Acquisitions and Technology Value Revision*

Xiangshang Cai[a], Amedeo De Cesari[a], Ning Gao[a], Ni Peng[b]

[a] *The Accounting and Finance Group, Alliance Manchester Business School, The University of Manchester, Manchester M15 6PB, United Kingdom*
[b] *School of Business and Management, Queen Mary University of London, Mile End Campus, London E1 4NS, United Kingdom*

September 4, 2019

Abstract

Acquisition announcements cause upward revisions in the market value of target firms' technology peers, whether targets and their peers belong to the same industry or not. Firms having deeper technology overlaps with the targets experience more dramatic price revisions. Consistent with the acquisition probability theory, a firm is more likely to be taken over if at least one of its technology peers has been acquired recently; and peers more vulnerable to acquisitions have greater upward price revisions. Our findings demonstrate that information diffusion along the technology links is essential for technology valuation.

Keywords: technology space, technology similarity, information spillover, mergers and acquisitions, innovation, valuation.
JEL Classification: G14; G32; G34.

*We are grateful for the helpful comments from Alice Bonaime, Michael Brennan, Jun Chen, Rüdiger Fahlenbrach, Davidson Heath, Chenchen Huang, Dirk Jenter, Xiang Li, Luca Xianran Lin, Qing Tong, Nianhang Xu, David Yermack, Cheng Zeng, and seminar participants at the 2019 Annual Corporate Finance conference, the 2019 EFMA Annual Meetings, Bath University, Nanjing University, and Renmin University. All errors are ours.

Email addresses: `xiangshang.cai@manchester.ac.uk` (Xiangshang Cai), `amedeo.decesari@manchester.ac.uk` (Amedeo De Cesari), `ning.gao@manchester.ac.uk` (Ning Gao), `n.peng@qmul.ac.uk` (Ni Peng)

Acquisitions and Technology Value Revision

Abstract

Acquisition announcements cause upward revisions in the market value of target firms' technology peers, whether targets and their peers belong to the same industry or not. Firms having deeper technology overlaps with the targets experience more dramatic price revisions. Consistent with the acquisition probability theory, a firm is more likely to be taken over if at least one of its technology peers has been acquired recently; and peers more vulnerable to acquisitions have greater upward price revisions. Our findings demonstrate that information diffusion along the technology links is essential for technology valuation.

Keywords: technology space, technology similarity, information spillover, mergers and acquisitions, innovation, valuation.
JEL Classification: G14; G32; G34.

1. Introduction

The idea that the stock market aggregates value-relevant information is well-established and has been discussed in well-known theoretical works (e.g., Hayek, 1945; Grossman and Stiglitz, 1980; Kyle, 1985; Dow and Gorton, 1997; Subrahmanyam and Titman, 1999). A strand of literature further investigates the information-diffusion channels through the lens of the spillover effects among economically-linked firms. Previous studies document significant spillover effects among industry peers (Eckbo, 1983; Stillman, 1983; Eckbo, 1985; Lang and Stulz, 1992; Song and Walkling, 2000; Shahrur, 2005; Hou, 2007; Bradley and Yuan, 2013; Servaes and Tamayo, 2013; Foucault and Fresard, 2014). A small number of studies find significant spillover effects along the supply chain (Fee and Thomas, 2004; Cohen and Frazzini, 2008; Hertzel et al., 2008; Menzly and Ozbas, 2010) or within the same geo-economic area (Dougal et al., 2015; Engelberg et al., 2018). This strand of literature offers important insights into the assesment of market informational efficiency, the pricing of financial assets, portfolio choices, and company financing and investment decisions.

In today's knowledge-based economy, economically-linked firms are often technology peers. Well-known companies like Apple, Cisco, Microsoft, Huawei, Intel, and Alphabet, while serving distinct product markets, complement and rival each other on multiple fronts in the technological arena. Previous literature also shows that technological innovation represents an essential driver of business success[1] and economic growth[2]. Nonetheless, the literature is agnostic about whether and how information diffuses among technology peers.

In this paper, we study the acquisitions of technology-dependent firms and ask the question whether technology links constitute an important channel of information diffusion in the context of acquisitions, and, if yes, why. Some anecdotal evidence suggests a positive answer to the first question. For example, according to a news report by Reuters published on May 15, 2006, the share price of biotechnology company Medarex Inc. rose by nearly ten

[1] Hall et al. (2005) and Kogan et al. (2017), among others.
[2] Solow (1956, 1957) and Aghion and Howitt (1992), among others.

percent amid speculation it could be an acquisition target, on the day AstraZeneca agreed to acquire Cambridge Antibody Technology. Medarex and Cambridge Antibody Technology are both developers of antibody drugs used for cancer treatment. However, Medarex and Cambridge Antibody Technology also arguably overlap on the product market. This adds to the complexity of the diffusion channel and creates a confounding effect that we explicitly address in our empirical analyses.

Our study also serves another objective. Technological innovation plays an increasingly important role in defining firm value over the past decades. Despite its significance, the value of innovation is well-known to be elusive (e.g., Kogan et al., 2017). The innovation process is crammed with uncertainties, and the path to productivity is long and convoluted (e.g., Bloom and Van Reenen, 2002). Technology-dependent companies are often secretive about their innovations in fear of inviting unintended competition (Bhattacharya and Ritter, 1983), which adds to the value uncertainties. Does the abundance of opaqueness render the stock market inefficient in evaluating technological innovation? To what extent do stock prices aggregate information on technology efficiently? What are the mechanisms the stock market uses to extract information that technology-dependent firms often prefer to hide? When valuation signals about a company emerge, does the share price of its technology peers respond? In this paper, we aim to explore these questions in the context of mergers and acquisitions. We answer the above questions by examining the acquisitions' spillover effect on target firms' technology peers. We hypothesize that a shared technology space among firms (i.e., the set of firms that have close technology overlaps) is an essential channel of information-diffusion, which facilitates the fair valuation of technology.

The M&A market allows us to examine how the share price of a target firm's technology peer responds when a value-relevant signal emerges from the acquisition announcement.[3] Upon receiving the signal, we hypothesize that, investors revise upward their expectation

[3]Technology peers are those firms that innovate and operate in a focal firm's technology space (defined using its patent portfolio and explained in detail in Section 3.2).

of the possible synergy from a future acquisition targeted at the technology peer as well as their estimation of the likelihood of the acquisition. To the extent that a firm's market value is the weighted average of its values under the incumbent and alternative management teams (Song and Walkling, 2000), a peer firm's share price should respond to the acquisition announcement, as a consequence of the signal.[4] In particular, the announcement signals the acquiring firm's private information about acquisition synergy. Given acquisition probability is a function of the expected synergy, the expected acquisition probability also revises. Such a signal is credible because the acquiring firm has an informational advantage about the target firm and the acquisition synergy, and commits significant financial resources to the acquisition proposal. Further, technology peers are linked fundamentally through their extensive network of citations, licensing, talent pool, and collaborations, and are likely to incur similar technology and economic shocks (e.g., Katz and Shapiro, 1986; Hall et al., 2001; Fulghieri and Sevilir, 2011; Baghai et al., 2019). Therefore, an initial signal from one firm may disseminate information about its peer firms' prospects along the technology links. A priori, we expect the signal to be positive because the premium offered to the target firm indicates that at least one company (the acquirer) expects the synergy to be higher than what the market previously believed. Consequently, the peers' abnormal returns upon announcement should be positive. However, a merger may also create a tough competitor for technology peers. When this concern prevails in the market, we may well observe a negative market-price response from the peers.

We test our hypothesis using an acquisition sample for the period from 1984 to 2010. For our empirical tests, we include the observations of listed technology-dependent firms (i.e., firms that have patented at least one innovation in the previous 60 months) with required data for the corresponding analysis.[5] On average, we find that target firms' technology peers

[4]The weights are the probabilities of different teams actually or potentially managing the firm. As is maintained by Song and Walkling (2000), the determinants of synergy and acquisition probability overlap, which makes it challenging to disentangle these two parts empirically.

[5]We use the event study methodology to measure the price revision of the merging firms, the target firms' technology peers, the target firms' product-market rivals, and any generic firms needed in our analyses.

receive a statistically significant CAAR of 0.26% over the window $(-2, +2)$ centered around the deal announcement (day 0), equivalent to $612 million in a target firm's technology space. We go a great distance to establish the robustness of this finding. We find the significant CAAR is not due to spillover effects within the same industry, along the supply chain, or within the same geo-economic area. A placebo test further demonstrates that the peer effect within technology space is genuine and cannot be obtained randomly. Further, we find that the positive market reaction to the acquisition announcement weakens, and disappears at a certain point, as a firm's patent portfolio overlaps less and less with the target firm. Moreover, Cai et al. (2011) find that the share prices of acquirers' industrial rivals also respond to an acquisition announcement. We verify that our results persist when we exclude from our analysis firms who are also the technology peers of the acquiring firm (untabulated but available upon request). When investigating subsamples, we find that the positive spillover effect is concentrated in the deals with high acquisition premium and among the technology peers in which technology contributes a large part to their market value. Altogether, these findings strongly demonstrate that information diffuses within technology spaces.

However, the spillover effect can be more complex than what we describe above. First, the sign of the effect can be negative due to competitive pressure because a successful synergistic merger may produce a tough competitor for technology peers (Eckbo, 1983; Eckbo and Wier, 1985; Akdoğu, 2009). Nonetheless, the net effect we report is on average positive, indicating that the spillover due to competitive pressure is at the best of second-order importance. Second, previous literature suggests merger gains can arise from taking over an under-valued target firm (e.g., Bradley et al., 1983; Edmans et al., 2012). If the undervaluation is due to one or more factors that are common within a technology space, the market value of peers could increase to correct the undervaluation of these firms' stand-alone values. However, we do not find any positive spillover effect from unsuccessful deals in which the targets are not subsequently acquired. In the spirit of Bradley et al. (1983), the absence of a spillover effect

Therefore, all the firms we analyze are public firms, including the target firms.

in such context suggests that mis-valuation is unlikely to be a significant factor.

As we argued earlier, increased acquisition probability plays a central role in the information-diffusion within a technology space. We provide two pieces of empirical evidence in line with this argument. First, a firm is more likely to be acquired if its technology peer(s) have been acquired in the previous year. The increment in acquisition probability is around 0.8 percentage points, relative to an unconditional sample-average acquisition probability of five percent. Second, we find that the market reaction is stronger for a target firm's technology peer when this peer is more vulnerable to takeover threats. This is consistent with the acquisition probability hypothesis by Song and Walkling (2000). Our focus on technology space, however, represents a major departure from theirs on industry rivals. Phillips and Zhdanov (2013) maintain that firms' (especially small firms') research and development (R&D) activities respond positively to acquisition targets' abnormal returns. Enhanced R&D may boost the share price of technology peers in our sample. However, the second piece of the evidence above suggests against this alternative explanation because firms with greater bargaining power (less vulnerable to acquisitions) have stronger incentives to invest in R&D according to Phillips and Zhdanov (2013).[6]

What is the nature of acquisition synergies for technology-dependent firms? Theories suggest two kinds of synergies. In particular, the combining firms gain from either the enhancement of efficiency (the efficiency hypothesis, see Aghion and Tirole, 1994; Henderson and Cockburn, 1996; Rhodes-Kropf and Robinson, 2008) or from reduced competition (the market-power hypothesis, see Stigler, 1964). The first type of synergy is intuitive. The second type can be particularly relevant in our study, provided our measure of innovation is based on patenting activities which offer exclusivity to the issuing firms in a specific technology area. Eckbo (1983, 1985) postulate that the announcement returns on the merging firms' corporate customers can be used to distinguish between the efficiency hypothesis and the market power hypothesis. We find that customers have significantly positive abnormal returns at the

[6]In an untabulated analysis, we do not find that peers increase their investment in R&D.

deal announcement, which are more pronounced when the merging firms are under greater competitive pressure, the customers are smaller, local to the acquiring firm, or more reliant on the acquiring firm's output. These results suggest that the synergies are related primarily to efficiency gains.

There are very few studies dedicated to understanding the spillover effect along technology links. Extant literature has studied the spillover effects within industries, along the supply chain, and within geo-economic locations. A related paper we are aware of is Lee et al. (2019) who find that technology links have significant asset pricing implications. We contribute to the "spillover" literature by showing that the information diffusion between the M&A market and technology space constitutes an important channel of information aggregation. Extant literature has studied the spillover effect in a variety of settings. Some studies analyze the effect of stock price on firm decisions (e.g., Chen et al., 2006; Foucault and Fresard, 2014), some investigate the cross correlation among stock returns (e.g., Hou, 2007; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), and others study how corporate events impact related firms' stock prices (e.g., Eckbo, 1983; Stillman, 1983; Eckbo, 1985; Eckbo and Wier, 1985; Lang and Stulz, 1992; Song and Walkling, 2000; Fee and Thomas, 2004; Shahrur, 2005; Hertzel et al., 2008; Bradley and Yuan, 2013; Hameed et al., 2015). In this paper, the spillover effect runs from the market for acquisitions to technology peer firms. Undoubtedly, the spillover effect within technology spaces may manifest itself in a variety of forms and contexts. Due to space constraints, we prefer to delegate these possible investigations to future studies.

We also demonstrate that the acquisition market provides an important source of information for technology valuation. We argue that an acquisition announcement conveys a strong signal of the acquiring firm's private information about the synergy and prospect of similar deals. Our paper is, therefore, along the same line as Bhattacharya and Ritter's (1983) study that the primary equity market provides a mechanism incentivizing firms to disclose more technology-sensitive information. The idea of stock prices aggregating valuable information goes back to Hayek (1945), Grossman and Stiglitz (1980), and Kyle (1985). We demonstrate that the stock market possesses the ability to aggregate the private information generated in the course of mergers and acquisitions.

The goal of acquiring technology motivates many acquisitions (e.g., Holmström and Roberts, 1998). Mergers occur more frequently between companies with greater technological complementarity (Rhodes-Kropf and Robinson, 2008; Hoberg and Phillips, 2010; Sevilir and Tian, 2012; Bena and Li, 2014), and these transactions lead to greater synergistic gains (Kaplan and Weisbach, 1992; Hoberg and Phillips, 2010; Maksimovic et al., 2011; Bena and Li, 2014). We show that an acquisition announcement signals the prospects of further deals within the target firm's technology space. While related to acquisition probability, our focus is distinct from that of previous studies about macro or industrial merger waves (e.g., Mitchell and Mulherin, 1996; Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004; Harford, 2005). Rather, we emphasize the role of technology space in disseminating value-relevant information among peer firms.

The rest of this paper goes as follows. Section 2 elaborates on the hypothesis development. Section 3 describes the data and methodology. Section 4 presents our main results on the technology peers' abnormal returns. In Section 5, we investigate to what extent the acquisition probability theory can explain the technology peers' abnormal returns. Section 6 further explores the motives behind the acquisitions of technology firms. In Section 7, we conclude.

2. Hypothesis Development

We elaborate on our hypothesis in this section. For the spillover effect to exist, two conditions are essential. First, firms residing in the same technology space should have common components in their expected cash flows. It is safe to assume a firm's portfolio of technology bears substantially on its current and future cash flows. Further, firms with similar technology are economically-linked through their shared knowledge base and extensive networks of citations, licensing, the pool of talents, or collaboration (e.g., Katz and Shapiro, 1986; Hall et al., 2001; Fulghieri and Sevilir, 2011; Baghai et al., 2019). Therefore, peers are exposed to similar macro and technology shocks. Under rational expectation, shocks to one firm should convey information about the prospects of peer firms. Second, the acquisition process should generate novel information that the stock market has not aggregated previously. Extant studies show that acquiring innovation constitutes a prominent motive for acquisitions (Aghion and Tirole, 1994; Acemoglu et al., 2010; Sevilir and Tian, 2012; Phillips and Zhdanov, 2013; Bena and Li, 2014). Having a great deal at stake, the acquirers undoubtedly are keen to understand what they are to purchase. Further, distinct from investors at arm's length, acquirers often possess valuable private information about both the target firms' stand-alone value and acquisition synergies. Especially in friendly deals, which constitute the majority of acquisitions, acquirers have the privilege of accessing the target firms' value-sensitive information.[7] In cases where acquirers possess similar technologies to those of the targets (Bena and Li, 2014), acquiring firms also have the expertise to assess related technology with good accuracy. Owners of potential target firms, keen to sell out (Phillips and Zhdanov, 2013), are also more forthcoming regarding their private value-relevant information.

We assume that a firm's market value is the weighted average of its values under the incumbent and alternative management teams, in the spirit of the acquisition probability hypothesis (Song and Walkling, 2000). The weights are the probabilities of different teams actually or potentially managing the firm. Under the acquisition probability hypothesis, cateris paribus, the firm's value increases with the emerging prospect of any value-enhancing acquisition in which a target firm obtains a non-zero share of the synergy. Such an increment to the firm's value, denoted as VI, can be expressed as the product of the acquisition probability and the share of the expected synergy obtained by the prospective target firm's shareholders. Specifically, we have $VI = \pi \times G$ where π is the probability of the acquisition,

[7] Many popular readings describe how companies follow rigorous procedures to assess the value of a target firm's patent portfolio (for example http://info.ipvisioninc.com/IPVisions/bid/33855/Patent-Due-Diligence-in-Mergers-Acquisition-Transactions-Overview).

and G is the target firm's share of the expected synergy. Let S denote the overall synergy of the prospective acquisition targeted at the firm. Let $p(S)$ denote the density function of the distribution of S. Had the prospective acquisition indeed happened, the merging firms would split the synergy according to a sharing rule $\lambda \in (0,1)$, where the target gets $(1-\lambda)S$ and the acquirer λS. The outside investors of the firm do not know S but know $p(S)$ conditional on their information set. Then we have $\pi = \int_{\frac{C}{\lambda}}^{+\infty} p(S)dS$ because a bidder would not bid when $\lambda S < C$, where C is the bidding cost. Conditional on a bid, the target's share of expected synergy is $G = \int_{\frac{C}{\lambda}}^{+\infty} (1-\lambda)S \times p(S|bid)dS$. The emergence of the acquisition of a peer in the firm's technology space sends a positive signal s about S, which shifts both $p(S)$ and $p(S|bid)$ to the right. Consequently, VI increases as both π and G increase. Since S is a determinant for both the expected acquisition probability (π) and the target firm's share of the expected synergy (G), an empirical distinction between these two parts can be difficult.

3. Data and Methodology

3.1. Technology Proximity Score and Technology Peer Candidates

A key objective of our empirical analyses is to examine whether and how acquisition announcements alter the valuation of target firms' technology peers. We define technology peers as firms that innovate in analogous technology categories. The whole spectrum of innovation activities is represented by a comprehensive set of innovation categories available to all the firms. We can measure a firm's innovation activities using a vector whose element is the fraction of resources the firm dedicates to each category. A firm's vector could be compared with those of other firms, allowing the identification of technology peers. Unfortunately, the fraction of resources dedicated to each innovation category is not directly observable. Consistent with previous empirical research (e.g., Jaffe, 1986), we evaluate a firm's technological activities by using an output measure, namely the patents granted to the firm. The main limitation of this approach is that patents only reflect disclosed inventions for which the firm has successfully sought legal protection. Along the same lines, we assume that the set of possible innovation categories corresponds to the technology classes formally defined by the patent office. We specifically consider the patents granted by the United States Patent and Trademark Office (USPTO) to US-listed firms in the dataset of Kogan et al. (2017), which also provides United States Patent Classification (USPC) classes and patents' issue dates and market values.[8]

For each US-listed firm in a calendar month, we use the patent data mentioned above to calculate a technology proximity score with every one of other listed firms, following Jaffe (1986). Calculating the proximity score requires information on patents granted to both firms over the 60 months preceding the calendar month in question. We call these other listed firms with available required data a firm's technology peer candidates. From these candidates, we select a firm's technology peers (defined below in detail). The technology proximity score measures the extent to which the technology spaces of two firms overlap. We describe this score in details in Appendix A.II.

Some descriptive statistics on the sample of firm pairs with valid technology proximity scores are in Table B1 in Appendix B . Panel A shows that the number of firms in a month ranges from 1,652 to 2,927 and it peaks in the year 2001 and declines afterward. Panel B contains the average proximity score of all the firm pairs for each calendar month, which remains stable before 1998 and follows an upward trend afterward.

3.2. Technology Peers and Technology Space

A firm's technology space consists of its technology peers. Only peer candidates with high technology scores can be considered a firm's technology peers. However, choosing the threshold to distinguish technology peers from other peer candidates is inevitably subjective. We follow a method analogous to that adopted by Hoberg and Phillips (2010) and use a proximity-score threshold that gives a technology space that is similar in size to a three-digit

[8]We thank Professors Leonid Kogan, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman for making their dataset available online. The dataset covers all utility patents issued by the USPTO from January 1926 to November 2010.

SIC (SIC-3) industry. Around 2% of all possible pairs of firms in Compustat belong to the same SIC-3 industry and are industry peers. Thus, we name two firms technology peers if the technology proximity score between them is higher than the 98th percentile of the proximity scores of all the firm pairs in the same month. This definition essentially implies that the number of technology peers of a firm is comparable to that of the SIC-3 industry peers. This definition allows us to compare the technology peers to industry peers in some of our analyses.

Panel C of Table B1 in Appendix B reports the value of the 98th percentile of the pairwise technology proximity score by month. This threshold follows an increasing trend over our sample period. The 98th percentile ensures the size of a firm's technology space is constant over time relative to the number of firm pairs for which we can calculate a technology proximity score.

3.3. Acquisition Targets and their Technology Peers

Our dataset of acquisitions is from the Thomson SDC database and comprises the deals between the listed bidders and targets with announcement dates over the period 1984–2010. We only keep mergers and acquisitions of majority interests to ensure all deals involve a change of control rights. The targets and acquirers are not from the financial (SIC Code 6000–6999) or utility sectors (SIC Code 4900–4999). The transaction values are above 10 million. We drop the deals without the information required from other needed data sources. For each acquisition target, we calculate a technology proximity score with each peer candidate. Peer candidates from the financial and utility sectors are excluded. We expect the impact of the target's acquisition announcement to be more pronounced on the technology peers than on other peer candidates.

Panel A of Table I reports some descriptive statistics by the calendar year for the acquisition targets and their technology peers. Over the whole sample period, there are 1,307 targets with patent data and a total (average) of non-unique 2,382,596 (1,822.95) peer candidates (i.e., a firm can be a candidate for more than one target). Based on the set of proximity score thresholds, only 1,300 targets have at least one technology peer, and the total (average) number of non-unique technology peers is 51,728 (39.79). Observations for some targets and peers cannot be used in our tests owing to the lack of CRSP stock return data, which further reduces the number of targets to 1,257. The average number of technology peers and peer candidates for each acquisition target peaks during the internet bubble period 1998-2002. There is no other obvious trend.

In Panel B of Table I, we observe that the acquisition targets are concentrated in the business equipment industry (494 targets). While the business equipment industry is also represented prominently in the sample of technology peers, the "healthcare, medical equipment, and drugs" industry contributes the largest number of technology peers. These findings are not surprising, given both industries are very innovative. We report more detailed information on the cross-industry distribution of acquisition targets and target technology peers in Figure B1 in Appendix B. In the graph, there is a positive correlation across the industries between the number of targets and the number of technology peers. In other words, an industry that contributes more acquisition targets also contributes more technology peers. But this does not necessarily mean a target's technology space overlaps with its product industry because a firm operating in one industry can be a technology peer of a target firm from another industry. Three industries stand out regarding contribution to the number of acquisition targets and technology peers, namely, "drug" (SIC 283); "surgical, medical, and dental instruments and supplies" (SIC 384); and "computer programming, data processing, and other computer-related services" (SIC 737).

In panel C of Table I, we provide evidence on the overlap between technology and industry peers. The panel contains the number of technology peers that belong to the same SIC-3 industry as their acquisition target and the number of peers from different industries, in total and by the calendar year. Over the whole period, around two-thirds of technology peers are from different industries, which indicates a weak overlap between the technology space and conventional SIC industry. Thus, the findings of our study are likely to be novel and unique to technology peers. We investigate this conjecture more directly through formal tests in subsequent parts of the paper.

Table B2 in Appendix B contains the descriptive statistics for the characteristics of the acquiring firms, target firms, technology peer candidates, technology peers, and acquisition deals in our dataset. Acquiring firms are larger, more profitable, and with higher revenue growth than their targets and the targets' peers. They have lower ownership concentration with a smaller fraction of closely-held shares. 46% of our sample acquisitions are horizontal, and 80% of the deals are completed. A target obtains an average acquisition premium of 25% over the period $(-2, +2)$ around the deal announcement (day 0 is the announcement day). The number of days since a previous acquisition announcement in the same technology space is approximately 165 on average.

3.4. Calculation of the Abnormal Returns

We measure technology value revision using the technology peers' abnormal returns during the deal announcement period. We calculate the abnormal returns using the market model, and the estimation period is from 300 to 61 days before the acquisition announcement and has at least 100 trading days of return data. As every target has one or more technology peers and the stock returns on the technology peers to the same target are measured over the same period, these returns are affected by cross-correlation (Fama, 1998). However, we show in Table VI that our results are robust to the clustering by deal. In most of our tests, we use the cumulative average abnormal return (CAAR) on the peers of each acquisition target, i.e., the average of the cumulative abnormal returns (CARs) on the equal-weighted portfolios of target peers. This method is consistent with a trading strategy by which a rational investor wants to systematically exploit the announcement of an acquisition by investing in a portfolio of target technology peers. Additional details on the computation of the peers' abnormal returns are in Appendix A.

4. Abnormal Returns on Target Technology Peers

4.1. Abnormal Returns on the Portfolios of Technology Peers of Acquisition Targets

In Panel A of Table II, we report the CAARs for the targets' technology-peer portfolios, averaged across targets for several windows around the deal announcement date. Over the different windows, the CAARs are always positive and statistically significant at the 5% level or above. The CAARs over the (−2,0), (0,+2), (−2,+2), and (−5,+5) event windows are 0.06%, 0.20%, 0.26%, and 0.40% respectively. These abnormal returns are economically significant. For instance, a CAAR of 0.26% translates to a value increase of $612 million in an average target's technology space in 2010 dollars (the median increase is $211 million). The magnitude of the technology peers' CAAR is comparable to the industry rivals' CAAR that Song and Walkling (2000) report, i.e., 0.35% for the window (−1, 0) and 0.56% for the window (−5, +5). We carry out several robustness tests. In untabulated analyses, we obtain qualitatively similar findings by calculating the average of CARs on individual technology peers. We also investigate whether our findings are sensitive to the estimator of abnormal returns and test statistics. In Panel B of Table II, we consider several alternative estimators for the (−2,+2) event window, namely the market-model adjusted return, the market-model estimator using regression with GARCH (1,1) errors, the Scholes-Williams abnormal return, and the Fama-French three-factor model adjusted return. Across all of these alternative estimation approaches, the portfolios of technology peers earn statistically significant positive abnormal returns during the deal announcement period. The CAAR during the (−2,+2) event window ranges from 0.19% to 0.47%.

So far, we have defined technology peers by imposing a strict threshold for the technology proximity score, which produces technology spaces whose coarseness or granularity is comparable to that of SIC-3 industries. Our technology peers have greater technology overlaps with acquisition targets than 98% of all peer candidates. This way, we have a high level of confidence that the identified technology peers indeed engage in very similar innovation activities as the acquisition target. The value relevance of the technology proximity score is of a high order of importance for our definition of technology space. Therefore, it is crucial to investigate to what extent the technology overlap between an acquisition target and its peer candidates matters for peer candidates' abnormal returns. We expect the abnormal returns on technology peer candidates to have lower statistical and economic significance as the overlap reduces. We observe this precisely in Table III, which contains the CAAR (estimated for the $(-2, +2)$ event window) on portfolios of peer candidates whose technology proximity scores with the target firm belong to different deciles of the technology proximity scores. In particular, we form the deciles each calendar month based on the non-zero proximity scores among all firms in that month. The peer candidates of a target may fall into several deciles and, therefore, each target may correspond to several different deciles. We report the CAAR for all the peer-candidate portfolios in a decile. The results show that the CAAR on peer-candidate portfolios increases from the first decile (lowest proximity) to the tenth decile (highest proximity), except for the fourth decile. For example, the CAAR is -0.02% and statistically insignificant for the first decile; for the fifth decile, the CAAR is 0.10% and significant at the 5% level; for the tenth group, the CAAR is 0.27% and significant at the 1% level.

We conclude from these findings that the technology peers of an acquisition target experience an economically significant boost to their stock market valuation from the deal announcement. Equity investors believe that the acquisition of a target firm produces some significant benefits, in present value terms, that are also available for the shareholders of the target firm's technology peers. We investigate the economic mechanisms that drive this empirical regularity in subsequent sections.

4.2. Alternative Information-Diffusion Channels

Significant economic links and information spillover effects may exist between firms that do not belong to a shared technology space. Previous studies investigate the diffusion of information among industry peers (Eckbo, 1983; Stillman, 1983; Eckbo, 1985; Lang and Stulz, 1992; Song and Walkling, 2000; Shahrur, 2005; Hou, 2007; Bradley and Yuan, 2013;

Servaes and Tamayo, 2013; Foucault and Fresard, 2014), along the supply chain (Fee and Thomas, 2004; Cohen and Frazzini, 2008; Hertzel et al., 2008; Menzly and Ozbas, 2010), and within the same geo-economic area (Dougal et al., 2015; Engelberg et al., 2018). It is, therefore, crucial to show our findings are not driven by alternative economic links between technology peers that are unrelated to technology.

Table B3 in Appendix B contains acquisition announcement CAARs on the equal-weighted portfolios of several categories of firms related to acquisition targets. We observe that upon an acquisition announcement, firms that are vertically related to the target (i.e., customers and suppliers) of the transaction or that are located in the same state or region as the target do not experience a statistically significant change in their market valuation. In contrast, the CAARs for companies that are part of the same industry space as the target are positive and statistically significant, ranging from 0.22% under the industry classification based on the SIC-3 industry to 0.24% under the TNIC-3 industry classification (Hoberg and Phillips, 2010, 2016). These results for industry peers are aligned with previous empirical studies showing that the industry peers of acquisition targets earn positive abnormal returns during the deal announcement (e.g., Eckbo, 1983, 1985; Mitchell and Mulherin, 1996; Song and Walkling, 2000; Shahrur, 2005; de Bodt and Roll, 2014). Thus, a concern with our earlier findings is that the technology peers of acquisition targets earn positive abnormal returns merely because these firms are also in the corresponding target firms' industries. In other words, we are concerned that the entirety of our earlier findings is due to a significant overlap between the technology space and the industry. However, we already show that this overlap is limited (see Panel C of Table I) — only about a third of technology peers are from the same SIC-3 industry. Nevertheless, in the next section we perform additional tests to rule out this alternative explanation formally.

Another confounding factor to ponder about is that a target's technology peers may also be technologically related to the acquirer given that acquirers tend to target firms from the same technology space (Rhodes-Kropf and Robinson, 2008; Hoberg and Phillips, 2010;

Sevilir and Tian, 2012; Bena and Li, 2014). The information diffusion may originate from the acquirer rather than the target, affecting firms that are common peers. For example, Cai et al. (2011) show that firms experience positive reactions on the stock market when their rivals make a bid. We rule out this alternative channel through several tests (untabulated for brevity but available upon request). First, our findings are robust to the exclusion of the acquirers' technology peers. Second, all our multivariate results hold if we control for a dummy that identifies acquirers' technology peers. An expanded study on the acquirers' technology peers is beyond the scope of the current paper.

4.3. The Different Valuation Effects between Technology Space and Industry

In this section, we formally test the robustness of the technology spillover effect to the confounding industrial effect. In Table IV, we report the CAARs for the (−2,+2) event window on four different types of peer candidates sorted according to technology space and industry: peer candidates in different technology spaces and industries; peer candidates in the same technology space and different industries; peer candidates in different technology spaces and the same industry; peer candidates in the same technology space and industry. We use either the SIC-3 or the text-based TNIC-3 industry classification by Hoberg and Phillips (2010) and Hoberg and Phillips (2016). Across the four groups of peer-candidate portfolios, we observe positive and statistically significant CAARs, except for the peer candidates that operate in neither the same technology space nor the same industry space as their respective acquisition targets. More importantly, an acquisition target's technology peers benefit from a significant (at the 1% level) increase in their stock market valuations (0.18% and 0.32% for the two industry definitions respectively) even when they operate in a different industry from their respective target. The magnitude of the increase is comparable to the CAAR on the non-peer candidates (i.e., candidates that are not technology peers) in the same SIC-3 industry (0.22%), and it is significantly larger than that on the non-peer candidates in the same TNIC-3 industry (0.18%). It is not surprising that those peer candidates from the same technology space and industry as their targets experience even larger abnormal returns

(0.37% for both industry definitions). In further analyses, we replicate the tests above by relying on the two-digit SIC codes to identify industry peers and obtain qualitatively similar findings (untabulated).

In table V, we strengthen our findings from a statistical viewpoint using placebo tests based on randomly selected portfolios of peer candidates and compare the CAARs (-2,$+2$) of these portfolios with those of the actual technology peers. We find that the CAAR on actual technology peers is larger than the 99^{th} percentile of the empirical distribution of CAARs simulated from 1,000 randomly selected samples of peer candidates that innovate in a different technology space from the acquisition targets. This finding shows that it is very unlikely that our baseline findings in Table II are obtained by chance. It confirms our result that firms experience a statistically significant positive value revision upon the announcement of their technology peers' acquisitions. We draw similar conclusions for technology peers in or not in the same industry. For example, the CAAR for the peers in (not in) the same SIC-3 industry as their respective target is greater than the 95^{th} (99^{th}) percentile of the distribution of CAARs from 1,000 randomly selected samples of peer candidates that belong to a different technology space and operate in a SIC-3 industry that is the same as (different from) the acquisition targets'. The findings are less significant for the TNIC-3 industry classification. The CAAR for the technology peers in the same TNIC-3 industry as the target is just below the 90th percentile for the corresponding randomly created sample. This result suggests a non-negligible overlap between a firm's technology and TNIC-3 industry spaces.[9] For technology peers not in the same TNIC-3 industry as their corresponding targets, we, again, find their CAAR lies above the 99^{th} percentile of the distribution simulated using non-peer candidates operating in different TNIC-3 industry spaces.

We, next, estimate multivariate models that allow us to study the effects of both the technology and the industry overlaps on the abnormal returns on individual peer candidates

[9] In our regression analyses, we control for the variables capturing a firm's industry defined using both the SIC-3 and TNIC-3 classifications. We find that the superior CAR on technology peers is robust to controlling for the industry-peer effect.

at the deal announcement. In these tests, we control for a set of independent variables measured before the deal announcement for the peer candidates. We also control for deal fixed effects which reflect both observable and unobservable deal and target characteristics (e.g., the timing of the announcement; how the target interacts with its peer candidates). We estimate the regressions on a sample that includes all the peer candidates of our sample acquisition targets. The dependent variable is a peer candidate's CAR over the event window (−2,+2) surrounding the respective deal announcement. Detailed definitions of all the explanatory variables are in Appendix A.IV. Given that we have multiple peer candidates' CARs for each deal, the standard errors are clustered at the deal level. The findings are qualitatively the same if we use clustered standard errors at the year level.

In Table VI (Panel A, column (1)) we find that there is a positive and statistically significant relation between a peer candidate's *Technology proximity score* with the respective target and the peer candidate's CAR. The coefficient is 0.486 and statistically significant at the 1% level, indicating a one standard deviation increase in the proximity score is associated with a six-basis-point increase in the CAR. In column (2), we obtain similar findings for a dummy that identifies actual technology peers. The coefficient on the peer dummy is 0.281, indicating a peer on average has a CAR 0.281 percentage points greater than non-peer candidates. We conclude that peer candidates that overlap more with the targets in innovation activities witness a more significant boost to their stock market valuations when acquisition announcements arise. In column (3), we test whether the industry effect is also relevant to peer-candidate CAR, without controlling for any technology overlap. We find that peer candidates from the same SIC-3 industry as the target experience significantly larger CARs compared with the candidates from different industries. The coefficient on the *Same SIC-3 industry dummy* is 0.189 and statistically significant at the 1% level. This finding confirms the findings from previous literature (e.g., Eckbo, 1983; Song and Walkling, 2000). In columns (4) and (5), we observe that the coefficients on the two test variables of interest, namely the *Technology proximity score* and the *Technology peer dummy*, remain positive and statistically significant after controlling for the *Same SIC-3 industry dummy*. In particular, the coefficient on the *Technology peer dummy* is 0.234 and significant at the 1% level; the coefficient on the *Technology proximity score* is 0.414 at the same level of significance. In column (4), the coefficient on the *Same SIC-3 industry dummy* becomes marginally significant at the 10% level (t-statistic = 1.83). In columns (6), (7), and (8) we replicate the specifications of columns (3), (4), and (5) respectively, replacing the *Same SIC-3 industry dummy* with the *Same TNIC-3 industry dummy*. The coefficients on the two test variables, namely *Technology peer dummy* and *Technology proximity score* remain positive and highly significant. The coefficients on the *Same TNIC-3 industry dummy* becomes insignificant in columns (7) and (8) when we include the two test variables of interest respectively.

We expect a technology peer to experience a stronger price revision when the premium offered to a target is higher. A larger premium is a more salient signal and indicates a greater value update to the kind of technology the target firm possesses, which is value-relevant to technology peers too. We will elaborate on this channel in more detail in Section 5. Another prediction we make is that technology proximity should be more relevant to peer candidates whose firm value is more dependent on their patent portfolios. We calculate the value of a firm's patent portfolio by aggregating the values of individual patents provided by Kogan et al. (2017) (details in Appendix A.IV). In Panel B of Table VI, we introduce several interaction terms to test these two expectations. We find that the coefficient on the interaction between the *High acquisition premium dummy* and the *Technology proximity score* is positive and significant at the 5% level across several alternative specifications in columns (1), (4), and (7). The results are qualitatively the same if we interact the *Acquisition premium* itself with the *Technology peer dummy* in columns (2), (5), and (8). In columns (3), (6), and (9), we find that the coefficient on the *Technology proximity score* is significantly more positive for peer candidates when the *Peer candidate high patent value dummy* equals one. In all the columns of Panel B, we control for year fixed effects. In Panel C, we control for deal fixed effects instead, which subsume the year fixed effects and the other deal-specific variables. All the results persist.

In summary, in this section, we show that technology peers of acquisition targets earn significantly positive abnormal returns during the deal announcement, even when they operate in different industries from the acquisition targets. The abnormal returns are significant, both statistically and economically. The results are not due to chance. They are also robust to alternative ways of CAR estimation and various multivariate test specifications. The cross-sectional tests based on targets' acquisition premiums and peers' value-dependence on patent portfolios offer further corroborating evidence on the importance of technology proximity between targets and peer candidates to the value revision of peer candidates.

5. The Acquisition Probability Theory and Peer Abnormal Returns

The findings we describe in the previous section are, to a considerable extent, consistent with the acquisition probability theory developed by Song and Walkling (2000). According to their theory, upon an acquisition announcement, the target firm's industry rivals earn positive abnormal returns on the stock market owing to the increased probability that they will also become acquisition targets in the future, which benefits their shareholders.

Consistent with the acquisition probability theory, Table VII shows that the technology peers of acquisition targets experience more favorable abnormal returns if they are smaller, they become acquisition targets in the following year, the deal is an initial acquisition within the technology space, or the deal's acquisition premium is larger. These results indicate that an acquisition causes a more dramatic value revision to a technology peer when the peer is more likely to be taken over in the future. The acquisition probability theory does not carry clear-cut implications as to the different impact of completed and withdrawn deals (Song and Walkling, 2000). Consistent with this view, the average CAR on the peers of completed deals (0.25%) is quite close to that on the peers of withdrawn deals (0.28%). Acquisition announcements generate larger peer CARs if the targets or their technology peers have their firm value more dependent on their patent portfolios, which indicates that the signal from an acquisition announcement leads to greater revision in the peers' acquisition probability when the peers and/or the targets are more technology-dependent. The announcement abnormal returns are larger for both the peers of high-analyst-coverage targets and for peers with low analyst coverage. An information-diffusion process in which a signal is transferred from high-profile firms to firms that are more neglected by investors is coherent with these results (e.g., Hameed et al., 2015).

The univariate tests in this section may not be sufficient to validate the acquisition probability theory comprehensively and rule out alternative channels. Based on this theory, we can formulate two predictions which we test below in a multivariate setting. First, the acquisition of a firm's technology peer shifts the distribution of future deals' synergy to the right and increases the acquisition probability of the firm in the future, as is argued in Section 2. Second, firms that are easier to be acquired (i.e., more vulnerable to acquisitions) are more likely to become future acquisition targets. Thus, we expect them to earn higher abnormal returns during the acquisition announcement of their technology peers. We also consider and formally investigate a plausible alternative mechanism that could explain our findings, on which we elaborate below.

5.1. Likelihood of a Technology Peer's Future Acquisition

If the acquisition probability theory plays importantly in the information diffusion process, we expect firms having technology peers acquired in the preceding year to be more likely to be acquired in the current year. In Table VIII, we report the estimates from alternative logistic specifications for a firm's acquisition probability. We consider a sample that includes all the firm-years (excluding firms from the financial and utility sectors, and firms without patents) in the Compustat-CRSP merged database and acquisitions from SDC over the period 1984–2010. The two key test variables are *Previous acquisition dummy*, set to one if a firm is the technology peer of one or more of the acquisition targets in the preceding year, and *Previous acquisition proximity score*, the value-weighted average of the technology proximity scores between the firm and all the acquisition targets in the previous year. All the control variables, defined in Appendix A, are measured in the preceding year and are selected following the studies by Cremers et al. (2009) (from *MB* to *ROA* in the table) and Cain et al. (2017) (from *Log age* to *Hostile takeover index* in the table). In some specifications, we control for industry and year fixed effects separately, while in others we include industry-year fixed effects. We cluster the standard errors at the firm level.

The six alternative models in Panel A of Table VIII offer a consistent conclusion: the likelihood of a firm becoming an acquisition target in the current year is significantly higher when one or more of the firm's technology peers have been the targets of acquisitions in the preceding year. Consistent with the acquisition probability theory, the coefficient on *Previous acquisition dummy* is always positive and highly statistically significant (at the 5% level or above). If we hold all the other variables at their means, firms with technology peers acquired in the preceding year have a higher likelihood of being an acquisition target in the current year by around 0.69 to 0.90 percentage points. Given that the unconditional average probability of a firm being acquired in our sample is around 5%, the increase is economically significant. In Panel B, we consider the test variable *Previous acquisition proximity score* instead. As expected, the coefficient on this variable is always positive and statistically significant at the 5% level or above.

5.2. Acquisition Vulnerability and Abnormal Returns on Technology Peers

In line with the acquisition probability theory, we observe a positive relation between a firm's acquisition vulnerability (i.e., the firm's ex-ante acquisition probability) and its abnormal return upon the acquisition announcement targeted at a technology peer. In Panel B of Table IX, we follow the studies by Cremers et al. (2009) and Cain et al. (2017) to formulate three alternative models estimating a firm's acquisition vulnerability, and formally test whether acquisition vulnerability is associated with the firm's abnormal returns upon the announcement of its technology peer being acquired. We calculate a firm's *Acquisition vulnerability* using the coefficients estimated from the logistic models in Panel B. Consistent with the acquisition probability theory, in Panel A of Table IX, we find that the coefficient on *Acquisition vulnerability* is universally positive and statistically significant, robust to the alternative methods used. This result indicates that firms that can more easily be taken over experience greater abnormal increases in their stock market valuations in response to the announcement of a peer's acquisition. The findings are robust across several specifications comprising alternative sets of firm-specific and deal-specific control variables, together with industry and year fixed effects. We cluster the standard errors at the deal level. Detailed definitions for all the variables in this table are in Appendix A. Overall, the findings we provide in this and the previous sections are in line with the predictions of the acquisition probability theory.

5.3. The Mispricing Hypothesis

From the angle of the M&A market, a firm's value is a weighted average of the values under incumbent and alternative management teams, where the weights are the probabilities the firm is under the control of the various possible teams (Song and Walkling, 2000). An acquisition becomes possible whenever an alternative team emerges attributing a higher value to the firm. This can be a result of estimated merger synergies or of market undervaluation of a firm's stand-alone value (Gort, 1969). Accordingly, two possible hypotheses are in place to explain the positive price revision of technology peers, namely the acquisition probability hypothesis and the mispricing hypothesis. We have already established the relevance of the former hypothesis. Under the mispricing hypothesis, an acquisition attempted at the target is triggered by low valuation (Edmans et al., 2012). Since misevaluation can be correlated across similar firms, the upward price revision in technology peers' market valuations could merely represent a correction of the mispricing signaled by the target's merger announcement. This alternative hypothesis does not require an upward revision in peers' acquisition probability.

Consistent with Bradley et al. (1983), we find evidence showing that the acquisitions in our sample are attempted to exploit potential synergies rather than undervaluation. In Panel A of Table X, we show that it takes only 12 months for the target firms of withdrawn deals to lose the positive value revision at the time of the deal announcement, if they are not subsequently taken over within five years. For instance, the average target CAR is 39% between month -1 and month $+12$ (month 0 is the announcement month) and statistically significant (t-statistic = 6.396) for the targets that are subsequently taken over. In contrast, for targets that are not subsequently acquired, the average CAR is only 4.27% and statistically insignificant, indicating a reversal in abnormal returns (i.e., a wipe-out effect). It appears that only when their subsequent acquisition probability does not decline considerably, targets experience significant and long-lasting increases in their market valuations after deal withdrawal. We cannot reconcile this evidence with the mispricing hypothesis since mispricing predicts a permanent value revision even if a target is not acquired subsequently. In Panel B of Table X, we further clean up the sample of withdrawn deals where the target is not subsequently acquired, by removing the deals that have been withdrawn because the deal price is considered excessive by the acquirer or there has been a deterioration in the fundamentals of the target firm and/or business environment.[10] To obtain the reason for withdrawal, we manually gather information from four sources, including Dow Jones Newswires, Reuters Newswires, the Wall Street Journal, and the Financial Times. We perform this additional robustness check because we are concerned that withdrawals caused by the acquirer's perception of excessive price or the deterioration in fundamentals may convey negative information on the targets. This would directly cause the price reversal that we observe for the withdrawn deals targeted at the firms not taken over subsequently, which has no implications on mispricing. However, for the clean sample, we find the target gains are still wiped out in 24 months — the CAAR is 6.35% over the $(-1, +24)$ window but statistically insignificant (t-statistic = 0.763).

[10]More specifically, the reasons behind the withdrawals include poor target performance (nine deals), the objection from the shareholders of the acquirer (eight deals), poor business environment (six deals), reduction of the bid price by the acquirer (two deals), or undetermined reasons (nineteen cases).

6. Sources of Gains to Acquisitions

The acquisition probability theory (Song and Walkling, 2000) contends that technology peers of acquisition targets earn positive abnormal returns during the announcement period because of the increased probability that they will be acquired in the future. Thus, the theory implies that acquisitions are value-enhancing projects beneficial to the parties involved. While the acquisition probability theory does not specify where the benefits come from, the previous literature suggests that they arise from either increased efficiency or enhanced opportunities of anticompetitive collusion (e.g., Stigler, 1964; Eckbo, 1983, 1985). These channels are not mutually exclusive.

According to the efficiency argument, acquisitions are beneficial because they allow the merging firms to achieve efficiency gains. The previous literature has identified several possible sources of such gains, including economies of scale, economies of scope, better use of assets, the elimination of overlapping facilities, and the execution of joint research and innovation activities (e.g., Aghion and Tirole, 1994; Henderson and Cockburn, 1996; Maksimovic and Phillips, 2001; Rhodes-Kropf and Robinson, 2008). The collusion argument is instead based on market power considerations and anti-competitive practices. Acquisitions are beneficial to the merging parties because they reduce the number of competing firms and boost their market power to set price. This argument is applicable particularly for horizontal mergers involving firms from the same industry (Stigler, 1964). Acquisitions enhance collusion opportunities among industry peers (e.g., coordination to set product and factor prices), making the industry more profitable at the expense of customers, suppliers, and other stakeholders (Eckbo, 1983, 1985; Fee and Thomas, 2004; Shahrur, 2005).

We attempt to distinguish between the efficiency and collusion channels by studying whether and in which direction an acquisition affects the market value of a bidder's corporate customer. We choose to do so following Eckbo (1983) who maintains that the impact on customers provides the most clear-cut evidence on the motive of acquisitions. Given that the two channels are not mutually exclusive, the impact on customers shows which channel dominates. The efficiency improvement following an acquisition could benefit the bidder's customers since some of the efficiency gains could be passed to the customers when the merging firms face competition pressure. Lacking competition pressure, the merging firms may retain all efficiency gains without benefiting the downstream firms. The efficiency channel predicts the corporate customers of acquiring firms to earn non-negative abnormal returns during the deal announcement period. This prediction is valid regardless of the type of acquisition (i.e., horizontal, vertical, and diversifying), even for a transaction targeted at a firm without any business linkage to the acquirer. In contrast, consistent with the collusion channel, acquisitions should reduce the market valuation of a corporate customer's stock as increased market power in the upstream harms corporate customers in the downstream.

In Table XI, we report the abnormal returns upon an acquisition announcement for several types of customers of the acquiring firms. We follow the method used by Shahrur (2005), which exploits information on a firm's potential customers (including actual customers). It is important to consider potential rather than just actual customers since the costs of switching suppliers may be low. We explain this method in Appendix A.III and related variable construction in Appendix A.VIII. We find that the CAARs on the portfolios of potential customers are always positive and, in general, statistically significant, across the different types of customers. The CAAR on generic potential customers is 0.11% and statistically significant at the 1% level. The returns are particularly large for reliant, small, and regional (i.e. local) customers (0.16%, 0.37% and, 0.41% respectively), all statistically significant at the 5% level or above. Next, we consider the split between deals in the industries with high competition (i.e., low Herfindahl-Hirschman-index (HHI) industries) and those from the industries with low competition (i.e., high HHI industries). Competition should boost the likelihood that efficiency gains from acquisitions are passed to customers. Our results support this expectation since we observe that customer abnormal returns are considerably larger for deals in competitive industries, except for regional customers. We conclude that, on average, the potential customers of an acquiring firm benefit from the deal because of the efficiency gains passed to them. Our findings demonstrate that acquisition gains are more likely due to efficiency improvement than enhanced collusion opportunities.

It is worth investigating whether the results above also hold in the sub-sample of acquisitions where the merging firms engage in similar innovation activities, as technology space is at the center of our study. The tests in Table XII lead us to conclude that, indeed, acquisitions between firms in the same technology space also generate substantial benefits for the customers of the bidder. These acquisitions are more beneficial to customers compared to deals between firms that operate in different technology spaces. For example, when the merging firms are from the same technology space (Panel A), the CAAR is 0.31% if they are in different SIC-3 industries, and 0.36% if they are in the same SIC-3 industry (both significant at the 5% level). Acquisitions do not benefit customers when the firms are in different technology spaces, which is true even when merging firms are in the same SIC-3 industry. Using the text-based TNIC-3 industry classification to define a firm's industry space, we observe the same pattern. The overall conclusion we can draw is that acquisitions benefit customers when the merging firms conduct similar innovation activities. This again confirms the importance of technology proximity in acquisitions.

7. Conclusion

In this paper, we find evidence for a strong and robust spillover effect inside a firm's technology space. Specifically, acquisitions attempted at technology-dependent firms, on average, lead to a positive value revision of $612 million (in 2010 dollars) in the target firm's technology space. Information diffusion among economically-linked firms has profound implications on the assessment of market efficiency, the pricing of financial assets, portfolio choices, and firm investment and finance decisions. In an increasingly technology-dependent economy, the information-diffusion among technologically-linked firms constitutes an important consideration of the decisions by both asset managers and company executives. Nonetheless, the literature is largely agnostic about such an effect and related mechanisms. Our study fills this gap.

Previous studies have demonstrated the significance of spillover effects among industrial rivals (Eckbo, 1983; Stillman, 1983; Eckbo, 1985; Lang and Stulz, 1992; Song and Walkling, 2000; Shahrur, 2005; Hou, 2007; Servaes and Tamayo, 2013; Foucault and Fresard, 2014), along the supply chain (Fee and Thomas, 2004; Cohen and Frazzini, 2008; Hertzel et al., 2008; Menzly and Ozbas, 2010), and within close geo-economic areas (Dougal et al., 2015; Engelberg et al., 2018). We contribute to the literature by demonstrating a significant spillover effect from acquisition announcement to the stock-market valuation of target firms' technology peers.

The spillover effect is an important mechanism by which the financial markets process information. In this sense, our study also relates to a broader literature postulating that the stock market aggregates value-relevant information (e.g., Hayek, 1945; Fama, 1970; Grossman and Stiglitz, 1980; Kyle, 1985; Fama, 1991; Dow and Gorton, 1997; Subrahmanyam and Titman, 1999). Given the tremendous amount of uncertainties in technology valuation, previous studies have raised concerns on whether the stock market can evaluate technology-dependent firms efficiently (e.g., Bhattacharya and Ritter, 1983; Kogan et al., 2017). Our results show that the M&A market is an important source of information for technology valuation and the spillover effect within technology spaces represents an essential channel of information diffusion. Our further analyses based on the acquisition probability theory of Song and Walkling (2000) corroborate these arguments.

Appendix A.

In this appendix, we define the technology proximity score and other variables.

I. Estimating Abnormal Returns around an Acquisition Announcement

We estimate the abnormal returns using the market model. The parameter estimation period is from 300 to 61 days before the acquisition announcement. We require at least 100 trading days over the estimation window. Stock return data is from CRSP. We calculate the cumulative abnormal returns (*CARs*) over the windows (−2, +2), (0, +2), (−2, 0), and (−5, +5).

II. The Technology Proximity Score of Firm Pairs and Technology Peers of Acquisition Targets

For a calendar month, we assume that a firm's technology can be represented by the technology classes of patents granted to the firm in the previous 60 months. For example, a firm's technology in February 1991 can be measured by the technology classes of the patents the firm received from February 1986 to January 1991. We follow Jaffe (1986) to calculate a firm-pair's *Technology proximity score*, which measures the closeness of the two firms' technology. We compute the score between two generic firms A and B as follows

$$P_{a,b} = \frac{S_a S_b'}{\sqrt{S_a S_a'}\sqrt{S_b S_b'}}$$

where the vectors $S_a = (S_{a,1}, S_{a,2}, \ldots, S_{a,K})$ and $S_b = (S_{b,1}, S_{b,2}, \ldots, S_{b,K})$ denote the technology of firms A and B, respectively, while $k \in (1, K)$ is the technology class. $S_{a,k}$ ($S_{b,k}$) is the total value of issued patents to firm A (firm B) in technology class k in the previous 60 months to the total value of issued patents to firm A (firm B) in all technology classes over the same period. The value of each patent is measured using the stock market response to the announcement of a new patent granted (Kogan et al., 2017). Thus, unlike Jaffe (1986), we rely on a value-weighted proximity score. The score cannot be computed for firm-months without patents in the previous 60 months. We exploit the patent dataset created by Kogan et al. (2017) to compute our score. This dataset contains information on granted patents, their USPC technology classes, and their market values.

If the technology proximity score between the target of an acquisition and a possible peer firm is higher than the 98$^{\text{th}}$ percentile of the distribution of pairwise technology proximity scores among all the firms in the month of the acquisition, the peer candidate is considered a technology peer of the acquisition target. A firm's technology space comprises all its technology peers. As we mentioned earlier, the technology spaces based on the 98$^{\text{th}}$ percentile are similar in granularity to the three-digit SIC industries. For the technology peer, the value of the binary variable *Technology peer dummy* is set to one.

III. Information Spillover across Different Channels

In Table B3 in Appendix B, we consider acquisition announcement abnormal returns across alternative categories of firms related to acquisition targets, excluding firms without patents over the 60 months preceding the acquisition announcement.

We identify the potential customers and suppliers of target firms following Shahrur (2005). In particular, we use the benchmark input-output tables from the Bureau of Economic Analysis to find the suppliers/customers in the upstream/downstream of the supply chain. These tables report the estimate of the dollar value a specific supplier industry's output is used as input by a customer industry. We define Customer Input Coefficient (CIC) as the value of an upstream industry's output sold to the downstream industry divided by the value of the downstream industry's total output. We only select single-segment firms as potential customers or suppliers. The stock returns on multiple-segment firms are contaminated by information from irrelevant industries. Moreover, some of the multi-segment customer firms even contain segments in the acquiring firm's or the target firm's industries.

The state of a firm's headquarters is identified using the information from the dataset created by Prof. Bill McDonald.[11] Since this dataset does not cover the early part of our sample period, we backfill the early years with missing values using information from the first year available in the dataset, unless a firm is delisted before this year. In such a case, we use Compustat data. Companies are classified further into the following six geographical regions based on the state of their headquarters: Northeast, Southeast, Southwest, Mideast, Midwest, and West.

Peer firms in the same technology space as target: technology peers of the corresponding acquisition target.

Peers in the same SIC-3 industry as target: firms with the same three-digit SIC code as the corresponding acquisition target in the month before the acquisition.

Peers in the same TNIC-3 industry as target: firms in the same text-based product market as the corresponding target firm as defined by Hoberg and Phillips (2010, 2016) in the fiscal year before the acquisition.

Firms vertically-related to target: firms in the upstream (suppliers) or downstream (customers) industries of the target firms' industries with CIC greater than 1%.

Firms in the same state as target: firms with headquarters in the same state as the corresponding acquisition target.

Firms in the same region as target: firms with headquarters in the same geographical region as the corresponding acquisition target.

IV. Determinants of a Peer Candidate's Cumulative Abnormal Return

In Table VI, besides *Technology proximity score* and *Technology peer dummy* (defined above), we also include other determinants. We define these other variables below. They are all specific to the peer candidates. They are based on information from Compustat for the fiscal year before the acquisition unless stated otherwise.

[11] We thank Prof. Bill McDonald for making this dataset available on his website https://sraf.nd.edu/data/augmented-10-x-header-data.

Acquisition premium: the premium of a deal measured using the five-day $(-2, +2)$ market-model abnormal return of the target firm during the deal announcement.

Closely held shares: the fraction of shares held by long-term shareholders such as insiders, corporations, and blockholders (source: Datastream).

HHI: the Herfindahl-Hirschman index for the SIC-3 industry in which the peer operates. The index is based on sales.

High acquisition premium dummy: a binary variable that equals one if the acquisition premium of a deal is higher than the median premium of all deals in the same year.

Leverage: debt in current liabilities plus long-term debt, scaled by total assets.

Log market cap: the natural logarithm of the market value of equity, which is inflation-adjusted using the consumer price index from FRED (item CPIAUCNS).

MB: total assets minus the book value of equity plus the market value of equity, scaled by total assets.

Peer candidate high patent value dummy: a binary variable that equals one if the ratio between the total value of patents a peer candidate received in the previous five years and the candidate's firm value (equity plus debt) is higher than the median value of the same ratio for all peer candidates in the same year.

ROA: earnings before interest and taxes over total assets.

Sales increase: change in sales relative to the previous year (in decimals).

Same SIC-3 industry dummy: a binary variable that equals one if the peer candidate and the corresponding target firm share the same first three-digit SIC code in the month before the acquisition.

Same TNIC-3 industry dummy: a binary variable that equals one if a peer candidate and the corresponding acquisition target are in the same product market (Hoberg and Phillips, 2010, 2016) in the fiscal year before the acquisition.

V. Target/Peer/Deal Characteristics and the Abnormal Returns on Technology Peers

In the univariate tests of Table VII, we form subsamples based on the yearly median values of several characteristics of the targets, technology peers, and deals. We then calculate the CAAR for the peers in each subsample. We explain the subsamples below.

Small vs. large technology peers: we distinguish between subsamples of large and small peers using their market capitalization.

Completed vs. withdrawn deals: the subsamples of completed and withdrawn deals are separated based on the information from Thomson SDC Platinum M&A database.

Initial vs. non-initial targets: we separate the subsamples of initial and non-initial targets, considering an acquisition target being initial if none of its technology peers received an acquisition offer over the year preceding the deal announcement.

Technology peers involved in subsequent acquisition activities vs. those that are not: a peer is classified as being involved in subsequent acquisition activities if it is the target of an acquisition bid over the year following the current acquisition announcement.

Deals of high acquisition premium vs. those of low premium: the premium of a deal is measured using the five-day (-2, $+2$) market-model abnormal return of the target firm during the deal announcement period, as is explained in Appendix A.IV.

Target firms of high relative patent value vs. those of low relative patent value: the relative patent value is measured by the ratio of a target firm's patent value (Kogan et al., 2017) to its total firm value. A firm's patent value is the total value of patents received by the firm in the previous five years. A firm's total market value is the sum of its market capitalization and the book value of total liabilities.

Technology peers of high relative patent value vs. those of low relative patent value: the relative patent value is the same as is defined above.

Target firms with low analyst coverage vs. those with high analyst coverage: analyst coverage is the number of analysts making 1-year-ahead earnings-per-share (EPS) forecasts (source:

I/B/E/S).

Technology peers with low analyst coverage vs. those with high analyst coverage: analyst coverage is defined above.

VI. The Determinants of the Probability that a Firm is Acquired in the Following Year

The main test variables in Table VIII, which are for the previous year, are the binary variable *Previous acquisition dummy* and the continuous variable *Previous acquisition proximity score*. The control variables are also for the preceding year and are formed using information from Compustat unless stated otherwise. We define all these variables below, except *MB*, *Log market cap*, *Leverage*, and *ROA* which are defined above.

Blockholder dummy: a binary variable that is one when there is at least one institutional blockholder with a 5% or higher ownership stake in the firm (source: Thomson/CDA Spectrum).

Capital liquidity and *Hostile takeover index*: these variables are defined following Cain et al. (2017). For the sake of brevity, we refer readers to the original paper.

Cash: the natural logarithm of cash and short-term investments over total assets.

Log age: the natural logarithm of the firm's age in years. It is based on Compustat's IPO date if available, otherwise on the beginning date from CRSP if available, otherwise on the first fiscal year in Compustat.

Log age squared: the square of the logarithm of firm age, which is defined above.

PPE: the net value of property, plant, and equipment over total assets.

Previous acquisition dummy: a binary variable that equals one if a firm is the technology peer of at least one acquisition target in the preceding year and zero otherwise.

Previous acquisition proximity score: the value-weighted average of the technology proximity scores between a firm and all the acquisition targets in the previous year.

VII. Acquisition Vulnerability and Abnormal Returns for Technology Peers

In Table IX, *Acquisition vulnerability* is the ex-ante likelihood that a technology peer is acquired. We estimate it using a binomial logistic model. The control variables rely on the information from Compustat unless stated otherwise. We have already defined the variables *Same SIC-3 industry dummy*, *Sales increase*, *Closely held shares*, *Leverage*, *Log market cap*, *ROA*, *MB*, and *HHI* above. We define the remaining variables below.

Completed deal dummy: a binary variable that is one for completed deals and zero otherwise. It is based on the information from Thomson SDC Platinum M&A database.
Horizontal merger dummy: a binary variable that is one if the target and the acquirer share the same three-digit SIC code.
Log deal value: the natural logarithm of the deal's value from Thomson SDC Platinum M&A database, which is inflation-adjusted using the consumer price index from FRED (item CPIAUCNS).
Log dormant period: the natural logarithm of the number of days since a previous acquisition announcement in the same technology space.

VIII. Customers of Acquiring Firms

In Tables XI and XII, we consider the potential customers of acquiring firms following Shahrur (2005), as is explained in Appendix A.III. We form portfolios of the several types of customers below.

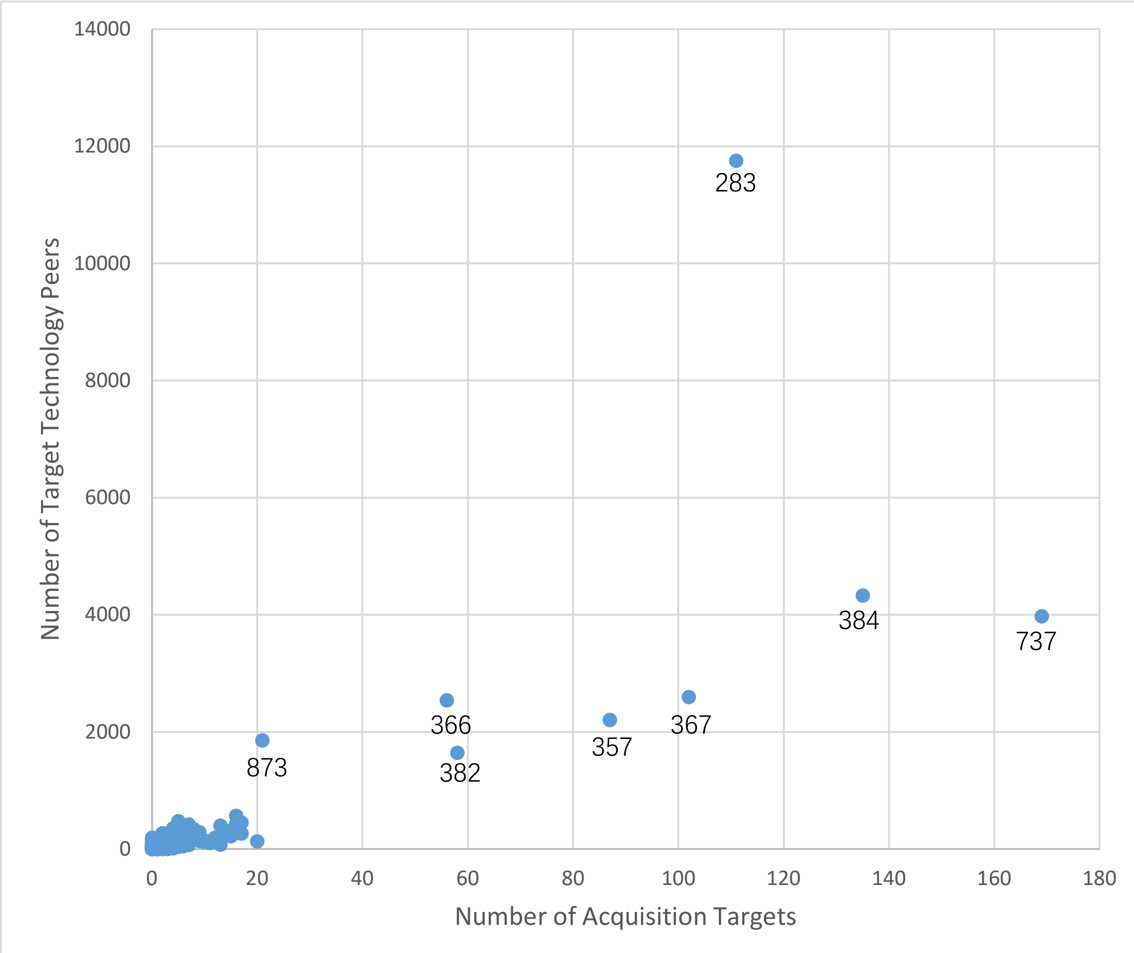
Generic customers: a generic customer refers to a firm that belongs to an industry in the downstream of the acquiring-firm industry with CIC greater than 1%.
Main customers: a main customer is a firm belonging to a customer industry that has the highest purchase volume from the acquiring-firm industry as a percentage of the acquiring-firm industry's output.
Reliant customers: a reliant customer is a firm in a customer industry with the highest CIC.

Small customers: a small customer has a below-median market capitalization among all the generic customers.

Regional customers: a regional customer has its headquarters in the same geographical region as the corresponding acquiring firm. Firms are grouped into the following six geographical regions based on the state of their headquarters: Northeast, Southeast, Southwest, Mideast, Midwest, and West. Firms' headquarters are obtained as explained in Appendix A.III.

Appendix B.

Figure B1: **The Number of Acquisition Targets and Technology Peers for Three-Digit SIC Industries**



This figure shows the number of acquisition targets and the number of target technology peers in each three-digit SIC industry. Each dot represents a three-digit SIC industry, and the number beneath each dot is the SIC code. The horizontal (vertical) axis gives the number of targets (target technology peers) for each industry. The samples of acquisitions and technology peers are described in Table I.

Table B1: **Summary Statistics for the Firm-pair Technology Proximity Score**

This table contains the descriptive statistics for the firm-pair technology proximity scores contained in our baseline dataset during 1984–2010. The technology proximity score is computed following Jaffe (1986), exploiting the patent dataset of Kogan et al. (2017) for US-listed firms. We use the technology proximity score for a specific pair of firms to measure the closeness of these two firms' technology. For each calendar month over the sample period, we rely on the patents granted in the previous 60 months to compute the proximity scores of all possible firm pairs in the patent dataset. We exclude from the computation the firms that do not receive any patent over the 60 months. A detailed definition of the score can be found in Appendix A.II. Panel A reports the number of firms in the firm-pair technology proximity score dataset by calendar month. Panel B contains the average proximity score of all the firm pairs for each calendar month. Panel C reports, for each month, the 98^{th} percentile of the proximity scores of all firm pairs. This value is important because we require the proximity score of a technology peer to be higher than this threshold.

Panel A. The number of firms in the firm-pair technology proximity score dataset by calendar month

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	1652	1664	1661	1664	1667	1669	1675	1683	1693	1694	1698	1704
1985	1708	1708	1712	1718	1719	1715	1720	1725	1726	1710	1706	1703
1986	1697	1696	1706	1709	1718	1719	1721	1737	1736	1740	1738	1746
1987	1748	1760	1774	1793	1795	1795	1808	1816	1813	1821	1828	1840
1988	1849	1855	1863	1873	1883	1890	1897	1902	1901	1904	1899	1900
1989	1893	1891	1891	1894	1899	1895	1895	1900	1909	1903	1910	1908
1990	1900	1904	1909	1908	1902	1903	1913	1904	1910	1910	1895	1899
1991	1896	1896	1893	1889	1880	1871	1873	1870	1867	1863	1873	1871
1992	1874	1879	1882	1885	1883	1892	1893	1891	1893	1887	1884	1884
1993	1887	1885	1891	1887	1885	1887	1890	1897	1897	1888	1898	1898
1994	1887	1899	1904	1924	1935	1946	1958	1958	1968	1970	1975	1981
1995	1976	1976	1983	1985	1998	2000	2007	2018	2028	2023	2046	2049
1996	2053	2067	2076	2084	2106	2123	2135	2154	2172	2178	2186	2196
1997	2216	2231	2246	2260	2288	2293	2296	2309	2320	2337	2348	2357
1998	2365	2379	2394	2404	2422	2441	2455	2479	2487	2499	2515	2525
1999	2538	2557	2579	2582	2580	2577	2581	2596	2599	2604	2614	2641
2000	2652	2672	2689	2697	2703	2715	2729	2730	2769	2787	2802	2814
2001	2826	2841	2848	2871	2875	2888	2889	2894	2907	2907	2915	2919
2001	2920	2924	2927	2923	2921	2925	2916	2919	2917	2915	2913	2913
2003	2904	2906	2911	2910	2989	2888	2872	2865	2857	2834	2820	2808
2004	2801	2802	2797	2778	2774	2761	2754	2737	2727	2705	2691	2657
2005	2632	2651	2656	2665	2661	2650	2636	2624	2617	2606	2586	2578
2006	2561	2572	2568	2562	2552	2550	2540	2529	2530	2525	2509	2504
2007	2498	2501	2503	2492	2477	2472	2468	2465	2457	2452	2450	2437
2008	2423	2424	2419	2408	2404	2402	2399	2395	2391	2383	2378	2377
2009	2360	2351	2343	2337	2331	2332	2321	2321	2309	2308	2308	2296
2010	2295	2288	2284	2273	2268	2257	2250	2239	2228	2213	2211	2192

Panel B. The average value of the technology proximity score by calendar month

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
1985	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.019	0.019	0.020	0.020	0.020
1986	0.020	0.020	0.020	0.020	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
1987	0.019	0.019	0.018	0.018	0.018	0.018	0.019	0.019	0.019	0.019	0.019	0.019
1988	0.018	0.019	0.019	0.019	0.018	0.019	0.018	0.018	0.018	0.018	0.018	0.019
1989	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.020	0.019	0.019
1990	0.020	0.019	0.019	0.019	0.019	0.019	0.019	0.020	0.019	0.019	0.019	0.019
1991	0.019	0.019	0.019	0.019	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
1992	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
1993	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
1994	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
1995	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
1996	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
1997	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.021	0.021	0.021	0.021
1998	0.021	0.021	0.021	0.021	0.021	0.021	0.022	0.021	0.022	0.022	0.022	0.022
1999	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
2000	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.023	0.022	0.022	0.022	0.022
2001	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
2001	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
2003	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
2004	0.024	0.024	0.024	0.024	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
2005	0.026	0.025	0.025	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.027	0.027
2006	0.027	0.027	0.027	0.027	0.028	0.028	0.028	0.028	0.028	0.028	0.029	0.029
2007	0.029	0.029	0.029	0.029	0.029	0.030	0.030	0.030	0.030	0.030	0.030	0.030
2008	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.032
2009	0.032	0.032	0.032	0.032	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.034
2010	0.034	0.034	0.034	0.034	0.034	0.035	0.035	0.035	0.035	0.035	0.035	0.035

Panel C. The 98th percentile of the firm-pair technology proximity score

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	0.258	0.257	0.258	0.259	0.259	0.259	0.258	0.257	0.256	0.256	0.255	0.256
1985	0.256	0.257	0.257	0.256	0.256	0.258	0.257	0.255	0.254	0.257	0.258	0.259
1986	0.260	0.261	0.258	0.259	0.259	0.257	0.256	0.257	0.255	0.254	0.255	0.254
1987	0.253	0.252	0.249	0.247	0.249	0.248	0.251	0.253	0.251	0.252	0.253	0.252
1988	0.251	0.251	0.251	0.252	0.251	0.252	0.251	0.250	0.249	0.249	0.250	0.252
1989	0.255	0.257	0.258	0.259	0.259	0.261	0.262	0.263	0.264	0.268	0.267	0.265
1990	0.268	0.267	0.267	0.266	0.264	0.267	0.268	0.269	0.268	0.268	0.269	0.268
1991	0.268	0.269	0.269	0.269	0.270	0.270	0.272	0.273	0.272	0.274	0.272	0.273
1992	0.272	0.272	0.273	0.276	0.275	0.276	0.276	0.277	0.279	0.283	0.284	0.285
1993	0.287	0.286	0.285	0.289	0.291	0.290	0.291	0.291	0.290	0.290	0.290	0.289
1994	0.289	0.287	0.287	0.289	0.286	0.286	0.285	0.288	0.290	0.289	0.289	0.290
1995	0.291	0.289	0.289	0.291	0.291	0.292	0.291	0.291	0.296	0.296	0.296	0.296
1996	0.294	0.291	0.289	0.292	0.295	0.295	0.296	0.295	0.297	0.299	0.301	0.304
1997	0.307	0.309	0.310	0.313	0.313	0.312	0.312	0.314	0.316	0.321	0.326	0.328
1998	0.330	0.332	0.331	0.333	0.333	0.334	0.343	0.342	0.347	0.345	0.347	0.349
1999	0.351	0.354	0.353	0.352	0.354	0.354	0.357	0.356	0.359	0.361	0.360	0.362
2000	0.364	0.364	0.367	0.367	0.367	0.367	0.370	0.370	0.368	0.369	0.369	0.368
2001	0.371	0.373	0.374	0.375	0.378	0.381	0.383	0.383	0.382	0.386	0.388	0.388
2001	0.392	0.392	0.396	0.398	0.400	0.401	0.401	0.401	0.401	0.400	0.400	0.402
2003	0.401	0.400	0.401	0.404	0.404	0.403	0.401	0.400	0.401	0.400	0.401	0.402
2004	0.403	0.407	0.407	0.405	0.411	0.416	0.422	0.420	0.426	0.427	0.427	0.427
2005	0.428	0.427	0.427	0.432	0.431	0.435	0.435	0.430	0.438	0.442	0.442	0.448
2006	0.451	0.454	0.454	0.455	0.461	0.459	0.461	0.468	0.469	0.470	0.474	0.473
2007	0.476	0.481	0.479	0.483	0.484	0.487	0.490	0.491	0.492	0.493	0.497	0.501
2008	0.504	0.506	0.505	0.505	0.503	0.503	0.508	0.512	0.516	0.516	0.517	0.521
2009	0.525	0.527	0.527	0.534	0.542	0.545	0.549	0.550	0.548	0.546	0.549	0.557
2010	0.558	0.562	0.564	0.574	0.579	0.582	0.582	0.586	0.592	0.594	0.596	0.597

Table B2: **Summary Statistics of Firm and Deal Characteristics**

This table contains the summary statistics of the characteristics of acquiring firms, target firms, technology peer candidates, technology peers, and deals. Detailed definitions of these variables are in Appendix A.IV and Appendix A.VII. The samples of acquisitions and technology peers are described in Table I. Panel A, Panel B, Panel C, Panel D, and Panel E report the characteristics of acquiring firms, target firms, technology peer candidates, technology peers, and acquisition deals respectively.

Panel A. Acquiring firms

Variable	Obs.	Mean	Median	Std.
Sales increase	1,116	0.1138	0.1073	0.2109
Closely held shares	1,053	0.157	0.111	0.188
Leverage	1,152	0.1832	0.1618	0.161
Log market cap	1,159	7.1889	7.1306	2.1761
ROA	1,158	0.0948	0.1091	0.1256
MB Ratio	1,158	2.5493	1.9571	1.8939
HHI	1,159	0.1518	0.1164	0.1093

Panel B. Target firms

Variable	Obs.	Mean	Median	Std.
Sales increase	1,195	0.0749	0.0853	0.2795
Closely held shares	833	0.2259	0.18	0.2
Leverage	1,230	0.1797	0.1312	0.1893
Log market cap	1,234	4.9744	4.8397	1.7986
ROA	1,238	−0.0119	0.0591	0.2496
MB Ratio	1,234	2.1653	1.5693	1.7859
HHI	1,242	0.1599	0.1225	0.1181

Panel C. Technology peer candidates

Variable	Obs.	Mean	Median	Std.
Sales increase	2,205,243	0.0424	0.0793	0.3826
Closely held shares	1,786,016	0.2316	0.1783	0.2076
Leverage	2,306,899	0.1921	0.1545	0.1916
Log market cap	2,307,661	5.2248	5.036	2.1869
ROA	2,311,579	−0.0209	0.065	0.2828
MB Ratio	2,307,467	2.3739	1.6265	2.1607
HHI	2,225,983	0.1446	0.1045	0.1352

Panel D. Technology peers

Variable	Obs.	Mean	Median	Std.
Sales increase	47,234	0.036	0.0908	0.4723
Closely held shares	38,694	0.2188	0.1667	0.2012
Leverage	49,993	0.1712	0.1111	0.1969
Log market cap	50,069	5.2888	5.0068	2.2265
ROA	50,130	−0.0935	0.0394	0.3474
MB Ratio	50,065	2.8245	1.9345	2.482
HHI	48,773	0.1112	0.0641	0.1077

Panel E. Deals

Variable	Obs.	Mean	Median	Std.
Log deal value	1,307	5.4273	5.2674	1.7979
Horizontal merger dummy	1,307	0.4614	0	0.4987
Completed deal dummy	1,307	0.8057	1	0.3958
Log dormant period	1,307	5.1032	4.8828	2.0677
Acquisition premium	1,252	0.2546	0.2032	0.2616

Table B3: **Information Spillover across Different Channels**

This table reports the cumulative average abnormal returns (CAARs) on the equal-weighted portfolios of firms with various economic links with the acquisition targets. The CAR on each firm, measured over the window (−2, +2), is estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. For each target firm, we form an equal-weighted portfolio of linked firms. These firms are classified into different categories according to their economic links to the acquisition target (detailed variable definitions can be found in Appendix A.III). The Standardized Cross-sectional test (StdCsect Z) is an extension of the Patell test (Patell, 1976) that takes into account information on the cross-sectional variance to correct for variance increases. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Category	Number of portfolios	Positive: Negative CAARs	CAAR	StdCsect Z
Same technology space as target	1257	688:569	0.26%	4.014***
Same SIC-3 industry as target	1218	637:581	0.22%	3.304***
Same TNIC-3 industry as target	758	418:340	0.24%	2.655***
Vertically related to target	880	446:434	0.05%	0.281
Same state as target	1187	600:587	0.12%	1.104
Same region as target	1189	611:578	0.07%	0.706

References

Acemoglu, D., R. Griffith, P. Aghion, and F. Zilibotti (2010). Vertical Integration and Technology: Theory and Evidence. *Journal of the European Economic Association 8*(5), 989–1033.

Aghion, P. and P. Howitt (1992). A model of growth through creative destruction. *Econometrica 60*(2), 323–351.

Aghion, P. and J. Tirole (1994). The management of innovation. *The Quarterly Journal of Economics 109*(4), 1185–1209.

Akdoğu, E. (2009). Gaining a competitive edge through acquisitions: Evidence from the telecommunications industry. *Journal of Corporate Finance 15*(1), 99 – 112.

Baghai, R., R. Silva, and L. Ye (2019). Teams and bankruptcy. *Working paper, Swedish House of Finance research paper*.

Bena, J. and K. Li (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance 69*(5), 1923–1960.

Bhattacharya, S. and J. R. Ritter (1983). Innovation and communication: Signalling with partial disclosure. *The Review of Economic Studies 50*(2), 331–346.

Bloom, N. and J. Van Reenen (2002). Patents, real options and firm performance. *The Economic Journal 112*(478), C97–C116.

Bradley, D. and X. Yuan (2013). Information spillovers around seasoned equity offerings. *Journal of Corporate Finance 21*, 106 – 118.

Bradley, M., A. Desai, and E. Kim (1983). The rationale behind interfirm tender offers: Information or synergy? *Journal of Financial Economics 11*(1), 183–206.

Cai, J., M. H. Song, and R. A. Walkling (2011). Anticipation, acquisitions, and bidder returns: industry shocks and the transfer of information across rivals. *The Review of Financial Studies 24*(7), 2242–2285.

Cain, M. D., S. B. McKeon, and S. D. Solomon (2017). Do takeover laws matter? Evidence from five decades of hostile takeovers. *Journal of Financial Economics 124*(3), 464–485.

Chen, Q., I. Goldstein, and W. Jiang (2006). Price informativeness and investment sensitivity to stock price. *The Review of Financial Studies 20*(3), 619–650.

Cohen, L. and A. Frazzini (2008). Economic links and predictable returns. *The Journal of Finance 63*(4), 1977–2011.

Cremers, K. J. M., V. B. Nair, and K. John (2009). Takeovers and the cross-section of returns. *The Review of Financial Studies 22*(4), 1409–1445.

de Bodt, E. and R. Roll (2014). Rival reactions—do value-increasing mergers bolster monopoly rents for strong rivals? *Working paper*.

Dougal, C., C. A. Parsons, and S. Titman (2015). Urban vibrancy and corporate growth. *The Journal of Finance 70*(1), 163–210.

Dow, J. and G. Gorton (1997). Stock market efficiency and economic efficiency: Is there a connection? *The Journal of Finance 52*(3), 1087–1129.

Eckbo, B. (1983). Horizontal mergers, collusion, and stockholder wealth. *Journal of Financial Economics 11*(1), 241–273.

Eckbo, B. E. (1985). Mergers and the market concentration doctrine: Evidence from the capital market. *The Journal of Business 58*(3), 325–349.

Eckbo, B. E. and P. Wier (1985). Antimerger policy under the Hart-Scott-Rodino Act: A reexamination of the market power hypothesis. *The Journal of Law & Economics 28*(1), 119–149.

Edmans, A., I. Goldstein, and W. Jiang (2012). The real effects of financial markets: The impact of prices on takeovers. *The Journal of Finance 67*(3), 933–971.

Engelberg, J., A. Ozoguz, and S. Wang (2018). Know thy neighbor: Industry clusters, information spillovers, and market efficiency. *Journal of Financial and Quantitative Analysis 53*(5), 1937–1961.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance 25*(2), 383–417.

Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance 46*(5), 1575–1617.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics 49*(3), 283–306.

Fee, C. and S. Thomas (2004). Sources of gains in horizontal mergers: evidence from customer, supplier, and rival firms. *Journal of Financial Economics 74*(3), 423 – 460.

Foucault, T. and L. Fresard (2014). Learning from peers' stock prices and corporate investment. *Journal of Financial Economics 111*(3), 554 – 577.

Fulghieri, P. and M. Sevilir (2011). Mergers, spinoffs, and employee incentives. *The Review of Financial Studies 24*(7), 2207–2241.

Gort, M. (1969). An economic disturbance theory of mergers. *The Quarterly Journal of Economics 83*(4), 624–642.

Grossman, S. J. and J. E. Stiglitz (1980). On the impossibility of informationally efficient markets. *The American Economic Review 70*(3), 393–408.

Hall, B. H., A. Jaffe, and M. Trajtenberg (2005). Market value and patent citations. *The RAND Journal of Economics 36*(1), 16–38.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001). The NBER patent citation data file: lessons, insights and methodological tools. *NBER working paper*.

Hameed, A., R. Morck, J. Shen, and B. Yeung (2015). Information, analysts, and stock return comovement. *The Review of Financial Studies 28*(11), 3153–3187.

Harford, J. (2005). What drives merger waves? *Journal of Financial Economics 77*(3), 529 – 560.

Hayek, F. A. (1945). The use of knowledge in society. *The American Economic Review 35*(4), 519–530.

Henderson, R. and I. Cockburn (1996). Scale, scope, and spillovers: The determinants of research productivity in drug discovery. *The RAND Journal of Economics 27*(1), 32–59.

Hertzel, M. G., Z. Li, M. S. Officer, and K. J. Rodgers (2008). Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics 87*(2), 374 – 387.

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

Holmström, B. and J. Roberts (1998). The boundaries of the firm revisited. *The Journal of Economic Perspectives 12*(4), 73–94.

Hou, K. (2007). Industry information diffusion and the lead-lag effect in stock returns. *The Review of Financial Studies 20*(4), 1113–1138.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. *The American Economic Review 76*(5), 984–1001.

Kaplan, S. N. and M. S. Weisbach (1992). The success of acquisitions: Evidence from divestitures. *The Journal of Finance 47*(1), 107–138.

Katz, M. L. and C. Shapiro (1986). How to license intangible property. *The Quarterly Journal of Economics 101*(3), 567–589.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics 132*(2), 665–712.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica 53*(6), 1315–1335.

Lang, L. H. and R. M. Stulz (1992). Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of Financial Economics 32*(1), 45 – 60.

Lee, C. M., S. T. Sun, R. Wang, and R. Zhang (2019). Technological links and predictable returns. *Journal of Financial Economics 132*(3), 76 – 96.

Maksimovic, V. and G. Phillips (2001). The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *The Journal of Finance 56*(6), 2019–2065.

Maksimovic, V., G. Phillips, and N. Prabhala (2011). Post-merger restructuring and the boundaries of the firm. *Journal of Financial Economics 102*(2), 317–343.

Menzly, L. and O. Ozbas (2010). Market segmentation and cross-predictability of returns. *The Journal of Finance 65*(4), 1555–1580.

Mitchell, M. L. and J. Mulherin (1996). The impact of industry shocks on takeover and restructuring activity. *Journal of Financial Economics 41*(2), 193 – 229.

Patell, J. M. (1976). Corporate forecasts of earnings per share and stock price behavior: Empirical test. *Journal of Accounting Research 14*(2), 246–276.

Phillips, G. M. and A. Zhdanov (2013). R&D and the incentives from merger and acquisition activity. *The Review of Financial Studies 26*(1), 34–78.

Rhodes-Kropf, M. and D. T. Robinson (2008). The market for mergers and the boundaries of the firm. *The Journal of Finance 63*(3), 1169–1211.

Rhodes-Kropf, M. and S. Viswanathan (2004). Market valuation and merger waves. *The Journal of Finance 59*(6), 2685–2718.

Scholes, M. and J. Williams (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics 5*(3), 309–327.

Servaes, H. and A. Tamayo (2013). The impact of corporate social responsibility on firm value: The role of customer awareness. *Management Science 59*(5), 1045–1061.

Sevilir, M. and X. Tian (2012). Acquiring innovation. *AFA 2012 Chicago Meetings Paper*.

Shahrur, H. (2005). Industry structure and horizontal takeovers: Analysis of wealth effects on rivals, suppliers, and corporate customers. *Journal of Financial Economics 76*(1), 61 – 98.

Shleifer, A. and R. W. Vishny (2003). Stock market driven acquisitions. *Journal of Financial Economics 70*(3), 295 – 311.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics 70*(1), 65–94.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics 39*(3), 312–320.

Song, M. H. and R. A. Walkling (2000). Abnormal returns to rivals of acquisition targets: A test of the 'acquisition probability hypothesis'. *Journal of Financial Economics 55*(2), 143–171.

Stigler, G. J. (1964). A theory of oligopoly. *Journal of Political Economy 72*(1), 44–61.

Stillman, R. (1983). Examining antitrust policy towards horizontal mergers. *Journal of Financial Economics 11*(1), 225–240.

Subrahmanyam, A. and S. Titman (1999). The going-public decision and the development of financial markets. *The Journal of Finance 54*(3), 1045–1082.

Table I: **The Sample Distribution and Attrition of the Acquisition Targets and Their Technology Peers**

This table reports the number of acquisition targets and their technology peers by the calendar year and industry. Panel A reports the sample distribution and attrition by year. Column 1 reports the number of targets in the acquisitions announced between January 1, 1984 and December 31, 2010, covered by the Thomson Reuters SDC Platinum M&A database. We require that (1) the form of the deal is recorded as either merger or acquisition of majority interest; (2) the target and acquirer are from neither the financial nor the utility sectors; (3) the transaction value is higher than 10 million. The sample attrition is due to additional data requirements imposed in subsequent columns. Column 2 reports the number of targets with patent data. Not all target firms in column 1 have patent data. Column 3 reports the average number of technology peer candidates per target. A target firm's technology peer candidate is any listed non-financial non-utilities firm that has a proximity score with the target (details in Section 3.1). Column 4 reports the average monthly threshold values used to define the technology peers (i.e., the 98^{th} percentile of the proximity scores in a month) (details in Section 3.2). Column 5 reports the number of targets that have technology peers. Not all targets firms have technology peers. Column 6 reports the average number of peers across the acquisition targets. Column 7 reports the number of targets that have technology peers which have the required stock return data from CRSP. Some target firms in column 5 do not have any technology peers with valid return data. Column 8 reports the average number of technology peers with valid stock return data across the target firms. Panel B reports the sample distribution across the Fama-French 12 industries. Panel C compares the number of technology peers that belong to their corresponding target firms' three-digit SIC industries to the number of technology peers that belong to different industries.

Panel A. Sample distribution by year

Year	Number of acquisition targets in SDC (1)	Number of targets with valid patent data (2)	Average number of technology peer candidates per target (3)	Average proximity score threshold values (4)	Number of targets having technology peers (5)	Average number of peers per acquisition target (6)	Number of targets with technology peers that have stock-return data (7)	Average number of peers that have stock-return data per acquisition target (8)
1984	89	28	1409.143	0.257	27	32.481	26	31.538
1985	119	45	1429.422	0.257	45	36.244	45	34.667
1986	119	52	1435.038	0.257	52	33.058	51	31.569
1987	118	38	1458.368	0.251	38	23.053	38	22.079
1988	125	45	1489.422	0.251	43	30.791	43	29.744
1989	88	33	1459.364	0.261	33	27.909	31	28.355
1990	50	15	1460.200	0.267	15	29.467	14	26.286
1991	52	16	1434.563	0.271	16	30.500	16	29.813
1992	43	15	1493.133	0.277	15	32.067	15	30.733
1993	74	17	1553.647	0.289	16	43.000	16	42.000
1994	133	43	1658.047	0.288	43	44.372	43	42.744
1995	179	54	1750.667	0.292	54	34.630	54	33.019
1996	192	55	1832.127	0.296	54	30.352	54	28.407
1997	245	70	1941.271	0.315	70	35.800	70	33.743
1998	276	103	2032.466	0.339	103	37.262	101	34.693
1999	262	102	2054.039	0.356	102	51.186	100	47.960
2000	225	85	2046.624	0.367	85	36.035	79	32.962
2001	162	59	2087.237	0.380	59	51.407	56	50.000
2002	91	45	2078.156	0.399	45	45.267	43	44.256

Continued On Next Page

Year	Number of acquisition targets in SDC	Number of targets with valid patent data	Average number of technology peer candidates per target	Average proximity score threshold values	Number of targets having technology peers	Average number of peers per acquisition target	Number of targets with technology peers that have stock-return data	Average number of peers that have stock-return data per acquisition target
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2003	99	45	2052.578	0.401	45	65.067	44	60.114
2004	96	44	1977.023	0.416	43	44.953	40	43.600
2005	110	56	1973.018	0.435	56	49.571	52	47.385
2006	108	54	1959.074	0.462	54	36.667	46	31.913
2007	107	56	1905.804	0.488	56	37.089	51	32.235
2008	80	50	1801.800	0.510	49	47.673	48	45.271
2009	75	48	1706.063	0.541	48	49.417	48	45.896
2010	72	34	1576.971	0.580	34	22.471	33	21.364
Total	3389	1307	1822.95	0.352	1300	39.791	1257	37.498

Panel B. Distribution of acquisition targets and technology peers by the Fama-French 12 industries

Fama-French 12 industry	Number of acquisition targets with technology peers	Number of technology peers
Consumer Non-Durables	48	1456
Consumer Durables	49	1221
Manufacturing	221	5494
Oil, Gas, and Coal Extraction and Products	19	705
Chemicals and Allied Products	39	2060
Business Equipment	494	13587
Telephone and Television Transmission	25	895
Wholesale, Retail, and Some Services	20	1154
Healthcare, Medical Equipment, and Drugs	260	16735
Others	82	3828
Total	1257	47135

Panel C. Difference between technology space and industry space

Year	Number of acquisition targets	Number of technology peers	Number of technology peers in the same SIC-3 as the targets	Number of technology peers in different SIC-3 from the targets
1984	26	820	82	738
1985	45	1560	199	1361
1986	51	1610	174	1436
1987	38	839	137	702
1988	43	1279	98	1181
1989	31	879	178	701
1990	14	368	39	329
1991	16	477	96	381
1992	15	461	116	345
1993	16	672	75	597
1994	43	1838	556	1282
1995	54	1783	529	1254
1996	54	1534	360	1174
1997	70	2362	693	1669
1998	101	3504	1253	2251
1999	100	4796	1750	3046
2000	79	2604	1001	1603
2001	56	2800	1347	1453
2002	43	1903	764	1139
2003	44	2645	1558	1087
2004	40	1744	803	941
2005	52	2464	1148	1316
2006	46	1468	702	766
2007	51	1644	682	962
2008	48	2173	1078	1095
2009	48	2203	1200	1003
2010	33	705	255	450
Total	1257	47135	16414	30721

Table II: **Abnormal Returns on the Portfolios of Technology Peers**

This table reports the cumulative average abnormal returns (CAARs) on the equal-weighted portfolios of technology peers during the deal announcement of their respective targets. Each peer portfolio corresponds to an acquisition target and vice versa. We describe the samples of acquisitions and peers in Table I. In Panel A, the cumulative abnormal returns (CARs) of each firm, measured over different windows (day 0 is the deal announcement day), are estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. The Standardized Cross-sectional test (StdCsect Z) is an extension of the Patell test (Patell, 1976) which takes into account information on the cross-sectional variance to correct for variance increases. Panel B reports the CAARs on the technology peer portfolios estimated using different models. The CAARs are measured over the five-day window (−2,+2) centered on the acquisition announcement day. In particular, we estimate each firm's CAR based on the market model (same as we do in Panel A), the market-adjusted returns (i.e., the actual stock returns minus the market returns), the market model with GARCH (1,1) errors, the Scholes-Williams procedure (Scholes and Williams, 1977), and the Fama-French three-factor model. Reported in Panel B is also the number of positive vis-à-vis negative abnormal returns. The Time-series (CDA) t-test is a time-series standard deviation test that uses the entire sample for variance estimation; the Generalized sign Z test is a nonparametric test that controls for the asymmetry of positive and negative abnormal returns in the estimation period. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. Abnormal returns over the acquisition announcement period (Market model adjusted)

Day	Number of portfolios	CAAR	StdCsect Z
CAAR (−2, 0)	1257	0.06%	1.826**
CAAR (0, +2)	1257	0.20%	3.477***
CAAR (−2, +2)	1257	0.26%	4.014***
CAAR (−5, +5)	1257	0.40%	3.768***

Panel B. CAAR (−2, +2) using alternative estimation methods and test statistics

Estimation method	Number of portfolios	CAAR	Positive : Negative ARs	StdCsect Z	Time-series (CDA) t	Generalized sign Z
Market model adjusted return	1257	0.26%	688:569	4.014***	3.145***	4.089***
Market-adjusted return	1257	0.47%	716:541	6.362***	5.538***	4.672***
Market model with GARCH (1,1)	1257	0.29%	704:553		3.484***	4.840***
Scholes-Williams abnormal return	1257	0.26%	688:569	4.018***	3.125***	3.981***
Fama-French-model adjusted return	1257	0.19%	658:599	3.506***	2.475***	2.768***

Table III: **Abnormal Returns across Technology Proximity Deciles**

This table reports the cumulative average abnormal return (CAAR) on the portfolios in each decile formed according to the technology peer candidates' proximity to their respective acquisition targets. The first (tenth) decile contains the portfolios of peer candidates with the lowest (highest) proximity scores, excluding zero scores. We group the peer candidates into a portfolio if they have the same corresponding target and belong to the same decile. The deciles are defined in each month according to the technology proximity scores among all the firms with valid data in that month. The cumulative abnormal returns (CARs) of each firm, which are over the window (−2, +2), are estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. The Standardized Cross-sectional test (StdCsect Z) is an extension of the Patell test (Patell, 1976) that takes into account information on the cross-sectional variance to correct for variance increases. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Technology proximity score group	Average proximity score	Number of portfolios	CAAR	StdCsect Z
1st decile	0.002	1256	−0.02%	−0.117
2nd decile	0.005	1250	0.09%	0.929
3rd decile	0.011	1249	0.10%	0.713
4th decile	0.02	1246	−0.01%	−0.081
5th decile	0.034	1246	0.10%	2.129**
6th decile	0.055	1247	0.13%	1.354*
7th decile	0.091	1248	0.14%	2.101**
8th decile	0.156	1244	0.15%	2.515***
9th decile	0.298	1247	0.16%	2.791***
10th decile	0.677	1255	0.27%	3.914***

Table IV: **Comparison between the Technology and Industry Spaces**

This table reports the cumulative average abnormal returns (CAARs) on the equal-weighted portfolios of technology peer candidates. The different peer-candidate portfolios are formed based on their relations to their corresponding target firms regarding technology spaces and industries: the portfolio containing peer candidates in different technology spaces and industries from their target firms'; the portfolio containing peer candidates in their target firms' technology spaces but in different industries; the portfolio containing peer candidates not in their target firms' technology spaces but in the same industries; the portfolio containing peer candidates in both their target firms' technology spaces and industries. We form these portfolios for each target firm respectively. A peer candidate is considered as being in its corresponding target's technology space if it is a technology peer (defined in Section 3.2). In Panel A, a peer candidate is in its corresponding target's industry if it has the same three-digit SIC code (SIC-3) as the target. In Panel B, a peer candidate is in its corresponding target's industry if it is in the target's text-based product-market industries (TNIC-3) (see Hoberg and Phillips, 2010). The cumulative abnormal returns (CARs) of each firm, which are over the window $(-2, +2)$, are estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. The Standardized Cross-sectional test (StdCsect Z) is an extension of the Patell test (Patell, 1976) that takes into account information on the cross-sectional variance to correct for variance increases. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. Technology spaces and SIC-3 industries

	Different SIC-3 industries			Same SIC-3 industry		
	Number of portfolios	CAAR	StdCsect Z	Number of portfolios	CAAR	StdCsectZ
Different technology spaces	1264	0.04%	0.391	1210	0.22%	2.930***
Same technology space	1249	0.18%	2.864***	903	0.37%	3.437***

Panel B. Technology spaces and TNIC-3 industries

	Different TNIC-3 industries			Same TNIC-3 industry		
	Number of portfolios	CAAR	StdCsect Z	Number of portfolios	CAAR	StdCsectZ
Different technology spaces	813	0.08%	1.035	750	0.18%	2.089**
Same technology space	805	0.32%	3.029***	599	0.37%	2.940***

Table V: **Placebo Tests based on the CAAR Distribution of Randomly Selected Portfolios of Peer Candidates**

This table compares the cumulative average abnormal returns (CAARs) on different technology-peer portfolios to the distribution of CAARs on randomly selected non-peer portfolios containing the peer candidates that are not technology peers to their corresponding acquisition target firms. In the first column, we report the CAARs on five different equal-weighted portfolios of technology peers (defined in Section 3.2). We form the technology-peer portfolios based on the peers' relation to their corresponding target firms' industries: all peers regardless their industries; those peers in their corresponding target firms' three-digit SIC code (SIC-3) industries; those peers not in their corresponding target firms' SIC-3 industries; those peers in their corresponding target firms' text-based product industries (TNIC-3)(see Hoberg and Phillips, 2010); those peers not in their corresponding targets firms' TNIC-3 industries. In each draw of non-peer candidates (i.e., candidates that are not peers), we randomly select a sample of non-peer candidates equal in size to the sample of peers used to calculate the peer CAARs, without replacement. We then allocate these non-peer candidates to their respective targets to form non-peer portfolios and calculate their CAARs. The randomly selected non-peer candidates should have the same industrial relation to the corresponding targets as the peers do. For example, when a peer is not in the corresponding target's SIC-3 industry, neither is the randomly-selected non-peer candidate. We replicate this process for 1000 times to form the empirical CAAR distribution. The cumulative abnormal returns (CARs) of each firm, measured over the window $(-2, +2)$, are estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window.

The CAARs on technology-peer portfolios	The CAAR distributions of randomly selected non-peer portfolios					
	Mean	Median	75th	90th	95th	99th
All technology peers	No restriction on the non-peer candidates' industries					
0.26%	0.05%	0.05%	0.07%	0.10%	0.11%	0.14%
Peers in the same SIC-3 industry	Non-peer candidates in the same SIC-3 industry					
0.37%	0.20%	0.20%	0.26%	0.33%	0.36%	0.43%
Peers NOT in the same SIC-3 industry	Non-peer candidates NOT in the same SIC-3 industry					
0.18%	0.05%	0.05%	0.08%	0.11%	0.13%	0.15%
Peers in the same TNIC-3 industry	Non-peer candidates in the same TNIC-3 industry					
0.37%	0.24%	0.24%	0.32%	0.39%	0.44%	0.55%
Peers NOT in the same TNIC-3 industry	Non-peer candidates NOT in the same TNIC-3 industry					
0.32%	0.08%	0.08%	0.12%	0.17%	0.19%	0.24%

Table VI: **The Determinants of the Abnormal Returns on Peer Candidates**

This table shows the estimates on the determinants of technology peer candidates' cumulative abnormal returns (CARs). The sample includes all the peer candidates with valid data. The dependent variable is a peer candidate's CAR. The CAR on each firm, measured over the window (−2, +2), is estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. In Panel A, we regress a peer candidate's CAR on two test variables respectively, namely the *Technology proximity score* and the *Technology peer dummy* (both are defined in Appendix A.II), controlling for other determinants. In Panel B and Panel C, we add several interaction terms formed using these two test variables respectively, the *High acquisition premium dummy*, the *Acquisition premium*, and the *Peer candidate high patent value dummy*. All the variables are defined in Appendix A.IV, apart from the *Technology proximity score* and the *Technology peer dummy*. We control for the year fixed effects and the deal fixed effects in Panel B and Panel C respectively. The t-statistics, clustered at the deal level, are in parentheses. The symbols *, **, and *** denote the statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. CARs of peer candidates – the *Technology proximity score* and the *Technology peer dummy*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology proximity score	0.486***			0.414***			0.444***	
	(3.78)			(3.46)			(3.29)	
Technology peer dummy		0.281***			0.234***			0.254***
		(3.69)			(3.29)			(2.92)
Same SIC-3 industry dummy			0.189**	0.129*	0.153**			
			(2.55)	(1.83)	(2.12)			
Same TNIC-3 industry dummy						0.186*	0.105	0.137
						(1.77)	(1.05)	(1.35)
Sales increase	0.0000879	−0.000382	−0.00120	−0.000577	−0.00109	0.0424	0.0432	0.0426
	(0.00)	(−0.01)	(−0.04)	(−0.02)	(−0.04)	(1.32)	(1.35)	(1.33)
Closely held shares	−0.0352	−0.0363	−0.0359	−0.0345	−0.0353	−0.0530	−0.0521	−0.0526
	(−0.94)	(−0.97)	(−0.96)	(−0.92)	(−0.94)	(−1.23)	(−1.20)	(−1.22)
Leverage	−0.0102	−0.0121	−0.00465	−0.00440	−0.00482	0.000879	0.00123	0.000546
	(−0.16)	(−0.18)	(−0.07)	(−0.07)	(−0.07)	(0.01)	(0.02)	(0.01)
Log market cap	−0.00315	−0.00197	−0.00135	−0.00274	−0.00169	0.000244	−0.00114	−0.0000379
	(−0.30)	(−0.18)	(−0.13)	(−0.26)	(−0.16)	(0.02)	(−0.09)	(−0.00)
ROA	−0.166*	−0.171*	−0.173*	−0.164*	−0.168*	−0.161	−0.154	−0.157
	(−1.76)	(−1.81)	(−1.83)	(−1.75)	(−1.79)	(−1.60)	(−1.54)	(−1.57)
MB	−0.138***	−0.139***	−0.139***	−0.139***	−0.139***	−0.144***	−0.144***	−0.144***
	(−10.38)	(−10.38)	(−10.41)	(−10.41)	(−10.42)	(−9.56)	(−9.57)	(−9.58)
HHI	−0.141*	−0.147*	−0.127	−0.123	−0.125	−0.208**	−0.200**	−0.204**
	(−1.80)	(−1.87)	(−1.61)	(−1.57)	(−1.59)	(−2.18)	(−2.09)	(−2.13)
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R_Square	0.036	0.036	0.036	0.036	0.036	0.038	0.038	0.038
Number of observations	1543391	1543391	1543391	1543391	1543391	1201980	1201980	1201980

Panel B. CARs of peer candidates – the technology space, interactions with acquisition premium and patent value, and year fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High acquisition premium dummy* Technology proximity score	0.670**			0.666**			0.829**		
	(2.28)			(2.27)			(2.45)		
Acquisition premium * Technology peer dummy		0.859**			0.850**			0.935**	
		(2.24)			(2.21)			(2.12)	
Peer candidate high patent value dummy * Technology proximity score			0.446***			0.424***			0.429**
			(2.91)			(2.80)			(2.49)
Technology proximity score	0.141		0.214*	0.0778		0.162	0.0422		0.228
	(0.75)		(1.65)	(0.42)		(1.26)	(0.20)		(1.61)
High acquisition premium dummy	0.0650			0.0648			0.0106		
	(0.79)			(0.79)			(0.10)		
Technology peer dummy		0.0415			−0.000627			−0.00909	
		(0.36)			(−0.01)			(−0.06)	
Acquisition premium		0.210			0.210			0.126	
		(1.22)			(1.22)			(0.63)	
Peer candidate high patent value dummy			0.097***			0.098***			0.120***
			(5.12)			(5.14)			(5.28)
Same SIC-3 industry dummy				0.117	0.140*	0.118			
				(1.38)	(1.65)	(1.41)			
Same TNIC-3 industry dummy							0.0576	0.0920	0.0345
							(0.48)	(0.76)	(0.29)
Other control variables in Panel A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R_Square	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
Number of observations	1526395	1526395	1543391	1526395	1526395	1543391	1186671	1186671	1201980

Panel C. CARs of peer candidates – the technology space, interactions with acquisition premium and patent value, and deal fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High acquisition premium dummy* Technology proximity score	0.659**			0.655**			0.771***		
	(2.58)			(2.56)			(2.62)		
Acquisition premium * Technology peer dummy		0.971***			0.961***			1.042***	
		(3.00)			(2.96)			(2.79)	
Peer candidate high patent value dummy * Technology proximity score			0.431***			0.409***			0.402**
			(2.91)			(2.81)			(2.43)
Technology proximity score	0.126		0.197	0.0578		0.143	0.0182		0.186
	(0.74)		(1.64)	(0.35)		(1.21)	(0.10)		(1.43)
Technology peer dummy		0.00222			−0.0412			−0.0659	
		(0.02)			(−0.41)			(−0.53)	
Peer candidate high patent value dummy			0.108***			0.109***			0.132***
			(5.78)			(5.81)			(5.87)
Same SIC-3 industry dummy				0.126*	0.147**	0.124*			
				(1.78)	(2.03)	(1.76)			
Same TNIC-3 industry dummy							0.107	0.138	0.0820
							(1.08)	(1.35)	(0.82)
Other control variables in Panel A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R_Square	0.036	0.036	0.036	0.036	0.036	0.036	0.038	0.038	0.038
Number of observations	1526395	1526395	1543391	1526395	1526395	1543391	1186671	1186671	1201980

Table VII: **Target/Peer/Deal Characteristics and the Abnormal Returns on Technology Peers**

This table summarizes the cumulative average abnormal returns (CAARs) on the subsamples of technology peers. The subsamples are formed based on the median value of several characteristics of acquisition targets, technology peers, and deals (more details in Appendix A.V). The CAR on each firm, measured over the window $(-2, +2)$, is estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. The Standardized Cross-sectional test (StdCsect Z) is an extension of the Patell test (Patell, 1976) that takes into account information on the cross-sectional variance to correct for variance increases. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Category	Number of portfolios	Positive : Negative CAARs	CAAR	StdCsect Z
All technology peers				
Target technology peers	1257	688:569	0.26%	4.014***
Firm size (market capitalization)				
Small peers	1228	665:563	0.61%	4.650***
Large peers	1238	630:608	0.04%	1.287*
Completed deals vs. withdrawn deals				
Peers of completed deals	1010	553:457	0.25%	3.569***
Peers of withdrawn deals	222	122:100	0.28%	1.552*
Initial acquisition targets vs. non-initial acquisition targets				
Peers of initial acquisition targets	387	210:177	0.37%	2.633***
Peers of non-initial acquisition targets	870	479:391	0.21%	3.066***
Subsequent acquisition activity after announcement				
Peers that become targets within one year	943	490:453	0.49%	2.809***
Peers that do not become targets within one year	1256	674:582	0.25%	3.750***
Acquisition premium				
Peers in high premium deals	619	354:265	0.37%	3.835***
Peers in low premium deals	626	326:300	0.12%	1.665**
Target firms' patent value relative to their total firm value				
Peers of targets with high relative patent value	612	356:256	0.34%	3.696***
Peers of targets with low relative patent value	596	306:290	0.16%	1.892**
Technology peers' patent value relative to their total firm value				
Peers of high relative patent value	1209	641:568	0.40%	4.124***
Peers of low relative patent value	1239	642:597	0.22%	3.113***
Target analyst coverage				
Peers of targets with low analyst coverage	576	319:257	0.21%	2.087**
Peers of targets with high analyst coverage	474	266:208	0.54%	4.010***
Peer analyst coverage				
Peers with low analyst coverage	1218	626:592	0.28%	2.073**
Peers with high analyst coverage	1222	647:575	0.16%	2.989***

Table VIII: **The Determinants of a Firm's Likelihood of being an Acquisition Target**

This table reports logistic regression estimates of the determinants of the likelihood a firm being an acquisition target in a year. The dependent variable is a binary variable equal to one when a firm is an acquisition target in a year (year t) and zero otherwise. The sample comprises all the firm-years (excluding firms from the financial and utility sectors) in the Compustat-CRSP merged database and the acquisitions from the Thomson SDC Platinum M&A database over the period 1984–2010 (more details in Table I). Firm-years that do not obtain any patents in the five years before year t are excluded because, for them, neither the technology space nor the technology peers can be identified. In Panel A, the variable *Previous acquisition dummy* is one if at least one of the firm's technology peers was an acquisition target in the previous year (year t–1) and zero otherwise. In Panel B, the variable *Previous acquisition proximity score* is the value-weighted average of the technology proximity scores between the firm in question and all the acquisition targets in the previous year (year $t-1$). All the independent variables are measured in the previous year (year $t-1$) and defined in Appendix A.VI. The industry fixed effects are based on the Fama-French 48 industry definitions. t-statistics clustered at the firm level are in parentheses. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. Acquisition likelihood – *Previous acquisition dummy*

	(1)	(2)	(3)	(4)	(5)	(6)
Previous acquisition dummy	0.174***	0.178***	0.175***	0.137***	0.140***	0.127**
	(3.54)	(3.61)	(3.38)	(2.65)	(2.72)	(2.34)
MB	−0.125***	−0.125***	−0.145***	−0.121***	−0.121***	−0.142***
	(−6.82)	(−6.81)	(−7.16)	(−6.59)	(−6.57)	(−7.00)
PPE	−0.488***	−0.479***	−0.488***	−0.476***	−0.468***	−0.493***
	(−2.91)	(−2.85)	(−2.73)	(−2.75)	(−2.70)	(−2.67)
Cash	−0.00940	−0.0112	0.0111	−0.0221	−0.0246	−0.00155
	(−0.50)	(−0.59)	(0.55)	(−1.13)	(−1.25)	(−0.07)
Blockholder dummy	0.321***	0.326***	0.239***	0.336***	0.342***	0.249***
	(6.73)	(6.82)	(4.67)	(6.88)	(7.01)	(4.75)
Log market cap	−0.0672***	−0.0720***	−0.0465***	−0.0687***	−0.0747***	−0.0478***
	(−5.06)	(−5.08)	(−3.05)	(−5.08)	(−5.17)	(−3.08)
Leverage	0.447***	0.453***	0.521***	0.493***	0.501***	0.569***
	(3.68)	(3.72)	(4.15)	(3.97)	(4.03)	(4.43)
ROA	−0.263**	−0.235**	−0.301***	−0.222**	−0.186*	−0.254**
	(−2.43)	(−2.17)	(−2.68)	(−2.01)	(−1.67)	(−2.22)
Log age		−0.207**			−0.263***	
		(−2.25)			(−2.79)	
Log age squared		0.0411**			0.0522**	
		(2.06)			(2.53)	
Capital liquidity		−0.104			−0.0177	
		(−1.00)			(−0.01)	
Hostile takeover index			0.145			0.0676
			(0.49)			(0.22)
Industry fixed effects	Yes	Yes	Yes	No	No	No
Year fixed effects	Yes	Yes	Yes	No	No	No
Industry-Year fixed effects	No	No	No	Yes	Yes	Yes
Pseudo R-squared	0.0356	0.0359	0.0352	0.0604	0.0608	0.0609
Number of observations	41528	41528	36725	36766	36766	31990

Panel B. Acquisition likelihood – *Previous acquisition proximity score*

	(1)	(2)	(3)	(4)	(5)	(6)
Previous acquisition proximity score	1.066***	1.095***	1.107***	1.308***	1.331***	1.242**
	(2.82)	(2.90)	(2.83)	(2.64)	(2.68)	(2.41)
MB	−0.125***	−0.126***	−0.146***	−0.120***	−0.121***	−0.142***
	(−6.84)	(−6.85)	(−7.22)	(−6.54)	(−6.55)	(−7.00)
PPE	−0.528***	−0.518***	−0.535***	−0.511***	−0.501***	−0.538***
	(−3.15)	(−3.09)	(−3.00)	(−2.95)	(−2.90)	(−2.92)
Cash	−0.0110	−0.0132	0.00854	−0.0247	−0.0275	−0.00481
	(−0.58)	(−0.69)	(0.42)	(−1.25)	(−1.38)	(−0.23)
Blockholder dummy	0.323***	0.328***	0.243***	0.338***	0.344***	0.252***
	(6.75)	(6.85)	(4.73)	(6.90)	(7.02)	(4.78)
Log market cap	−0.0659***	−0.0699***	−0.0448***	−0.0695***	−0.0748***	−0.0478***
	(−4.92)	(−4.90)	(−2.91)	(−5.05)	(−5.08)	(−3.02)
Leverage	0.445***	0.450***	0.524***	0.494***	0.503***	0.575***
	(3.63)	(3.67)	(4.15)	(3.95)	(4.02)	(4.45)
ROA	−0.269**	−0.242**	−0.306***	−0.221**	−0.186*	−0.253**
	(−2.48)	(−2.22)	(−2.72)	(−2.00)	(−1.66)	(−2.20)
Log age		−0.202**			−0.261***	
		(−2.17)			(−2.73)	
Log age squared		0.0391*			0.0506**	
		(1.94)			(2.43)	
Capital liquidity		−0.113			0.0145	
		(−1.09)			(0.01)	
Hostile takeover index			0.0940			0.0186
			(0.32)			(0.06)
Industry fixed effects	Yes	Yes	Yes	No	No	No
Year fixed effects	Yes	Yes	Yes	No	No	No
Industry-Year fixed effects	No	No	No	Yes	Yes	Yes
Pseudo R-squared	0.0334	0.0336	0.0332	0.059	0.0594	0.059
Number of observations	40157	40157	35480	35785	35785	31075

Table IX: **Acquisition Vulnerability and the Abnormal Returns on Technology Peers**

This table reports the regression estimates of how a technology peer's ex-ante vulnerability to acquisitions impacts its cumulative abnormal return (CAR) at the deal announcement. In Panel A, the sample contains the technology peers described in column (7) and (8) of Table I. The dependent variable (the CAR on each firm), measured over the window (−2, +2), is estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. The variable *Acquisition vulnerability* is measured by a firm's probability of being an acquisition target in the acquisition year. It is estimated based on the coefficients of columns (1), (2), and (3) of Panel B for columns (1)-(3), (4)-(6), and (7)-(9) of Panel A respectively. The other independent variables are defined in Appendix A. In Panel B, we report the logistic regression estimates of the likelihood of a firm being an acquisition target in a year (year t), same as in Table VIII. The dependent variable is a binary variable equal to one when a firm is an acquisition target in year t and zero otherwise. All the independent variables are measured in the year t–1 and defined in Appendix A. The sample comprises all the firm-years (excluding firms from the financial and utility sectors) in the Compustat-CRSP merged database and the acquisitions from the Thomson SDC Platinum M&A database over the period 1984–2010. Firm-years that do not have any patents granted in the five years before year t are excluded because, for them, neither the technology space nor the technology peers can be identified. The industry fixed effects are based on the Fama-French 48 industry definitions. t-statistics clustered at the deal level (Panel A) or firm level (Panel B) are in parentheses. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. CARs on technology peers – *Acquisition vulnerability*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Acquisition vulnerability	14.98***	16.34**	16.32**	13.63***	12.64**	12.64**	15.85***	20.43***	20.47***
	(4.52)	(2.57)	(2.57)	(4.58)	(2.25)	(2.26)	(4.48)	(2.92)	(2.93)
Same SIC-3 industry dummy		0.111	0.117		0.111	0.117		0.127	0.127
		(0.60)	(0.65)		(0.60)	(0.65)		(0.66)	(0.67)
Sales increase		0.150	0.150		0.139	0.140		0.158	0.159
		(1.10)	(1.11)		(1.03)	(1.03)		(1.14)	(1.14)
Closely held shares		−0.339	−0.346		−0.378	−0.384		−0.386	−0.393
		(−1.32)	(−1.35)		(−1.48)	(−1.51)		(−1.41)	(−1.43)
Leverage		−0.341	−0.335		−0.252	−0.247		−0.499	−0.496
		(−1.09)	(−1.07)		(−0.80)	(−0.79)		(−1.51)	(−1.51)
Log market cap		0.0207	0.0205		−0.00129	−0.00146		0.0204	0.0197
		(0.47)	(0.47)		(−0.03)	(−0.04)		(0.50)	(0.49)
ROA		−0.0937	−0.107		−0.0848	−0.0980		0.145	0.135
		(−0.32)	(−0.36)		(−0.28)	(−0.33)		(0.47)	(0.44)
MB		−0.0259	−0.0255		−0.0358	−0.0353		0.00177	0.00246
		(−0.64)	(−0.63)		(−0.88)	(−0.87)		(0.04)	(0.05)
HHI		−0.169	−0.182		−0.146	−0.159		−0.174	−0.189
		(−0.34)	(−0.37)		(−0.29)	(−0.32)		(−0.33)	(−0.36)
Log deal value			0.0119			0.0121			0.0177
			(0.20)			(0.21)			(0.30)

Continued On Next Page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Horizontal merger dummy			−0.0736			−0.0738			−0.0439
			(−0.41)			(−0.41)			(−0.24)
Completed deal dummy			0.370*			0.369*			0.354
			(1.67)			(1.67)			(1.57)
Log dormant period			0.0428			0.0431			0.0394
			(0.89)			(0.90)			(0.80)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.006	0.006	0.007	0.006	0.006	0.006	0.006	0.006	0.006
Number of observations	41420	31372	31372	41420	31372	31372	36677	28950	28950

Panel B. Acquisition vulnerability estimation

	(1)	(2)	(3)
Constant	−2.302***	−1.868***	−2.313***
	(−27.84)	(−13.90)	(−26.21)
MB	−0.108***	−0.122***	−0.130***
	(−6.21)	(−6.77)	(−6.77)
PPE	−0.589***	−0.663***	−0.621***
	(−3.93)	(−4.38)	(−3.83)
Cash	0.00745	0.0108	0.0302
	(0.41)	(0.59)	(1.58)
Blockholder dummy	0.298***	0.318***	0.238***
	(6.43)	(6.83)	(4.82)
Log market cap	−0.0661***	−0.0530***	−0.0299**
	(−5.62)	(−4.12)	(−2.20)
Leverage	0.469***	0.508***	0.552***
	(3.90)	(4.20)	(4.44)
ROA	−0.268***	−0.308***	−0.381***
	(−2.67)	(−3.06)	(−3.70)
Log age		−0.114	
		(−1.26)	
Log age squared		0.0133	
		(0.68)	
Capital liquidity		−0.186***	
		(−5.36)	
Hostile takeover index			−0.156
			(−0.56)
Pseudo R-squared	0.0126	0.0146	0.0107
Number of observations	41562	41562	36755

Table X: **Target Abnormal Returns for Withdrawn Deals**

This table reports the cumulative average abnormal returns (CAARs) on the targets of withdrawn deals for various time windows. The CAR on each firm is estimated using the Fama-French three-factor model based on monthly data. We estimate the model parameters using the data from 72 to 13 months before the deal announcement month, requiring valid data available for at least six months over the estimation window. Panel A reports the target CAARs for several windows relative to the acquisition announcement month (month 0). For example, (−1, +24) means the CAR on each firm is measured over the window from one month before to twenty four months after the announcement month. A target is classified as subsequently acquired if it is acquired within the five years after the acquisition announcement month. Otherwise, a target is not subsequently acquired. In Panel B, we further clean up the sample of withdrawn-deal targets that are not subsequently acquired, by removing the deals withdrawn because the deal price is considered too high by the acquirer or there has been a reported deterioration in the fundamentals of the target firm and/or business environment. We also drop the deals where the reason for withdrawal is unknown. We report the CAARs of this clean sample for the same set of time windows. The Time-series (CDA) t-test is a time-series standard deviation test that uses the entire sample for variance estimation. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. The target CAARs of withdrawn deals

Event time period	Total sample			Subsequently acquired			Not subsequently acquired		
(in months)	N	CAAR	Time-series t	N	CAAR	Time-series t	N	CAAR	Time-series t
(−1,0)	211	27.73%	18.944***	105	31.55%	13.656***	106	23.94%	12.565***
(−1, +1)	211	28.42%	15.852***	105	35.01%	12.373***	106	21.88%	9.379***
(−1, +6)	211	21.53%	7.356***	105	34.59%	7.486***	106	8.60%	2.257**
(−1, +12)	211	21.60%	5.578***	105	39.09%	6.396***	106	4.27%	0.847
(−1, +24)	211	20.73%	3.927***	105	40.83%	4.901***	106	0.81%	0.118
(−1, +48)	211	16.43%	2.245**	105	42.82%	3.707***	106	−9.71%	−1.019
(+1, +6)	204	−6.41%	−2.527***	100	3.19%	0.798	104	−15.63%	−4.738***
(+1, +12)	204	−6.34%	−1.767**	100	7.92%	1.400*	104	−20.05%	−4.296***
(+1, +24)	204	−7.24%	−1.428*	100	9.74%	1.217	104	−23.57%	−3.572***
(+1, +48)	204	−11.68%	−1.629*	100	11.83%	1.045	104	−34.29%	−3.674***

Panel B. The target CAARs of deals withdrawn due to non-price reasons (for targets not subsequently acquired)

Event time period (in months)	N	CAAR	Time-series t
(−1,0)	65	25.77%	11.162***
(−1, +1)	65	21.81%	7.715***
(−1, +6)	65	18.70%	4.050***
(−1, +12)	65	14.36%	2.351***
(−1, +24)	65	6.35%	0.763
(−1, +48)	65	−16.77%	−1.453*
(+1, +6)	63	−7.30%	−1.825**
(+1, +12)	63	−11.77%	−2.081**
(+1, +24)	63	−20.03%	−2.505***
(+1, +48)	63	−43.89%	−3.881***

Table XI: **Abnormal Returns on the Customers of Acquiring Firms**

This table reports the cumulative average abnormal returns (CAARs) on the portfolios of potential customers of the acquiring firms. The CAR on each firm, measured over the window (−2, +2), is estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. For each acquiring firm, we form equal-weighted portfolios for the different types of potential customers. The sample of acquisitions is described in Table I. *Generic customers* are firms that belong to an industry in the downstream of the acquiring-firm industry with Customer Input Coefficient (CIC) greater than 1%. The CIC is the value of the upstream industry's output sold to the downstream industry divided by the value of the downstream industry's total output. *Main customers* are firms belonging to the customer industry with the highest purchase volume from the acquiring-firm industry as a percentage of the acquiring-firm industry's output. *Reliant customers* are firms in the customer industry with the highest CIC. *Small customers* have a below-median market capitalization among all the generic customers. *Regional customers* have headquarters in the same geographical region as their corresponding acquiring firms (more details on variable definitions can be found in Appendix A.VIII). We assume a deal is in a high or a low competition industry based on the Herfindahl-Hirschman Index (HHI) of the acquiring firm's four-digit SIC industry. If the acquiring firm's HHI in the year before the deal announcement is lower (greater) than the sample median of the same year, the deal is classified as taking place in a high (low) competition industry. The Standardized Cross-sectional test (StdCsect Z) is an extension of the Patell test (Patell, 1976) that takes into account information on the cross-sectional variance to correct for variance increases. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Customer portfolio	Full sample	Subsamples:	
		high competition industry	low competition industry
Generic customers			
Number of portfolios	737	394	343
CAAR	0.11%	0.18%	0.04%
StdCsect Z	2.662***	2.875***	0.924
Main customers			
Number of portfolios	726	390	336
CAAR	0.15%	0.24%	0.04%
StdCsect Z	1.557*	1.954**	−0.067
Reliant customers			
Number of portfolios	728	390	338
CAAR	0.16%	0.22%	0.10%
StdCsect Z	1.882**	2.412***	0.04
Small customers			
Number of portfolios	710	386	324
CAAR	0.37%	0.47%	0.27%
StdCsect Z	5.181***	4.892***	2.408***
Regional customers			
Number of portfolios	682	378	304
CAAR	0.41%	0.42%	0.41%
StdCsect Z	3.271***	3.013***	1.667**

Table XII: **Acquisitions in the Same/Different Technology Space and the Abnormal Returns on Acquiring Firms' Customers**

This table reports the cumulative average abnormal returns (CAARs) on the equal-weighted portfolios of acquiring firms' customers, for four different subsamples of acquisitions. We separate our acquisition sample (described in Table I) into four subsamples according to whether or not the merging firms (i.e., the target and the acquirer) are in the same technology space and/or industry. Technology spaces are defined in Appendix A.II. The CAR on each firm, measured over the window (−2, +2), is estimated using the market model. We estimate the model parameters using the data from 300 to 61 days before the deal announcement day, requiring valid data available on at least 100 trading days over the estimation window. In Panel A, industries are defined based on the three-digit SIC code (SIC-3). In Panel B, industries are defined according to the text-based product industries (TNIC-3) (see Hoberg and Phillips, 2010). The Standardized Cross-sectional test (StdCsect Z) is an extension of the Patell test (Patell, 1976) that takes into account information on the cross-sectional variance to correct for variance increases. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. Technology spaces and SIC-3 industries

	Different SIC-3 industries			Same SIC-3 industry		
	Number of portfolios	CAAR	StdCsect Z	Number of portfolios	CAAR	StdCsectZ
Different technology spaces	203	0.19%	0.581	143	−0.01%	0.612
Same technology space	71	0.31%	2.323**	122	0.36%	1.760**

Panel B. Technology spaces and TNIC-3 industries

	Different TNIC-3 industries			Same TNIC-3 industry		
	Number of portfolios	CAAR	StdCsect Z	Number of portfolios	CAAR	StdCsectZ
Different technology spaces	127	0.27%	0.208	110	−0.07%	0.345
Same technology space	45	0.43%	1.581*	88	0.30%	1.341*