M&A and Technological Expansion *

Ginger Zhe Jin† Mario Leccese‡ Liad Wagman§

October 11, 2025

Abstract

We examine how public firms listed in North American stock exchanges acquire technology companies during 2010-2020. Combining data from S&P, Refinitiv, Compustat, and CRSP, and utilizing a unique S&P taxonomy that classifies tech M&As by tech categories and business verticals, we show that 13.1% of public firms engage in any tech M&A in the S&P data, while only 6.75% of public firms make any (tech or non-tech) M&A in Refinitiv. In both datasets, the acquisitions are widespread across sectors of the economy, but tech acquirers in the S&P data are on average younger, more investment efficient, and more likely to engage in international acquisitions than general acquirers in Refinitiv. Within the S&P data, deals in each M&A-active tech category tend to be led by acquirers from a specific sector; the majority of target companies in tech M&As fall outside the acquirer's core area of business; and firms are, in part, driven to acquire tech companies because they face increased competition in their core areas.

Keywords: Technology, M&A, acquisition, competition.

JEL Classifications: D22, D4, L1.

*We thank two anonymous referees, Daniel Sokol, and participants at the 2022 USC conference for constructive comments. We are grateful to S&P for providing access to the data and to our home universities and Washington Center for Equitable Growth for financial support. The content and analyses in this paper reflect the authors' own work and do not relate to any institution or organization with whom the authors are affiliated. All errors are our own.

†University of Maryland & NBER, Email: ginger@umd.edu.

‡University of Maryland. Email: leccese@umd.edu.

§Illinois Institute of Technology. Email: lwagman@stuart.iit.edu.

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 can 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.

In theory, 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. Furthermore, tech M&A can also enable an incumbent to leapfrog its expansion into new technology categories, and reshape competition among incumbent firms.

At the same time, tech M&A has attracted policy attention, especially from the antitrust perspective. It is of concern that some large incumbents may acquire young startups in nascent markets to eliminate competitors, preempt entry, or reduce innovation in the long run. Many policy reports in this area focus on a few leading technology platforms (such as Alphabet/Google, Apple, Facebook/Meta, Amazon, and Microsoft — known as GAFAM), citing their unusual volume and pace of M&As.[1] In both the US and the European Union, antitrust complaints were filed and legislative efforts were made to target a handful number of ”gatekeepers”[2] or ”covered platforms”[3], suggesting that tech M&As might be special activities that only apply to a small set of large technology companies. This stands opposite to the argument that incumbent acquisition of technology startups could disseminate and commercialize technology across all sectors of the economy.

In light of these diverging views, this paper aims to better understand tech M&As made by firms that are publicly listed in the North 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 (ICET), 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.

[1] See for example “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`; 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`; 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, available at `https://ec.europa.eu/competition/publications/reports/kd0419345enn.pdf`; the Majority Staff Report issued by the US Congression in 2020 on Investigation of Competition in Digital Markets, available at `https://www.govinfo.gov/content/pkg/CPRT-117HPRT47832/pdf/CPRT-117HPRT47832.pdf`; and the FTC staff report “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`.

[2] The European Union’s Digital Markets Act (DMA) (`https://ec.europa.eu/commission/presscorner/detail/en/ip_22_6423`), enacted in November 2022 and effective May 2023, requires “gatekeepers” to inform the European 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. 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 DMA (`https://www.bruegel.org/blog-post/which-platforms-will-be-caught-digital-markets-act-gatekeeper-dilemma`.

[3] For example, the Platform Competition and Opportunity Act proposed by the US Congress in 2021 would restrict “covered platforms” from acquiring competitors or potential competitors, where its criteria entail that only GAFAM firms, as of the time of the legislative proposal, would be impacted by the bill (`https://www.congress.gov/bill/117th-congress/house-bill/3826`).

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 S&P's 2010-2020 sample of tech M&A, we find that 13.1% of public firms acquire at least one technology company. In comparison, only 6.75% of public firms have made any majority-control acquisition in Refinitiv's database of M&As, which aims to track all types of M&As but has less coverage on ICET-specific M&A than S&P. In both S&P and Refinitiv data, acquisitions are widespread across sectors of the economy, but acquirers in S&P are on average younger, more investment efficient (measured by Tobin's Q), and more likely to engage in international acquisitions than acquirers in Refinitiv. Conditional on having any tech acquisition in the 2010-2020 S&P data, 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 partly 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 public firms, especially those that are larger and older in their own sectors, 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 Hovenkamp (2030) 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.[4]

[4]See, for example, Katz and Shelanski (2005), as well as a number of bills proposed in the US Congress. In particular, 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/`

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 competition as one potential mechanism that may drive public firms to engage in tech M&A. Section 6 concludes.

2 Data

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

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

`Antitrust-reform-is-uncertain-despite-bipartisan-support`).

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% of the transactions for the targets and 94.8% for the acquirers). This allows us to compute the age of most target firms at the time of the consummation of their acquisition.[5] 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."

We test the reliability of this classification by comparing the similarity of the business descriptions of technology targets belonging to the same S&P level-2s, the same level-1 but different level-2s, and completely different level-1s. To this end, we merge S&P with Crunchbase, a dataset that tracks investment rounds in technology ventures, including ventures' business descriptions and Crunchbase-assigned keywords representing a venture's business areas. We combine these two strings and use the resulting text to compute a matrix of cosine similarities for a random sample of 2,311 technology ventures acquired between 2010 and 2020.[6] Our results—reported in Table A.1—show that firms in the same S&P level-2s tend to have higher cosine similarities than firms in the same level-1 but different level-2s, which, in turn, tend to have higher similarities as compared to firms in different level-1s.[7] This is consistent with the argument that S&P classifies firms of more similar businesses as "closer" in its taxonomy.

The reliability of the S&P taxonomy of the technology space is also confirmed by its wide usage for financial analysis. According to an internal statistic reported by S&P, more than 85% of tech bankers advising more than 10 deals per year rely heavily on this dataset for their trend and valuation analysis. Moreover, we compare the partition of the tech space implied by the S&P taxonomy to that implied by the portion of CB Insights—another database that tracks technology M&As—used for related academic research by Prado and Bauer (2022). The comparison suggests that the S&P taxonomy has finer partitions. For example, we find that Google/Alphabet, Amazon,

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

[6]For these ventures we have the string used to compute cosine similarities as well as their S&P classification since they are recorded in both Crunchbase and S&P. In effect, we merge the two datasets and compute the matrix of cosine similarities for a 10% random sample. This is done to reduce the computational burden of the exercise.

[7]In Table A.2, we also check the robustness of our results by dropping similarity scores below 0.3 to avoid the noise caused by shorter text strings in Crunchbase.

Facebook/Meta, Apple, and Microsoft (GAFAM), combined, spread their acquisitions across 17 level-1s and 100 level-2s between 2010 and 2020 in the S&P data, while 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.

We also verify the coverage of S&P by cross-checking this database with the Worldwide Mergers, Acquisitions, and Alliances Database offered by Refinitiv's SDC (henceforth, Refinitiv). The Refinitiv data is by definition broader than S&P's, as it also tracks non-tech targets and includes both majority- and minority-control acquisitions. After merging the two datasets, 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 Refinitiv data.[8] Within this broad definition of tech industries, we find that, out of the transactions in the Refinitiv 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 Refinitiv, 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 Refinitiv data, rather than a lack of coverage by S&P. For ease of reference, we refer to all M&As in the S&P data as "tech M&As." When we summarize the S&P data later on, we benchmark the distribution of tech M&As in the S&P data with the distribution of majority control M&As in Refinitiv (which could be tech or non-tech).

Compustat tracks 19,064 public companies listed in North American stock exchanges in 2010-2020, recording financial statements and market data.[9] 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 Hoberg-Phillips Data Library (HPDL) includes a few publicly-accessible datasets[10] created by Professors Gerard Hoberg and Gordon Phillips, based on text analysis of public firms' 10K product descriptions. As detailed below, we use the "Product Market Fluidity" data from the HPDL, to measure the degree of competitive pressure and product market change surrounding a public firm. Except

[8] A mapping of the categories in the S&P data to NAICS codes was provided by S&P.
[9] This dataset also includes—for example—Canadian stock exchanges, such as the Toronto Stock Exchange (TSX).
[10] Available at `https://hobergphillips.tuck.dartmouth.edu`.

for the HPDL, all the other datasets are used under license through our home universities or for this study in particular.[11]

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. 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, 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, 2022). In particular, 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 data 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

[11]One shortcoming of our analysis is that none of the data we use contains detailed information about board members, hence we cannot examine how board connection may be related to M&A.

2020, which we believe is highly plausible. Overall, we identify 68 North American publicly-traded PE firms, of which 50 completed at least one majority tech acquisition in the S&P data and 33 completed at least one majority acquisition (tech or non-tech) in Refinitiv.[12] To ensure sectors are mutually exclusive in our summary statistics, we exclude these PE firms from the other sectors.

As shown in Table 1, Refinitiv reports more than twice majority-control M&A deals than S&P, which is not surprising because S&P focuses on tech M&As while Refinitiv includes both tech and non-tech M&As. However, S&P covers more M&As in the Information sector, suggesting that many tech M&A deals are covered by S&P but not by Refinitiv. In fact, Information accounts for 38.85% of all tech M&As reported by S&P between 2010 and 2020. Other sectors are less involved in tech M&As, but many of them have seen a substantial number of tech M&As: for example, there are 2,136 tech M&As in the Services sector and 3,584 in the Supply Chain sector, accounting for 16.93% and 28.4% of all tech M&As in S&P respectively. Tech M&As even occur in more traditional industries such as agriculture, fishing and hunting, and mining. Finance is somewhat special: it has the highest number of public firms among all sectors; it accounts for 4,205 majority-control M&As (14.26%) in Refinitiv but only 1,084 tech M&As (8.59%) in S&P. This is because S&P generally does not track targets belonging to the traditional finance and insurance sector, while most (70%) of the M&A deals closed by acquirers in Finance involve targets within the same sector.

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, Refinitiv tags an acquirer as "high-tech" based on an evaluation of its core business; 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 the S&P data 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 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

[12] Note that our definition of PE differs from the typical definition of private equity firms because we focus on publicly traded firms only. Since the main business model of private equity is to invest in private companies with the aim of eventually selling them for a profit, it is uncommon for private equity firms to be publicly traded themselves. That being said, private equity has become a core component of institutional investors' portfolios (Preqin, 2021). According to Cumming, Fleming and Johan (2011), 34% of the 171 surveyed institutional investors have listed private equity in their investment mandate.

Table 1: Industry Classification and NAICS Codes

Sector	2-digits NAICS Code	Industry	Number of Public Firms	Tech M&As (S&P)	M&As (Refinitiv)
Finance	52	Finance and Insurance	6,133	1,084	4,205
Information	51	Information	1,494	4,903	4,199
Services	53	Real Estate	614	309	2,631
	54	Professional and Technical Services	465	1,379	1,495
	56	Administrative Services	203	275	742
	61	Educational Services	82	53	98
	62	Healthcare and Social Assistance	197	64	977
	71	Arts and Entertainment	92	42	129
	72	Accommodation and Food	179	8	381
	81	Other Services	30	6	52
Supply Chain	11	Agriculture, Fishing and Hunting	52	2	48
	21	Mining	2,023	153	892
	22	Utilities	365	89	623
	23	Construction	160	38	321
	31	Manufacturing	347	24	671
	32	Manufacturing	2,068	332	2,548
	33	Manufacturing	2,168	2,946	5,409
Trade	42	Wholesale Trade	309	259	1,156
	44	Retail Trade	224	70	446
	45	Retail Trade	183	204	249
	48	Transportation and Warehousing	331	64	411
	49	Transportation and Warehousing	13	8	34
Private Equity			68	308	1,772
Total			17,800	12,620	29,489

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.

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, such as firms' IPO dates (when missing in Compustat), market valuations, and number of employees.[13] 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.[14] Hence, we obtain a 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?

Table 2 further compares M&A data in S&P and Refinitiv by sector. The first two columns convey the same observations as Table 1: Information is the sector with the highest total number of tech

[13]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.

[14]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%.

M&As completed by publicly-traded firms in the US exchanges between 2010 and 2020, followed by Supply Chain, Services, Finance, and PE. These statistics are partly driven by the different number of public companies across NAICS industries, as suggested by Table 1.

The third and fourth columns of Table 2 report the percent of public firms making any acquisitions in S&P and Refinitiv separately. Surprisingly, the percent of public firms engaging in any tech M&A in S&P (13.10%) is much higher than the percent of public firms engaging in any majority-control M&A (tech or non-tech) in Refinitiv (6.75%). This suggests that tech M&As may be more accessible to public firms than M&As under the more classical coverage of Refinitiv, possibly because tech M&As tend to involve younger startups and S&P does a better job tracking tech M&As of smaller or missing-value transactions. To support this conjecture, we observe the median deal value is $15 million lower for the tech M&As reported only in S&P than those reported in both S&P and Refinitiv. One may wonder why Refinitiv, as compared to S&P, demonstrates a higher count of M&A deals but a lower percent of public firms making any M&A. This can be explained by more M&A intensity per acquirer in Refinitiv. In particular, as shown in the fifth and sixth columns of Table 2, a public acquirer in Refinitiv makes an average 7.58 acquisitions between 2010 and 2020, which is significantly higher than the counterpart in S&P (5.47). Again, this is not surprising, as Refinitiv has a broader M&A coverage.

Sector-wise, within the S&P data, almost half of the public 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.

The second panel of Table 2 compares M&As in S&P and Refinitiv in terms of acquirer attributes and the international nature of acquisitions. Acquirers of tech targets in the S&P data are 3.5 years younger than those in Refinitiv, mostly because the Information sector is much more prevalent in tech M&A and acquirers in the Information sector are significantly younger than those in other sectors. For the same reason, the average acquirer in the S&P data is only slightly older than an average public firm in Compustat (17.73 years old versus 17.4), while acquirers in Refinitiv are significantly older (21.66) on average. Following Dong and Doukas (2022), we label a public firm as investment efficient at the time of acquisition if its Tobin's Q is greater than the median of all public firms traded in North American stock exchanges in the same year.[15] Table 2 suggests that a higher percent of tech acquirers in the S&P data are investment efficient than acquirers in the Refinitiv data (57.39% versus 51.15%), and this difference appears in most sectors except for Trade and PE.[16]

We define an acquisition deal as international if the headquarter country of the acquirer is different from the headquarter country of the target. Although our pool of potential acquirers is represented by firms publicly traded in North American stock exchanges, 14.45% of them are not headquartered in the US or Canada. There is even less restriction on where the target company locates its headquarter. Thus, it is common to observe international M&A deals. Interestingly, 40.45% of tech M&As in the S&P data are international, which is much higher than that of general M&As tracked in Refinitiv (26.64%). This is because of the global nature of technology—with many companies operating across borders and offering products and services to customers around the world—and the purpose of these acquisitions, which often aim at incorporating the technology of the target, rather than looking to gain physical market opportunities. As reported by Forbes,[17] well–known examples of such deals include Visa's acquisition of U.K.-based fintech Currencycloud to enhance its existing cross-border payment technology, Microsoft's acquisition of Slovakia-based startup Minit to secure their process mining technology, and Amazon's acquisition of Umbra, a Finnish startup that creates visibility solution technology for video games.

Figure 1 highlights the time trends of M&As, with panels (a) and (b) focusing on tech M&As reported by S&P and panels (c) and (d) focusing on any M&A deals reported by Refinitiv. According to Panel (a), the two largest sectors in tech M&A—Information and Supply Chain—exhibited

[15] Tobin's Q is defined as the ratio between the market value of a firm over the replacement cost of its assets. Empirically, following Kaplan and Zingales (1997) and Gompers, Ishii and Metrick (2003), we define Tobin's Q using Compustat variables as: $\frac{\text{Total Assets + Market equity - Book Equity}}{\text{Total Assets}}$.

[16] Because Tobin's Q is a summary statistics at the acquirer-year level, it is difficult to tell whether the difference in acquirer investment efficiency is driven by acquirers in the S&P data being more investment efficient before an M&A deal or the tech deals in S&P are themselves more investment efficient than deals in Refinitiv. We observe a similar difference if we use the acquirer's Tobin's Q in the year before the M&A deal, which suggests that acquirer selection may contribute to some of the difference reported in Table 2.

[17] For additional details, see: `https://www.forbes.com/sites/forbestechcouncil/2022/12/05/why-have-cross-border-acquisitions-reached-an-all-time-high/?sh=6b8ea9ec24ba`.

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

Sector	Number of Acquisitions		% of Firms with any Acquisition		Number of M&As per Public Acquirer	
	Tech	**Refinitiv**	**Tech**	**Refinitiv**	**Tech**	**Refinitiv**
Finance	1,084	4,205	4.66	3.13	3.79	7.38
Information	4,903	4,199	45.11	8.43	7.27	8.12
Services	2,136	6,505	19.92	10.10	5.76	9.87
Supply Chain	3,584	10,512	11.18	7.32	4.46	5.94
Trade	605	2,296	13.87	12.74	4.12	6.92
Private Equity	308	1,772	73.53	48.53	6.16	41.21
Total	12,620	29,489	13.10	6.75	5.47	7.58
Sector	**Acquirer Age (years)**		**% of International Acquisitions**		**% of Deals by Investment Efficient Acquirers**	
	Tech	**Refinitiv**	**Tech**	**Refinitiv**	**Tech**	**Refinitiv**
Finance	20.72	21.01	41.42	16.96	75.09	52.77
Information	13.77	14.60	35.79	28.65	58.96	53.80
Services	18.90	19.57	43.35	22.01	56.37	51.08
Supply Chain	26.53	24.51	44.61	32.56	54.10	51.27
Trade	23.46	22.74	35.04	19.38	47.11	47.43
Private Equity	20.30	20.49	53.25	36.06	35.39	45.43
Total	17.73	21.66	40.45	26.64	57.39	51.15

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. Acquier age is computed weighting equally any public company company making at least an acquisition (tech or any, depending on the column).

overall decreases in their number of tech M&As between 2010 and 2020, whereas this number increased in the Services sector. In particular, in 2010, public firms in the Supply Chain sector engaged in almost 200 more tech M&A deals than firms in the Services sector, and this gap shrank to less than 100 in 2020. In the other sectors, the number of tech M&As remained relatively stable over the sample period. In comparison, as seen in Panel (c), the number of any majority-control deals reported by Refinitiv (which could be tech or non-tech M&A) is the highest in Supply Chain and the second highest in the Services sector. This number also declines the most between 2010 and 2020 in Supply Chain, and it has declined for Services in 2017-2020.

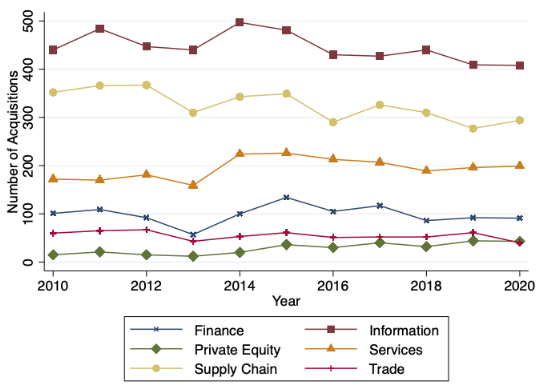
Returning to the S&P data, Panel (b) reports that the Information, Services and PE sectors exhibited substantial increases in the percentage of firms acquiring tech targets after 2013. To be clear, the figure plots the percentage of publicly-traded firms in each sector that completed at least one tech 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. In comparison, as shown in Panel (d), the percent of PE firms engaging in any M&A in Refinitiv far exceeds the percent of acquirers in any other sectors. This is a sharp contrast to the high percent of firms in the Information or Services sectors engaging in tech M&A, as shown in Panel (b).

One may argue that 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 S&P-tracked 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&As in the S&P data 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.

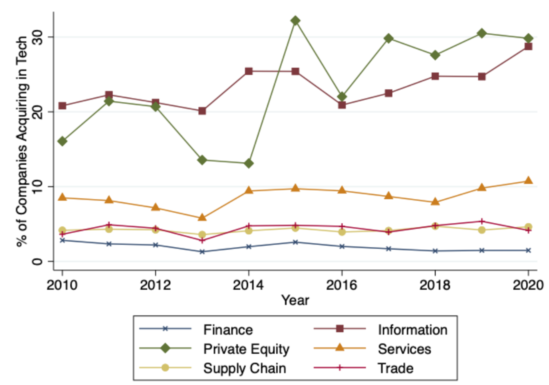
To systematically examine which firm characteristics are correlated with a higher probability of engaging in tech M&A (as recorded in the S&P data), we run several regressions utilizing a cross-

Figure 1: Trends in M&A

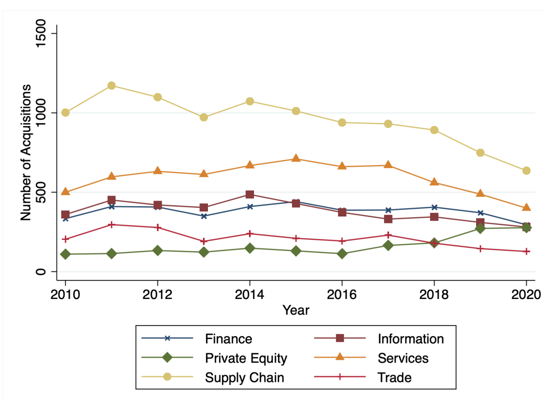
(a) Number of Tech Acquisitions (S&P)



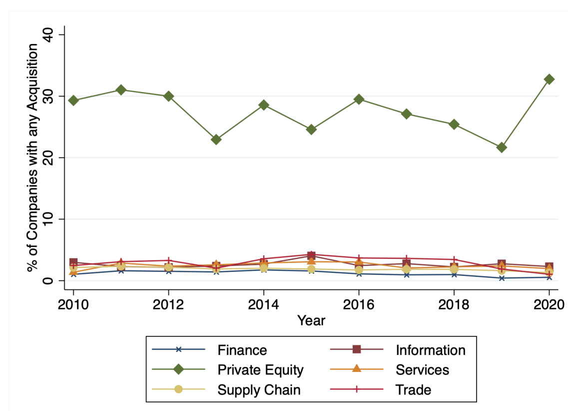
(b) % of Firms with any Tech Acquisition (S&P)



(c) Number of Acquisitions (Refinitiv)



(d) % of Firms with any Acquisition (Refinitiv)



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

Table 3: Tech M&As (in S&P data) 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.

section of publicly-listed acquirers from the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges. We use logit and Poisson 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 (including zero).

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 age, sales and cash flow as of 2010 (or the first 4 quarters since the firm's IPO), where sales and cash flow are both in logs.

Table 4 reports the results. Columns (1) and (4) find that, as compared to companies in Finance (the default sector), firms in the Information sector are almost 50% more likely to engage in any tech M&A, and have acquired 778% more tech targets, on average.[18] 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 329.7%, 193.3%, and 57.8% additional acquisitions.[19] Firms in

[18]In column (4), we report coefficients estimated from Poisson, so the marginal effect corresponding to the coefficient of Information is $\exp(2.172) - 1 = 7.78$.

[19]According to Column (4), the coefficients imply marginal effects $\exp(1.458) - 1 = 329.7\%$, $\exp(1.076) - 1 = 193.3\%$ and $\exp(0.456) - 1 = 57.8\%$.

Trade, on the other hand, overall are not more likely to acquire tech targets than firms in Finance.

Columns (2) and (5) control for a firm's technology intensity, with "traditional" as the default and including a dummy to indicate whether a firm has missing definition of technology intensity. As a robustness check, Columns (3) and (6) repeat the exercise but exclude the firms with missing technology intensity. All these columns suggest that, technology intensity is positively correlated with both the probability of engaging in any tech M&A and the number of transactions completed. In particular, firms classified as high-tech are about 31.3% more likely to acquire a tech target than firms classified as traditional, and, on average, they acquire about 362.7% targets.[20] Table 4 also indicates that older firms, as well as firms that have higher sales, are more likely to engage in tech M&A.[21]

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 categorized as Traditional with respect to their tech intensity is set as the default in Table 5, and we exclude companies with missing information on tech intensity from the analysis. In all specifications, we include controls for the age of the potential acquirer, sales and cash flow as of 2010 (or the first 4 quarters since the IPO) in logs, and two dummies to control for the fact that sales and cash flows can potentially be negative.

The coefficients reported in Table 5 suggest that the likelihood to engage in tech M&A is heterogeneous across sectors, and, in all sectors except PE, Finance and Services, firms whose core businesses are more tech-intensive are also more likely to engage in tech M&A. For PE, we do not find any significant difference across tech intensity categories. In contrast, in Finance and Services, tech-leaning companies are respectively 454.0% and 258.2% more likely than traditional firms to complete a tech acquisition, while high-tech companies are 415.0% and 228.1% more likely, although for each sector the difference between these two numbers is not statistically significant. For the Information sector, the estimated coefficients show that a high-tech information company is 66.9% more likely to complete its first tech M&A in comparison to to a firm classified as traditional.[22]

[20] According to Column 5, $\exp(1.532) - 1 = 362.7\%$.

[21] We use log(sales) and log(cash flow) as of 2010 on the right hand side because both variables are highly skewed to the right. Because firms may have negative sales (very rare) or negative cash flow, we control for two dummies indicating negative sales or negative cash flow.

[22] Exponentiating the coefficients in Table 5 provides hazard ratios from which one can obtain the percentages reported. For instance, the hazard ratio of high-tech to traditional is $\exp(0.512) = 1.6686$, which implies that a

Table 4: Selection in Tech M&As reported by S&P

VARIABLES	(1) Logit (Marginal effects)	(2) Logit (Marginal effects)	(3) Logit (Marginal effects)	(4) Poisson (Coeff.)	(5) Poisson (Coeff.)	(6) Poisson (Coeff.)
Information	0.484***	0.308***	0.316***	2.172***	1.265***	0.914***
	(0.0184)	(0.0214)	(0.0315)	(0.146)	(0.169)	(0.171)
Private Equity	0.549***	0.484***	0.418***	1.458***	1.347***	1.154***
	(0.0716)	(0.0731)	(0.0721)	(0.327)	(0.277)	(0.292)
Services	0.134***	0.0814***	0.0694***	1.076***	0.711***	0.308*
	(0.0162)	(0.0168)	(0.0244)	(0.161)	(0.170)	(0.168)
Supply Chain	0.0596***	-0.00296	-0.0293	0.456***	0.0482	-0.173
	(0.0120)	(0.0133)	(0.0205)	(0.141)	(0.140)	(0.156)
Trade	-0.0133	-0.0342**	-0.0389	0.0569	-0.0659	-0.0940
	(0.0153)	(0.0171)	(0.0268)	(0.214)	(0.201)	(0.212)
Age	0.00161***	0.000664**	0.00108**	0.0125***	0.00900***	0.0101***
	(0.000330)	(0.000322)	(0.000461)	(0.00259)	(0.00258)	(0.00287)
log(Sales)	0.0443***	0.0403***	0.0513***	0.262***	0.255***	0.230***
	(0.00330)	(0.00315)	(0.00456)	(0.0286)	(0.0301)	(0.0330)
log(Cash Flow)	-0.0131***	-0.00766**	-0.0152***	0.0396	0.0541	0.0483*
	(0.00384)	(0.00361)	(0.00516)	(0.0359)	(0.0360)	(0.0288)
Missing tech intensity		-0.0282***			0.235	
		(0.0102)			(0.171)	
Tech-leaning		0.284***	0.314***		1.278***	1.333***
		(0.0319)	(0.0336)		(0.210)	(0.209)
High-tech		0.313***	0.346***		1.532***	1.616***
		(0.0150)	(0.0168)		(0.111)	(0.112)
Observations	7,549	7,549	4,491	7,551	7,551	4,493

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), (2) and (3)) 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 poisson model (Columns (4), (5) and (6)) 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 (4). 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 categorized as Traditional is set as acquirers' default technology intensity. In all regressions we include controls for the age of the acquirer, sales and cash flow as of 2010 (or the first 4 quarters since the IPO), with both variables in logs, and two dummies to control for the fact that sales and cash flows can potentially be negative.

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
Tech-leaning	1.712***	0.386*	1.276***	1.297***	0.726*	0.103
	(0.321)	(0.202)	(0.230)	(0.164)	(0.424)	(0.868)
High-tech	1.639***	0.512***	1.188***	1.564***	1.959***	0.982
	(0.290)	(0.155)	(0.134)	(0.0928)	(0.213)	(0.691)
Age	0.00132	0.00923*	0.00347	0.00703**	0.0120*	0.00162
	(0.00872)	(0.00495)	(0.00473)	(0.00279)	(0.00660)	(0.0163)
log(Sales)	0.345***	-0.0249	0.110**	0.321***	0.184**	-0.0717
	(0.0766)	(0.0432)	(0.0555)	(0.0342)	(0.0716)	(0.119)
log(Cash Flow)	0.0239	0.0316	-0.0381	-0.191***	0.0321	0.150
	(0.0821)	(0.0443)	(0.0618)	(0.0338)	(0.0803)	(0.123)
Observations	701	589	751	1,989	416	47

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 categorized as Traditional with respect to their tech intensity is set as the default level. We include controls for acquirer age, sales and cash flow as of 2010 (or the first 4 quarters since the IPO), with both variables in logs, and two dummies to control for the fact that sales and cash flows can potentially be negative.

In comparison to estimates from other sectors, the magnitude of this gap is relatively low. Moreover, tech-leaning information companies are not more likely than traditional firms to make a tech acquisition. This can be explained by the proximity of the Information sector to tech, which may lead even more traditional firms to acquire tech targets early in our sample. On the other hand, Trade is the sector where the gap in the likelihood of an acquisition by high-tech company—in comparison to that of a traditional firm—is the largest (609.2%). However, at the same time, in Trade, tech-leaning companies are not more likely than traditional firms to make a tech acquisition. In between, in Supply Chain, high-tech (tech-leaning) companies are roughly 378% (266%) more likely than traditional firms to make a tech acquisition.

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. Focusing on the S&P data, 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 tech targets 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

high-tech information company is 66.9% (i.e., $100 \times (\exp(0.512) - 1)$) more likely to complete its first tech M&A in comparison to a firm classified as traditional.

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

Sector	Acquirer-Target 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

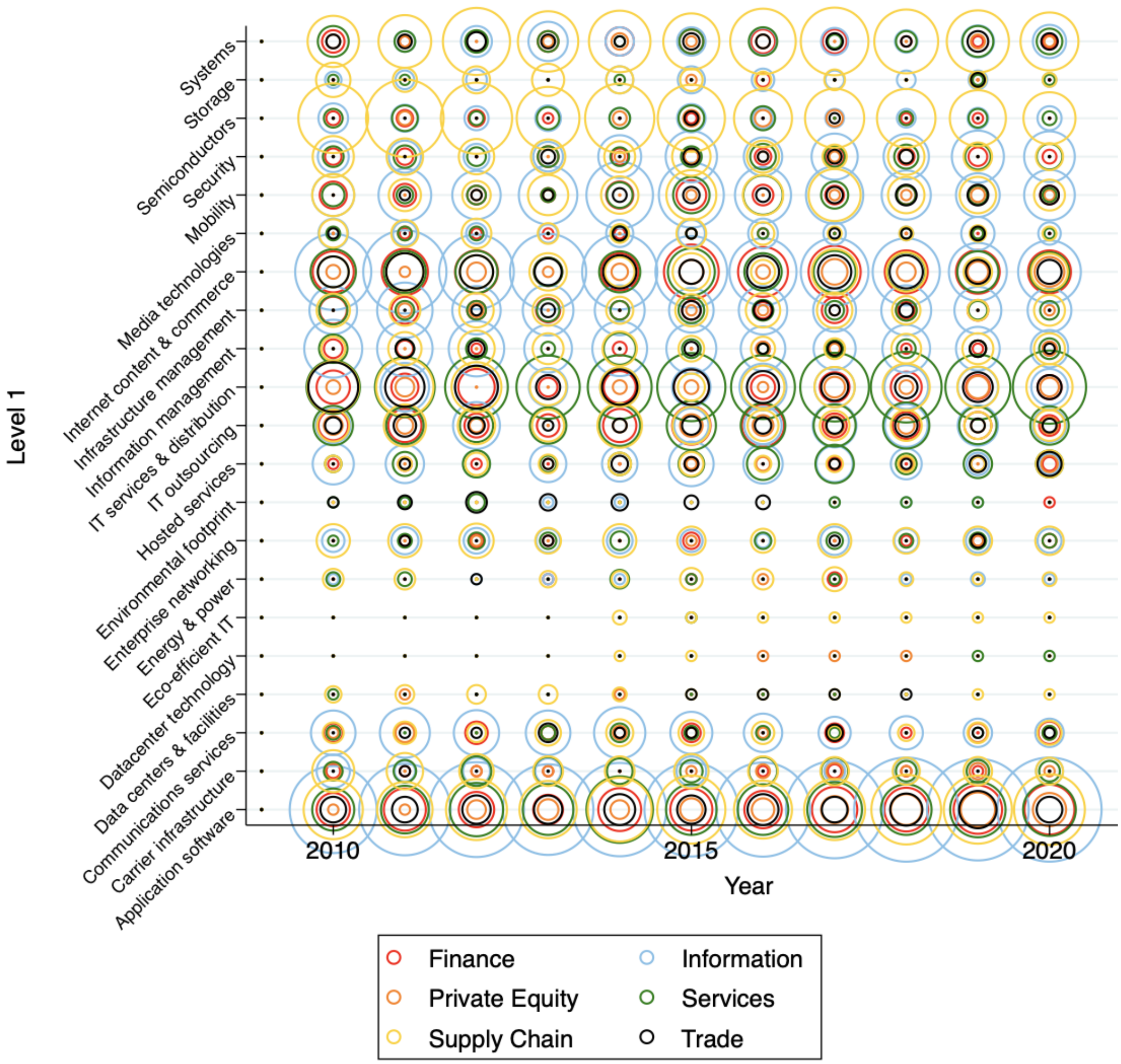
Notes: Statistics refer to tech M&As of publicly listed firms from all North American stock exchanges. The measures for distance exclude acquisitions from acquirers classified as "Non-tech" by S&P since these would be by construction "Unrelated." Results are similar if we include these acquisitions.

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, 2018; Ewens, Gupta and Howell, 2021) Indeed, we observe a higher average target age (17 years) for PE acquisitions. On average, firms in 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, such as the Gramm–Leach–Bliley Act, which may make incumbent development of data-intensive offerings a more viable path.

Based on the S&P data, 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

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 Services sector focused their M&A on target companies in the "IT services & distribution" and "IT outsourcing" categories, whereas the M&A targets 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 the level-1 category "Security", 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:

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

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, i.e. Pr(Tech M&As $\geq$ 2). 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) —

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.

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, 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.

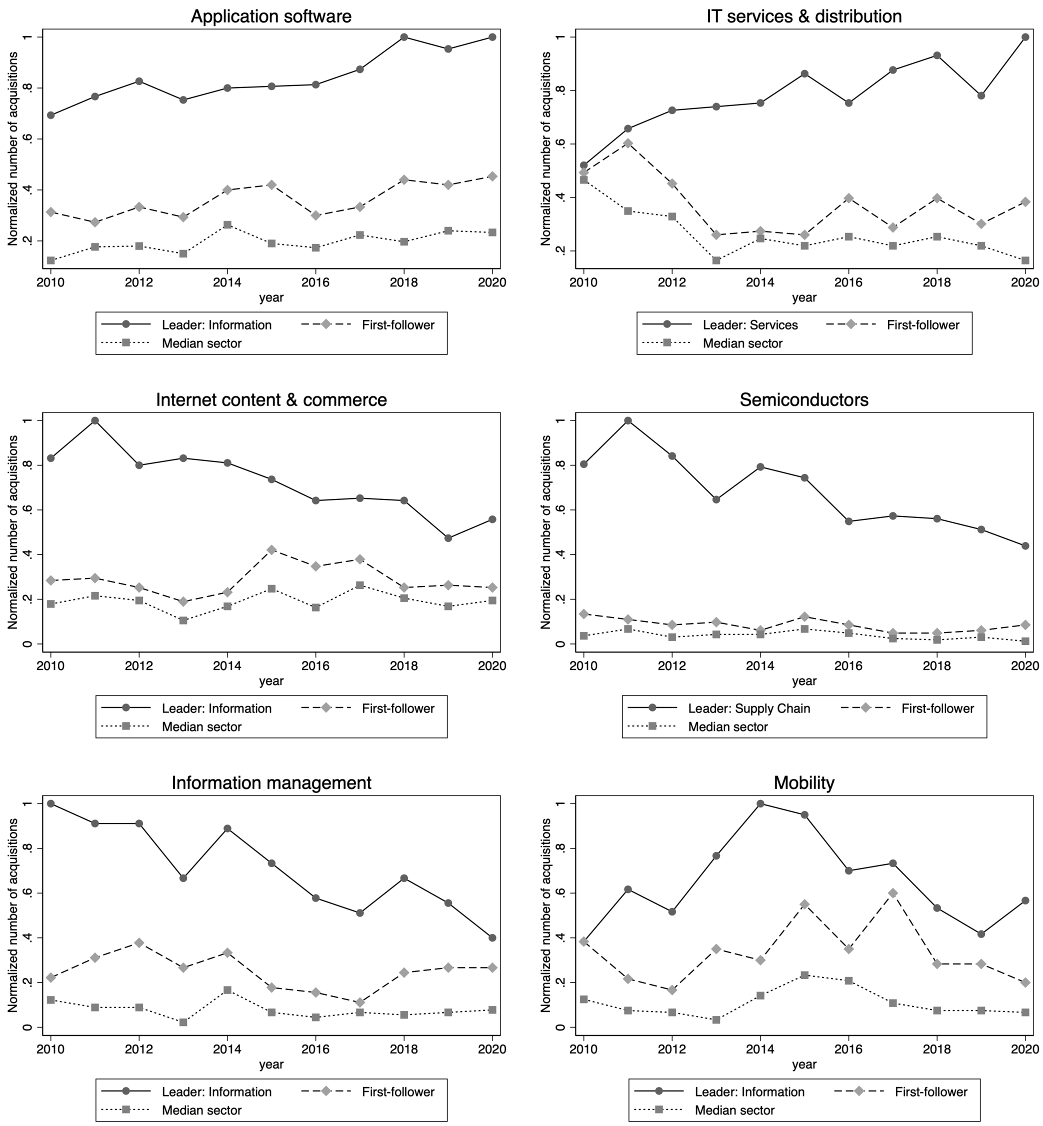
Figure 3 zooms into the leader-followers dynamics in tech M&A in the five level-1 categories that have the highest number of tech M&A transactions in 2010 ("Application Software," "IT Services & Distribution," "Internet Content & Commerce," "Semiconductors," and "Information Management"), with the addition 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.

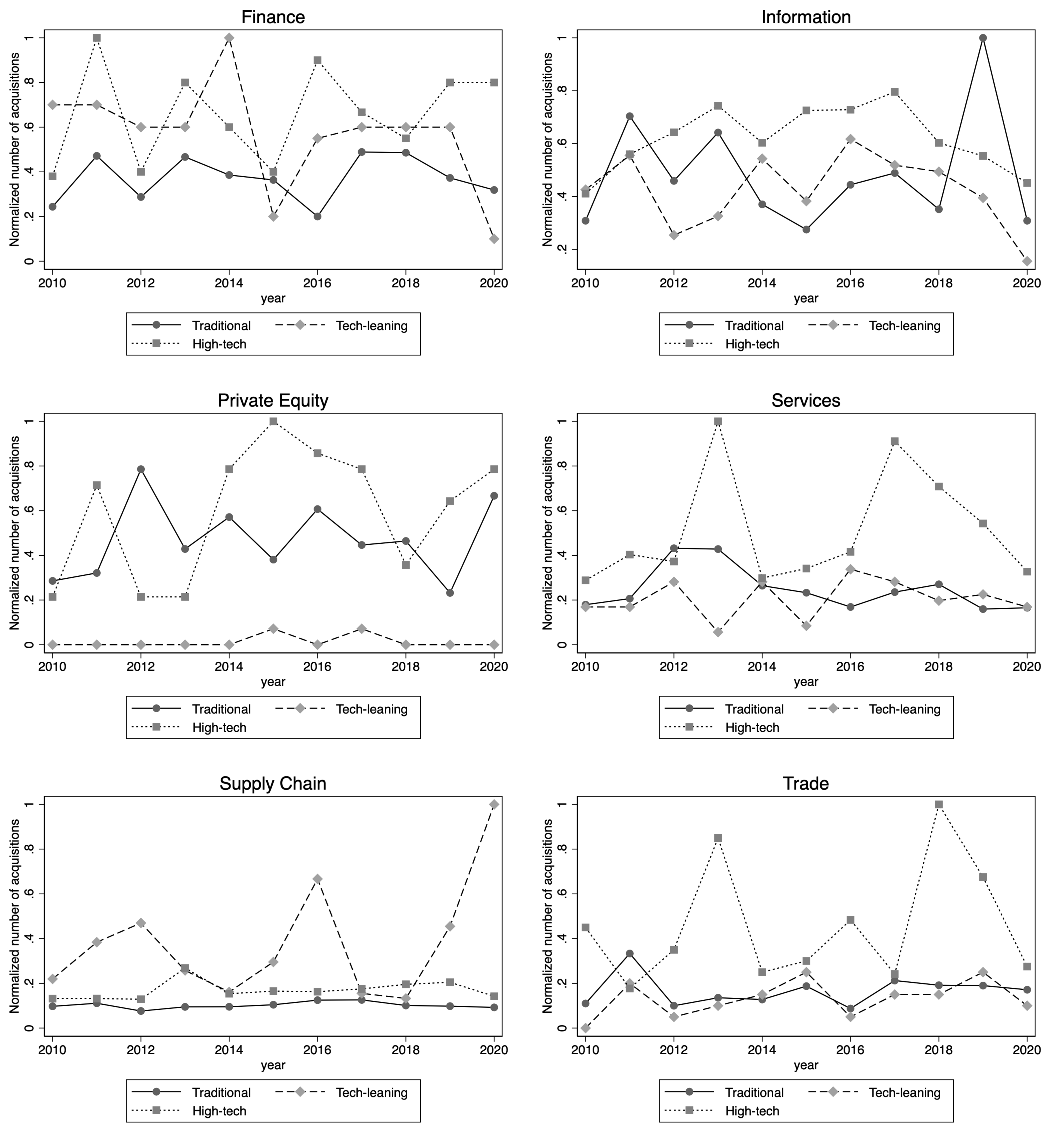
Figure 4 depicts the counts of M&A transactions completed in each sector by acquirers classified as high-tech, tech-leaning, and traditional. The graphs in each sub-figure are normalized on a per-firm basis and by the highest number of per-firm per-year M&A transactions across groupings (high-tech, tech-leaning 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 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.

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.

5 Competition as a Possible Driver 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 whether increased competition in the product space may lead firms to expand their business by acquiring access to new technologies.

In particular, 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 Poisson regressions, using the firm-year panel of publicly-listed firms on the AMEX, NYSE American, NYSE Arca, and NASDAQ exchanges between 2010 and 2019.[23] 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-2 business verticals

[23] 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.

(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[24]) and therefore should already be recognized by firm i as competitors before year t. We control for firm i's concurrent age, 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 both the firm's same level-2 business vertical (Column 2) and the unrelated bucket (Column 4). Because the coefficient of lagged product competition is greater in Column (4), it suggests that public firms are more likely to respond to increased competition in their product spaces through technological expansion into new technology areas, although some firms also complete tech M&As in their core business areas.

Some illustrative examples may help understand these results. After 2015, AT&T expanded outside of its core-business via a series of unrelated M&As, following a 25.98% growth in its product market fluidity index between 2010 and 2015. In particular, AT&T—which is classified as "Communication Services/General" in S&P taxonomy—acquired QuickPlay Media in "Media Technologies/Content delivery" in 2016 and Brocade in "Infrastructure Management/Virtualization" in 2017. According to the "Deal Profile" variable in S&P (which, when non-missing, reports the rationale of the deal relying on information from the news), AT&T sought to "increase its push in OTT video" with the first acquisition and to "increase its commitment to network virtualization" with the second. On the other hand, in other business areas, companies increased their tech acquisitions in the same business areas in response to intensifying incumbent competition. For example, in 2013, Tripadvisor—which operates in "Internet content & commerce/Services", completed three acquisitions (CruiseWise, Jetsetter and Oyster.com) in its core business area following a 16.40% increase in its product market fluidity index.

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. For example, in 2018, Zillow decreased the number of tech acquisitions in its core business area ("Internet content &

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

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

VARIABLES	(1) Tot Tech M&A (Poisson Coeff.)	(2) Same Tech M&A (Poisson Coeff.)	(3) Adjacent Tech M&A (Poisson Coeff.)	(4) Unrelated Tech M&A (Poisson Coeff.)
L.prodmktfluid	0.0398***	0.0287**	0.0260	0.0465***
	(0.00904)	(0.0146)	(0.0167)	(0.0108)
IPO competition	-0.00136	-0.00891**	0.00187	-0.000190
	(0.00226)	(0.00385)	(0.00381)	(0.00268)
Observations	34,308	34,308	34,308	34,308

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 Poisson 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 include year and 4-digits NAICS codes fixed-effects in all regressions.

commerce/Classifieds") after three formerly-private companies (Cars.com, Redfin, and SendGrid), which operate in the same market according to the TNIC-3 classification by Hoberg and Phillips (2010, 2016), launched their IPOs in 2017.

Overall, 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. We are reluctant to associate a public firm's tech M&A with its market value change from 2010 to 2020 because it is difficult to discern whether tech M&A causes a change in market value or firms of different market values differ in their tendencies to engage in tech M&A.

6 Conclusion

Combining data from multiple proprietary databases, we illustrate the prevalence and heterogeneity of majority-control acquisitions of technology companies by public firms listed in North American stock exchanges during 2010-2020. In particular, we show that (1) 13.1% of public firms engaged in any tech M&A in the S&P data, while only 6.75% of public firms make any (tech or non-tech) M&A in the Refinitiv data; (2) in both datasets, acquisition activities are widespread across sectors of the economy, but tech acquirers in the S&P data are on average younger, more investment efficient, and more likely to engage in international acquisitions than general acquirers in Refinitiv; and (3) within the S&P data, deals in each M&A-active tech category tend to be led by acquirers from a specific sector, the majority of target companies in tech M&As fall outside the acquirer's core area of business, and 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 as well as the consequences of regulatory restrictions on tech acquisitions in specific sectors offers directions for future work. Another fruitful direction is associating tech M&As with patent filings, in line with the initial steps undertaken in Cheng et al. (2023). Other future directions may involve a deeper dive into the role of private equity in technology M&As, including both listed and private PE firms, as well as extending the literature on M&A activity, board attributes, and board connections (Cai and Sevilir, 2012; Redor, 2016; de Sousa Barros, Cardenas and Mendes-Da-Silva, 2021).

References

Arora, Ashish, Sharon Belenzon, Andrea Patacconi, and Jungkyu Suh. 2020. "The changing structure of American innovation: Some cautionary remarks for economic growth." *Innovation Policy and the Economy*, 20(1): 39–93.

Bernstein, Shai, Josh Lerner, and Filippo Mezzanotti. 2018. "Private Equity and Financial Fragility during the Crisis." *The Review of Financial Studies*, 32(4): 1309–1373.

Bryan, Kevin, and Erik Hovenkamp. 2030. "Antitrust limits on startup acquisitions." *Review of Industrial Organization*, 56: 615–636.

Cai, Ye, and Merih Sevilir. 2012. "Board Connections and M&A Transactions." *Journal of Financial Economics*, 103(2): 327–349.

Cheng, Zhaoqi, Ginger Zhe Jin, Mario Leccese, Dokyun Lee, and Liad Wagman. 2023. "M&A and Innovation: A New Classification of Patents." *American Economic Association Papers & Proceedings*, forthcoming.

Cumming, Douglas, Grant Fleming, and Sofia A. Johan. 2011. "Institutional Investment in Listed Private Equity." *European Financial Management*, 17(3): 594–618.

de Sousa Barros, Thiago, Julian Cardenas, and Wesley Mendes-Da-Silva. 2021. "The Effect of Interlocking Directorates on Mergers and Acquisitions in Brazil." *Journal of Management & Goverance*, 25: 811–839.

Dong, Feng, and John Doukas. 2022. "The Effect of Corporate Investment Efficiency on Cross-Border M&As." *Review of Corporate Finance*, 2(2): 235–294.

Ewens, Michael, Arpit Gupta, and Sabrina T. Howell. 2021. "Local Journalism under Private Equity Ownership." SSRN Working Paper 3939405.

Gans, Joshua S., David H. Hsu, and Scott Stern. 2002. "When Does Start-Up Innovation Spur the Gale of Creative Destruction?" *The RAND Journal of Economics*, 33(4): 571–586.

Gompers, Paul, Joy Ishii, and Andrew Metrick. 2003. "Corporate Governance and Equity Prices*." *The Quarterly Journal of Economics*, 118(1): 107–156.

Greenstein, Shane. 2015. *How the Internet Became Commercial: Innovation, Privatization, and the Birth of a New Network. The Kauffman Foundation Series on Innovation and Entrepreneurship*, Princeton University Press; Princeton N.J.

Hoberg, Gerard, and Gordon Phillips. 2010. "Product market synergies and competition in mergers and acquisitions: A text-based analysis." *The Review of Financial Studies*, 23(10): 3773–3811.

Hoberg, Gerard, and Gordon Phillips. 2016. "Text-based network industries and endogenous product differentiation." *Journal of Political Economy*, 124(5): 1423–1465.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala. 2014. "Product market threats, payouts, and financial flexibility." *The Journal of Finance*, 69(1): 293–324.

Jin, Ginger Zhe, Mario Leccese, and Liad Wagman. 2022. "How Do Top Acquirers Compare in Technology Mergers? New Evidence from an SP Taxonomy." *International Journal of Industrial Organization*, 102891.

Jovanovic, Boyan, and Peter L Rousseau. 2008. "Mergers as reallocation." *The Review of Economics and Statistics*, 90(4): 765–776.

Kaplan, Steven N., and Luigi Zingales. 1997. "Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?*." *The Quarterly Journal of Economics*, 112(1): 169–215.

Katz, Michael L, and Howard A Shelanski. 2005. "Merger policy and innovation: Must enforcement change to account for technological change?" *Innovation Policy and the Economy*, 5: 109–165.

Ozcan, Yasin, and Shane Greenstein. 2016. "Technological Leadership (de) concentration: Causes in ICTE." National Bureau of Economic Research.

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.

Preqin. 2021. "2021 PREQIN Global Private Equity & Venture Capital Report." *https://www.preqin.com/insights/global-reports/2021-preqin-global-private-equity-and-venture-capital-report.*

Redor, Etienne. 2016. "Board Attributes and Shareholder Wealth in Mergers and Acquisitions: A Survey of the Literature." *Journal of Management & Governance*, 20: 789–821.

Appendix A Additional Figures and Tables

Table A.1: Cosine Similarities and the S&P Taxonomy

Cosine Similarity	Same Level-2	Same Level-1 & Different Level-2	Different Level-1
Average	0.208	0.151	0.117
Std. Dev.	0.184	0.159	0.142
Median	0.177	0.104	0.065
Min	0	0	0
Max	0.917	0.909	0.956

Notes: The table summarizes the cosine similarities between 2,311 technology companies of technology ventures which were acquired between 2010 and 2020—corresponding to the 10% of the total—across and within S&P level-1s and level-2s.

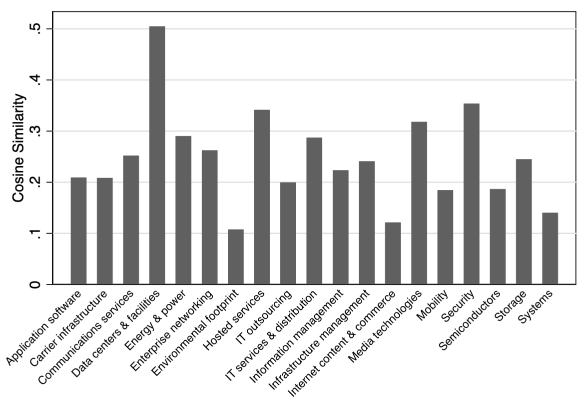
Table A.2: Cosine Similarities and the S&P Taxonomy with a 0.3 Similarity Threshold

Cosine Similarity	Same Level-2	Same Level-1 & Different Level-2	Different Level-1
Average	0.441	0.418	0.411
Std. Dev.	0.109	0.097	0.091
Median	0.417	0.393	0.388
Min	0.3	0.3	0.3
Max	0.917	0.909	0.956

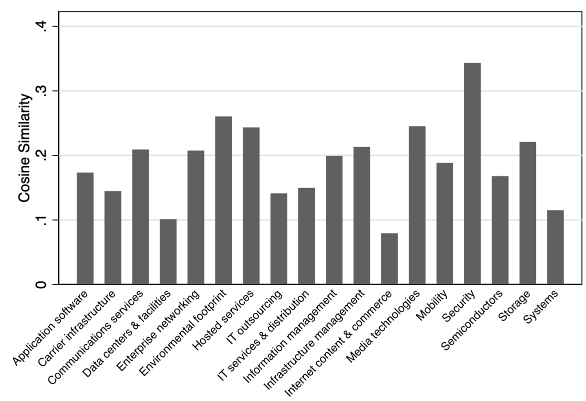
Notes: The table summarizes the cosine similarities between 2,311 technology companies of technology ventures which were acquired between 2010 and 2020—corresponding to the 10% of the total—across and within S&P level-1s and level-2s. Cosine similarities below 0.3 are dropped to avoid the noise caused by shorter business descriptions in Crunchbase.

Figure A.1: Heterogeneity in Cosine Similarities across S&P Level-1s for Different Groups of Tech Ventures

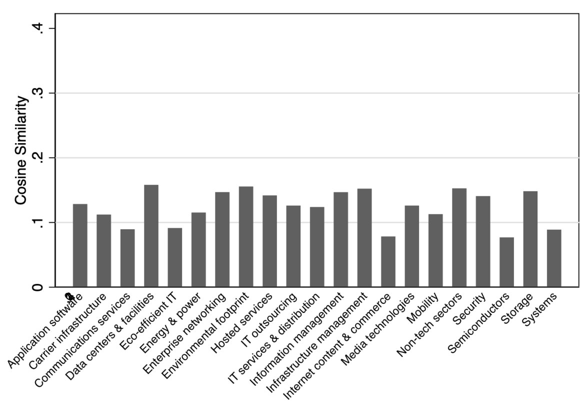
(a) Same Level-2



(b) Same Level-1 & Different Level-2



(c) Different Level-1



Notes: Panel (a) illustrates average cosine similarities across all S&P level-1s between technology ventures belonging to the same S&P level-2. Panel (b) illustrates average cosine similarities across all S&P level-1s between technology ventures belonging to the same S&P level-1, but different S&P level-2s. Panel (c) illustrates average cosine similarities across all S&P level-1s between technology ventures belonging to a different S&P level-1.