Tech Industry Acquisitions and Competition: Counterpoints to an Incomplete FTC Study and Legislation that Relies on It

Part I: Tech Merger and Acquisition (M&A) Activity Fuels Expansion and Innovation Across Many Industries

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Summary

Recent scrutiny of potential anticompetitive behavior by large technology companies has shined a bright light on the corporate acquisition activities of those firms, particularly Google (Alphabet), Amazon, Facebook (Meta), Apple, and Microsoft (collectively "GAFAM"). In particular, Congress is currently considering several new laws that would dramatically change merger-review policies – when acquisitions involve GAFAM.

These proposed changes to merger-review policies are based on the broad assumption that GAFAM acquisitions predominantly reduce competition. This assumption led to a 2021 Federal Trade Commission (FTC) study, "Non-HSR Reported Acquisitions by Select Technology Platforms, 2010–2019: An FTC Study," that provides an analysis of GAFAM's acquisitions during 2010-2019 for which merger filings were not required. The counterpoint to this view that GAFAM acquisitions predominantly reduce competition is that GAFAM acquisitions are not particularly different from the M&A activities of other acquirers, and have the broad aims of bringing in new talent and ideas, producing and commercializing new product innovations, and enhancing shareholder value. Moreover, GAFAM acquisitions may in fact be reflective of and followed by an increase in competition.

A substantial weakness of the FTC 2019 study referenced above is that it lacked one or more "control groups" to compare to GAFAM. Fundamentally, if the FTC's hypothesis is that the M&A behavior of GAFAM firms is extraordinary and requires novel regulation, then GAFAM's acquisitions should be directly compared to acquisitions by similar "peer" firms. Conversely, if the M&A behavior of GAFAM firms does not substantially differ from that of peer firms, that would constitute evidence against the hypothesis that GAFAM's M&A activities merit specific regulatory changes, and reject the premise that GAFAM acquisitions provide a basis for a radical overhaul of U.S. merger-review policies.

Thus, in order to understand GAFAM's M&A in the proper context, in a series of two reports we examined technology acquisitions over the period of 2010-2020 – a comparable timespan to the FTC study – but instead of focusing only on five firms, we analyzed the M&A activities of all publicly-listed North American companies as well as several GAFAM "peer groups," including:

- Leading non-GAFAM firms operating in the digital space
- Leading non-GAFAM acquirers of technology companies
- Leading private equity (PE) firms

(Academic pre-prints of this research are available here and here.)

When the M&A behavior of GAFAM is compared to that of these different groups of firms, the reports demonstrate that GAFAM acquisitions are not particularly unusual, do not have the characteristics of so-called "killer acquisitions," do not create so-called "kill zones," and that they are emblematic of broader technological trends in which acquisitions of technology companies are symptoms of more intense competition and the increase in overlaps between firms' offerings. These findings directly counter the conclusion that GAFAM acquisitions predominantly reduce competition, and thus challenge the assumptions underlying policy proposals for overhauling the merger review process, and for specifically targeting technology markets.

Specifically, together the two reports find:

- Technology companies are acquired by firms from all sectors of the economy. Over the period 2010-2020, for instance, acquirers from the Services and Supply Chain sectors completed 5,720 acquisitions, in comparison to 4,903 acquisitions by firms in the Information sector over the same time period.

- Larger and older public firms are more likely to acquire tech companies.

- The vast majority of acquired tech companies offer products and services that fall outside the acquiring firm's core area of business.

- There is a positive link between a public firm's likelihood to engage in technology M&A and the amount of competition the firm faces from other public firms at the time of M&A. In other words, tech M&A is associated with firms that face more intense competition in their home markets from other incumbent public firms.

- These results suggest that public companies that acquire technology companies are motivated to expand through M&A into new technology and business areas because they face increased competition in their core areas.

- Acquiring relatively young tech startups is a common practice, particularly by firms in the Information sector.

- Using a technology categorization from Standard & Poor's, when the ages of acquired firms are normalized based on the average age of all firms operating in their technology category, GAFAM is not significantly different from other top technology firms in acquiring relatively younger companies.

- According to a dataset compiled by Standard & Poor's, out of the 41,796 majority-control acquisitions of technology companies operating in the Information, Communications and Energy Technologies (ICET) space during 2010-2020, GAFAM acquired 595, accounting for less than 1.5%.

- On a per-firm basis, some top technology acquirers, including private equity companies and other non-GAFAM firms, have matched or exceeded GAFAM in their volume of majority-control acquisitions per year since 2018.

- Utilizing a technology categorization from Standard & Poor's, the analysis finds that GAFAM and other top technology acquirers increasingly compete with each other across categories over 2010-2020. Moreover, competition within GAFAM has steadily increased over this time period as well.

- The analysis finds that GAFAM acquiring in a technology area is positively correlated with other firms also entering the area via M&A. These findings go counter to antitrust theories such as kill zones. For the kill zone theory to hold insofar as the M&A context, GAFAM's acquisitions should deter competitors from acquiring in the same technology and business areas; however, rather than deter competition, relatively more new competitors acquire in the areas where GAFAM acquired than in other areas where GAFAM did not acquire. This suggests that in a tech area may in fact increase following a GAFAM acquisition.

- GAFAM primarily acquires tech companies in order to expand into new areas beyond their core businesses. Moreover, in comparison to other groups of top technology acquirers during 2010-2020, percentage-wise, GAFAM acquisitions were the least concentrated around the acquirer's core business area, with the vast majority of GAFAM acquisitions branching into new technology categories.

The additional context and findings provided by these reports calls for a reevaluation of policymakers' assumptions about GAFAM acquisitions of technology companies. In particular, these findings suggest that technology acquisitions are a symptom of healthy competition and of competitors' need to bolster their offerings by expanding into new technological areas in order to offer additional features, products, and services.[1]

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[1]This report is based on ongoing academic research developed by author Liad Wagman in conjunction with co-authors.

1 Introduction

Technological innovation is a key driver of economic development, but it is unclear how innovative ideas arise, develop, and transform into final products and services. According to Arora et al. (2020), total factor productivity growth has slowed down in the US since the 1970s, although investment in science has increased substantially in terms of public funding, number of high-degree workers trained, and research articles published. At the same time, large US corporations such as AT&T, Xerox, IBM, and DuPont have gradually shifted away from scientific research and towards commercial development, making technical leadership more decentralized over time (Greenstein 2015; Ozcan and Greenstein 2016). Although the growing disconnect between scientific research and commercial applications is in part bridged by venture-capital (VC) funded technology ventures, VC investments tend to concentrate in certain sectors, primarily information and communication technologies, and life sciences. This could be of concern if other technologies are under-developed, or if VC-backed technologies are inaccessible by all sectors of the economy that may benefit from them.

This background suggests that mergers and acquisitions involving technology companies (henceforth 'tech M&A'), especially concerning transactions in which established incumbents acquire VC-backed startups, could be an effective channel to disseminate and commercialize technology. On the one hand, established incumbents may be more familiar with market demand than an emerging startup, and may have processes in place for incorporating new technologies into new products and services. On the other hand, younger technology ventures are often driven by their innovating founders' original ideas, and do not face the same inertia as large corporations. As a result, acquisitions of technology ventures by established incumbents could speed up technology diffusion from innovators to wider-reaching commercial applications. Examples include Facebook's acquisition of FriendFeed, Salesforce's acquisition of Quip, and Walmart's acquisition of Vudu. At the same time, tech M&A can also enable an incumbent to leapfrog its expansion into new technology categories, and reshape competition among incumbent firms.

This paper aims to better understand the general landscape of tech M&A by firms that are publicly listed in the Northern American stock exchanges. To do so, we collect information about tech M&A between 2010 and 2020 from a database managed by S&P Global Market Intelligence. Mostly focused on M&A in information, communication and energy technologies, the S&P database adopts a taxonomy to categorize the product areas of the acquirer and the target in each M&A transaction into tech categories (level-1) and business verticals (level-2). Combined with classical NAICS codes that categorize the industries of all public firms and a classification from Refinitiv regarding whether or not those firms can be classified as "high-tech," we proceed to identify (a) the sectors of public firms that engage in tech M&A, (b) how their acquisitions relate to their core businesses, (c) to what extent the acquirers conduct serial acquisitions in the same tech categories and business verticals, and (d) what mechanisms may have driven public firms to acquire technology companies.

We find that tech M&A is widespread across sectors. It is common to observe firms operating in finance, health care, supply chain, trade, or services acquiring targets that specialize in internet content and commerce, application software, mobility, or information management. The prevalence of cross-sector acquisitions suggests that the information and communication sector referenced in Arora et al. (2020) encompasses general-purpose technologies that can be widely incorporated into industries beyond information services. Utilizing Refinitiv's classification regarding whether an acquirer's core businesses can be regarded as "high-tech," we find that 24.44% of tech M&As have a non-high-tech acquirer, supporting the argument that M&A is an effective way for entities that do not focus on technological innovation themselves to expand into new technology categories.

Based on our 2010-2020 sample of tech M&A, only 13.1% of public firms acquire at least one technology company, but those that acquire are systematically older in age and larger in sales revenue. Conditional on having any tech acquisition in the sample period, over 70% of acquirers acquire more than once. In the majority of tech M&As, the acquirer and the target do not operate in the same S&P-defined tech category; that is, the acquired company appears to fall outside the area of the acquirer's core business. Further analysis finds that such "unrelated" acquisitions are correlated with acquirers facing more intense competition in their core businesses. This implies that M&A may help facilitate an on-ramp for incumbent firms to expand into new technological categories, as a way of addressing competitive pressure.

Although this paper is descriptive in nature, our results can help inform policymakers and practitioners of the ongoing trends in technology acquisitions and market competition. In particular, the widespread nature of tech M&A is encouraging, as it suggests that firms across industries are actively seeking technological expansion and enhancements, even if those firms themselves do not specialize in technological innovation. However, it seems that tech M&A tends to be concentrated in a relatively small percentage of larger and older public firms, likely because they have more resources and processes in place to manage acquisitions. It is unclear whether the same or similar technologies can diffuse to other firms via licensing, intermediary products, or other non-M&A formats.

As for market competition, we find that transactions in each M&A-active tech category tend to be led by acquirers from a specific sector, to varying extents over time. For example, the Information sector always accounts for the largest number of M&As in the category of Application Software, with an overall widening leadership gap over time, while the Supply Chain sector leads M&A transactions in the category of Semiconductors, with an overall shrinking leadership gap over time. At the same time, we observe incumbent public firms from the sectors that lag behind in overall M&A activity in some tech categories also acquire targets in those categories, even if their own core businesses are not closely related to the business verticals of the targets. This suggests that M&A can intensify competition in some technology markets, although at the same time M&A may help the acquirers differentiate their offerings in an attempt to escape competition in their core business areas.

These patterns are consistent with earlier studies on mergers and technology diffusion: For example, Jovanovic and Rousseau (2008) show that mergers played a major role in speeding up the diffusion of electricity and the internal combustion engine in the US during

1890-1930 and the diffusion of information technology during 1971-2001. There is also a growing literature about the relationship between incumbents and innovative startups. As shown in Gans, Hsu and Stern (2002), startup entrants may choose to cooperate with incumbents in the form of licensing, strategic alliances or acquisitions (rather than compete with them in product markets), and the cooperation could be pro-competitive under some market conditions. In comparison, Bryan and Hovenkemp (2020) explicitly model entrepreneurs' choice to enter a market in the hope of an incumbent buyout. They show that imposing no limits on startup acquisitions may entail market inefficiencies in some situations. Although our descriptive findings say nothing about the pro- or anti-competitive nature of startup acquisitions, our work can inform policymakers of the scope and dynamics of tech M&A, which may help their consideration of how to account for technology innovations and the evolution of the space more broadly in a potential reform of merger enforcement policies (Katz and Shelanski 2005; see, also, a number of bills proposed in the US Congress[1]).

The remainder of the paper is organized as follows. Section 2 describes the datasets we use and the samples we construct. Section 3 highlights the types of public firms that engage in tech M&A, and Section 4 further investigates the M&A strategy of those acquirers. Section 5 examines two potential mechanisms that may drive public firms to engage in tech M&A. Section 6 concludes.

2 Data

We use data from five sources: Compustat, Standard and Poor's (S&P) Global Market Intelligence, Center for Research in Security Prices (CRSP), Refinitiv, and the Hoberg-

[1]In June 2021, six bills on antitrust reform were passed by the U.S. House Committee on the Judiciary, and some analogous bills have been proposed in the US Senate. Many if not all of them propose changes in merger enforcement, especially with regard to incumbent acquisition of innovative startups. However, it is unclear whether any of them will eventually be enacted into law, despite the fact that some have received bipartisan support. More details can be found at CNBC 06-24-2021 (`https://www.cnbc.com/2021/06/24/house-committee-passes-broad-tech-antitrust-reforms.html`), congress.gov (`https://www.congress.gov/bill/117th-congress/senate-bill/225/text`), and techtarget.com 11-12-2021 (`https://searchcio.techtarget.com/news/252509429/Antitrust-reform-is-uncertain-despite-bipartisan-support`.

Phillips Data Library (HPDL).[2] Compustat tracks 19,064 public companies listed in North American stock exchanges in 2010-2020, recording financial statements and market data.[3]

The tech M&A database maintained and operated by S&P Global Market Intelligence is called 451 Research (henceforth, S&P). In the S&P database, each observation is an M&A transaction associated with a change in majority ownership. In total, it covers 41,796 M&A transactions involving 15,323 unique acquirers recorded between 2010 and 2020. All target entities are technology firms but acquirers can operate in any sector. Important to our analysis, S&P classifies the acquiring and acquired companies into a hierarchical technology taxonomy that has 4 levels, with level-1 being the broadest tech category (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 market niche, such as "Benefit and Payroll Management" and "Video-On-Demand Servers").

All level-1 "parent" categories in the S&P technology taxonomy have level-2 "children" categories, but not all level-2 categories have further children levels. We refer to level-1 categories as "tech categories" and to the combination of a level-1 and a level-2 category as a "business vertical," or simply a "vertical." In total, there are about two dozen tech categories and two hundred verticals, yielding an average of approximately nine verticals per tech category. We refer to two business verticals as "adjacent" if they share the same level-1 tech category. Each firm in the S&P database is assigned a primary category, representing the firm's core business, which 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 (organized analogously in the taxonomy). The database additionally provides the location of each firm's headquarter, whether a firm is publicly traded, a business description, the consummation date for each acquisition, and the founding dates for the firms tracked (available in 87.64%

[2]The HPDL includes several different datasets and can be accessed at: `https://hobergphillips.tuck.dartmouth.edu`. All the other datasets are used under license through our home universities or for this study in particular.

[3]This dataset also includes—for example—Canadian stock exchanges, such as the Toronto Stock Exchange (TSX).

of the transactions for the targets and 94.80% for the acquirers). This allows us to compute the age of most target firms at the time of the consummation of their acquisition.[4] For the purpose of distinguishing acquisitions of data-intensive targets, we crudely group target firms into greater and lesser propensities to rely on data based on their S&P business descriptions. Specifically, target companies that have the keywords "data," "statistics," "AI," "social media," or "e-commerce" are grouped as "data intensive."

The CRSP data contains historical descriptions and market data on companies listed in the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges, which are a subset of the stock exchanges covered in Compustat. The data is available at the security-level. We additionally use the Worldwide Mergers, Acquisitions, and Alliances dataset from Refinitiv's SDC database to collect information on acquirers. The SDC database is naturally broader than S&P's, as it also tracks non-technology target entities and includes minority acquisitions.[5]

As a first step, we merge the Compustat and S&P data by using the acquirer's stock exchange symbol, which is widely available in both databases. For the remaining observations that we were unable to match in the first stage due to missing stock exchange symbols, we perform a fuzzy matching on the acquirer's url domain, manually checking the quality of the resulting matches. This process allows us to identify a set of 2,435 public companies in Compustat that completed at least one tech M&A between 2010 and 2020. We use this data to provide summary statistics on the tech M&A activity of publicly listed companies in any North American stock exchange.

In our analysis, we examine how tech M&A differs across acquirers from different sectors.

[4]The S&P database also provides the number of employees a firm has and the transaction sizes in dollars, though these are sparsely populated.

[5]We find that the S&P data is more comprehensive for majority acquisitions of technology companies. 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 (a mapping of the tech categories and business verticals in the S&P data to NAICS codes was provided by S&P). 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.

We refer to the set of products identified by 2-digits NAICS codes as industries, and we aggregate industries into sectors, exploiting the wide availability of 2-digits NAICS codes in Compustat. Table 1 summarizes the mapping from industries (2-digit NAICS codes) to sectors. In particular, we define "Finance" and "Information" following the NAICS taxonomy directly. We collapse "Educational services," "Arts & Entertainment," "Healthcare," "Professional & Scientific & Technical services," "Real Estate," "Accommodation & Food services," "Administrative Services" and "Other Services" into a sector that we name "Services." We similarly collapse "Agriculture," "Mining," "Manufacturing," "Utilities," and "Construction" into "Supply Chain," and we collapse "Wholesale trade," "Retail trade" and "Transportation" into "Trade." As part of this process, we drop 1,264 companies whose 2-digit NAICS codes are either missing or equal to 99 ("Non-classifiable Establishments"). We distinguish private equity (PE) firms as a separate category of acquirers, given their specific market positioning as far as M&A and their relative proclivity for acquiring technology companies between 2010 and 2020 (Jin, Leccese and Wagman, 2021).[6] Overall, we identify 68 North American publicly-traded PE firms, 50 of which completed at least one majority tech acquisition in the S&P data.

We supplement the dataset with a measure of the acquirers' technology-intensity — the extent to which they can be classified as "high-tech" — from the Refinitiv database. Specifically, the Refinitiv SDC M&A database tags an acquirer as "high-tech" based on an evaluation of its core business; in addition, Refinitiv also provides a categorization of the technology used by the company if its overall business has a high-tech component, independent of whether this component is part of the firm's core business. Using these two variables, we divide the acquirers in our sample into three groups. First, we denote a firm as "high-tech" if its core business is classified by Refinitiv as such. Second, we denote a firm

[6]The S&P database includes a PE designation for the firms that are tracked as technology acquirers. While Compustat does not offer a PE designation for the firms they track, we are able to use the "Acquirer Business Description" in the Refinitiv M&A database to determine whether a (non-tech acquirer) firm is PE; we then merge this information with firms listed in the Compustat database by using firms' 6-digits CUSIP codes, to complement the set of PE firms identified in S&P data. The implicit assumption is that the vast majority of PE firms participated in at least a single M&A transaction in between 2010 and 2020, which we believe is highly plausible.

Table 1: Industry Classification and NAICS Codes

Sector	2-digits NAICS Code	Industry	Number of Public Firms	Number of Tech M&As
Finance	52	Finance and Insurance	6,133	1,084
Information	51	Information	1,494	4,903
Services	53	Real Estate	614	309
	54	Professional and Technical Services	465	1,379
	56	Administrative Services	203	275
	61	Educational Services	82	53
	62	Healthcare and Social Assistance	197	64
	71	Arts and Entertainment	92	42
	72	Accommodation and Food	179	8
	81	Other Services	30	6
Supply Chain	11	Agriculture, Fishing and Hunting	52	2
	21	Mining	2,023	153
	22	Utilities	365	89
	23	Construction	160	38
	31	Manufacturing	347	24
	32	Manufacturing	2,068	332
	33	Manufacturing	2,168	2,946
Trade	42	Wholesale Trade	309	259
	44	Retail Trade	224	70
	45	Retail Trade	183	204
	48	Transportation and Warehousing	331	64
	49	Transportation and Warehousing	13	8
Private Equity			68	308
Total			17,800	12,620

Notes: This table includes information from Compustat on public firms listed in all North American stock exchanges between 2010 and 2020. We start with a total of 19,064 and drop 1,264 (i.e., 6.63%) of them due to missing 2-digit NAICS codes or the codes being equal to 99 ("Non-classifiable Establishments"). The 2-digits NAICS codes and Industry names are missing for Private Equity in this table because we use the "Acquirer Business Description" in Refinitiv and the S&P data to identify PE firms. This means that, for example, the Private Equity sector includes some public firms which fall under the industry "Finance and Insurance" in Compustat. All the non-PE sectors reported in this table exclude PE firms.

as "traditional" if it has no high-tech component. Third, we denote a firm as "tech-leaning" if its core business is not high-tech but it does have a tech component. For instance, a firm such as reAlpha Tech Corp, which is primarily a lessor of real-estate property (hence, non high-tech), but also develops a digital real-estate platform that uses machine learning to support making real-estate investment decisions, would be classified as "tech-leaning." The grouping of high-tech, tech-leaning and traditional does not change within a firm, because the original variations in Refinitiv are time-invariant.

We use the CRSP database for the purpose of incorporating additional information on the publicly-traded companies we consider, such as firms' IPO dates (when missing in Compustat), market valuations, and number of employees.[7] Throughout our regression analyses, we restrict attention to the main U.S. stock exchanges (i.e., AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges). These exchanges are covered by the HPDL and the CRSP database, which we merge with Compustat by using the common variable "GVKEY."

From the HPDL database, we use the "Product Market Fluidity" data, which assesses the degree of competitive pressure and product market change surrounding a firm, based on Hoberg, Phillips and Prabhala (2014). We additionally use the TNIC-3 classification data developed by Hoberg and Phillips (2010, 2016) to assign public companies to product spaces. In particular, for each pair of public firms listed on either the AMEX, NYSE American, NYSE Arca, or the NASDAQ, the dataset specifies a real number in the interval [0,1] that captures the similarity between the products offered by the two firms. This measure is generated via textual analysis of firms' 10K reports by using cosine similarity. Given these similarity scores, markets are defined at the "pair-level," such that any two firms belong to the same market whenever their pairwise similarity is above a certain threshold.[8] Hence, we obtain a

[7]While some of these variables are available in Compustat, they may have missing values. In particular, when a firm's IPO date is missing in Compustat, we proxy for this date by using the first date that the firm's share price is recorded in CRSP. We use this information to compute the ages of the firms as public companies, which we include as a control in our regressions.

[8]This threshold is set in a way to match the classification of three-digits SIC codes in terms of similarity likelihoods. For example, if any two firms are picked at random, the likelihood of them belonging to the same three-digit SIC code is 2.05%. Analogously, in the dataset we use, the likelihood of two randomly drawn firms belonging to the same market is also 2.05%.

set of (often distinct) competitors for each firm. This set may vary over time, as companies' 10K reports change from year to year.

3 Who Buys Technology Companies?

We begin by examining the sectors that are more likely to engage in tech M&A. Table 2 reports that Information is the sector with the highest total number of such transactions completed by publicly-traded firms in the US exchanges between 2010 and 2020. Supply Chain is the second largest sector, followed by Services, Finance and PE. These statistics are partly driven by the different number of public companies across NAICS industries, as suggested by Table 1. Hence, we examine the average number of tech M&As per acquirer; firms in the Information sector lead the pack in the per-firm average, followed by PE, where the gap between the two exceeds one additional tech M&A per firm.

Column (2) of Table 2 reports the percentage of firms that engage in tech M&A in each sector. Almost half of the firms in the Information sector completed at least one tech M&A between 2010 and 2020. This percentage is significantly lower in all of the other sectors, except PE, where 73.53% engaged in tech M&A. This is consistent with PE firms specializing in M&A, and with a vast majority of them targeting technology companies for acquisitions, as tech played an oversized role in the economy in 2010-2020. In the Services sector, about a fifth of publicly-traded firms acquired at least one technology company between 2010 and 2020, demonstrating the extent to which technology has become pervasive even in some traditional sectors. In contrast, in the Finance sector, only 4.66% of publicly-traded firms acquired a tech company during our sample period.

Panel (a) of Figure 1 indicates that the two largest sectors—Information and Supply Chain—exhibited overall decreases in their number of tech M&A between 2010 and 2020, whereas this number increased in the Services sector. In particular, in 2010, firms in the Supply Chain sector engaged in tech M&A almost 200 more times than firms in the Services sector, and this gap shrank to less than 100 in 2020. In the other sectors, the number of tech

Table 2: Tech M&A across Sectors between 2010 and 2020

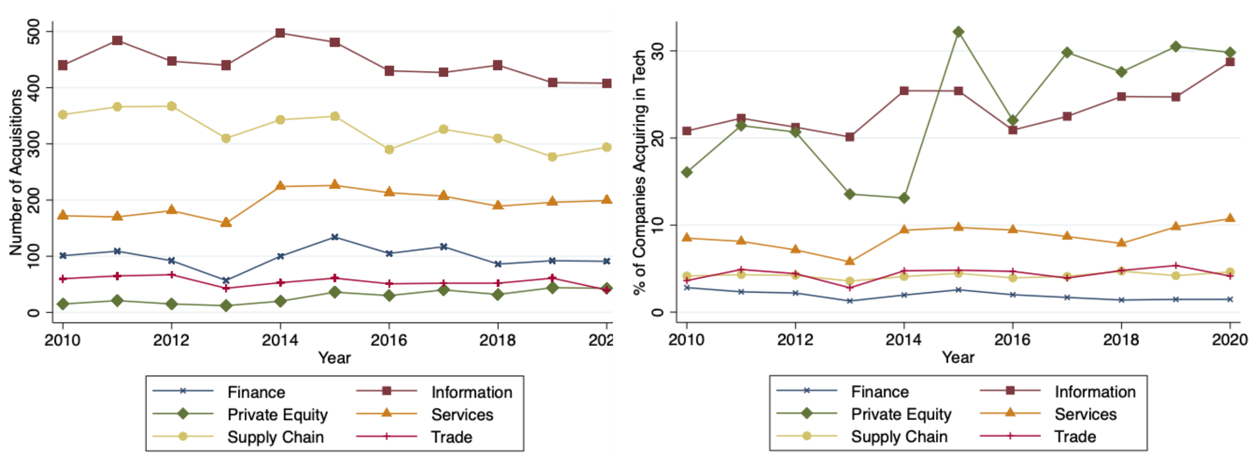
Sector	Number of Tech Acquisitions	% of Firms with any Tech Acquisition	Average Number of Tech M&As per Public Acquirer
Finance	1,084	4.66	3.79
Information	4,903	45.11	7.27
Services	2,136	19.92	5.76
Supply Chain	3,584	11.18	4.46
Trade	605	13.87	4.12
Private Equity	308	73.53	6.16
Total	12,620	13.10	5.47

Notes: This table includes information from all North American stock exchanges between 2010 and 2020. Results are similar if we restrict attention to the set of publicly-listed acquirers from the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges.

M&As remained relatively stable over the sample period. Panel (b) of Figure 1 reports that the Information, Services and PE sectors exhibited substantial increases in the percentage of firms acquiring tech targets after 2013. To be clear, the figure plots the percentage of publicly-traded firms in each sector that completed at least one tech M&A in a given year (not cumulatively). For instance, in the Information sector, the percentage of firms that engaged in tech M&A at least once rose from 20% in 2013 to almost 30% in 2020.

Figure 1: Trends in Tech M&A

(a) Number of Tech Acquisitions (b) % of Firms with any Tech Acquisition



Notes: The figure uses data for all North American stock exchanges.

Table 3: Tech M&A and Technology Intensity of Acquirers across Sectors

Sector	Traditional	Tech-leaning	High-tech	Missing
Finance	386	74	154	470
	(35.61%)	(6.83%)	(14.21%)	(43.36%)
Information	304	255	3,823	521
	(6.20%)	(5.20%)	(77.97%)	(10.63%)
Services	512	84	1,003	537
	(23.97%)	(3.93%)	(46.96%)	(25.14%)
Supply Chain	685	364	1,978	557
	(19.11%)	(10.16%)	(55.19%)	(15.54%)
Trade	205	34	315	51
	(33.88%)	(5.62%)	(52.07%)	(8.43%)
Private Equity	180	2	104	22
	(58.44%)	(0.65%)	(33.77%)	(7.14%)
Total	2,272	813	7,377	2,158
	(18.00%)	(6.44%)	(58.45%)	(17.10%)

Notes: For each sector the first row reports the absolute number of tech acquisitions, while the second row shows percentages (in parentheses). This table includes information from all North American stock exchanges. We use data on M&A deals from Refinitiv to classify acquirers by technology intensity.

The extent to which technology is a primary component of a firm's core business may relate to the firm's propensity to acquire technology companies. As indicated in the previous section, we use data on M&A deals from Refinitiv to classify acquirers into three technology intensity groups. Table 3 reports for each sector the absolute number and the percentage of tech M&A completed by traditional, tech-leaning and high-tech firms, as well as statistics for those acquirers that we were unable to classify (denoted as "missing"). In all sectors except PE and Finance, most tech M&A transactions are completed by high-tech firms, with the percentage of acquisitions by high-tech firms ranging between 46.96% (Services) to 77.97% (Information). For PE and Finance, it is important to note that banks and most financial companies fall under our "traditional" (non-tech) firm grouping; in Finance, there is also the added issue that Refinitiv is missing classifications for a non-negligible number of firms.

To systematically examine which firm characteristics are correlated with a higher probability of engaging in tech M&A, we run several regressions utilizing a cross-section of publicly-listed acquirers from the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges.

We use logit and tobit models where the dependent variable is either an indicator of whether or not a firm engaged in tech M&A between 2010 and 2020, or the number of the firm's tech M&As between 2010 and 2020.

We are interested in the correlation between tech M&A activity and the sector in which the acquirers operate as well as the technology intensity (i.e., high-tech, tech-leaning and traditional grouping) of their core businesses. In all specifications, we include controls for the potential acquirer's sales and cash flow as of 2010 (or the first 4 quarters since the firm's IPO), and concurrent age.

Table 4 reports the results. We find that, as compared to companies in Finance (the default sector), firms in the Information sector are 50% more likely to engage in tech M&A, and have acquired 17 more tech targets, on average. Firms in the PE, Services and Supply Chain sectors also tend to engage in more tech M&A than firms in Finance, and, on average, complete approximately 15, 7, and 2 additional acquisitions. Firms in Trade, on the other hand, overall are not more likely to acquire tech targets than firms in Finance.

When controlling for a firm's technology intensity, as Columns (2) and (4) reflect, the difference between firms in Finance and Supply Chain is no longer statistically significant, and the differences between Finance and the PE and Services sectors somewhat diminish as well. Technology intensity also appears to be positively correlated with both the probability of engaging in tech M&A and with the number of transactions completed. In particular, firms classified as high-tech are about 30% more likely to acquire a tech target than firms classified as traditional, and, on average, they acquire about 10 additional targets. Table 4 also indicates that older firms, as well as firms that have higher sales, are more likely to engage in tech M&A.

As an additional test, we use the Cox proportional-hazards model to study the association across sectors between the number of days to a firm's first tech M&A transaction since January 1, 2010 and the technology intensity of the firm's core business. The group of companies with missing tech intensity classification is set as the default in Table 5. In all specifications, we include controls for sales and cash flow as of 2010 (or the first 4 quarters

Table 4: Selection in Tech M&A

VARIABLES	(1) Logit	(2) Logit	(3) Tobit	(4) Tobit
Information	0.519***	0.348***	17.04***	11.14***
	(0.0183)	(0.0222)	(1.686)	(1.362)
Private Equity	0.621***	0.547***	15.36***	13.56***
	(0.0614)	(0.0654)	(2.217)	(2.059)
Services	0.153***	0.0982***	7.201***	4.945***
	(0.0169)	(0.0173)	(1.049)	(0.930)
Supply Chain	0.0480***	-0.00872	2.406***	-0.237
	(0.0118)	(0.0134)	(0.673)	(0.630)
Trade	0.0267	0.00971	1.698*	0.704
	(0.0172)	(0.0185)	(0.925)	(0.853)
Sales	0.00368***	0.00336***	0.105***	0.109***
	(0.00107)	(0.000930)	(0.0212)	(0.0207)
Age	0.00383***	0.00265***	0.207***	0.164***
	(0.000317)	(0.000308)	(0.0210)	(0.0193)
Cash Flow	-0.00320	-0.00263	0.00831	0.0223
	(0.00341)	(0.00283)	(0.0794)	(0.0747)
Traditional		0.0568***		1.409***
		(0.0104)		(0.520)
Tech-leaning		0.331***		9.358***
		(0.0339)		(1.318)
High-tech		0.354***		11.14***
		(0.0147)		(0.975)
Observations	7,551	7,551	7,551	7,551

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

Notes: The relevant unit is a cross-section of publicly-listed firms from the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges. In the logit model (Column (1) and (2)) the dependent variable is a dummy for whether the firm acquired any tech target—as defined in the S&P data—between 2010 and 2020, while in the tobit model (Columns (3) and (4)) the dependent variable is the number of tech acquisitions between 2010 and 2020. The coefficients on the six sectors are those of primary interest for the regressions in Columns (1) and (3). In the remaining columns we examine the technology intensities of the acquirers (Traditional, Tech-leaning, High-tech). Finance is the default sector, and the group of companies with missing tech intensities is set as acquirers' default technology intensity. In all regressions we include controls for sales and cash flow as of 2010 (or the first 4 quarters since the IPO), and the age of the acquirer.

Table 5: Duration Model for the First Tech M&A by Sector

VARIABLES	(1) Finance	(2) Information	(3) Services	(4) Supply Chain	(5) Trade	(6) Private Equity
Traditional	0.694***	0.628***	0.184	0.386***	0.904***	-0.937**
	(0.196)	(0.172)	(0.160)	(0.118)	(0.276)	(0.426)
Tech-leaning	2.313***	0.973***	1.422***	1.493***	1.781***	-1.034
	(0.374)	(0.171)	(0.227)	(0.172)	(0.440)	(0.767)
High-tech	2.655***	1.064***	1.367***	1.706***	2.827***	-0.0854
	(0.271)	(0.105)	(0.161)	(0.100)	(0.296)	(0.655)
Age	0.00652	0.00957**	0.00539	0.0234***	0.0131***	0.0261**
	(0.00742)	(0.00384)	(0.00429)	(0.00207)	(0.00507)	(0.0128)
Sales	3.22e-05***	1.69e-05	2.08e-05	7.01e-06**	1.66e-05***	2.03e-06
	(3.38e-06)	(1.36e-05)	(1.61e-05)	(2.94e-06)	(5.08e-06)	(8.57e-06)
Cash flow	-1.10e-05**	-2.54e-05	0.000184	-1.84e-05	-0.000165*	-1.59e-05
	(5.51e-06)	(4.82e-05)	(0.000116)	(2.40e-05)	(9.03e-05)	(1.67e-05)
Observations	1,174	904	1,094	3,653	672	54

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

Notes: The relevant unit is a cross-section of publicly-listed acquirers from the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges. The table displays the hazard logs for several Cox proportional-hazards models to examine the association in each sector between the days to firms' first tech M&A since 1/1/2010 and the degree of tech intensity of the acquirers' business. The group of firms with missing tech intensities is set as the default level. We include controls for sales and cash flow as of 2010 (or the first 4 quarters since the IPO) and acquirer age in all specifications.

since the IPO), and the age of the potential acquirer.

The hazard logs reported in Table 5 suggest that, in all sectors except PE, firms whose core businesses are more tech-intensive also tend to be the ones that are most likely to engage in tech M&A. Moreover, this likelihood is heterogeneous across sectors. In particular, the hazard ratio of high-tech to traditional — measured by the ratio of the likelihood of high-tech firms acquiring their first tech target to the likelihood of the same event for firms classified as traditional — is lowest for the Information sector (1.55), where the proximity of the sector to tech may lead even more traditional firms to acquire tech targets early in our sample. In contrast, the hazard ratio of high-tech to traditional is the highest for the Finance (7.11) and Trade (6.84) sectors, where firms classified as traditional began engaging in tech M&A much later. In between, the firms in the sectors of Supply Chain and Services have hazard ratios equal to 3.74 and 3.92, respectively.[9]

[9]Hazard ratios of high-tech to traditional are computed by exponentiating the estimated hazard logs in

4 The Characteristics of Technology Acquisitions

We next examine the extent to which firms expand into tech categories and business verticals via M&A. To that end, we consider each level-2 business vertical in the S&P taxonomy (of which there are approximately 200) as a separate technological business area. We refer to an acquisition as "same" if the acquirer and the target are in the same level-2; as "adjacent" if they are in different level-2s under the same parent level-1; and as "unrelated" if they are under different level-1s.

Table 6 reports the percentage of target companies that fall in same, adjacent and unrelated verticals for acquirers in different sectors. With the exception of PE, the percentage of adjacent acquisitions is around 20% across all sectors; the percentages of acquisitions in the same and unrelated buckets range in 22.02–28.29% and 51.03–56.52%, respectively, with Trade being the only exception. In the Trade sector, tech acquisitions tend to skew somewhat more towards the same bucket (34.55%) and less towards the unrelated bucket (43.35%). Overall, most targets operate in a level-2 different from the acquirer's core business, suggesting that acquirers in each sector tend to expand into new tech categories and business verticals via tech M&A.

Column (4) of Table 6 reports how sectors (of acquirers) differ in the average age of the target companies they acquire. The results indicate that the average target age is the lowest in the Information sector (12.92 years). A potential explanation is that in the Information sector success may more often be driven by faster-paced technological innovation, and younger technology companies may grant access to more innovative and frontier technologies. In contrast, PE firms historically tend to acquire older companies, potentially with some level of financial distress, with a strategy that often aims to quickly turn them around to generate profits (Bernstein, Lerner and Mezzanotti, 2019; Ewens, Gupta and Howell, 2021). Indeed, we observe a higher average target age (17 years) for PE acquisitions. On average, firms in

Table 5. For example, for Information, the calculation is as follows: $\frac{\exp(1.064)}{\exp(0.628)} \simeq 1.55$. In terms of hazard logs, this can be interpreted as the fact that a high-tech company is 43.6% ($= 100 \times (1.064 - 0.628)$) more likely to complete its first tech M&A in Information as compared to a firm classified as traditional.

Table 6: Distance, Average Target Age and Target Data-intensity of Tech Acquisitions

Sector	Distance			Target Age (Years)	% Data-intensive Targets
	% Same	% Adjacent	% Unrelated		
Finance	25.51	23.46	51.03	15.72	15.77
Information	22.02	21.46	56.52	12.92	21.42
Services	28.29	19.49	52.23	15.91	22.71
Supply Chain	24.62	21.34	54.04	18.38	17.49
Trade	34.55	22.10	43.35	17.08	18.02
Private Equity	11.07	9.45	79.48	17.00	16.87
Total	21.44	18.55	60.02	15.74	19.76

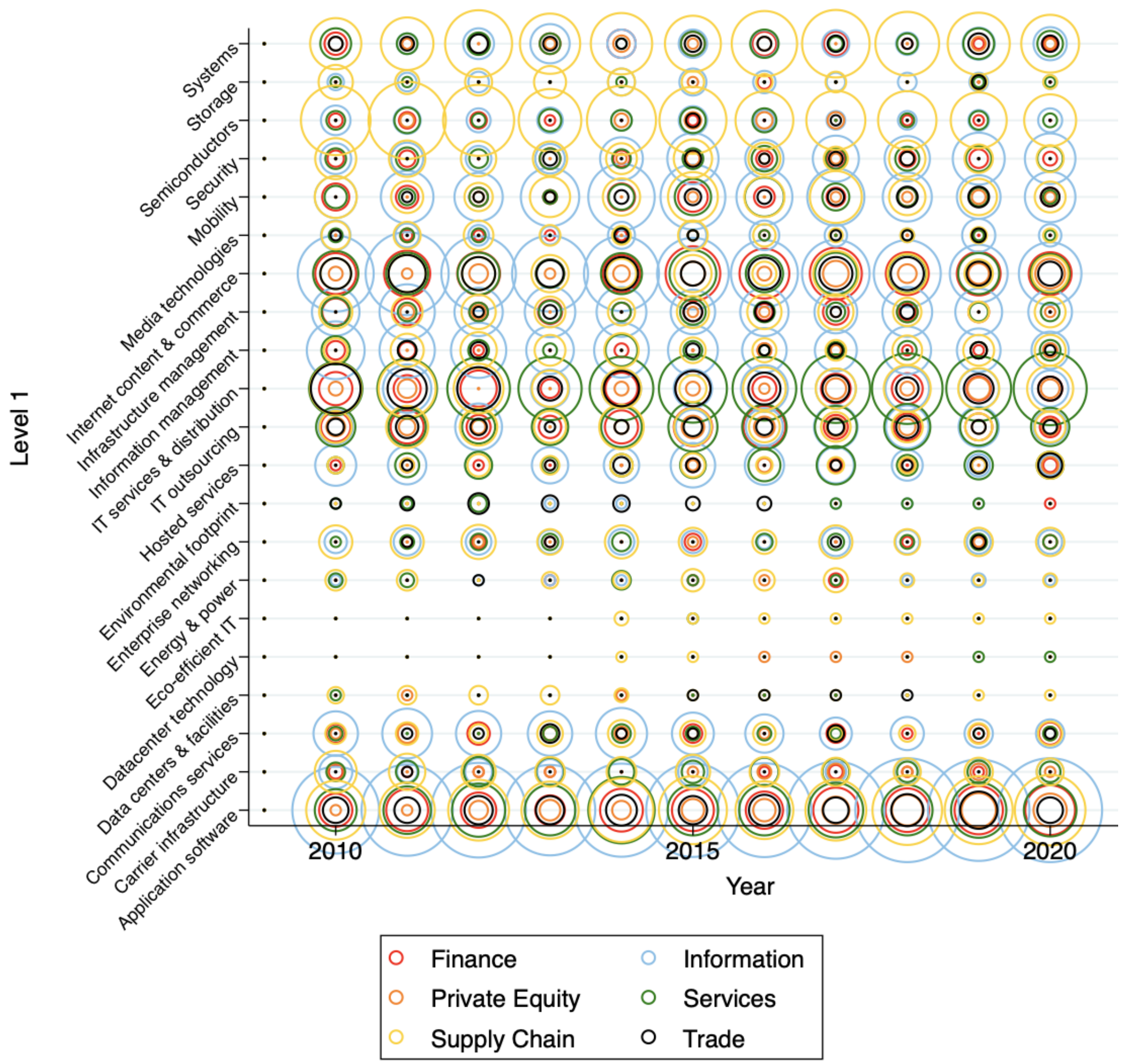
Notes: Statistics refer to M&As of publicly listed firms from all North American stock exchanges. The measures for distance exclude acquisitions from acquirers classified as "Non-tech" by S&P since these would be by construction "Unrelated". Results are similar if we include these acquisitions.

the Supply Chain and Trade sectors acquire even older target companies than PE firms, with average target company ages of 18.38 and 17.08 years, respectively. This may be emblematic of the difficulties for newer startups to disrupt markets in those sectors.

Column (5) reports the differences across sectors in terms of the data intensity of the target companies. This is of interest because in many of the verticals, data may be an essential input. We find that target companies acquired by firms in the Services and Information sectors have similar data intensities (22.71% and 21.42%, respectively). This may be due to the potential for data-reliant companies to disrupt markets in those sectors. In contrast, the percentage of data-intensive targets is the lowest for Finance companies (15.77%), potentially due to heavier-handed regulations concerning data flows in this sector.

Figure 2 illustrates the flow of tech M&A transactions in each acquirer sector across the level-1 tech categories of the targets they acquire. For each tech category and year, a bubble represents the total number of acquisitions completed by firms from a given sector, enabling two main comparisons. First, for each sector, in many of the years, it is possible to identify the categories towards which acquirers focused their tech M&A. For example, acquirers in the Services sector focused their M&A on target companies in the "IT services & distribution" and "IT outsourcing" categories, whereas the M&A of firms in the Information sector tended to be more dispersed across level-1s. Second, within each level-1 category, we can observe which sector began acquiring first and which sectors followed their lead. For example, in

Figure 2: Flow of Tech M&A in Different Sectors Across Level-1s Tech Categories



Notes: For every level-1–year, each bubble in the graph represents the total number of acquisitions completed by acquirers from a given sector of target companies in that particular level-1 category.
Source: 451 Research M&A KnowledgeBase, part of S&P Global Market Intelligence, data as of 02/16/2021.

the "Security" level-1 category, M&A by acquirers from the Supply Chain sector tended to be dominant up until 2013, at which point acquirers from the Information sector closed the gap, with Information becoming the dominant sector since 2014.

To formalize these insights, we compute measures that quantify the concentration of acquirers' tech M&A across level-1 categories. Column (1) of Table 7 reports the Herfindahl–Hirschman Index (HHI) of acquirer k from sector i (averaged across all acquirers in a sector), defined as:

$$\mathrm{HHI}_{ki} = \sum_{j \in \mathcal{J}_i} \left(\frac{q_{kj}}{q_{ki}} \times 100 \right)^2 ,$$

where $\mathcal{J}_i$ is the set of level-1 categories in which at least one firm from sector i completed a tech M&A, q_{kj} is the number of acquisitions by acquirer k in level-1 category j, and q_{ki} is the total number of acquisitions by acquirer k from sector i. As expected, firms in the PE and Information sectors tend to disperse their tech M&A across level-1 categories more so than firms in other sectors. This may be because the sets of technologies that appeal to more traditional sectors like Finance, Services, Supply Chain, and Trade is smaller.

Column (2) of Table 7 reports the share of acquirers with at least two tech acquisitions, Pr(Tech M&A $>$ 1). The values reported highlight heterogeneity across sectors with respect to the number of firms with serial tech M&As. Since the HHI may be inflated by the existence of acquirers with only a single tech acquisition between 2010 and 2020, we report the HHI conditional on acquirers completing at least two tech acquisitions in Column (3), averaged across acquirers in a sector. By construction, these HHIs are lower, though the differences across sectors remain qualitatively similar.

Columns (4) and (5) of Table 7 report the fraction of tech acquisitions that are completed by firms with prior tech acquisitions and the average number of days between any two transactions by the same acquirer (averaged across firms in a sector), respectively. The results indicate that across sectors, the vast majority of acquisitions — between 73.62% (Finance) and 86.25% (Information) — are consummated by firms with prior tech M&As, and that the average time period between any two same-acquirer tech acquisitions is relatively short,

Table 7: Concentration in M&A and Sequential Acquisitions across Sectors

Sector	HHI	Pr(Tech M&A > 1)	HHI | Tech M&A	Pr(Sequential Tech M&A)	Average Lag
Finance	5,666.61	57.69%	4,464.00	73.62%	615.84
Information	4,700.70	72.85%	4,089.24	86.25%	418.69
Services	5,497.00	70.08%	4,779.88	82.63%	538.29
Supply Chain	5,287.26	64.13%	4,332.78	77.59%	578.42
Trade	6,264.86	61.22%	5,251.03	75.70%	586.35
Private Equity	3,380.43	47.06%	2,931.93	84.66%	541.85
Total	5,152.26	66.11%	4,331.29	81.56%	524.88

Notes: Acquirer HHI is a measure of acquirer concentration across S&P level-1s; Pr(Tech M&A > 1) is the share of acquirers with at least two tech acquisitions; HHI | Tech M&A is the same as the first column but conditional of having at least two tech acquisitions; Pr(Sequential Tech M&A) is the fraction of tech acquisitions that are completed by a company which already made a tech acquisition before; Average Lag is the average number of days between any two tech acquisitions by the same acquirer. The numbers reported are all averages across acquirers within each sector, except for the second-last column which is a statistic at the acquisition-level. The data used refer to publicly-listed firms from all North American stock exchanges.

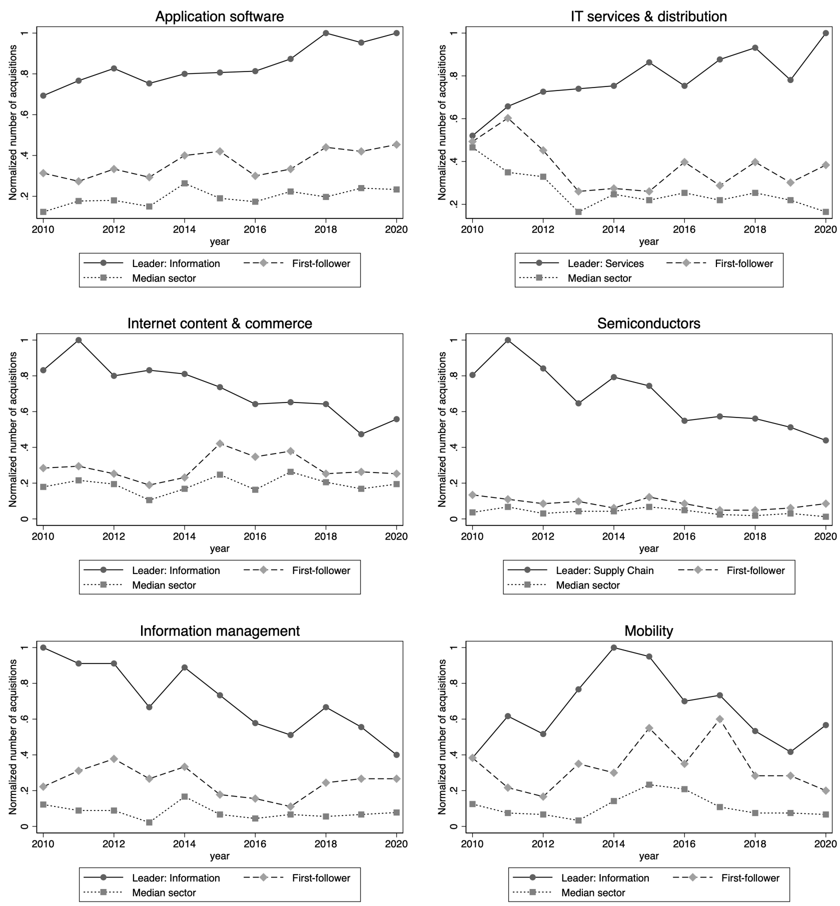
ranging between 1.15 years (Information) and 1.69 years (Finance). The combination of these findings suggests economies of scale or firm-specific preference in technological expansion via M&A.

Figure 3 zooms into the leader-followers dynamics in tech M&A in the five level-1 categories that have the highest number of tech M&A transactions in 2010 ("Application Software," "IT Services & Distribution," "Internet Content & Commerce," "Semiconductors," and "Information Management"), with the addition of "Mobilty" (a category characterized by intense cross-sector tech M&A dynamics during our sample period). Each sub-figure depicts the (normalized) number of tech acquisitions completed by firms in the sector with the highest ("leader") number of transactions, the second-highest ("first-follower"), and the median number across sectors ("median sector") in a given year. All numbers are normalized by the highest number of deals in a given level-1 category between 2010 and 2020. In all of the level-1 categories in Figure 3, the leader is constant across years, whereas the first follower and the median sector may change over the sample period.

In the level-1 category of Application Software — the one with the highest overall number of tech M&A transactions during 2010-2020 — the leading sector (Information), the first-follower and the median sector all exhibit rising levels of tech M&A activity over time, suggesting the growing importance of this tech category to the economy. It is noticeable, however, that the leading sector increased its tech acquisitions at a faster clip, widening the gap with the other sectors over time. In the Internet Content & Commerce, Semiconductors and the Information Management level-1 categories, the follower sectors closed the gap with the leading sector over time, but this was primarily driven by a reduction in the number of acquisitions completed by firms in the leading sector. In contrast, in the IT Services & Distribution category, the opposite holds: the leading sector (Services), the first-follower and the median sector started off fairly close in 2010, but after 2011 firms in the Services sector engaged in tech M&A at a much faster rate, dramatically widening the gap with other sectors in this category. In Mobility, the leading sector (Information), initially had the exact same number of transactions as the first-follower, but the leader exhibited a dramatic rise in tech M&A between 2010 and 2014, widening the gap with other sectors. This gap substantially decreased between 2014 and 2017, in part due to the first-follower catching up and in part due to a slowdown in acquisitions by the leader, though the gap widened again between 2019 and 2020. Overall, Figure 3 illustrates additional dimensions of the heterogeneity across sectors, whereby firms in different sectors appear to engage in tech M&A expansions into different technology categories, with different volumes and frequencies of acquisitions.

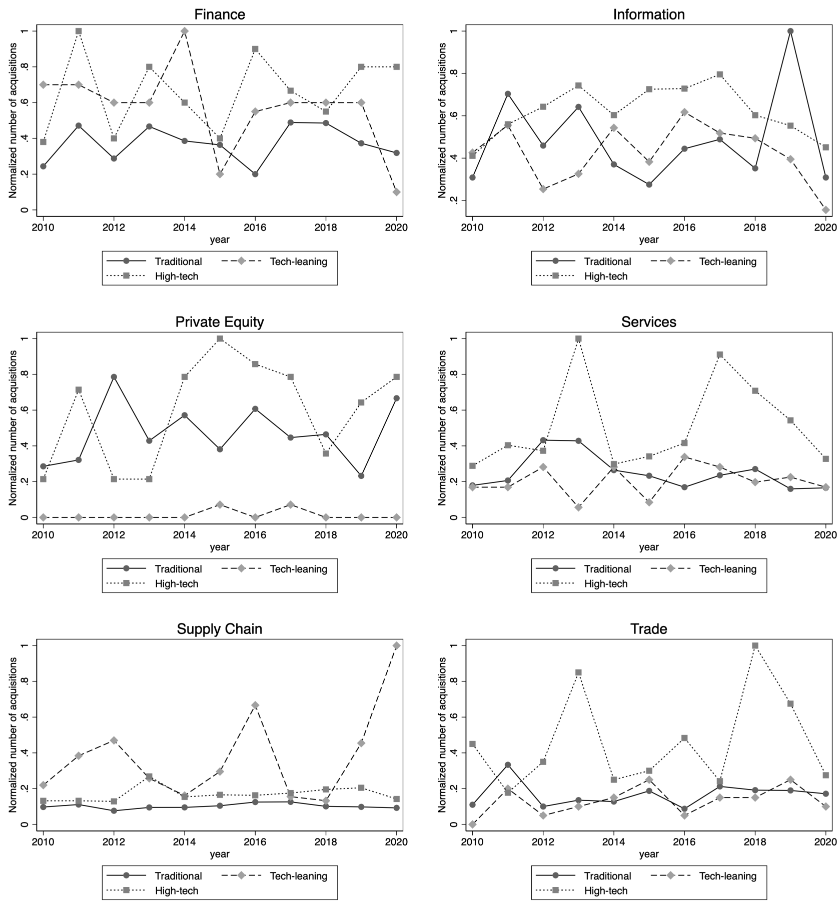
Figure 4 depicts the counts of M&A transactions completed in each sector by acquirers classified as high-tech, tech-leaning, and traditional. The graphs in each sub-figure are normalized on a per-firm basis and by the highest number of per-firm per-year M&A transactions across groupings (high-tech, tech-leaning and traditional) in a given sector. Excluding the Supply Chain sector, the high-tech group of acquirers in each sector tends to lead the pack in tech acquisitions, particularly in the later years of the sample period and in the Services and Trade sectors, with few exceptions (e.g., in the Information sector, M&A activity by firms classified as traditional picks up during 2019). The M&A activity of firms classified as tech-leaning tends to resemble that of firms classified as traditional, except for the Finance, PE and Supply Chain sectors. In the Supply Chain sector, tech-leaning acquirers lead the pack. Overall, Figure 4 demonstrates that acquirers classified as high-tech do not dominate

Figure 3: Relative Gap in Tech M&As over Time between Leading and Following Sectors in the Largest Level-1s Tech Categories



Notes: Each graph depicts the number of M&A deals completed by the sector with the highest (leader), the second-highest ("First-follower"), and the median number ("Median sector") of deals in a given year. In all the level-1s displayed, the leader is constant across years, whereas the first follower and the median sector can change over time. All numbers are normalized by the highest number of deals in a level-1 category between 2010 and 2020. The five largest level-1s in terms of M&A activity as of 2010 are depicted, along with "Mobilty," which is another large level-1 characterized by intense cross-sector competition between 2010 and 2020. Figures are ordered according to the "size" of the level-1 as of 2010.

Figure 4: Relative Gap in M&As over Time between Firms of Different Tech Intensities in each Sector



Notes: Each graph depicts the number of per-acquirer M&A deals completed by Traditional, Tech-leaning and High-tech firms in every sector in each year of the sample period, normalized in each sector by the highest number of deals by a group of firms (high-tech, tech-leaning, traditional) between 2010 and 2020.

tech M&A across all sectors — in fact, excluding the Services and Trade sectors, acquirers classified as tech-leaning and traditional are either not far behind or, at times, ahead in their tech M&A activities than their high-tech counterparts.

5 Possible Drivers of Technology Acquisitions

A natural policy-related question is what drives public firms to acquire outside their core business areas. To take a step towards answering this question, we explore two possible mechanisms: (1) increased competition in the product space, which, for example, may lead firms to expand their business by acquiring access to new technologies; and (2) a more general desire to improve a firm's financial performance.

For (1), we study the correlation between a public firm's M&A activity and the competition it faces from other public firms in the same business area, as well as the competition from new entrants to the firm's business area via an initial public offering (IPO). Our approach entails two challenges — defining a public firm's market, and quantifying the firm's competition from other incumbents.

To address the first challenge, we define the "market" for each public firm by using the TNIC-3 classification data developed by Hoberg and Phillips (2010, 2016). In that data, any pair of public firms are assigned to the same market if their product descriptions in the 10-Ks are similar enough. As this definition identifies a specific set of competitors for each firm listed on the AMEX, NYSE American, NYSE Arca, and NASDAQ, we can measure competition from entrants by tracking the number of new IPOs in a given market-year.

To address the second challenge, we measure competition from incumbents by using "Product Market Fluidity" — a firm-year specific continuous measure developed by Hoberg, Phillips and Prabhala (2014). It aims to measure the competitive pressure imposed on any public firm listed on the AMEX, NYSE American, NYSE Arca, or NASDAQ from other public firms in the same set of stock exchanges. More specifically, for each firm i, the measure quantifies the extent to which rival incumbents — firms belonging to the same pairwise market as delineated above — change the wording of a product description in their 10K reports along with firm i's change of product description (in firm i's 10K reports).

To correlate these competition measures with a firm's tech M&A activity, Table 8 reports a few tobit regressions, using the firm-year panel of publicly-listed firms on the AMEX, NYSE American, NYSE Arca, NASDAQ exchanges between 2010 and 2019.[10] For firm i in year t, the dependent variables are firm i's total number of tech acquisitions in year t (Column 1) and firm i's number of tech acquisitions in the same, adjacent and unrelated S&P level-

[10]We use data through 2019 instead of 2020 because the CRSP and Compustat databases did not offer 2020 accounting measures for some firms as of the time of our analysis.

Table 8: Tech Acquisitions and Competition from Incumbents and New Entrants

VARIABLES	(1) Tot Tech M&A	(2) Same Tech M&A	(3) Adjacent Tech M&A	(4) Unrelated Tech M&A
L.prodmktfluid	0.00429***	0.000666	0.000526	0.00310***
	(0.00138)	(0.000422)	(0.000411)	(0.00108)
Ipo competition	-0.000184	-0.000141*	1.18e-05	-5.40e-05
	(0.000293)	(7.41e-05)	(8.34e-05)	(0.000236)
Observations	34,287	34,287	34,287	34,287

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

Notes: The unit of the regression is a panel of publicly listed firms from the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges between 2010 and 2019. Columns (1) to (4) display the results of tobit regressions in which the dependent variables are the total number of tech acquisitions, and the number of tech acquisition in the same, adjacent and unrelated S&P level-2 business verticals, respectively. We report the two coefficients of interest, i.e., those for product market fluidity in the previous year ("L.prodmktfluid") and the number of new IPOs in the market ("Ipo competition"), but we also control for acquirer age and sales, and include year and 4-digits NAICS codes fixed-effects in all regressions.

2 business verticals (Columns 2,3, and 4). The key right-hand-side variables are firm i's product market fluidity as of year $t-1$ ("L.prodmktfluid") and the number of new IPOs in firm i's market as of year t ("Ipo competition"). Ipo competition is not lagged in the regression since IPOs need to be planned in advance (often six to nine months in advance[11], and therefore should already be recognized by firm i as competitors before year t. We control for firm i's concurrent age and sales revenue, as well as year and 4-digits NAICS codes fixed effects in all specifications.

The results indicate that an acquirer that faces more competition from incumbents in year $t-1$ is associated with a higher propensity to engage in tech M&A in year t, and this higher propensity is reflected by more acquisitions of target companies in the unrelated bucket. This finding suggests that public firms respond to increased competition in their product spaces through technological expansion into new technology areas. As far as entrants, the results indicate that the IPO of a competitor is correlated with a reduction in the number of tech acquisitions in the same business vertical, although this is only statistically significant at the 10% level.

[11] see, e.g., `https://pitchbook.com/blog/ipo-process-explained`

For (2), to check whether performance enhancement is a general motivation for tech acquisitions, we compare the performance change of public firms that engage in tech M&A versus those that do not record any M&A in our data. In particular, for each firm i listed on the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges, we measure its percentage change in market value, sales and number of employees over the 10 year period from 2010 to 2019. We are motivated to track a firm's number of employees because new technologies may make some of the firm's labor redundant (see, e.g., Akst, 2013; Autor and Dorn, 2013; Brynjolfsson and McAfee, 2014). These dependent variables are then regressed on firm i's total number of tech acquisitions between 2010 and 2019, or its interaction with sector dummies. In all specifications, we control for firm age and include 4-digit NAICS codes fixed effects.

As reported in Table 9, an additional tech acquisition by firm i is associated with a 2.08% increase in firm i's market valuation from 2010 to 2019. This result is primarily driven by the Finance and Information sectors, where Column (2) indicates that an additional tech acquisition is related to a 10.3% increase in market value in Finance and 2.91% in Information. As for sales, tech M&A is only correlated with a significant change in sales for acquirers in the Information (3.46%) and Trade (6.53%) sectors. Similarly, for the number of employees, Column (6) suggests that tech M&A is only correlated with an increase in the number of employees for the Trade sector (26.5%).

To shed some light on what drives the findings for firms in the Trade sector, we rerun the analysis when excluding the 25 firms with the highest number of tech M&A transactions in our sample (across all sectors). These firms include Google/Alphabet, Apple, Facebook, Amazon, and Microsoft. We find that the coefficient on Trade$\times$#TechM&A loses significance (at the 5% level) in Columns (4) and (6) of Table 9.[12] This suggests that Amazon, the only top 25 acquirer in the Trade sector, drives the results in that sector.

For robustness, we run two additional sets of tests. First, we find that the results are

[12] In all of the other specifications and sectors, the estimated coefficients in Table 9 are qualitatively similar. Results are reported in Table A.2 in the Appendix.

Table 9: Intensity of Tech M&A and Firm Change in Performance between 2010 and 2019

VARIABLES	(1) %ΔMarket Value	(2) %ΔMarket Value	(3) %ΔSales	(4) %ΔSales	(5) %ΔEmployee Number	(6) %ΔEmployee Number
Fin×#TechM&A		0.103**		-0.0610		-0.306
		(0.0507)		(0.0963)		(0.420)
Info×#TechM&A		0.0291**		0.0346**		0.0286
		(0.0116)		(0.0136)		(0.0248)
PE×#TechM&A		0.0648		-0.00675		0.136
		(0.0432)		(0.0426)		(0.188)
Serv×#TechM&A		-0.00212		-0.0420		-0.205
		(0.0281)		(0.0345)		(0.161)
SupCh×#TechM&A		-0.00263		-0.0292		-0.0337
		(0.0112)		(0.0330)		(0.0909)
Trade×#TechM&A		0.0785*		0.0653**		0.265***
		(0.0413)		(0.0301)		(0.0896)
#TechM&A	0.0208**		0.00474		-0.0251	
	(0.00942)		(0.0140)		(0.0474)	
Observations	5,152	5,152	4,451	4,451	4,485	4,485
R-squared	0.039	0.040	0.009	0.009	0.100	0.100

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

Notes: In all specifications we control for firm age and include 4-digit NAICS codes FE; #TechM&A indicates the number of tech M&As.

robust if we control for acquirers' number of employees or sales as of 2010; the only change is that the coefficient on Info x #TechM&A turns significant in Column (5). Second, Table A.1 in the Appendix replicates the analysis in Table 9, but in lieu of the number of an acquirer's acquisitions, incorporates a dummy variable that equals one if an acquirer has any tech acquisition between 2010 and 2019. The results suggest that acquiring tech targets is correlated with: (i) a percentage increase in the acquirer's market valuation (primarily driven by the increase in valuations for firms in the Information sector); (ii) no significant change in the effect on acquirers' sales; and (iii) a percentage decrease in acquirers' number of employees (primarily driven by firms in the Services sector).

Overall, while, on average, we observe positive correlation between a public firm's tech M&A and its change in market value from 2010 to 2019, this correlation is small and not always significant for some sectors. The correlations between tech M&A and sales or employment changes are also weak, suggesting that absolute performance enhancement is unlikely to be a main driver for tech acquisitions in our sample.[13] In contrast, we find evidence suggesting that competitive pressure from incumbents in the same market may have motivated public firms to engage in tech M&A and expand to "unrelated" business areas.

6 Conclusion

Combining data from multiple proprietary databases, we illustrate the prevalence and heterogeneity of control (majority) acquisitions of technology companies by public firms listed in North American stock exchanges during 2010-2020. In particular, we show that (1) only 13.1% of public firms engaged in tech M&A, but such M&A activities are widespread across different sectors of the economy; (2) larger and older firms are more likely to acquire tech companies; (3) the majority of target companies fall outside the acquirer's core area of business; (4) transactions in each M&A-active tech category tend to be led by acquirers from a specific sector, to varying extents over time; and (5) firms are, in part, driven to acquire because they face increased competition in their core business.

Our findings contribute to ongoing policy debates by shedding light on the fact that technology companies are acquired by firms from all sectors of the economy, to varying extents in different time periods, and that such acquisitions may provide on-ramps for incumbents to expand technologically. Our findings also help demonstrate that some sectors of the economy may have an inherently different pace of seeking technological expansions, as well as the role that competition plays in driving firms to diversify technologically. Examining the competitive implications of tech acquisitions in specific markets, both for firms and their employees, as well as the consequences of regulatory restrictions on tech acquisitions in specific sectors, offers a number of directions for future work.

[13] As shown by Gorton, Kahl and Rosen (2009), managers may engage in defensive M&As even if they are unprofitable to the acquirer.

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Appendix A Additional Tables

Table A.1: Tech M&A and Firm Change in Performance between 2010 and 2019

VARIABLES	(1) %ΔMarket Value	(2) %ΔMarket Value	(3) %ΔSales	(4) %ΔSales	(5) %ΔEmployee Number	(6) %ΔEmployee Number
Fin×$\mathbb{1}\{\#\text{Tech M\&A} > 0\}$		0.495		-1.170		-4.130
		(0.375)		(1.188)		(4.510)
Info×$\mathbb{1}\{\#\text{Tech M\&A} > 0\}$		3.147***		1.891		-67.90
		(0.636)		(1.266)		(48.91)
PE×$\mathbb{1}\{\#\text{Tech M\&A} > 0\}$		0.339		-0.301		-2.591
		(0.512)		(1.011)		(3.355)
Serv×$\mathbb{1}\{\#\text{Tech M\&A} > 0\}$		-8.041***		0.423		-16.71**
		(0.872)		(2.006)		(7.660)
SupCh×$\mathbb{1}\{\#\text{Tech M\&A} > 0\}$		0.863		-3.256		-5.752
		(0.903)		(2.409)		(4.937)
$\mathbb{1}\{\#\text{Tech M\&A} > 0\}$	0.429***		-0.341		-4.963**	
	(0.162)		(0.545)		(2.215)	
Observations	5,152	5,152	4,451	4,451	4,485	4,485
R-squared	0.039	0.041	0.009	0.009	0.101	0.102

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

Notes: In all specifications we control for firm age and include 4-digit NAICS codes FE. Finance is the default sector, while Trade is omitted because of collinearity; #TechM&A indicates the number of tech M&As.

Table A.2: Intensity of Tech M&A and Firm Change in Performance between 2010 and 2019 Excluding Top 25 Tech Acquirers

VARIABLES	(1) %ΔMarket Value	(2) %ΔMarket Value	(3) %ΔSales	(4) %ΔSales	(5) %ΔEmployee Number	(6) %ΔEmployee Number
Fin×#TechM&A		0.103**		-0.0603		-0.303
		(0.0507)		(0.0965)		(0.420)
Info×#TechM&A		0.114***		0.106***		0.0206
		(0.0323)		(0.0346)		(0.0964)
PE×#TechM&A		0.0852		0.0213		0.263
		(0.0707)		(0.0677)		(0.296)
Serv×#TechM&A		0.0608		-0.0791		-0.426*
		(0.0485)		(0.0568)		(0.259)
SupCh×#TechM&A		0.00588		-0.0998		-0.159
		(0.0222)		(0.0763)		(0.217)
Trade×#TechM&A		0.0358		0.128*		0.182
		(0.0376)		(0.0780)		(0.151)
#TechM&A	0.0675***		-0.00100		-0.108	
	(0.0169)		(0.0311)		(0.0953)	
Observations	5,127	5,127	4,426	4,426	4,460	4,460
R-squared	0.040	0.041	0.009	0.009	0.100	0.100

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

Notes: In all specifications we control for firm age and include 4-digit NAICS codes FE. Finance is the default sector, while Trade is omitted because of collinearity; #TechM&A indicates the number of tech M&As.

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