across group members, where the HHI of each firm is computed as in Equation (1). The top panel summarizes groups' concentration across level-1s; the middle panel across level-2s; and the bottom panel considers concentration across level-2s within the five level-1s in which GAFAM completed the greatest number of acquisitions.

involving a target belonging to a level-1 different from “Mobility” would be categorized as unrelated. Moreover, an acquisition is “adjacent” if the acquirer and the target share the same level-1, but differ in the level-2 category. For example, if a target acquired by Apple belongs to ”Mobility / Applications,” this would be an adjacent acquisition. The last case concerns acquisitions within the same level-2 category. Continuing Apple’s example, any acquisition in which the target belongs to “Mobility / Mobile devices” will be a “same” acquisition for Apple.

The top panel of Table 4 shows that GAFAM is the group that acquires the least in “same” and the most in “unrelated,” suggesting that GAFAM tends to reach categories far away from their original core business in 2010. At the same time, Top 25 Tech is the group that invests the most in adjacent acquisitions, so that their expansion is more concentrated around their original core business. Finally, Top 25 PE has a remarkably high percent of “same” deals, suggesting that some top PE firms may specialize in particular level-2 categories.

Figure 3 shows the pattern of same, adjacent and unrelated acquisitions across different groups. Compared to other groups of top acquirers, the curve of “same” acquisitions flattens out relatively early for GAFAM — i.e., around the second quarter of 2014 — and their pace of adjacent acquisitions is lower than that of other groups.

This static description abstracts from the fact that the set of adjacent categories expands as the acquirer enters new unrelated level-2s via M&A. To account for this, we conduct a dynamic analysis, where each acquirer’s core level-1 and level-2 business expands every time an adjacent or unrelated acquisition is consummated. For example, suppose Apple first acquired a target in “Information management / info retrieval” and then another target in “Information management / Data management.” Under the previous static approach, both acquisitions would have been categorized as unrelated. However, under the new dynamic approach, we would categorize the first acquisition as unrelated, but the second one as adjacent. Furthermore, we distinguish acquisitions within the “same” grouping: “same original” acquisitions are those in the same level-2 category as the acquirer’s original core business as of 2010, and hence coincide with the "same" of the static approach; "same new" are all the others.

The second panel of Table 4 summarizes the dynamic characterization of acquisitions, by same original, same new, adjacent, and unrelated, for all four groups of top acquirers. Compared to the static description in the first panel, we find that GAFAM has the lowest percentage in same original, but the highest in same new and adjacent. As a result, GAFAM's fraction of unrelated acquisitions is the lowest under the dynamic approach, though it is the highest under the static approach. This pattern suggests that, on average, each member of GAFAM achieves a widespread category coverage by first acquiring targets in adjacent categories and then expanding around them, rather than acquiring in unrelated categories all of the time.

This interpretation is consistent with Figure 4, which plots the cumulative number of same original, same new, adjacent and unrelated acquisitions (under the dynamic approach) for all four groups of top acquirers. For GAFAM, the unrelated and same original curves flatten out relatively early, while the curves for adjacent and same new continue to increase through 2020. This is in sharp contrast to the other groups of top acquirers, who all have a smaller gap between the adjacent and unrelated curves than GAFAM. More specifically, other top acquirers tend to keep investing in their original core businesses, and their expansions do not rely as much as GAFAM on the apparent strategy of "step-by-step" expansion into adjacent categories.

One may argue that these summary statistics may reflect omitted variables rather than a distinction of acquisition strategy between GAFAM and other top acquirers. To address this, Table 5 reports a few binary logit regressions, where the unit of observation is an acquisition, and the dependent variable is whether the acquisition is of a particular type (unrelated, adjacent, same original, or same new under the dynamic approach), controlling for level-1 fixed effects (of the acquirer), year fixed effects, the location of the target, and whether the target is publicly traded.

The results suggest that, compared to all other non-top acquirers (the default), being

Table 4: Acquisitions by Distance from Acquirer's Category

STATIC

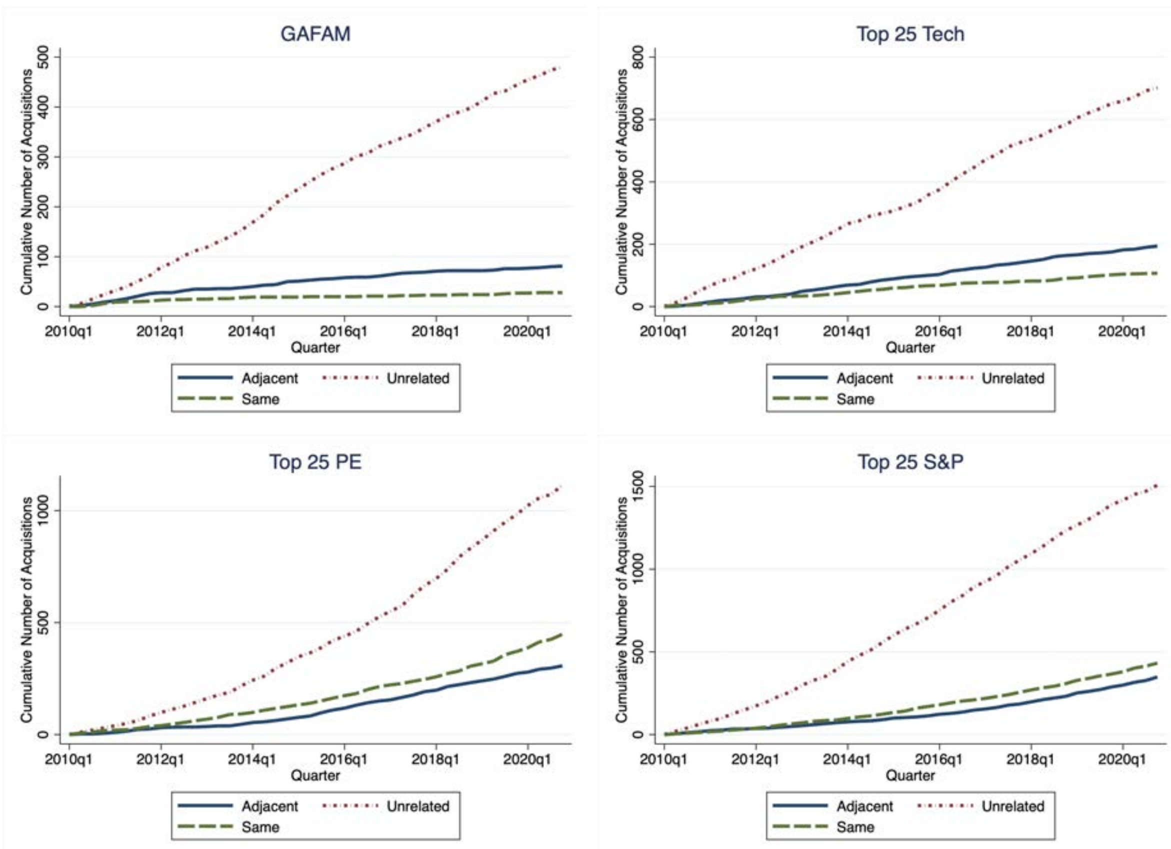
Distance	GAFAM	Top 25 Tech	Top 25 PE	Top 25 S&P
Adjacent	82	199	323	362
	(13.80%)	(19.26%)	(16.45%)	(15.34%)
Same	28	112	473	454
	(4.71%)	(10.84%)	(24.08%)	(19.24%)
Unrelated	485	722	1,168	1,544
	(81.61%)	(69.89%)	(59.47%)	(65.42%)

DYNAMIC

Distance	GAFAM	Top 25 Tech	Top 25 PE	Top 25 S&P
Adjacent	173	255	388	458
	(29.12%)	(24.96%)	(19.76%)	(19.41%)
Same Original	28	112	473	454
	(4.71%)	(10.84%)	(24.08%)	(19.24%)
Same New	332	486	770	1,176
	(55.89%)	(47.05%)	(39.21%)	(49.83%)
Unrelated	62	180	333	272
	(10.42%)	(17.42%)	(16.96%)	(11.53%)

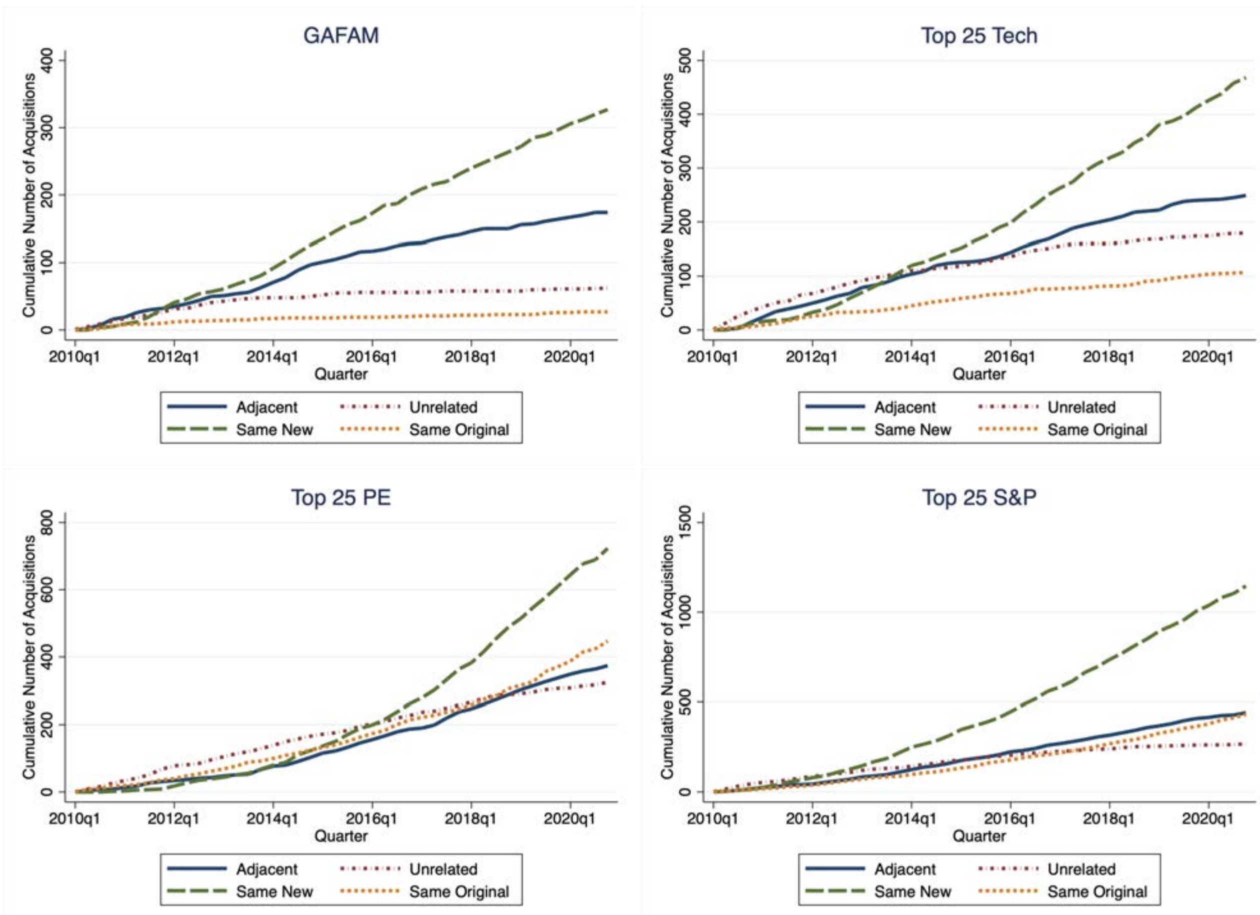
Notes: The top panel presents the number of acquisitions by the distance of the target from the acquirers under the static approach. Percentages of the total number of acquisitions are reported in parentheses. The bottom panel presents the same information under the dynamic approach, where the additional distance "Same new" includes acquisitions in which the targets operate in a level-2 that is the same as the one to which the acquirer had expanded through prior acquisitions in the sample.

Figure 3: Cumulative Acquisitions Over Time by Distance: Static



Notes: Each figure plots for one of the top groups the cumulative number of acquisitions in each quarter grouped by the 'distance' of the target's category from the acquirer's one under the static approach.

Figure 4: Cumulative Acquisitions Over Time by Distance: Dynamic



Notes: Each figure plots for one of the top group the cumulative number of acquisitions in each quarter grouped by the 'distance' of the target's category from the acquirer's under the dynamic approach.

Table 5: Likelihood of an Acquisition and Distance from the Core-business

VARIABLES	(1) Unrelated	(2) Adjacent	(3) Same Original	(4) Same New
GAFAM	-0.302***	0.123***	-0.221***	0.456***
	(0.00997)	(0.0194)	(0.00960)	(0.0181)
Top25 PE	-0.220***	0.00616	-0.0294***	0.241***
	(0.00852)	(0.00955)	(0.00986)	(0.0103)
Top25 S&P	-0.187***	0.0121	-0.0818***	0.252***
	(0.00821)	(0.00859)	(0.00833)	(0.00962)
Top25 Tech	-0.230***	0.0653***	-0.165***	0.355***
	(0.0105)	(0.0141)	(0.00974)	(0.0143)
Observations	41,742	41,657	41,736	41,704

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Columns (1) to (4) report the correlation between being acquired by a top group — compared to being acquired by any other firm — and the probability that the category of the target is unrelated, adjacent, the same as the original one of the acquirer, or the same as one of the categories in which the acquirer had previously expanded in the sample, respectively. In all of the logit regressions in the table we include level-1 and year fixed effects, and we control for the location of the target and for whether the target is a public entity.

acquired by GAFAM increases the probability of the acquisition being adjacent by 12% and the probability of being "same new" by 45%. These probabilities are larger for GAFAM than for any other group of top acquirers. In addition, all groups of top acquirers are less likely to engage in unrelated acquisitions than the default, but this gap in likelihood is the largest for GAFAM. In short, the regression results confirm the impression that GAFAM follow an uncommon "step-by-step" strategy to expand into adjacent and unrelated categories.

6 Overlapping Expansion via M&A

Given that we observe top acquirers complete most of their acquisitions outside their core business areas and expand into new categories, a natural question is whether they also acquire in the same "direction," and, in particular, in the same S&P categories. Assuming an acquirer's first acquisition into a new category coincides with its entry into that category, an observation that more top acquirers consummate their first acquisitions in the same categories may imply more *potential* competition among these acquirers.

We begin this section by investigating the extent to which top acquirers expand in the same S&P categories, and hence potentially enter via M&A as well as potentially compete in new business areas of the ICET space. It is important to emphasize that because our dataset does not provide information on the extent to which top acquirers effectively compete in a given category after having acquired in it, nor on how acquirers may utilize targets' assets, we focus on potential rather than actual competition.

For example, an acquirer could add a target's products and services to its offerings or shut some or all of them down post-acquisition. While the former is consistent with increased competition in the category, this is not necessarily the case for the latter, which could be pro- or anti-competitive if the target's assets are integrated into the acquirer's ecosystem or anti-competitive if the deal is a killer acquisition. It is also worth highlighting that acquisition is only one of many possible ways through which a company may enter a given category (e.g., entry may happen via in-house R&D). This implies that increases in the extent to which top acquirers acquire in the same direction do not always translate into increased competition. In addition, the categories defined by S&P do not necessarily align with relevant antitrust markets, but it is possible that firms that have entered an S&P category via M&A face less of a barrier to enter antitrust markets within or near this category. In this sense, an overlap of M&A in the same category may facilitate potential competition among acquirers in or near that category.

As a start, Figure 5 depicts the percentage of level-2 categories which 0, 1, 2, 3 or all 4 groups of top acquirers have acquired in a given year. We consider 178 level-2s, which is the total number of level-2s in which at least one top acquirer made any acquisition up through 2020. Two main forces are at play: First, each acquirer (or a specific group of acquirers) may 'enter' new level-2s via M&A over time, thus reducing the extent to which their level-2 'territories' overlap with those of other top acquirers (who may not acquire in the same new level-2s). Second, other top acquirers may acquire in the level-2s in which another top acquirer had already consummated an acquisition, thus increasing the degree of overlapping. The presence of the first effect can be seen from the fact that, at any point in time, there are always roughly 35 level-2s in which only one group of top acquirers acquired.[29] Driven by the second force, the share of the level-2s in which two or more top groups acquired increased over time, reaching roughly 80% of all of the 178 level-2s as of the end of 2020.[30]

We follow the same logic in describing entry via M&A in overlapping categories within GAFAM. The same forces are at play, but this time we observe a greater extent to which a GAFAM firm expands into new level-2 categories. Figure 6 shows that, out of all of the level-2 categories that would see at least one GAFAM acquisition by the end of 2020, roughly 20% had acquisitions by only one GAFAM firm as of 2010. This number increased to more than 30% in the next two years, and remained constant from 2013 to 2020. In comparison, the number of level-2s in which two or more GAFAM firms acquired is increasing over time, from being less than 15 in 2010 to more than 50 in 2016, and more than 60 in 2020. This suggests that, while individual members of GAFAM continue to acquire in new level-2s in which other members have not, they are more and more likely to see each other acquiring in the same level-2s over time.

Figure 7 depicts the same phenomenon in a different way. For each year from 2010 to 2020, the lower (blue, with squares) line plots the average number of GAFAM firms that were present in a level-2 category — via original business coverage or through M&A — conditional on all the level-2s that had at least one GAFAM member's acquisition up to that year. For example, in 2010, GAFAM firms acquired in 30 level-2 categories, and on average, only 1.2 GAFAM firms acquired in each of these level-2s. Fast forward to 2020,

[29]Note that this does not mean that there is only one top acquirer, as possibly several firms belonging to the same top group may have acquired.

[30]Figure A.3 in the appendix provides another representation of the extent of potential competition among the groups of top acquirers over time. In each year, the size of each bubble is proportional to the cumulative number of acquisitions completed by the respective top acquirer group up to that year, inclusive. The figure thus describes how potential competition among top acquirers evolved over the years across level-1s, depicting the categories in which top acquirers tend to focus their acquisitions, as well as categories where potential competition among them is more intense. For example, the figure suggests that GAFAM members are particularly frequent acquirers in the "Mobility" category, whereas Top 25 Tech tend to acquire relatively more in "Communications Services."

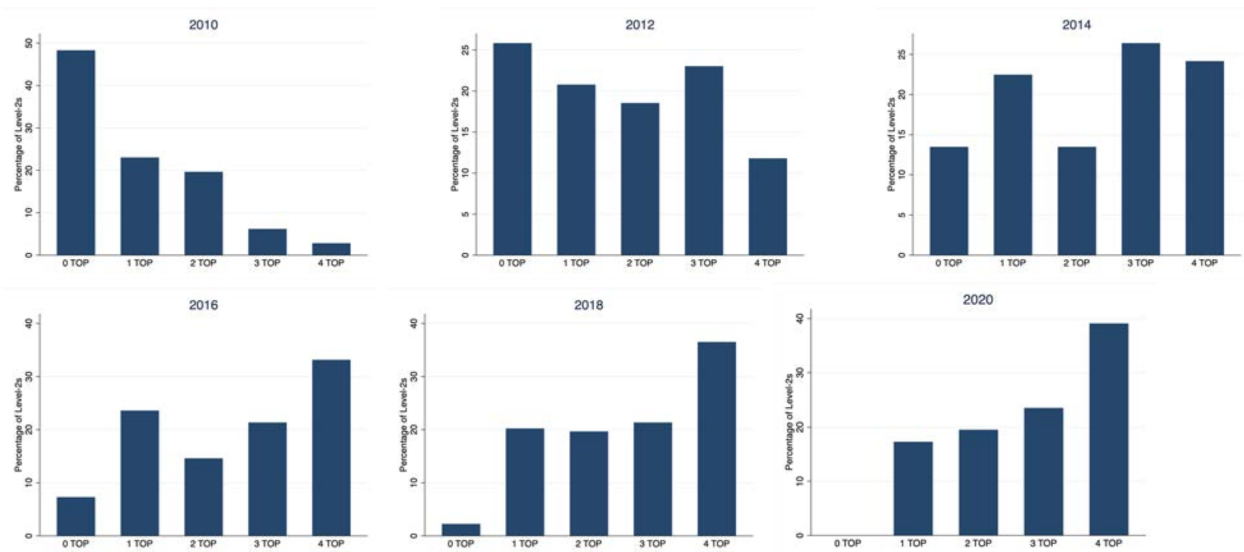
GAFAM firms acquired in 100 level-2s and each of these level-2s is associated, on average, with 2.3 GAFAM firms that acquired in it. Similarly, the upper (red, with circles) line plots the average number of top groups per level-2 category, conditional on the level-2s that had an acquisition from at least one top group up till the year in question. By definition, both lines are conditional on GAFAM or another top group's acquisition presence, so the lowest possible value is one, while the highest possible value is 5 for GAFAM, and 4 for the count of groups of top acquirers.[31]

The two lines in Figure 7 are remarkably similar in their upward trends, despite a different starting point in 2010. Nonetheless, while the top line depicting the average number of top groups is monotone over time, its increase has slowed down in the second half of the sample. The bottom line depicting the average number of GAFAM members demonstrates more steady growth between 2011 and 2019, but slightly declines from 2019 to 2020. Although each point on the two lines is based on cumulative acquisitions up to the year in question, a line could slope downward from year t to $t+1$ if the groups or group members venture more into acquisitions in new level-2s than acquire in the categories in which other firms or groups have already acquired. In short, both lines in Figure 7 suggest that more GAFAM firms and more groups of top acquirers overlap in the categories of their acquisition targets. To the extent that these acquirers would continue to offer the target firms' products or services post acquisition, it implies that more and more top acquirers may potentially compete against each other in these categories.

These graphs focus on the extent to which top acquirers acquire in the same S&P categories over time. However, it does not articulate the sequence of entry by acquisition, which seems the center of some antitrust concerns. In particular, acquisitions made by an incumbent — in its own core business or in an adjacent/unrelated category — may affect the incentives of other firms to acquire in those categories. Since acquisition is one way to

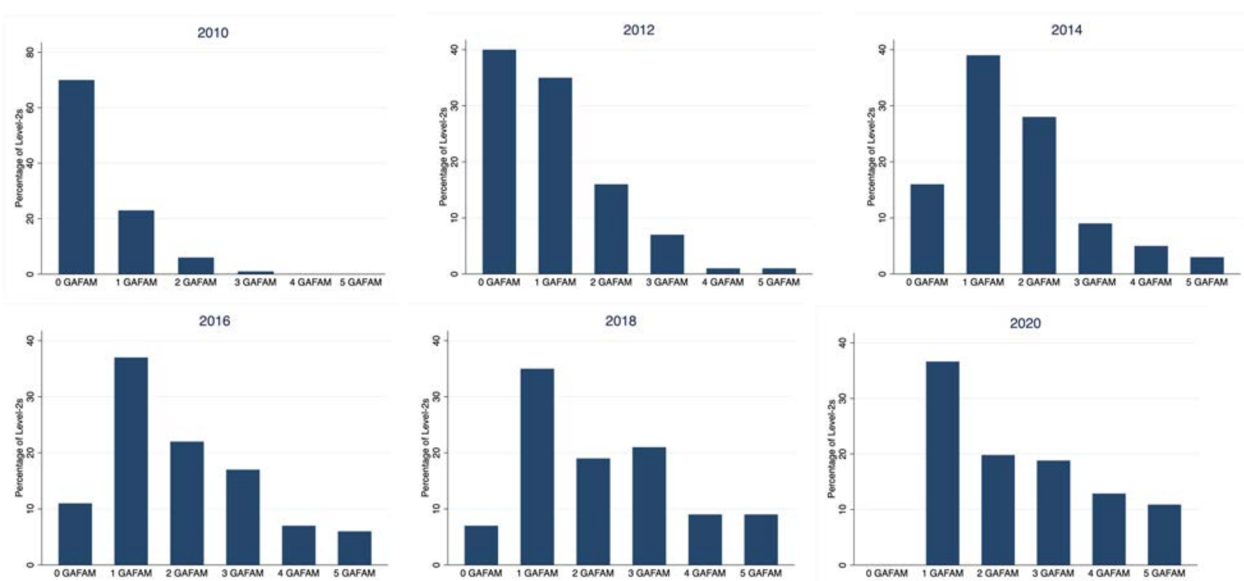
[31] Similar to Figure A.3, Figure A.4 in the appendix describes how potential competition among GAFAM firms evolved over the years across level-1s. For example, while Google (Alphabet) had the most acquisitions among the GAFAM members in the "Mobility" category, in other categories, such as "Internet Content & Commerce," other GAFAM members acquired at a pace similar to Google's.

Figure 5: Top Groups Overlapping Across Level-2 Categories



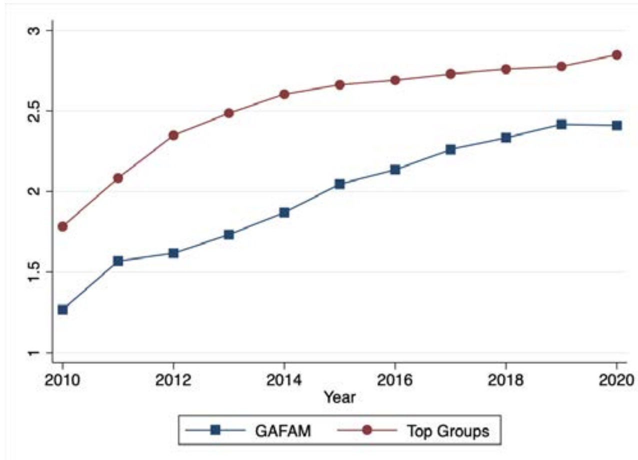
Notes: Top groups acquired in 178 level-2 categories between 2010 and 2020. This figure describes the distribution of the number of top group acquisitions across all the categories in which at least one top group acquired as of 2020.

Figure 6: GAFAM Overlapping Across Level-2 Categories



Notes: GAFAM acquired in 100 level-2 categories between 2010 and 2020. This figure describes the distribution of the number of GAFAM acquisitions across all the categories in which at least one GAFAM acquired as of 2020.

Figure 7: Average Number of GAFAM and Top Groups in a Level-2 Category



Notes: The figure plots in each year the average number of GAFAM members across the level-2 categories into which at least one GAFAM had acquired up to that year, and the average number of top groups across the categories into which at least one top group had acquired up to that year. These measures assume that only GAFAM or top groups can acquire in any level-2 category, so that the lowest possible value of for both is one, while the highest is 5 for the average number of GAFAM, and 4 for the average number of top groups.

enter a category, the incumbent's acquisitions can affect the incentives of other acquirers to acquire in the same categories.

In theory, the effect on acquisition incentives can be positive or negative. On the positive side, a large incumbent acquiring in an unrelated category could stimulate other firms to acquire in the same category, because it may signal a high potential of growth in that category. On the negative side, it could also deter other firms from entering, if they anticipate that competition against a large established incumbent would be challenging and unprofitable (akin to the kill zone theory). To the extent that the same level-2 category also covers complementary inputs (rather than products and services in direct horizontal competition), a negative perception could arise if other firms anticipate more difficulty to access complementary inputs produced by the category that the incumbent has entered (akin to the foreclosure or raising-rivals'-costs theory).

Given this ambiguity, it would be interesting to uncover the empirical correlation between GAFAM's entry in a category and future M&A of other acquirers in that same category. To do so, we adopt a Difference-in-Differences (DiD) design, where the unit of observation is a level-2 category in a given year. We define a level-2 category as "treated" in a certain year if GAFAM has made at least one acquisition in that level-2 in or before that year. For example, Facebook was the first GAFAM firm to acquire a target in "Application Software / Business intelligence;" in our design, this level-2 category is defined as treated starting from the beginning of 2014, while it is considered as "not-yet-treated" before 2014. Categories in which GAFAM firms did not acquire are considered "untreated."[32] We then study whether this tag of treatment is correlated with the number of other acquirers that would make any acquisition in the same category (for the first time) on or after an acquisition by a GAFAM firm. We consider a firm to be a new acquirer in a target's level-2 category if the acquirer had not made any prior acquisitions in that category.

Under this setup, the main econometric challenge is the staggered nature of treatments, since GAFAM firms acquired in different level-2 categories in different years. To address this issue, we follow the approach developed in Callaway and Sant'Anna (2021), which allows us to recover time-specific average treatment effects on the treated (henceforth, ATT). In particular, suppose a level-2 category (i) had the first GAFAM acquisition in year t_1. Conceptually, the treatment may have an effect for i in any year $t_2 \geqslant t_1$. Hereafter, we refer to t_1 as the category's treatment-starting year, and t_2 as the calendar year of effect. Following Callaway and Sant'Anna (2021), we can estimate the average effect by t_1, t_2, or length of treatment exposure ($t_2 - t_1$). Note that we interpret the estimated ATT as a correlation rather than a causal effect (Peukert et al., 2022), though we borrow the method and language from the causal impact literature for ease of illustration.

Due to the lack of a pre-treatment period, in order to estimate time-specific ATTs, we drop all level-2 categories in which GAFAM firms acquired in 2010 — which reduces the number of level-2 categories to 170 — and keep all level-2 categories in which GAFAM firms have not yet made an acquisition up to that year as the pool of potential controls. Compared to traditional DiD approaches, which only consider never-treated units as potential controls,

[32] In particular, as our sample runs from 2010 to 2020, for a level-2 category to be "treated" in a certain year, we require that an acquisition by a GAFAM firm happened between 2010 and that year. In the same way, a level-2 with no GAFAM acquisitions after 2010 is consider "untreated."

this approach increases the size of the control group (Goodman-Bacon, 2021).[33] As it might affect GAFAM firms' decisions to initially acquire in a given level-2 category, we include the "size" of the level-2 category — approximated by the total number of acquisitions completed in 2010 — as a covariate and weight every control unit based on a propensity score.[34] We then implement the doubly robust estimator described in Sant'Anna and Zhao (2020), clustering standard errors at the level-2 categories and computing them using a multiplier bootstrap with 1,000 iterations.[35] Finally, as we are interested in the overall correlation between first-time GAFAM acquisitions in any category and the subsequent pace of entry via acquisitions in that same category, we aggregate time-specific ATTs by treatment-starting year or the year of effect.[36]

Table 6 presents the weighted average ATT across all treatment-starting years, using weights proportional to the number of treated categories in each treatment-starting year. Regardless of whether we use not-yet-treated units or never-treated units only in the comparison group, we find no evidence of significant negative correlation — the correlation is actually positive and significant at the 95% level — between an initial acquisition by a GAFAM firm in a level-2 category via M&A and the number of other firms making a first acquisition in the same level-2 categories afterwards.

However, as the correlation may be dynamic, our preferred method aggregates time-specific effects into an event study plot by different years of exposure since GAFAM's initial acquisitions in the treated level-2 categories. Figure 8 suggests that the parallel trends hypothesis holds in the pre-treatment periods, and that an initial GAFAM acquisition is

[33] In our robustness checks we also use only never-treated level-2 categories as controls and the results continue to hold. In this way, we account for the fact that level-2s within the same level-1 can be related, and hence treatment in one level-2 could contaminate another level-2 in the same level-1.

[34] The propensity score describes how a control level-2 category is comparable to the treated level-2 categories in the total number of acquisitions completed in 2010. In particular, it indicates the probability that a level-2 category's treatment-starting year is t, conditional on the total number of acquisitions completed in 2010.

[35] The described procedure can be implemented using the R `did` package, as explained in Callaway and Sant'Anna (2021).

[36] All level-2 categories-year ATTs are reported in Figure A.5 of the Appendix. One should be cautious when interpreting the ATTs for those of treatment-starting year 2015 to 2020, as they are "small groups," i.e., groups with five or fewer level-2 categories (Callaway and Sant'Anna, 2021). Note that this has no impact on the interpretation of the other time-specific ATTs, nor the aggregated ones.

Table 6: ATT with Simple Aggregation

Control Group	ATT	Std. Error	[95% Conf.	Int.]
Not-yet-treated	6.206	2.145	2.001	10.411
Never-treated	6.001	2.146	1.7949	10.2072

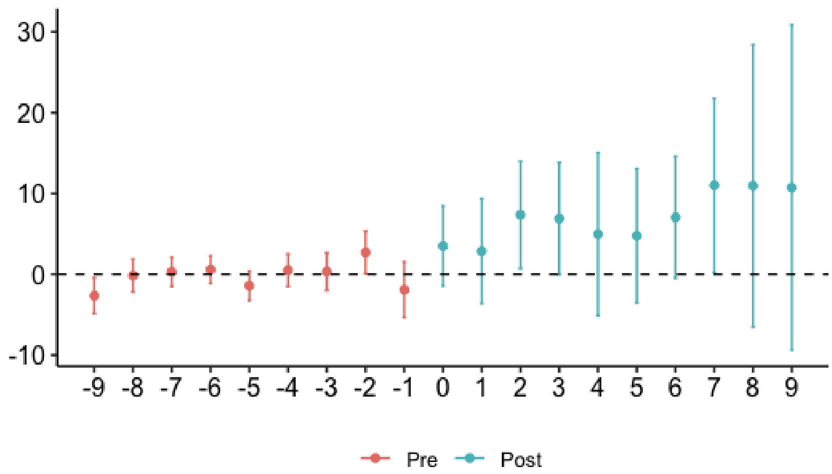
Notes: The table reports a weighted average ATT across all treatment-starting years, with weights proportional to the number of treated categories in each treatment-starting year. The first line reflects estimates using not-yet-treated units as controls, and the second line uses only never-treated units as controls. In both cases we find no evidence of significant negative correlation — correlation is actually positive and significant at the 95% level — between GAFAM entry in a level-2 category via M&A and the number of new firms acquiring in the same level-2 categories afterwards.

generally not significantly correlated with the number of new acquirers in a level-2 category. The only exception is the positive correlation displayed in the second year after an initial GAFAM acquisition in a level-2 category. However, two dynamics may affect our estimates. First, we do not observe divestitures, which implies that we do not observe whether new acquirers in a level-2 category after a GAFAM acquisition divested afterwards. To account for this effect, we repeat the analysis excluding from the sample all private-equity (PE) firms, which are most likely to divest after an acquisition.[37] The results are reported in Figure A.7 and are consistent with our main finding of the absence of a slowdown in the number of new, non-GAFAM acquirers. Second, our treatment does not capture the intensity of GAFAM entry via acquisition in a level-2 category, in that it does not account for the fact that the correlation between GAFAM's initial M&A activity in a level-2 and the number of new acquirers in that level-2 could change after the first $n > 1$ GAFAM acquisitions. To check the robustness of our results, we consider an alternative treatment in which we define a level-2 category to be treated in a certain year if GAFAM had made at least two acquisitions in that level-2 by that year, inclusive. Figure A.8 demonstrates that our finding is also robust to this alternative design.

As shown in Figure 9, we also aggregate time-specific ATTs by treatment-starting year and the calendar year of the effect, respectively. The average effect by treatment-starting year

[37] In fact, in our sample we observe only 17 cases in which a non-PE firm acquires a target entity and this entity is later acquired by a different acquirer.

Figure 8: Dynamic Correlations: Average Effect by Length of Exposure



Notes: The figure plots average treatment effects by different length of exposure since GAFAM's first acquisitions in each treated level-2 category (x-axis). Length of exposure equal to 0 refers to the year when GAFAM's first acquisition occurred. Length of exposure equal to -1 corresponds to the year before GAFAM's first acquisition, and length of exposure equal to 1 corresponds to the year after.

shows that for most cases the correlation is insignificant. However, for the level-2 categories in which GAFAM first acquired in 2012, an initial GAFAM acquisition is correlated with an average of roughly ten more new acquirers per year in the following years. This effect is significantly different from zero with 95% confidence.[38]

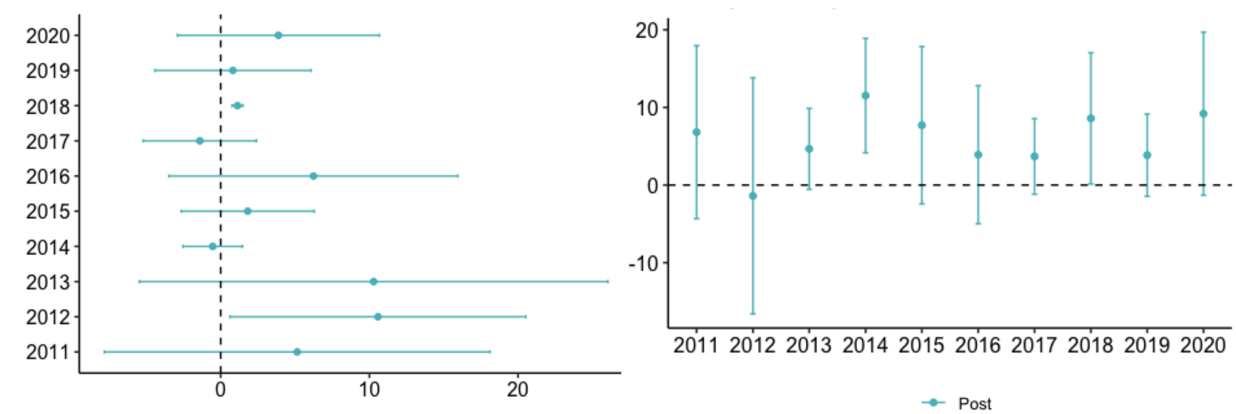
The ATTs by the calendar year of effect suggests that, in all sample years except for 2014, there was no correlation between an initial GAFAM acquisition and the number of new acquirers in the treated level-2 categories, while in 2014 the correlation was positive and significant.[39] One potential explanation for these results is that an initial GAFAM acquisition in a level-2 category may convey a positive signal about the profitability of the category, thus stimulating other firms to pursue acquisitions in the category. At the same time, it is also possible to observe a positive correlation when both GAFAM and other companies simultaneously receive positive signals about the profitability of a category, but

[38]A similar interpretation could potentially apply to groups 2016 and 2018; however, as previously indicated, the interpretation in these cases is more difficult given that these groups are small.

[39]We check the robustness of our results to a different comparison group in which we only include those level-2 categories with no GAFAM acquisitions between 2010 and 2020. Figure A.6 in the Appendix shows that the average effect by length of exposure, treatment-starting year, and the calendar year of effect, are all consistent with those obtained when including not-yet-treated level-2 categories in the pool of potential controls.

Figure 9: ATTs by Treatment-Starting Year and Calendar Year of Effect

(a) Average Effects by Treatment-starting year (b) Average Effects by Calendar Year of Effect



Notes: The left figure plots average treatment effects (ATTs) by treatment-starting year, i.e. the year in which GAFAM first acquired in a level-2 category. Each line in this figure displays the average and confidence interval of ATTs (x-axis) across all level-2 categories that became treated in a specific treatment-starting year (y-axis). The right figure plots ATTs by calendar year, where the x-axis is the year of effect and the y-axis is the average effects of being treated in that year for all level-2 categories that experienced a GAFAM acquisition in or before that year. Both figures aggregate estimated ATTs using not-yet-treated units as controls.

perhaps because GAFAM has greater and easier access to liquidity, and/or larger and better positioned M&A teams and procedures, it is able to acquire in those categories first. For this reason, we caution that all ATTs reported in this paper reflect correlation rather than causal impact (though we borrow the method and some corresponding language from the causal impact literature).

To sum up, the results presented suggest the absence of a correlation between GAFAM acquisitions in categories and a slowdown in the number of new acquirers in the same categories afterwards. In net, as far as our dataset and analyses indicate, the results seem inconsistent with competition concerns regarding kill zones, foreclosure, or raising rivals' costs, though of course, we cannot rule out the possibility that these concerns do exist but may be associated by non-majority transactions or are potentially cancelled out or affected by the potential positive signal that GAFAM acquisitions may convey about the profitability of the target category.[40] Similarly, since our estimate for a treatment-starting year reflects

[40] As we cannot separate between vertical and horizontal mergers in our data, we cannot test a specific theory of harm.

an average across all the level-2s that have the first GAFAM acquisition in the same year, we cannot rule out that the absence of a significant correlation is because the true impact of GAFAM entry via M&A is positive in some level-2s but negative in others — we do not have evidence for or against this possibility. It is also important to note that our analysis is limited to an acquiring firm's first acquisition in a level-2 category; the firm, of course, could enter the category organically via internal R&D, and we do not know how or whether such internal R&D efforts may relate to GAFAM acquisitions in that category.

7 Conclusion

The M&A activity of the top technology platforms has been at the forefront of recent antitrust debates. By using a unique technology taxonomy developed by S&P Global Market Intelligence, we offer a deep dive into this dataset, and help inform the debates in several ways. We examine whether GAFAM and other groups of top acquirers differ in their acquisitions in terms of the nascency, reliance on data, and customer-orientation of the target firms they acquire. We find that GAFAM's targets are more likely to be younger and consumer oriented. Although the apparent M&A frenzy towards data-intensive target firms appears to be common among all groups of top acquirers, GAFAM firms have consistently increased the focus of their M&A activity towards data-intensive targets, especially after 2016. We further find that GAFAM's acquisitions are significantly less concentrated across target technology categories than any of the other top acquirer groups we consider.

At the same time, while it may be argued that acquisitions by GAFAM firms, as the larger incumbents, could amount to claiming competitive turf in the target firms' categories, and could consequently deter entry by competitors into those categories, our findings suggest otherwise: we do not find evidence indicating that GAFAM entry via acquisitions in categories, in comparison to similar categories in which GAFAM has not yet acquired, are correlated with any slowdown in the number of new acquirers acquiring in the same categories after the initial acquisitions by GAFAM. In addition, our findings demonstrate that the overlap in the categories in which GAFAM members and other top acquirers acquire exhibited an upward trend over 2010-2020, and suggest that potential competition within GAFAM, as well as across top acquirer groups, have both increased.

It is important to emphasize that our examination offers aggregate statistical analyses of relationships in the dataset, whereas actual antitrust investigations would have much more detailed information on any particular acquisition. Moreover, although our findings cannot accept or reject any specific antitrust theory regarding tech acquisitions, they may have two broad implications for antitrust agencies. First, GAFAM firms are not the only large incumbents that pursue M&As in the technology sector. Both GAFAM and non-GAFAM acquirers expand their territories through M&As in adjacent and unrelated areas, away from their original core businesses. Should it be deemed needed, an evaluation of antitrust reform, as far as acquisitions by incumbents of small, young and innovative startups, would benefit from not being confined to GAFAM firms. Second, our findings do not support the stylized concern that the presence of GAFAM in a category automatically shuts down competition in that category. Our findings show that at least some other acquirers choose to acquire in the same categories as GAFAM, implying potential competition among acquirers, which may encourage entry for buyout in those categories.

Despite these insights, it is important to emphasize that our study comes with a number of empirical limitations. In particular, first, while the technology categories we consider are relatively narrow, they are not relevant antitrust markets. Second, we have sparse information on the transaction amounts and no information on firms' market shares. Third, we have no information on products and services developed internally by the acquiring firms over time. Fourth, our analysis focused strictly on majority (control) transactions and not on minority acquisitions or other types of non-majority transactions. Because the current legislative or policy focus on GAFAM may be motivated by other reasons beyond M&A patterns (such as network effects, market power concerns, antitrust history, or specific practices), our findings do not imply that the proposed or enacted legislations or reforms are groundless. Our analyses can only speak to technology acquisitions in the ICET space, which is an important part but not all of the M&A activity under the radar of antitrust authorities.

How to address these limitations and how to link our findings to anti-competitive theories are potential directions for future work. In particular, this descriptive paper points to the promise of research on competition, M&A and innovation. Future research can examine the causal effects of technology M&As on innovation, venture survival, and other market and venture outcomes, which are central to the ongoing debate.

References

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. "Competition and Innovation: an Inverted-U Relationship." *The Quarterly Journal of Economics*, 120(2): 701–728. _eprint: https://academic.oup.com/qje/article-pdf/120/2/701/5449016/120-2-701.pdf.

Andrews, Dan, Chiara Criscuolo, and Peter N. Gal. 2015. "Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries." OECD.

Argentesi, Elena, Paolo Buccirossi, Emilio Calvano, Tomaso Duso, Alessia Marrazzo, and Salvatore Nava. 2019. "Assessment of Merger Control Decisions in Digital Markets: Evaluation of Past Merger Decisions in the UK Digital Sector." Report by Lear for the Competition and Markets Authority.

Argentesi, Elena, Paolo Buccirossi, Emilio Calvano, Tomaso Duso, Alessia Marrazzo, and Salvatore Nava. 2021. "Merger Policy in Digital Markets: An Ex Post Assessment." *Journal of Competition Law and Economics*, 17(1): 95–140.

Baily, Martin Neil, and Nicholas Montalbano. 2016. "Why is U.S. Productivity growth so Slow?" The Brookings Institution Working Paper 22.

Bryan, Kevin A., and Erik Hovenkamp. 2020. "Antitrust Limits on Startup Acquisitions." *Review of Industrial Organization*, 56(4): 615–636.

Cabral, Luís M B. 2018. "Standing on the Shoulders of Dwarfs: Dominant Firms and Innovation Incentives." C.E.P.R. Discussion Papers CEPR Discussion Papers 13115.

Callaway, Brantly, and Pedro H.C. Sant'Anna. 2021. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics*, 225(2): 200–230. Themed Issue: Treatment Effect 1.

Calvano, Emilio, and Michele Polo. 2020. "Market Power, Competition and Innovation in digital markets: A survey." *Information Economics and Policy*, 54: 100853.

Chipty, Tasneem. 2001. "Vertical Integration, Market Foreclosure, and Consumer Welfare in the Cable Television Industry." *American Economic Review*, 91(3): 428–453.

Cunningham, Colleen, Florian Ederer, and Song Ma. 2021. "Killer Acquisitions." *Journal of Political Economy*, 129(3): 649–702. _eprint: https://doi.org/10.1086/712506.

DeVaro, Jed, Jin-Hyuk Kim, Liad Wagman, and Ran Wolff. 2018. "Motivation and Performance of User-contributors: Evidence from a CQA Forum." *Information Economics and Policy*, 42: 56–65.

Gautier, Axel, and Joe Lamesch. 2021. "Mergers in the Digital Economy." *Information Economics and Policy*, 54: 100890. Antitrust in the Digital Economy.

Gilbert, Richard, and David M Newbery. 1982. "Preemptive Patenting and the Persistence of Monopoly." *American Economic Review*, 72(3): 514–26.

Goodman-Bacon, Andrew. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics*, 225(2): 254–277.

Kamepalli, Sai Krishna, Raghuram Rajan, and Luigi Zingales. 2020. "Kill Zone." National Bureau of Economic Research Working Paper 27146.

Lemley, Mark A., and Andrew McCreary. 2019. "Exit Strategy." Stanford Law and Economics Olin Working Paper 542.

Letina, Igor, Armin Schmutzler, and Regina Seibel. 2021. "Killer Acquisitions and Beyond: Policy Effects on Innovation Strategies." Universitaet Bern, Departement Volkswirtschaft Diskussionsschriften dp2003.

Mermelstein, Ben, Volker Nocke, Mark A. Satterthwaite, and Michael D. Whinston. 2020. "Internal versus External Growth in Industries with Scale Economies: A Computational Model of Optimal Merger Policy." *Journal of Political Economy*, 128(1): 301–341. _eprint: https://doi.org/10.1086/704069.

Motta, Massimo, and Martin Peitz. 2021. "Big Tech Mergers." *Information Economics and Policy*, 54: 100868. Antitrust in the Digital Economy.

Ordover, Janusz A., Garth Saloner, and Steven C. Salop. 1990. "Equilibrium Vertical Foreclosure." *The American Economic Review*, 80(1): 127–142.

Peukert, Christian, Stefan Bechtold, Michail Batikas, and Tobias Kretschmer. 2022. "Regulatory Spillovers and Data Governance: Evidence from the GDPR." *Marketing Science*, 41(4): 318–340.

Prado, Tiago S., and Johannes M. Bauer. 2022. "Big Tech Platform Acquisitions of Start-ups and Venture Capital Funding for Innovation." *Information Economics and Policy*, 59: 100973.

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

Salop, Steven C., and David T. Scheffman. 1983. "Raising Rivals' Costs." *The American Economic Review*, 73(2): 267–271.

Sant'Anna, Pedro H.C., and Jun Zhao. 2020. "Doubly Robust Difference-in-differences Estimators." *Journal of Econometrics*, 219(1): 101–122.

Scott Morton, Fiona M., and David C. Dinielli. 2020*a*. "Roadmap for a Monopolization Case Against Google Regarding the Search Market."

Scott Morton, Fiona M., and David C. Dinielli. 2020*b*. "Roadmap for an Antitrust Case Against Facebook."

Segal, Ilya, and Michael D. Whinston. 2007. "Antitrust in Innovative Industries." *American Economic Review*, 97(5): 1703–1730.

Shannon, Claude Elwood. 1948. "A Mathematical Theory of Communication." *The Bell system technical journal*, 27(3): 379–423.

Straathof, Sebastiaan M. 2007. "Shannon's Entropy as an Index of Product Variety." *Economics Letters*, 94(2): 297–303.

Werden, Gregory J, and Luke M Froeb. 2018. "Don't Panic: A Guide to Claims of Increasing Concentration." *Antitrust*, 33: 74.

Wollmann, Thomas G. 2019. "Stealth Consolidation: Evidence from an Amendment to the Hart-Scott-Rodino Act." *American Economic Review: Insights*, 1(1): 77–94.

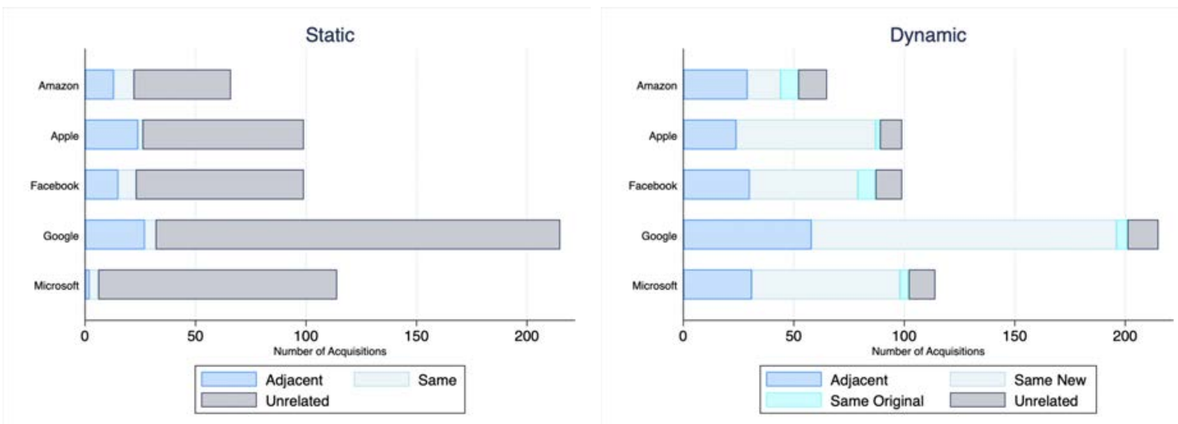
Appendix A Additional Figures and Tables

Table A.1: Pairwise Correlation Coefficients Between Age of the Target, Value of the Deal and Number of Employees of the Target

	Target's Age	Deal Amount ($)	Target's Employees
Target's Age	1.00		
Deal Amount ($)	0.12*	1.00	
Target's Employees	0.06*	0.40*	1.00

Notes: * means that correlation coefficients are significant with the 95% confidence.

Figure A.1: GAFAM's Acquisitions by Distance



Notes: The left figure presents for the static algorithm the number of acquisitions by the distance of the target for each GAFAM firm. The right figure presents the same information for the dynamic algorithm, where the additional distance "Same New" refers to acquisition in which the target belongs to a level-2 category that is the same as the one in which the acquirer has expanded before in the sample.

Table A.2: Likelihood of an Acquisition Based on Distance and Target Age

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Unrelated	Adjacent	Same Original	Same New	Target Age
GAFAM	-0.353***	0.116***	-0.208***	0.449***	-4.154***
	(0.0132)	(0.0185)	(0.00919)	(0.0199)	(0.582)
Top25 PE	-0.228***	0.00602	-0.0300***	0.252***	2.931***
	(0.00899)	(0.00944)	(0.0100)	(0.0110)	(0.361)
Top25 S&P	-0.193***	0.0121	-0.0831***	0.264***	2.137***
	(0.00844)	(0.00862)	(0.00846)	(0.0102)	(0.294)
Top25 Tech	-0.248***	0.0629***	-0.166***	0.351***	-2.375***
	(0.0117)	(0.0136)	(0.00983)	(0.0152)	(0.392)
Observations	41,758	41,758	41,758	41,758	36,594
R-squared	0.070	0.019	0.026	0.110	0.163

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Columns (1) to (4) show the correlation between being acquired by a top group — compared to being acquired by any other firm — and the probability that the level-2 of the target is unrelated, adjacent, the same as the original one of the acquirer, or the same as one of the level-2s in which the acquirer has expanded before in the sample, respectively. Column (5) displays the correlation between being acquired by any of the top groups and the age of the target. We use a linear probability model and in all regressions include level 1 and year fixed effects, and control for the location of the target as well as for whether the target is a public entity.

Table A.3: GAFAM and Other Groups Dispersion (Shannon Entropy) Across Level-1s and Level-2s

	Level-1s			
	mean	sd	min	max
GAFAM	2.14	0.09	2.04	2.22
Top 25 Tech	1.59	0.69	0.00	2.40
Top 25 PE	1.70	0.49	0.00	2.43
Top 25 S&P	1.60	0.46	0.48	2.23
Other	0.22	0.41	0.00	2.35

	Level-2s			
	mean	sd	min	max
GAFAM	3.49	0.24	3.21	3.84
Top 25 Tech	2.42	0.87	0.00	3.36
Top 25 PE	2.60	0.86	0.00	3.58
Top 25 S&P	2.68	0.67	1.00	3.66
Other	0.32	0.54	0.00	3.19

Notes: For each group, dispersion is measured through the average Shannon Entropy across group members. The top panel summarizes groups' dispersion across level-1s, and the bottom panel considers dispersion across level-2s.

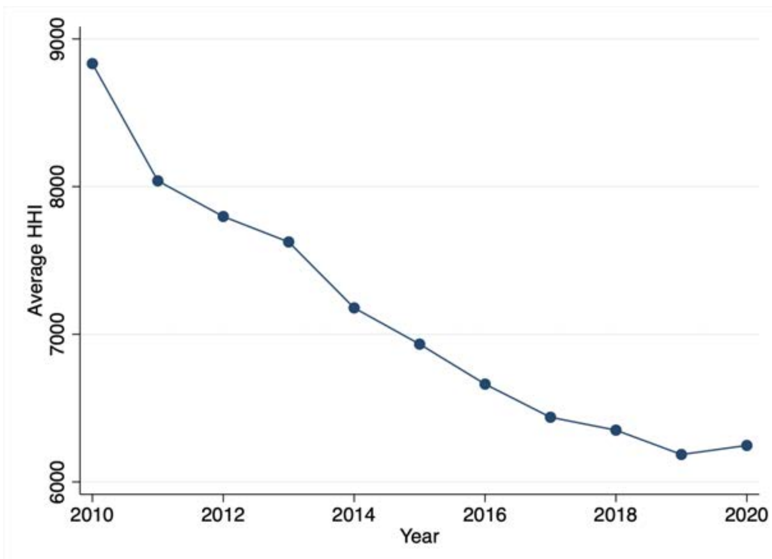
Table A.4: GAFAM and Other Groups Concentration (HHI) Across Level-1s and Level-2s: Subsample with Only Companies with at Least Ten M&As

Level-1s	mean	sd	min	max
GAFAM	1,530.28	92.64	1,390.67	1,625.1
Top 25 Tech	2,474.82	1,317.72	1,093.75	5,254.83
Top 25 PE	2,322.06	867.66	1,088.39	4,633.47
Top 25 S&P	3,277.79	1,765.54	1,368.15	7,997.63
Other	4,236.87	2,143.51	1,005.92	10,000.00

Level-2s	mean	sd	min	max
GAFAM	455.27	107.60	336.38	609.12
Top 25 Tech	982.64	519.11	453.65	2,200.00
Top 25 PE	831.60	367.12	389.18	1,715.98
Top 25 S&P	1,512.10	1,571.16	311.91	6,406.49
Other	2,353.05	1,667.17	498.61	10,000.00

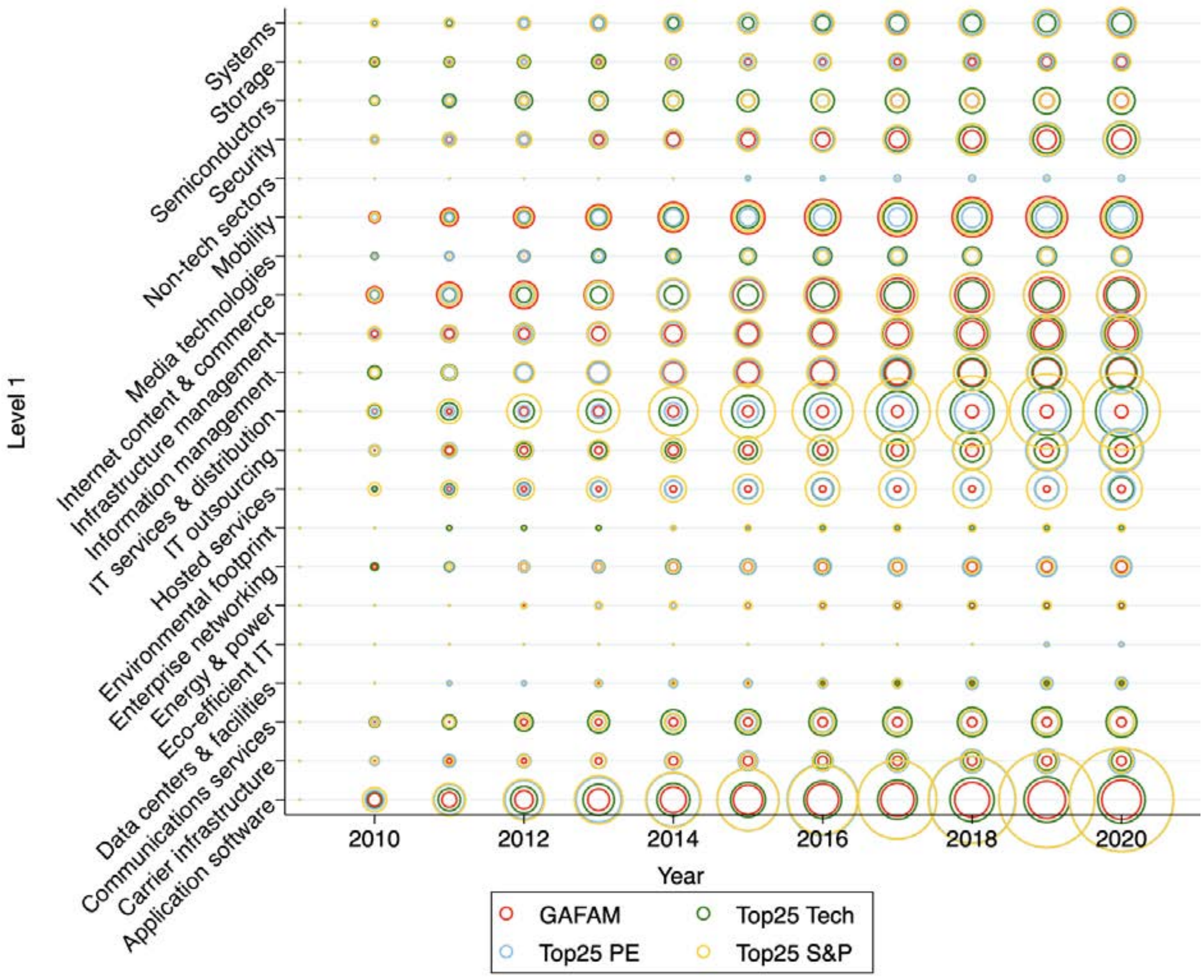
Notes: For each group, concentration is measured through the average HHI across group members, where the HHI of each firm is computed as in Equation (1). As a robustness check, differently from Table 3, here we exclude companies with strictly less than 10 acquisitions as these may inflate HHIs of Top 25 Tech and Top 25 PE companies. The top panel summarizes concentrations for groups across level-1s, and the bottom panel considers concentration across level-2s.

Figure A.2: Average HHI across GAFAM-entered Level-2 Categories



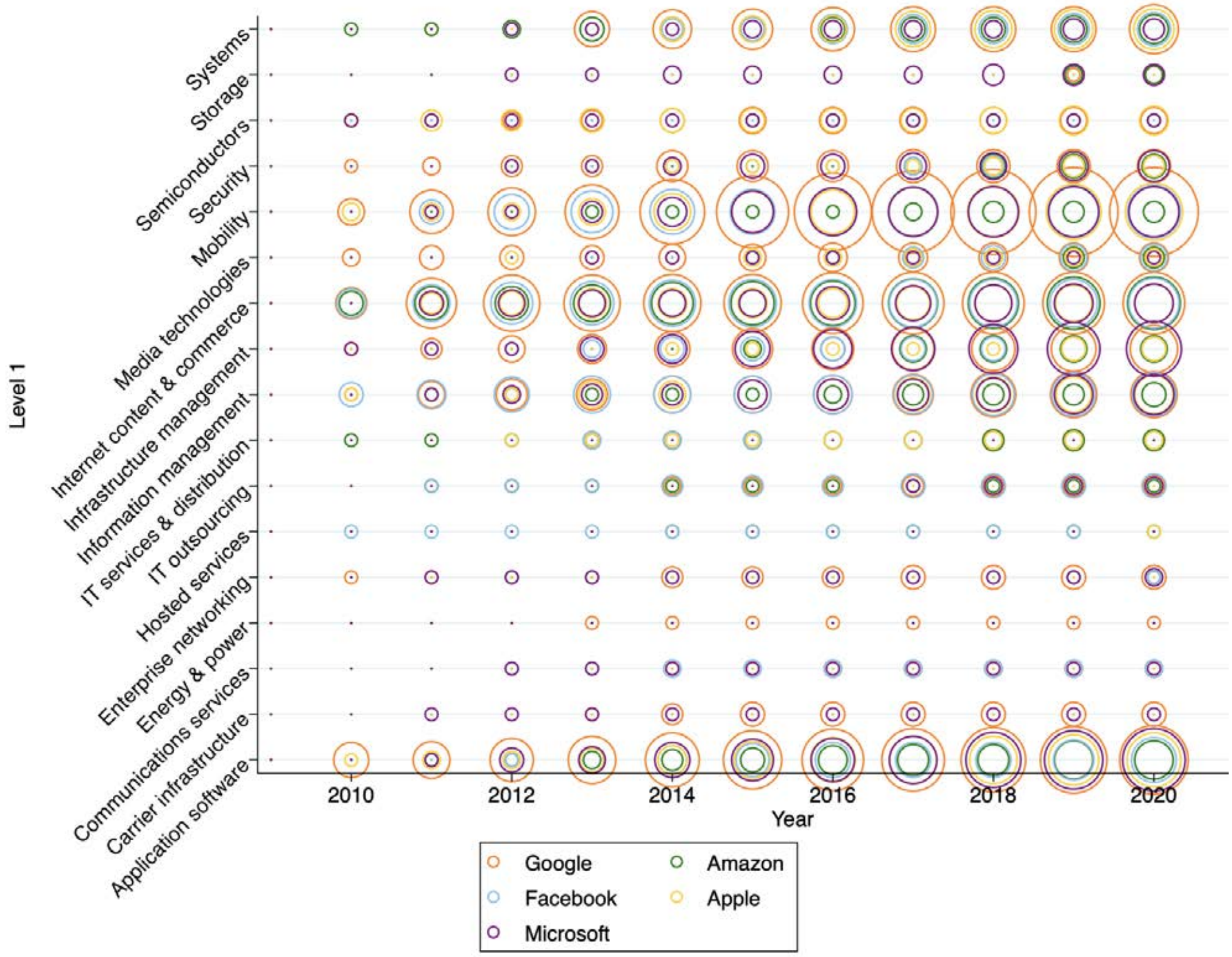
Notes: The figure shows in each year the average HHI across the level-2 categories in which at least one GAFAM firm acquired up to that year. This measure focuses on GAFAM's acquisitions in each level-2 category (while ignoring other acquirers), so that the lowest possible value of this HHI is 2,000.

Figure A.3: Alternative Representation of the Potential Competition between Top Acquirers



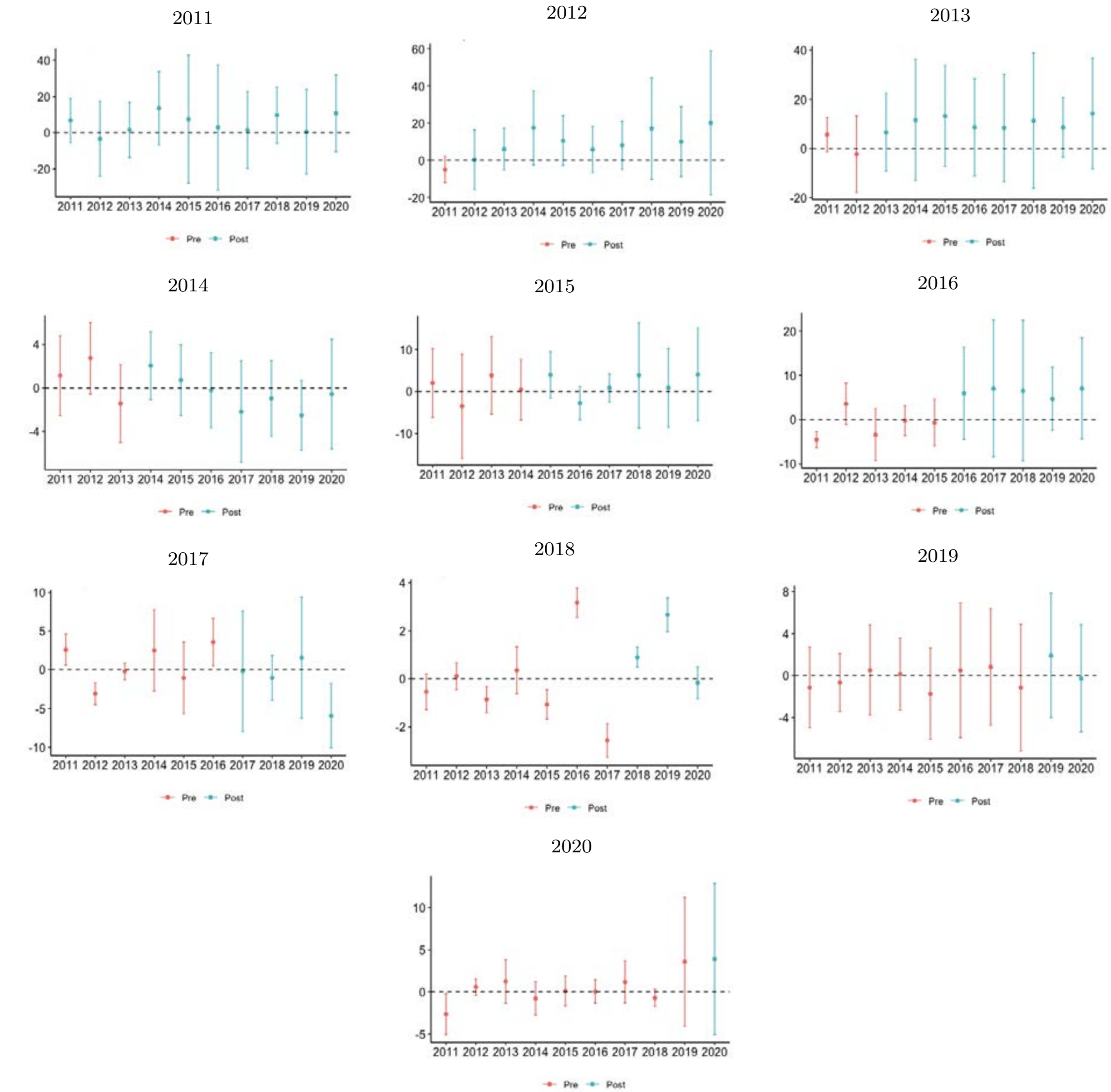
Notes: The figure illustrates the relative numbers of acquisitions by the groups of top acquirers in the 21 level-1 categories in which at least one top acquirer made an acquisition over the sample time period. The size of each bubble in a given year is proportional to the cumulative number of acquisitions completed by the respective group up to that year, inclusive.
Source: 451 Research M&A KnowledgeBase, part of S&P Global Market Intelligence, data as of 02/16/2021.

Figure A.4: Alternative Representation of the Potential Competition between GAFAM Firms



Notes: The figure illustrates the relative numbers of acquisitions by each of the five GAFAM firms in the 17 level-1 categories in which at least one GAFAM firm made an acquisition over the sample time period. The size of each bubble in a given year is proportional to the cumulative number of acquisitions completed by a GAFAM firm up to that year, inclusive.
Source: 451 Research M&A KnowledgeBase, part of S&P Global Market Intelligence, data as of 02/16/2021.

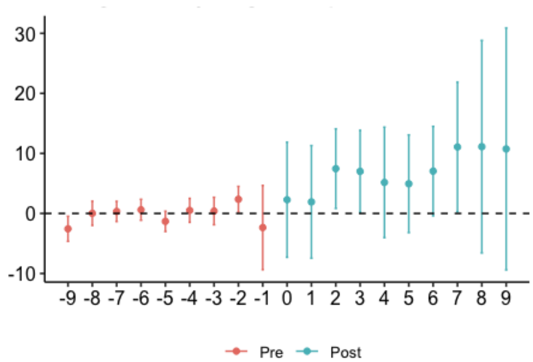
Figure A.5: ATTs by Treatment-Starting Year



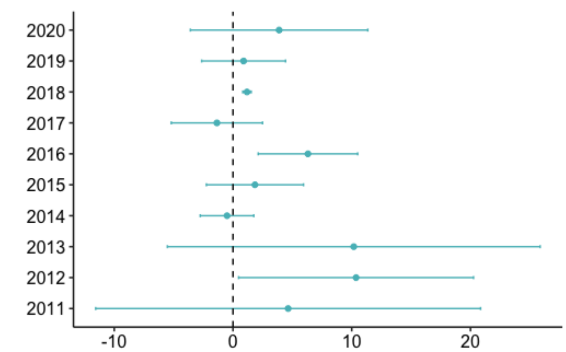
Notes: The figure plots the average treatment effects of the treated (ATTs) by treatment-starting year, all estimated including not-yet-treated units in the control group. Each plot of treatment-starting year t includes all level-2 categories in which GAFAM first acquired in that year. Plots of treatment-starting year 2011 to 2014 satisfy the parallel trend assumption and show no significant correlation between GAFAM acquisition and the number of new acquirers acquiring in the level-2 category. Plots of treatment-starting year 2015 to 2020 have five or less level-2 categories which makes interpretation harder. However, in general the results suggest the absence of a significant correlation.

Figure A.6: ATTs with Only Never-treated Units in the Control Group

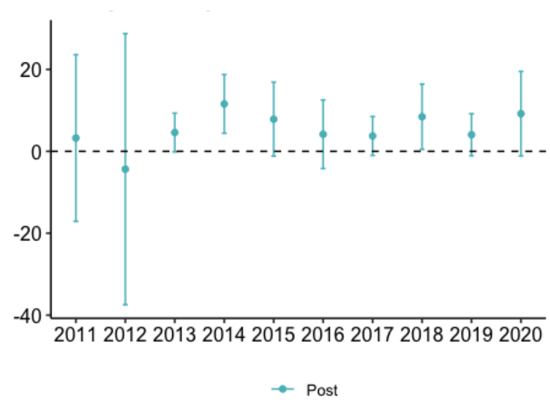
(a) Average Effect by Length of Exposure



(b) Average Effects by Treatment-starting year



(c) Average Effects by Calendar Year of Effect

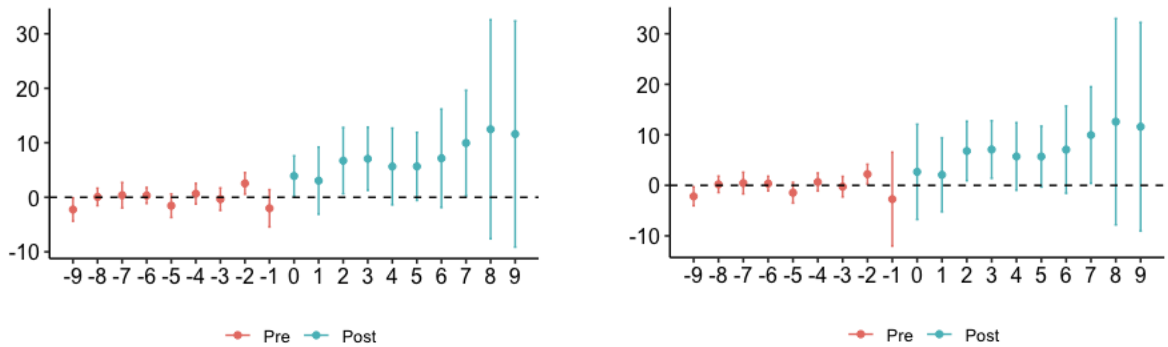


Notes: Figure (a) plots the average treatment effects on the treated (ATTs) by years of exposure since GAFAM's first acquisitions in a treated level-2 category. Figure (b) plots the ATTs by treatment-starting year. For example, the ATT for treatment-starting year 2012 averages across all level-2 categories that became treated in 2012. Figure (c) plots the ATTs by the calendar year of effect. For example, the ATT for calendar year 2012 averages the ATTs in 2012 for all level-2 categories that became treated in or before 2012. All three figures aggregate ATTs estimated using only never-treated units as controls.

Figure A.7: Dynamic Correlations Excluding PE Firms

(a) Not-yet-treated as Control Group

(b) Never-treated as Control Group

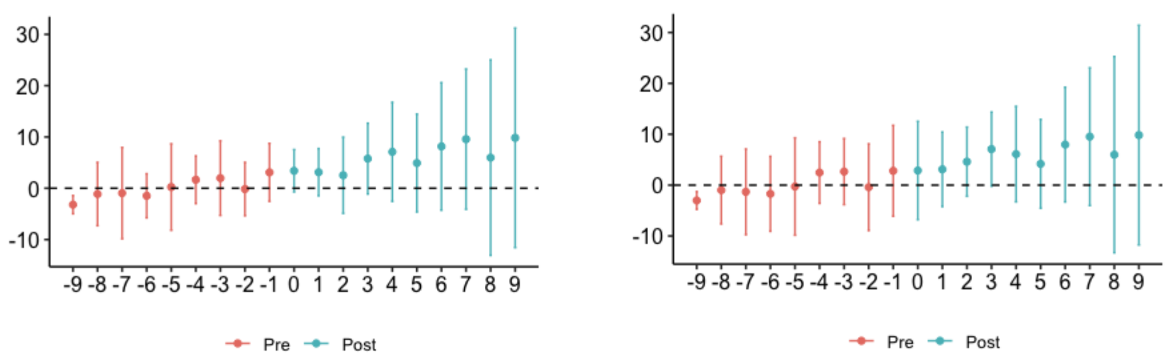


Notes: The two figures plot the average treatment effects on the treated (ATTs) by years of exposure since GAFAM's first acquisition in a treated level-2 category excluding all PE firms from the sample. Figure (a) plots the ATTs using not-yet-treated units as control, while Figure (b) plots the ATTs using never-treated units as control.

Figure A.8: Dynamic Correlations with Alternative Treatment

(a) Not-yet-treated as Control Group

(b) Never-treated as Control Group



Notes: To account for the fact that more than one GAFAM acquisition in a level-2 category may be required to be negatively associated with entry via M&A in that level-2, we consider an alternative treatment. In particular, we define a level-2 category to be treated in a certain year if GAFAM had consummated at least two acquisitions in that level-2 in or before that year. Figure (a) plots the average treatment effects on the treated (ATTs) by years of exposure using not-yet-treated units as control, while Figure (b) plots the same ATTs using never-treated units as control.