Acquisitions and Technology Value Revision*

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Abstract

Acquisition announcements coincide with upward value revisions for the target firms' technology peers, which are not due to economic relations based on product market, supply chain, or geographical location. Such a phenomenon is robust across sub-sample periods, not specific to merger or technology waves, and not related to product-market structure and the unique innovation features of certain technology-intensive industries. Firms experience more dramatic value revisions when they have deeper technology overlaps with their targets, are more dependent on technology, or when a transaction features higher premium or greater technology overlap between the acquirer and target. Our mechanism analysis provides evidence that is primarily consistent with the *Acquisition-Probability Hypothesis* whereby acquisition announcements elevate expected technology synergies and merger prospects for peers; and partially in line with the *Enhanced-Investment Hypothesis* that peers' revaluations correlate with increased technology investments. We do not find any evidence in line with the *Competition-Balance Hypothesis* which attributes peers' value revisions to the change in industrial competition intensity. Overall, our results demonstrate that acquisition announcements disseminate novel information about the value of technology that is of common interest among firms with close technologies.

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1. Introduction

A quest widely pursued by financial economists is to understand how information diffuses from informed parties to uninformed ones, and how asset prices facilitate such processes (e.g., Duffie et al., 2010b; Grossman, 1976; Grossman and Stiglitz, 1980; Hayek, 1945; Kyle, 1985). A notable literature shows that acquisitions, consequential as they are, disseminate information of common interest about the fundamentals of economically-related firms. Studies have shown that acquisitions impact not only stock prices but also the real behavior of those firms that relate to the merging firms through product markets (e.g., Cai et al., 2011; Eckbo, 1983; Fee and Thomas, 2004; Phillips and Zhdanov, 2013; Servaes and Tamayo, 2013; Shahrur, 2005; Song and Walkling, 2000; Stillman, 1983) or supply chains (e.g., Bernile and Lyandres, 2019; Fee and Thomas, 2004; Shahrur, 2005). Missing from this literature, however, is another essential economic relation—technology links.

The importance of technology and technology links is evident. First, previous literature has established technological innovation as a primary driver of business success (e.g., Bloom and Van Reenen, 2002; Hall et al., 2005; Jaffe, 1986; Kogan et al., 2017) and economic growth (e.g., Aghion and Howitt, 1992; Romer, 1986; Schumpeter, 1942; Spence, 1984). Second, technology synergies constitute an essential merger motive for companies (e.g., Acemoglu et al., 2010; Ahuja and Katila, 2001; Bena and Li, 2014; Cassiman and Veugelers, 2006; Frésard et al., 2020; Phillips and Zhdanov, 2013; Sevilir and Tian, 2012; Zhao, 2009). Third, companies often possess technologies that are close to each other. In today's knowledge-based economy, firms are often technology peers who innovate in closely analogous technology categories (henceforth called "technology peers" or "peers"; we formally define peers in Sections 2.1 and 2.2). Well-known companies like IBM and Intel, while serving distinct product markets, overlap on multiple technological fronts (Bloom et al., 2013). Peers are related through their extensive network of citations, licensing agreements, talents, and collaborations, may compete with one another, and, therefore, have correlated fundamentals (e.g., Baghai et al., 2019; Fulghieri and Sevilir, 2011; Hall et al., 2001; Katz and Shapiro, 1986). In this paper, we ask two questions: 1) to what extent do acquisitions generate and transmit information about the value of technology that is of common interest among technologically close firms? and 2) what is (are) the mechanism(s) of the underlying information transmission process?

It may be hard to appreciate, in the first instance, that firms in the same technology space could operate in different industries or product markets. However, previous literature has provided ample evidence on the differences between technology space and product market. Schmookler (1966, p.20) and Jaffe (1986, p.985) note that the products designed based on the patent for solids dispensing range from toothpaste tubes to manure spreaders. Bloom et al. (2013) highlight that IBM, Apple, Motorola, and Intel are all close in technology; however, only IBM and Apple compete in the personal computer market, and Motorola and Intel compete in the semiconductor market. Bena and Li (2014) also claim that technological overlap transcends traditional industry classifications. In our sample, only 22%, 36%, 40%, and 34% of a target firm's technology peers fall into the target firm's segment-based product market (Bloom et al., 2013), 3-digit SIC code industry, Fama-French 48 (FF-48) industry, and Text-based Network Industry Class (TNIC)(Hoberg and Phillips, 2010), respectively. Moreover, technology space has limited overlap with other economic relations—only 12% (14%) of the peers are target firms' customers (suppliers) and only 14% reside in the states in which target firms are headquartered.

Our analysis contains two inter-related parts. In the first part, we establish that acquisitions disseminate novel information about the value of technologies that are closely linked, via examining the stock-price reaction of target firms' technology peers at the acquisition announcement. For a sample of acquisitions announced during the 1984–2010 period, we find that target firms' technology peers receive a statistically significant cumulative average abnormal return (CAAR) ranging from 0.20% to 0.29% over the window $(-2, +2)$ centered around the announcement day (day 0), under various definitions of peers according to the previous literature. This is equivalent to \$612–1,517 million (in 2010 dollars) in an average target firm's technology space (i.e., a set of around 40 firms closest to a target firm in technology). When we sort all the firms, for which we can measure the closeness of their technology to that of the target firms, into deciles, we find that the abnormal returns increase almost monotonically from the most distant decile to the closest decile. As is indicated at the beginning of this paper, firms could be linked through other economic relations, and the concern for our study is that technology links may simply reflect product-market relations (e.g., Eckbo, 1983; Hoberg and Phillips, 2010; Hou, 2007; Song and Walkling, 2000; Stillman, 1983), supply-chain partnerships (e.g., Bernile and Lyandres, 2019; Cohen and Frazzini, 2008; Chu et al., 2019; Fee and Thomas, 2004; Hertzel et al., 2008; Menzly and Ozbas, 2010; Shahrur, 2005), or geographical neighborhood effects (Chu et al., 2019; Dougal et al., 2015; Engelberg et al., 2018; Korniotis and Kumar, 2013; Pirinsky and Wang, 2006). However, we find the positive association between peers' abnormal returns and their technology closeness with target firms remains significant after we control for these alternative economic links using various methods. These methods include double sorting based on technology closeness and an alternative economic link, placebo tests based on empirical distributions simulated using the non-peer firms linked via an alternative economic relation, and regression analysis incorporating other economic links. These results show that technology links convey additional information in the presence of alternative economic relations.

Moreover, we find that the positive value revision strengthens for peers that invest more in research and development (R&D) or whose value is more dependent on technology, confirming the observed value revision is related to technology. Such value revision is also stronger for deals with larger acquisition premia and deals in which the acquirer and the target are peers, reinforcing the information-disseminating role of acquisitions.

In our tests designed to explore the boundary of the baseline finding, we demonstrate that peer value revision is a robust economic phenomenon rather than being specific to sub-sample periods or being the byproduct of merger or technology waves, industrial structure, and the unique innovation features of the pharmaceutical and IT industries.

In the second part of our analysis, we investigate several possible underlying mechanisms of the information dissemination process along technology links. According to the theories presented in the literature, three mechanisms have been suggested, namely the *Acquisition-Probability Hypothesis*, the *Enhanced-Investment Hypothesis*, and the *Competition-Balance Hypothesis*.

As was mentioned earlier, a substantial body of literature shows that technology drives merger synergies (e.g., Bena and Li, 2014; Sevilir and Tian, 2012; Zhao, 2009). The *Acquisition-Probability Hypothesis* maintains that acquisition announcements convey information about the common component of technology synergies available to firms that are technologically close. At the deal announcement, the acquiring firm bids up the price of the target firm's technology assets in the expectation of high technology synergies. The peers' market reaction reflects the elevated expectation of technology synergies and the concurrent increase in acquisition probability (Song and Walkling, 2000). Specifically, an acquisition announcement reveals the acquiring firm's private information about the technology synergies common to a target firm and its peers. The announcement, therefore, increases the expected synergies for technology peers and raises the anticipated acquisition probability, which is a positive function of the expected synergies. Such a signal is credible because of the acquiring firm's information advantage and its financial commitment to the proposed deal. In line with the *Acquisition-Probability Hypothesis*, we find technology peers' abnormal returns are greater when peers are more vulnerable to acquisitions. Furthermore, a firm is more likely to be an acquisition target in a year when one or more of its peers received an acquisition bid in the previous year. Consistent with acquisitions disseminating information, peers' abnormal returns in withdrawn deals are nearly as large as they are in successful deals because truthful information about acquisition prospects and synergies, once revealed, cannot be nullified. Moreover, the target firms' abnormal returns do not dissipate if the target is subsequently acquired, further demonstrating the relevance of acquisition prospects to value revisions. In an extended analysis, we examine who acquires the peers subsequently. We find that subsequent acquirers are more likely to be those that overlap with peers in technology, product market, and geographical location, or those that are peers' suppliers. A priori, these economically–related firms are more likely to benefit from the expected elevation in synergies. However, we also find that firms that overlap with peers in both technology and product markets are not more likely to be acquirers than other randomly selected firms, consistent with the notion that "business stealing" reduces expected technology synergies (Bena and Li, 2014, p.1945 and Table VI; Bloom et al., 2013). In another extended analysis, we ask whether the peers' value revisions become weaker as more and more peers in a technology field are taken over, bidding costs start to rise, the novelty of an acquisition announcement reduces, and the update in acquisition probability mitigates. Indeed, we find that the peers' CAAR is indistinguishable from zero when the acquisition intensity in a technology space begins to decline.

The disseminated new information could incentivize peer firms to enhance their value-increasing innovation activities (Phillips and Zhdanov, 2013). The *Enhanced-Investment Hypothesis* postulates that the prospect of selling out to large firms motivates small firms to innovate. Upgraded technology and enhanced innovation capacity, in turn, makes firms more attractive acquisition targets. Stronger technology fundamentals should increase the value of independent firms too, if the realization of technology value does not depend on bringing resources together under common control. To test the validity of the *Enhanced-Investment Hypothesis*, we investigate how firms' R&D investments change after their peers are pursued as acquisition targets. We find that, although firms on average do not increase their R&D expenditure after their peers become targeted, small firms do raise their R&D spending, as predicted by Phillips and Zhdanov (2013). Nonetheless, we fail to find any significant relation between the change in peers' R&D spending and their abnormal returns.

Acquisitions built on technology synergies could shift the competition balance in peers' product markets. A priori, the *Competition-Balance Hypothesis* predicts mixed effects of technology closeness on peers' stock prices. To the extent that mergers produce more efficient rivals (e.g., Bena and Li, 2014; Henderson and Cockburn, 1996; Sevilir and Tian, 2012), peers should suffer from negative abnormal returns, which contradicts the positive peer abnormal returns found in our baseline analysis. However, it is also possible that acquirers take over the target firms in so-called "killer acquisitions" with the intention to discontinue the targets' on-going R&D projects to preempt future competition (Cunningham et al., 2021). Positive peer returns could, therefore, be explained by the enhanced anti-competitive rents that benefit all peers and harm the customers of the merging firms (Eckbo, 1983). Contrary to this view, however, we find that the customers of acquiring firms do not suffer from negative abnormal returns on average, or in deals most likely to be classified as "killer acquisitions." Furthermore, peers' positive returns are not significantly stronger even when the acquirer is in a less competitive product market and supposed to possess greater anti-competitive power. Similarly, the customers' abnormal returns in deals that are most likely to be anti-competitive (defined following Cunningham et al. (2021)) are not distinguishable from those in similar deals that are unlikely to be anti-competitive.

Overall, our evidence does not point to the *Competition-Balance Hypothesis*. There is some mixed evidence in support of the *Enhanced-Investment Hypothesis*. The evidence is primarily in line with the *Acquisition-Probability Hypothesis*.

Our study adds to three strands of literature. First, we contribute to the literature showing that mergers and acquisitions disseminate novel information about company fundamentals. In particular, by highlighting the essential role that acquisitions play in conveying information of common interest about the value of technology among technology peers, we add to the previous studies that have examined the informational role of acquisitions in industries and product markets (e.g., Cai et al., 2011; Eckbo, 1983; Fee and Thomas, 2004; Shahrur, 2005; Song and Walkling, 2000; Stillman, 1983) and along supply chains (e.g., Bernile and Lyandres, 2019; Fee and Thomas, 2004; Shahrur, 2005). Second, our study adds to the literature showing that economic links serve as important information conduits in financial markets. A strand of literature examines return predictability (or lead-lag price relations) along economic links such as product market rivalry, supply-chain relations, and geo-economic neighborhood (e.g., Cohen and Frazzini, 2008; Hou, 2007; Menzly and Ozbas, 2010). In a closely related paper, Lee et al. (2019) find significant return predictability along the technology links. Conceptually, these studies build on slow information diffusion and investors' inattention. In contrast, our study relies on the stock market's rational reaction to new information revealed by significant corporate events whose importance for information transmission has been suggested but not investigated in previous studies (e.g., Cohen and Frazzini, 2008; Hirshleifer et al., 2013; Hong and Stein, 2007). Return-predictability analysis also faces the critique on its underlying rationale and econometric soundness (Harvey et al., 2016; Hou et al., 2020). Ali and Hirshleifer (2020) further show that the return predictability along technology links and other economic relations can be subsumed by an analyst coverage factor. While the return-predictability-based evidence has been dubious in terms of substantiating technology links' information-transmission role, we establish such a role through peers' stock-market responses to significant corporate events. Importantly, the context of significant corporate events allows us to analyze in depth the mechanisms of the underlying information dissemination which would be impossible using the return-predictability framework. Third, we contribute to a broad literature that analyzes how markets and the price system aggregate information dispersedly held by economic agents with heterogeneous information sets (e.g., Duffie et al., 2010a,b; Grossman, 1976; Grossman and Stiglitz, 1980; Hayek, 1945). Our study relates to this literature and provides micro evidence on the essential roles played by corporate-control transactions and technology links in the information-transmission process.

Several recent works have also studied the role of technology links in relation to acquisitions, applying different focuses. Bena and Li (2014) find that technology overlap positively predicts merger pairing and enhances the patenting outcome of the combined firm. Sears and Hoetker (2014) meanwhile report that technology overlap between merging firms significantly influences merger performance. We, however, focus on the role of acquisitions and technology links in transmitting information of common interest among technology peers. Using the text-based measure of Arts et al. (2018), Testoni (2022) also finds that the stock price of technology peers reacts positively to acquisitions. Building on the strategy literature (e.g., Barney, 1988; Rumelt, 1991; Wernerfelt, 1984), he posits that technology resources underpin firm-value spillover. Our study is distinct from his in that we conduct a comprehensive analysis to establish peers' value revision as a robust economic phenomenon, highlight the informational role of corporate-control transactions and technology links, and importantly, investigate the validity of various information-transmission mechanisms suggested in the previous literature.

The rest of our paper proceeds as follows: Section 2 describes the data and methodology; and Section 3 presents our baseline results on the technology peers' abnormal returns. In Sections 4, 5, and 6, we investigate the mechanisms of information transmission. Finally, in Section 7, we conclude.

2. Data and Methodology

In this section, we introduce our sample and data, and define the measures of firms' technology closeness and abnormal returns. We describe all variables used in our analysis in Table 1 and provide more details where necessary in the Online Appendix.

2.1. The Technology Proximity Score and Technology Peer Candidates

A key objective of our empirical analysis is to examine whether and how acquisition announcements disseminate information about technology value that is of common interest among technology peers. Since the spectrum of innovation activities can be represented by a comprehensive set of innovation categories available to all firms, in principle, we can measure a firm's innovation activities using a vector whose element is the fractional resources (e.g., knowledge, inventors, equipment, and funds) the firm dedicates to each category. Importantly, this vector can be compared across two firms to measure the technology components that are of common interest, allowing us to measure technology closeness between two firms and to identify technology peers. Firms' technologies have more in common when their vectors overlap to a greater extent. Unfortunately, the fraction of resources dedicated to each innovation category is not directly observable. Therefore, following the previous literature (e.g., Bena and Li, 2014; Ma, 2020), we use the output-based measure of innovation activities in the spirit of Jaffe (1986), namely the *Technology Proximity Score* (see Section III of the Online Appendix for a technical note). This measure is based on the patents granted to firms and reflects the common components in patented innovation output between two firms. While being widely used, this measure admittedly has some limitations. First, it does not reflect all the resources invested in a firm's innovation activities, for example the input of prior knowledge. Second, it assumes the technology components of common interest exist only within the same category rather than across categories (Bloom et al., 2013). Third, a few technology classes contain a disproportionate fraction of patents and could undermine this measure's representativeness. To address such weaknesses, in Section 3.4, we adopt two alternative measures of technology proximity, namely the *Knowledge-Base Overlap Ratio* (see Bena and Li, 2014; Ma, 2020) and the *Mahalanobis Distance* (see Bloom et al., 2013), and confirm our findings to be robust. We define these alternative measures in Table 1 of the main body and provide more details of their construction in Section IV of the Online Appendix.

It is also pertinent to ask whether technology closeness reflects innovations that are substitutes or complements. While previous literature does not provide a clear indication (to the best of our knowledge), we posit that technology closeness among firms represents both complementary and substitutionary opportunities. We clarify this conceptual issue in Section V of the Online Appendix.

Regarding innovation categories, we specifically consider the patents granted to US-listed firms by the United States Patent and Trademark Office (USPTO), and compiled by Kogan et al. (2017), who also provide United States Patent Classification (USPC) classes, patents' issue dates, and estimates of patents' market values.[1] For each pair of US-listed firms in a calendar month, we use the patent data mentioned above to calculate their *Technology Proximity Score* (Jaffe, 1986). This calculation requires information on patents granted over the 60 months preceding the calendar month in question. We use the *Technology Proximity Score* to select a firm's technology peers (defined below in detail) from all the listed firms with required data available (which we call peer candidates).

We provide the descriptive statistics of the sample of all firm pairs with valid *Technology Proximity Scores* in Table OAT2 of the Online Appendix. Panel A shows that the monthly number of firms ranges from 1,652 to 2,927 and it peaks in year 2001 after which it declines. Panel B contains the average *Technology Proximity Score* of all the firm pairs for each calendar month, which is stable before 1998 and trends upward thereafter. In Table OAT3 and Table OAT4 of the Online Appendix, the summary statistics of the *Mahalanobis Distance* and the *Knowledge-Base Overlap*

[1]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, at the time when we downloaded the data.

Ratio, respectively, exhibit broadly similar patterns.

2.2. Technology Peers and Technology Space

A firm's technology space consists of all of its technology peers. Only those peer candidates with sufficiently high values of the *Technology Proximity Score* are selected as a firm's technology peers. While it is inevitably subjective to choose the threshold to define technology peers, we follow a procedure analogous to that adopted by Hoberg and Phillips (2010) which identifies technology spaces that are similar in coarseness to three-digit SIC (SIC-3) industries. Since around 2% of all possible pairs of Compustat firms belong to the same SIC-3 industry, we define two firms as technology peers if their *Technology Proximity Score* is higher than the 98^{th} percentile across all the firm pairs in a month. This definition implies that the number of technology peers in a month is comparable to the number of SIC-3 industry peers, and it allows us to compare the technology peers to industry peers in some of our subsequent analyses. The 98^{th} percentile also ensures that 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.

Panel C of Table OAT2 in the Online Appendix reports the value of the 98^{th} percentile of the pairwise *Technology Proximity Score* by month. This threshold follows an increasing trend throughout our sample period.

2.3. Product Proximity Score and Segment Product Market

Previous literature has identified the product market as an important channel of information dissemination. In our baseline and additional analyses, we control for this important information channel. To do this, we follow Bloom et al. (2013) to build a segment-based *Product Proximity Score* that allows us to ascertain how close a firm is to an acquisition target in the product market. The formula for this score is analogous to that for our *Technology Proximity Score* with the important difference being that, instead of using patent data, we now use the information on the distribution of a firm's sales across SIC-3 segments retrieved from Compustat. A firm is deemed to be in a target firm's product market if, in the previous year, the firm's *Product Proximity Score* relative to the target is above the 98$^{\text{th}}$ percentile of the distribution of this score across all possible firm pairs. The binary variable *Product Market Dummy* identifies peers from the same segment-based product market.

2.4. Acquisition Targets and Their Technology Peers

Our sample of acquisitions is from the Thomson SDC mergers and acquisitions (M&A) database and comprises the deals between listed bidders and targets announced during the 1984–2010 period. We only keep those transactions defined by SDC as "mergers" or "acquisitions of majority interests" to ensure all deals involve a change of control rights. The targets and acquirers are required not to be from the financial (SIC Code 6000–6999) or utilities (SIC Code 4900–4999) sectors, similar to Phillips and Zhdanov (2013). The transaction values must be above 10 million as reported in Thomson SDC M&A database. We drop those deals without the information required to be available from other data sources. For each acquisition target, we calculate a *Technology Proximity Score* with each peer candidate. After calculating this score, we also exclude the peer candidates from the financial and utilities sectors.

Panel A of Table OAT5 of the Online Appendix reports the number of acquisition targets and their technology peers by year of deal announcement. 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 (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 around the internet bubble period (1998–2003) and there is no obvious trend.

In Panel B of Table OAT5 of the Online Appendix, we observe that 58% of the acquisition targets are concentrated in the following five Fama-French 48 (FF-48) industries: "business services" (184), "electronic equipment" (171), "medical equipment" (138), "computers" (121), and "pharmaceutical products" (111). In the sample of technology peers, the share of these five industries altogether is slightly above 60%. These findings are not surprising considering these are innovative industries.

In Table OAT6 of the Online Appendix, we show that the overlap between technology space and product market is limited, by reporting the number of technology peers inside and outside the targets' product markets. Over the whole sample period, the fraction of technology peers from outside the targets' product markets is between 60% and 78%, depending on the industry classification used (namely, the segment product market, the SIC-3 industry, the FF-48 industry, and the text-based industry classification industries that are calibrated to match SIC-3 industries on granularity (TNIC-3 here after)(Hoberg and Phillips, 2010, 2016)). In the same table, we also show that the overlap is limited between technology space and other economic relations (namely, customers or suppliers of the target firms and firms with headquarters in their target firms' headquarter states). Such limited overlaps suggest our baseline finding along the technology links is likely to be novel and distinct from other economic relations. We formally test this conjecture in subsequent sections.

Table OAT7 of the Online Appendix contains the descriptive statistics of 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 have higher revenue growth than their targets and the targets' peers. They also have lower ownership concentration, with a smaller fraction of closely-held shares. In our sample of acquisitions, 46% are horizontal and 81% are completed.

2.5. Calculation of Abnormal Returns

We measure technology value revision using the technology peers' abnormal returns during the deal announcement period. To calculate the abnormal returns, we use the market model estimated between 300 and 61 trading days before the acquisition announcement with at least 100 valid daily-return observations, where the market index is the value-weighted index of all CRSP firms. Since every target has one or more technology peers and the peers' stock returns are measured over the same period, cross-correlation among peers' returns could bias the return standard error downward

(Fama, 1998). Therefore, when examining the significance of peers' value revision, we use the abnormal returns measured on an equal-weighted portfolio of all the peers of an acquisition target. This method is consistent with a trading strategy by a rational investor who wants to systematically exploit the announcement of an acquisition by investing in an equal-weighted portfolio of target technology peers.

3. Abnormal Returns on Target Technology Peers

3.1. Abnormal Returns on the Peer Portfolios

In Panel A of Table 2, we report the cumulative average abnormal returns (CAARs) for the peer portfolios, averaged across all targets, over various event windows around the deal announcement day. The CAARs are positive and statistically significant at the 5% level or above for all the windows. Specifically, 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. A CAAR of 0.26% measured over the window of (−2,+2) translates into a value increase of $612 million in an average target's technology space in 2010 dollars (the median increase is $211 million). The magnitude is comparable to the industry rivals' CAAR that Song and Walkling (2000) report, i.e., 0.35% for the window of (−1, 0) and 0.56% for the window of (−5, +5). In Panel B of Table 2, we consider several alternative estimators for the abnormal returns over the (−2,+2) event window, namely the market-model-adjusted return, the market-model estimator using regressions with GARCH (1,1) errors, the Scholes-Williams abnormal return (Scholes and Williams, 1977), and the Fama-French three-factor model adjusted return (Fama and French, 1993). Across these alternative estimators, the peer portfolios earn significant positive abnormal returns ranging from 0.19% to 0.47%. In Table OAT8 of the Online Appendix, we obtain qualitatively similar findings by calculating the CAARs on individual technology peers. In Panel C of Table 2, we define technology peers using the *Mahalanobis Distance* and the *Knowledge-Base Overlap Ratio*, and we find the CAAR on peer portfolios is statistically significant at the 1% level and equal to 0.29% and 0.20%, respectively, consistent with the CAAR for peers defined based on the *Technology Proximity Score*. In Panel D, we report the CAAR on target firms over various windows. Consistent with the previous literature (e.g., Fee and Thomas, 2004), the target CAAR is statistically significant at the 1% level and ranges from 19.99% to 27.82%. The substantial positive target CAAR is consistent with a significant value of the technology synergies expected by the combining firms.

We have defined technology peers such that they all have a *Technology Proximity Score* with their corresponding acquisition targets greater than 98% of all peer candidates. In Table OAT9 of the Online Appendix, we establish the value relevance of the *Technology Proximity Score*, by examining how this score relates to the CAAR (estimated for the (−2, +2) event window) on portfolios of peer candidates. Specifically, in each calendar month, we form the deciles of all candidate firms based on the non-zero values of the *Technology Proximity Score*. A peer candidate may fall into several deciles due to its varying degree of overlap with various target firms. Again, we form an equal-weighted portfolio of all candidate firms for each target. We find that the CAAR on peer-candidate portfolios increases monotonically from the first decile (lowest proximity) to the tenth decile (highest proximity), except for the fourth decile.

3.2. Alternative Information-Transmission Channels

Our baseline result above shows that acquisition announcements disseminate information on technology value that is of common interest among technology peers. However, information spillover due to alternative economic relations may also exist between firms that are close in technology. As mentioned above, previous studies have provided evidence showing that information is diffused among product-market rivals, supply-chain partners, and geographical neighbors. Therefore, a concern with our baseline result is that the technology links simply capture other underlying economic relations.

In this section, we perform several robustness tests to examine whether peers' value revision is due to alternative economic links. In Table 3, we report the CAARs for the (−2, +2) event window on the following four portfolios of peer candidates, sorted according to their relation with the respective target firms in terms of technology space and product market: 1) peer candidates that are neither in the target firms' technology spaces nor in the target firms' product markets; 2) peer candidates that are in the target firms' technology spaces but not in the target firms' product markets; 3) peer candidates that are not in the target firms' technology spaces but in the target firms' product markets; and 4) peer candidates that are in both the target firms' technology spaces and product markets. We consider four definitions of product market based on 1) segment product market (Bloom et al., 2013), 2) SIC-3 industry, 3) FF-48 industry, and 4) the TNIC-3 industry (Hoberg and Phillips, 2010, 2016). Regardless of how we define the product market, the CAARs on peer-candidate portfolios are significantly positive at the 5% level or above, except for the first type of portfolios, i.e., those that contain the peer candidates that reside neither in their corresponding targets' technology spaces nor in the targets' product markets. Importantly, technology peers benefit from a significant (at the 1% level) increase in their stock market valuations even when they operate in product markets different from those of their corresponding targets (ranging from 0.18% to 0.32% across various product-market definitions). The magnitude of the increase is comparable to the CAAR on the non-peer candidates in the same product market (ranging from 0.17% to 0.25%). It is not surprising that those peer candidates that reside in both the targets' technology spaces and product markets experience even greater abnormal returns (between 0.33% and 0.46%).

Similarly, in Table 3, we observe that the CAARs on the portfolios of technology peers are positive and statistically significant at the 1% level even when peers are not in their target firms' supply chains or not from the target firms' states (we provide more details about their construction in Section XII of the Online Appendix). Furthermore, the abnormal returns on the portfolios of firms that are not technology peers are statistically insignificant.

In Section XIII of the Online Appendix, we further strengthen our baseline finding using placebo tests based on the empirical distributions of CAAR (-2, $+2$) on randomly selected portfolios of peer candidates. These placebo tests indicate that our baseline result is robust.

Overall, we show that technology links and product-market links play roles of similar importance in the process of information transmission. Importantly, the informational role of technology links is statistically and economically significant even in the absence of product-market relations, supply-chain partnerships, and geographical proximity.

3.3. Multivariate Analysis

In Panel A of Table 4, we estimate several multivariate models to study the significance of technology closeness in the information transmission to peer firms, controlling for the influence of product-market overlap and other factors. 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 acquisition targets, including the peers. The dependent variable is peer candidates' CAR measured over the event window (-2, $+2$). Detailed definitions and the construction of all the explanatory variables are in Table 1 and the Online Appendix. Given that we have multiple peer candidates for each deal, the standard errors are adjusted for clustering within deals. The findings are qualitatively the same if we cluster the standard errors by year or by patent class (see Table OAT11 and Table OAT12 in the Online Appendix).

In the first column of Panel A, we find a positive and statistically significant relation between a peer candidate's CAR and its technology closeness to its corresponding acquisition target as measured by the *Technology Proximity Score*. The coefficient is 0.486 and statistically significant at the 1% level. In column (2), we obtain a similar result for a dummy variable that indicates technology peers. The coefficient on the peer dummy is 0.281, indicating that a peer on average has a CAR that is 0.281 percentage points greater than non-peer candidates. We obtain qualitatively similar findings when we control for product-market overlap in columns (3) and (4) through the inclusion of the *Product Proximity Score* whose coefficient is positive and statistically significant at the 10% level or above. Our result persists when we use alternative measures of product-market overlap (see Section XV and Table OAT13 of the Online Appendix), namely the SIC-3 industry, TNIC-3 industry, and the segment-based *Product Market Dummy*. In columns (5) and (6), we conduct a horse race of all possible information channels that could underpin the information transmission of an acquisition announcement to target firms' technology peers. Specifically, we include the *Same State Dummy*, *Supplier Dummy*, and *Customer Dummy* to evaluate the effects of geographical location (e.g., Chu et al., 2019) and supply-chain relations (e.g., Fee and Thomas, 2004). We find that, while the coefficients on *Technology Proximity Score* and *Technology-Peer Dummy* remain statistically significant at the 1% level, the coefficients on *Same State Dummy*, *Supplier Dummy*, and *Customer Dummy* are economically weak and statistically insignificant. An F-test shows that the coefficients on these three dummies are jointly insignificant. Adding these three variables does not contribute much to the goodness of fit of the model either. Overall, the result in Panel A confirms technology closeness and product-market overlap as two prominent channels of information transmission for target firms' technology peers. Since the geographical location and supply-chain relations have a negligible effect on peers' market response, we use the more parsimonious models specified in columns (3) and (4) as our preferred specifications for our subsequent analyses, following the recommendation of Wooldridge (2010, p. 148).

A confounding issue remains that a target's technology peers may also be technologically close to the acquirer, given that acquirers tend to pursue firms from the same technology space (Bena and Li, 2014). The information transmission process may originate from the acquirer rather than the target. We rule out this possibility by excluding the acquirers' technology peers from our sample. Our findings are robust to this alteration (see Section XVI and Table OAT14 of the Online Appendix). Another issue may arise due to the disproportional clustering of patents in several classes, as is discussed in Section 2.1. However, our result persists when we adjust the standard errors for clustering within patent classes (see Section XIV and Table OAT12 of the Online Appendix). In Section 3.4, we also adopt an alternative measure of technology closeness (i.e., the *Knowledge-Base Overlap Ratio*) to address the possible issues with our variable of interest due to disproportional patenting in some classes.

3.4. Robustness of Peer Value Revision to Alternative Measures of Technology Closeness

Measuring technology closeness is central to our analysis. As was mentioned earlier, while Jaffe's (1986) measure is arguably the most widely used, it has some limitations, and other meaningful measures have since been developed in the literature. In this subsection, we examine to what extent our findings are robust to two alternative measures of technology closeness.

The first measure is the *Mahalanobis Distance* proposed by Bloom et al. (2013). This measure considers not only the overlap among patents filed in the same patent class (as the *Technology Proximity Score*, i.e., Jaffe's (1986) measure, does) but also the interaction across patent classes, based on the extent to which different classes are co-located in the same firms (Bloom et al., 2013, pp.1358–1359). As we show earlier in Panel C of Table 2, the technology peers defined based on the *Mahalanobis Distance* have a significant CAAR of 0.29%, slightly higher than the CAAR when we define technology peers based on the *Technology Proximity Score* (0.26%). In the multivariate results reported in column (1) in Panel B of Table 4, we find the coefficient on the *Mahalanobis Peer Dummy* is 0.308 and statistically significant at the 1% level, confirming our baseline finding.

The second measure is the *Knowledge-Base Overlap Ratio* used in Bena and Li (2014) and Ma (2020). Instead of focusing on innovation outputs, this alternative measure emphasizes the previous knowledge based on which firms conduct their innovation. A firm's knowledge base is measured using the pool of prior patents cited by the firm's existing patents and, accordingly, the *Knowledge-Base Overlap Ratio* measures the common component of all the citations made by a pair of firms. Therefore, this measure focuses on the knowledge input to firms' innovation activities. Since this measure does not rely on innovation output, it is less subject to the issue of disproportional patenting in some classes mentioned in Section 2.1. As we showed earlier in Panel C of Table 2, when we define technology peers using the *Knowledge-Base Overlap Ratio* (i.e., *Knowledge-Base Peer Dummy*), the CAAR on peers is 0.20% and significant at the 1% level. In column (2) in Panel B of Table 4, we find the coefficient on the *Knowledge-Base Peer Dummy* is 0.153 and statistically significant at the 5% level.

In columns (3) and (4), we control for the *Product Proximity Score*, and report slightly smaller but positive and statistically significant (at the 10% level or higher) coefficients on the *Mahalanobis Peer Dummy* and the *Knowledge-Base Peer Dummy*, respectively.

Overall, the technology peers' positive abnormal returns are robust to alternative measures of technology closeness.

3.5. Further Validation of the Information Spillover via Technology Links

To further validate the presence of information spillover via technology links, we perform several conditioning tests based on the significance of information signaled by an acquisition announcement and the relevance of technology. The intuition is that our baseline result should be stronger if the signal is more consequential or the technology is more relevant.

First, we expect peers to experience stronger price revisions when the premium offered to a target is higher. A higher premium sends a stronger signal and indicates a greater technology value revision of technology. Second, information transmission along technology links should be more relevant for peer candidates that are more technology dependent. To measure a firm's technology dependence, we construct two variables, namely, the *High Patent-Value Dummy* and the *High R&D Dummy*. Third, Bena and Li (2014) report that firms with close technology spaces are more likely to put their resources under common control to exploit technology synergies. Thus, we expect peer abnormal returns to be more positive for deals involving firms having common technologies because the merger of two firms that are closer in technology arguably sends a stronger signal about the value of technology synergies common among peers.

In Panel C of Table 4, we introduce several interaction terms to test the predictions above. As expected, 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 in column (1). In column (2), the coefficient on the *Technology Proximity Score* is significantly more positive when the *High Patent-Value Dummy* equals one. We observe similar findings when we replace *High Patent-Value Dummy* with *High R&D Dummy* in column (3). Finally, the result of column (4) shows that peers' positive value revision is concentrated among deals where the acquirer is in the target's technology space. In columns (1) and (4), the *High Acquisition-Premium Dummy* and the *Acquirer-Target Same Technology-Space Dummy*, which are defined at the deal level, are absorbed by the deal fixed effects.

3.6. The Boundaries of the Main Finding

In this subsection, we explore the boundaries of our main finding. The objective is to understand whether our main finding is a robust economic phenomenon or just a byproduct of merger waves, technology waves, or certain industry structure or technology features. For this purpose, in Table OAT15 of the Online Appendix, we examine the heterogeneity of our main finding over various sample periods and across various industrial structures and technological features.

We begin by examining whether our main finding is confined to the earlier sample period (no later than 1997) or the later one (after 1997). Column (1) of Table OAT15 shows that our main finding is present in both sample periods. The coefficient on the interaction term between *Later Sample-Period Dummy* and *Technology Proximity Score* is statistically insignificant while the positive coefficient on the *Technology Proximity Score* is significant at the 1% level. In column (2), we proceed to examine whether the dot-com bubble period (1998–2001) makes any difference, considering the boom of dot-com investment may have driven both the peers' abnormal returns and their technology closeness with respect to target firms. The result shows that the dot-com bubble period does not make a significant difference to our main finding. In columns (3) and (4), we examine whether our result is specific to the periods of aggregate merger waves. If our finding only appears during merger waves, there is a concern that broad merger waves may underpin both acquisition announcements and peers' abnormal returns, which leads to our result. Therefore, we follow Harford (2005) and consider an *Industry Merger-Wave Dummy* that captures the years of merger waves. We also form another variable (*High Capital Liquidity Dummy*) to indicate the years when overall capital liquidity is abundant because Harford (2005) finds that high capital liquidity is a necessary condition for merger waves to occur. The results in columns (3) and (4) show that the effect of *Technology Proximity Score* on peers' abnormal returns is not significantly different during merger waves (column (4)) or when capital liquidity is high (column (3)). In columns (5) and (6), we interact the *Technology Proximity Score* with two innovation-wave dummies (one built at the industry level and the other at the patent-class level), based on breakthrough patents (Kelly et al., 2021). The coefficients on these interactions with *Industry Innovation-Wave Dummy* and *Patent-Class Innovation-Wave Dummy* are statistically insignificant, while on *Technology Proximity Score* the coefficients remain positive and significant. In columns (7) to (10), we further examine whether our main finding is related to the technology or product structure of targets' and peer candidates' industry. Specifically, we construct a *Low Technology-Concentration Dummy* for both target and peer candidate according to the patent-based Herfindahl-Hirschman Index (HHI) of SIC-3 industries and similar dummies according to the sales-based HHI of SIC-3 industries (namely, the *Low Product-Concentration Dummy* for both target and peer candidate). The former and the latter pair of dummy variables measure the level of technological and product-market competition in an industry, respectively. The results presented in columns (7) to (10) show that our main finding is present regardless of the targets' and peer candidates' industry structure. In columns (11) to (14), we specifically examine how our main finding varies for pharmaceutical and IT industries because of their unique innovation feature (Guler and Nerkar, 2012; Lyytinen and Rose, 2003). The results of these tests do not show that our main finding differs significantly in those two industries. Overall, the results presented in Table OAT15 demonstrate that our main finding is a robust economic phenomenon across various time periods, industrial structures, and innovation features.

3.7. Summary of Findings

In summary, the technology peers of acquisition targets earn significantly positive abnormal returns during the acquisition announcement. These are robust to alternative CAR estimators, alternative definitions of technology closeness, and various tests that control for a comprehensive set of confounding inter-firm economic relations and firm and deal characteristics. Additional analyses confirm that our main finding is a robust economic phenomenon rather than a byproduct of merger or technology waves, a certain industry structure, or technology features. The cross-sectional tests based on targets' acquisition premiums, peers' value-dependence on technology, and target and acquirer technology overlap offer evidence corroborating the importance of technology links for the peers' value revision.

As we have introduced in Section 1, theory suggests several possible mechanisms underpinning the peers' value revision. Which mechanism(s) is (are) more consistent with the data than others? We will analyze the validity of these alternative hypotheses in the following sections.

4. The *Acquisition-Probability Hypothesis*

Previous studies show that technology synergies constitute a primary merger motive (Acemoglu et al., 2010; Ahuja and Katila, 2001; Bena and Li, 2014; Cassiman and Veugelers, 2006; Frésard et al., 2020; Phillips and Zhdanov, 2013; Sevilir and Tian, 2012; Zhao, 2009). Building on the previous literature, the *Acquisition-Probability Hypothesis* posits that an acquisition announcement disseminates novel information about the common component of technology synergies, which raises both the expected value of synergies and merger prospects for technology peers. For information dissemination to occur, two conditions are necessary. First, firms with close technology spaces should have fundamentals in common that affect firm value. It is safe to assume that a firm's technology resource bears substantially on its current and future cash flows. Moreover, firms with similar technology have common fundamentals through their shared categories of innovation output and knowledge base, and shared networks of citations, licensing agreements, talents, and collaborations (e.g., Baghai et al., 2019; Fulghieri and Sevilir, 2011; Hall et al., 2001; Katz and Shapiro, 1986), and these firms interact through the effects of technology spillover (Bloom et al., 2013). Therefore, it is also safe to argue that technology peers have common components in their valuations, and signals about the value of one firm should convey useful information about its peers. Second, the acquisition process should generate novel information that the stock market has not possessed previously. Having much at stake, the acquirers are keen to understand what they are about to acquire. Distinct from investors at arm's length, acquirers are often in a suitable position to gather private information about a target firm's value both as a stand-alone firm and in a combined business. Especially in friendly deals, which constitute most acquisition transactions, acquirers have the privilege of accessing the target firms' value-sensitive information.[2] Moreover, in cases where the acquirer and target are closer in their technology space (Bena and Li, 2014), acquiring firms have even better expertise to assess technologies. In contrast, investors in the stock market are often poorly informed about technology value. Firms are often reluctant to disclose sensitive information about their technologies (e.g., Bhattacharya and Ritter, 1983; Maksimovic and Pichler, 2001) and stock market is often slow in processing technological information (e.g., Chan et al., 2001; Cohen et al., 2013; Eberhart et al., 2004; Hirshleifer et al., 2013; Lee et al., 2019; Lev and Sougiannis, 1996). Previous research has also found that individuals put less emphasis on complicated information (Song and Schwarz, 2010). Therefore, a clear gap exists between the informed acquirers and the less informed investors regarding technology value and possible synergies. Overall, we expect acquisitions to play an essential role in transmitting novel information to the stock market about technology valuation.

To elaborate on the mechanism, we conceptualize the *Acquisition-Probability Hypothesis* as follows. An acquisition announcement sends a positive signal that the common component of technology synergies is greater than previously expected, which in turn increases the value of a target firm's peer that is a prospective acquisition target. The increment to the value of the peer, denoted as VI, can be expressed as a function of the change in its acquisition probability and the change in the share of the expected synergies obtained by the peer firm's shareholders upon an acquisition. Assume the ex-ante expected synergies to be zero for simplicity, without loss of generality. The ex-ante expected acquisition probability would be zero too because of the lack of synergy. We then have $VI = \pi \times G$ where π is the expected acquisition probability and G is the peer firm's share of expected synergies, conditional on a bid being announced. Let S denote the total synergy value from the prospective acquisition of a peer firm and $p(S)$ denote the

[2]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).

density function of the distribution of S. Importantly, S contains components that are common across technology peers. In other words, S contains a component that is achievable both in a currently announced acquisition and in subsequent acquisitions of the target firm's technology peers. If the prospective acquisition does indeed happen, the merging firms would split the synergies according to a sharing rule $\lambda \in (0,1)$, where the target gets $(1-\lambda)S$ and the acquirer λS. The outside investors do not know S but know $p(S)$ conditional on their information set. Then we have $\pi = \int_{\frac{C}{\lambda}}^{+\infty} p(S|bid)dS$ because a bidder would not bid when $\lambda S < C$, where C is the bidding cost. The peer's share of expected synergy is $G = \int_{\frac{C}{\lambda}}^{+\infty} (1-\lambda)S \times p(S|bid)dS$. The emergence of an acquisition announcement in a firm's technology space sends a positive signal s about S, which adds to the outside investors' information set and shifts $p(S)$ to the right for the technology peers. In other words, $p(S)$ becomes $p(S|bid)$ after being shifted to the right. Consequently, VI is positive as both π and G increase from zero to positive after the right shift. It becomes clear that a peer's value revision is the outcome of the updates to both the value of expected synergies and the acquisition prospects. Since S is a determinant of both the expected acquisition probability (π) and the peer firm's share of the expected synergy (G), an empirical distinction between these two parts can be difficult to draw.

The above framework predicts positive abnormal returns for the target firms' technology peers, which we find from our baseline empirical analysis. Apart from this prediction, this framework also implies several additional predictions. First, since a higher premium sends a stronger signal and shifts the distribution of S by more, the value revision for technology peers should increase with the premium. Second, since S is driven by technology, the value revision should be stronger for those peers that are more dependent on technology (as reflected in more investments in R&D or greater contribution of technology to total firm value). Third, Bena and Li (2014) posit that technology synergy is greater between two firms with greater technology closeness. Therefore, the acquisition signal should be more relevant for technology valuation when an acquisition happens between firms with closer technologies, which leads to greater value revision among peers, ceteris paribus.

Our empirical findings in Panel C of Table 4 are consistent with the predictions above. That said, these predictions could also be consistent with the *Enhanced-Investment Hypothesis* which we explain in Section 5. To further examine the validity of the *Acquisition-Probability Hypothesis*, we perform additional analyses below.

4.1. Additional Evidence for the Acquisition-Probability Hypothesis

We test three predictions that closely relate to acquisition probability. First, as is explained in Section 4, the acquisition announcement shifts the distribution of synergies to the right for targets' technology peers, which increases the peers' subsequent acquisition probability. Second, peers that are easier to acquire (i.e., more vulnerable to acquisitions) are more likely to become future acquisition targets, ceteris paribus. Thus, we expect these peers to earn higher abnormal returns during the acquisition announcement. Third, since the truthful information revelation about synergies cannot be reversed, peers' abnormal returns should not be reversed even if the current acquisition is withdrawn, as long as the withdrawal is not due to reasons related to the deterioration of expected synergies.

4.1.1. The Likelihood of a Technology Peer's Future Acquisition

As explained above, if the *Acquisition-Probability Hypothesis* plays an important role in the information-transmission process, we expect firms having acquired technology peers in the preceding year to be more likely to be acquired in the current year. In Table 5, we report the estimates from alternative linear-probability specifications for a firm's acquisition probability.[3] We consider a sample that includes all the firm-years (excluding firms from the financial and utilities sectors, and firms without any patents) in the Compustat-CRSP merged database and acquisitions from SDC over the 1984–2010 period. The key test variable is the *Previous-Acquisition Dummy* which is one if a firm is the technology peer of one or more of the target firms receiving an acquisition bid in

[3] We use the linear-probability specifications because non-linear models, such as the Probit model, yield biased estimates when the number of fixed effects is large and the group size is small (e.g., Hsiao, 1996; Kalbfleisch and Sprott, 1970).

the preceding year and zero otherwise. All the control variables are measured in the preceding year and are selected following Cremers et al. (2009) and Cain et al. (2017).

The six alternative models in Table 5 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 received an acquisition bid in the preceding year. Consistent with the *Acquisition-Probability Hypothesis*, the coefficient on the *Previous-Acquisition Dummy* is always positive and 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 0.70 to 1 percentage points. Given that the unconditional sample average probability of a firm being acquired is around 5%, the increase is economically significant. In Table OAT16 of the Online Appendix, we use the test variable *Previous-Acquisition Proximity Score* instead. *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. As expected, the coefficient on this variable is always positive and statistically significant at the 5% level or above, consistent with our finding in Table 5.

4.1.2. Acquisition Vulnerability and Abnormal Returns on Technology Peers

In line with the *Acquisition-Probability Hypothesis*, in Table 6, we observe a positive relation between a peer's acquisition vulnerability (i.e., the firm's ex-ante acquisition probability) and its abnormal returns at the acquisition announcement. In Table OAT17 of the Online Appendix, we follow Cremers et al. (2009) and Cain et al. (2017) to specify three alternative models estimating a firm's acquisition vulnerability, and to test whether acquisition vulnerability is associated with the peers' abnormal returns. We calculate a firm's *Acquisition Vulnerability* using the coefficients estimated from the logistic models in Table OAT17 of the Online Appendix. Consistent with the *Acquisition-Probability Theory*, in Table 6, we find that the coefficient on *Acquisition Vulnerability* is universally positive and statistically significant. This result indicates that peers more exposed to acquisition opportunities experience greater value revision.

4.1.3. *Abnormal Returns on Targets and Peers of Withdrawn Deals*

As mentioned in the Introduction (Section 1), peers' abnormal returns are nearly as large in withdrawn deals as those in completed deals. This result can be interpreted in the framework of the *Acquisition-Probability Hypothesis.* Specifically, because it involves a costly search and investigation to identify technology synergies (e.g., Rhodes-Kropf and Robinson, 2008), potential acquirers often rely on price signals to infer possible sources of synergy. According to the *Acquisition-Probability Hypothesis*, acquisition announcements generate and transmit novel information about the common component of technology synergies available among peers, and such announcements put the targets and their peers under the spotlight as valuable sources of synergy. Once highlighted, these companies will attract potential bidders, which is true even if the current deal is not completed because the cancellation of a transaction cannot nullify the novel and true information revealed. Therefore, peers' abnormal returns at deal announcement should be insensitive to the deal withdrawal. Similarly, a target's abnormal returns at announcement should not dissipate over time if it is subsequently acquired.[4]

In Panel A of Table OAT18 of the Online Appendix, we find the CAAR on technology peers is 0.28% (significant at the 10% level) for withdrawn deals, even slightly higher than the peer CAAR of 0.25% for completed deals. In Panel B, we show that it takes only 12 months for the target firms of withdrawn deals to lose their positive value revision at the deal announcement, if they are not subsequently acquired within five years. For instance, the target CAAR 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 acquired. In contrast, for targets that are not subsequently acquired, the CAAR is only 4.27% and statistically insignificant, reversing their abnormal returns at announcement. It appears that only when their subsequent acquisition prospects do not vanish, do targets experience significant and lasting value revisions after deal withdrawal. In

[4]While it is tempting to claim the same for peers, the magnitude of peers' short-term CARs is small. Thus, the long-term CAR is insignificant given that it is small relative to the standard error. There is a statistical power issue here.

Panel C, we further clean up the sample of withdrawn deals where the target is not subsequently acquired, by removing those deals withdrawn because the deal price is deemed excessive by the acquirer or because the fundamentals of the target firm and/or business environment deteriorate.[5] The remaining withdrawals would be most likely due to non-price reasons, such as regulatory injunction and antitrust investigations, which also affect the prospects of future acquisitions. We perform this additional robustness check because we are concerned that the post-transaction difference in target CAAR between the completed and withdrawn deals is caused by the acquirer's negative perception rather than subsequent acquisition prospects. However, for this clean sample, we find the target gains are still reversed within 24 months—the CAAR is 6.35% over the (−1, +24) window but statistically insignificant (t-statistic = 0.763). In Table OAT19 and Section XX of the Online Appendix, we alternatively use the targets' average buy-and-hold abnormal returns (ABHAR) and find similar results.

Overall, the findings we provide in this and the previous sections are in line with the predictions of the *Acquisition-Probability Hypothesis*.

4.2. Who Later Acquires the Peers?

The *Acquisition-Probability Hypothesis* posits that peers' value revision is driven by their elevated expectation of technology synergies and merger prospects. It would be natural to ask who subsequently acquires the peers. To answer this question, we need to ask: which companies are likely to benefit from the technology synergies common for peers? In Section XXII of the Online Appendix, we report the results of our empirical analysis. Our findings are in line with the view that various economically-related firms are more likely to be future acquirers, as is suggested by the previous literature. Specifically, we observe that future acquirers are more likely to be close to peers in terms of technology (Bena and Li, 2014), products (Eckbo, 1983; Hoberg and Phillips, 2010),

[5] More specifically, the reasons behind these withdrawals include poor target performance (nine deals), 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 deals). To obtain the reasons for withdrawal, we manually gather information from four sources, including Dow Jones Newswires, Reuters Newswires, the Wall Street Journal, and the Financial Times.

geographical locations (Jaffe et al., 1993), or be the suppliers of the peers (Fan and Goyal, 2006). However, customers are unlikely to be future acquirers. Moreover, we find that the likelihood of being an acquirer is lower for firms that are also product-market rivals of the peers, consistent with the finding of Bena and Li (2014). We do not find any evidence showing that local firms, customers, or suppliers that are close in technology are more likely to acquire the peers, contrary to the prediction based on the previous literature (e.g., Jaffe et al., 1993; Frésard et al., 2020). We provide more details about the hypothesis development, empirical method, and empirical results in Section XXII of the Online Appendix.

4.3. Peer Abnormal Returns and the Declining Acquisition Intensity

As more and more peers are acquired in a technology field, the novelty of an acquisition announcement should decline and bidding costs should rise (e.g., greater searching cost). Accordingly, our baseline result should weaken for the remaining firms in the technology space as the acquisition prospects of peers begin to diminish.

To test this hypothesis, we construct a *Declining Acquisition-Intensity Dummy* to indicate the acquisitions announced in a period when the peers' subsequent acquisition probabilities are likely to update negatively. Specifically, *Declining Acquisition-Intensity Dummy* takes the value of one if the count of the target firm's peers acquired in the 12 months after the deal announcement is smaller than the count in the 12 months before the deal announcement. In Table OAT20 of the Online Appendix, we regress peers' CAR on the *Declining Acquisition-Intensity Dummy* and find this variable has a significantly negative coefficient in all specifications, ranging from -0.446 to -0.368. Since the *Declining Acquisition-Intensity Dummy* is defined at the deal level, we cannot control for deal fixed effects. Instead, we control for several deal characteristics, e.g., *Deal Value* and *Horizontal-Merger Dummy*. Our result is robust to the inclusion of these deal characteristics.

5. The Enhanced-Investment Hypothesis

The primary argument of the *Enhanced-Investment Hypothesis* is that firms increase their innovation activities following the acquisitions of their technology peers, which is value-enhancing. Phillips and Zhdanov (2013) argue that an active acquisition market boosts firms' incentives to innovate, which makes the firms and their technology assets more attractive to potential acquirers. Even in the absence of prospective acquisitions, valuable innovation activities (such as R&D) could enhance the value of firms as independent entities. Phillips and Zhdanov (2013) expect increases in R&D expenditures to be more substantial for small firms because their likelihood of being taken over is higher.

In Table 7, we evaluate whether and how firms alter their R&D investments following acquisitions of their technology peers. Our specifications are largely based on Table 3 in Phillips and Zhdanov (2013), except that we also control for the lagged value of R&D investments since these investments are highly persistent and we are interested in the change in R&D rather than the level itself. In columns (1) and (4) of Table 7, the coefficient on *Previous-Acquisition Dummy* is positive but statistically insignificant. Therefore, the circumstance that at least one of a firm's technology peers is acquired in the previous year, on average, does not lead to a significant revision in the firm's R&D investments. The *Previous-Acquisition Dummy* is then interacted with two different firm-size measures in columns (2), (3), (5), and (6). An obvious split emerges as predicted by Phillips and Zhdanov (2013)—following the acquisitions of peers, small firms' R&D expenditures increase significantly by around 5.9% and 5.4% of firms' revenues (columns (2) and (5), respectively). The same does not happen to larger firms for which there is a significant decline of approximately 4.2% and 4.9% of revenues (columns (2) and (5), respectively). In Table OAT22 of the Online Appendix, we show that the findings are robust if we use the alternative test variable *Previous-Acquisition Proximity Score* that captures the average level of technology proximity between the focal firm and those that are taken over in the prior period. In Table 8, we further analyze whether the peers' abnormal returns at announcement vary according to the level of R&D increase from the year before the acquisition announcement to the year after. We find that the peers' returns are insensitive to the change in their R&D spending, irrespective of peers' size, indicating peers' upward value revisions are unlikely to be related to the changes in their innovation activities.

Overall, there is rather limited support for the *Enhanced-Investment Hypothesis*. This hypothesis cannot explain the value revisions that peers systematically experience. Small peers appear to react to the deal announcement by spending more on R&D, which nontheless does not appear to be value-enhancing. However, other peers seem to follow a different strategy.

6. The Competition-Balance Hypothesis

The technology synergies of business combinations could tip the balance of competition in the product market because technology peers are often, although not always, product-market rivals. A priori, the *Competition-Balance Hypothesis* has mixed predictions for the peers' abnormal returns. On the one hand, peer returns could react negatively to the extent that mergers produce more efficient rivals. Henderson and Cockburn (1996) posit that merging firms enjoy economies of scale and scope in their R&D activities. Previous literature (e.g., Bena and Li, 2014; Sevilir and Tian, 2012) find companies' innovation capacity improves after acquisitions. Bloom et al. (2013) suggest that companies that benefit from mutual technology spillover could also suffer from "business stealing" (i.e., loss of revenue to rivals). On the other hand, rivals could benefit from the market power generated by acquisitions. In their novel study, Cunningham et al. (2021) highlight the presence of "killer acquisitions" among merger transactions. They find that a considerable proportion of acquirers take over innovative targets simply to discontinue the targets' R&D projects and preempt competition. The enhanced market power enables incumbent companies to obtain anti-competitive rents, benefiting product-market rivals while hurting customers. Our baseline finding of positive peer value revision contradicts the argument that acquisitions create more efficient rivals that harm peers, but could be consistent with the possibility of "killer acquisitions." In further analysis reported in Panel A of Table 9, we find customers of acquiring firms, on average, do not suffer value loss from the acquisitions. Some sub-groups of customers (e.g., small customers and regional customers; defined in Section XXIII of the Online Appendix) even earn positive abnormal returns upon the deal announcement. When we separate our sample into acquisitions in the high-competition industries and those in the low-competition industries (measured by the sales-based Herfindahl-Hirschman Index), we find the CAARs on customer portfolios are statistically indistinguishable between these two groups, suggesting the effect of market power is unlikely to be a major force driving our results. While the sign of customer CAAR is negative on average (-0.02%) when industrial competition is low, the statistical significance is low too ($t = -0.465$). In Panel B, the non-negative customer CAAR persists when we restrict our acquisition sample to deals that fall just below the antitrust thresholds (by either 5% or 10%) where "killer acquisitions" are most likely (Cunningham et al., 2021, p.686). We also compare these deals to those that fall within 5% (or 10%) above the antitrust thresholds. These two groups are arguably distinct in their anti-competitive intentions but similar on other aspects (Cunningham et al., 2021). However, we find that peers' abnormal returns are statistically indistinguishable between these two groups, again suggesting market power is unlikely a primary driver of peers' value revision.

7. Conclusion

We find acquisitions disseminate information of common interest about the value of technology among the target firms' technology peers. This finding is a robust economic phenomenon not explained by other economic relations, merger or technology waves, specific product-market structures, or innovation features. Our study shows that corporate-control transactions and technology links, combined, play an important role in the information dissemination process regarding the value of technology. Our analysis of possible mechanisms shows that the elevated expectation of technology synergies and acquisition prospects for technology peers play a primary role in the information transmission. While the value of technology is often elusive, our study shows that technology links and the market for corporate control contribute significantly to the price discovery of technology assets.

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Table 1: **Variable Definitions**

Name	Definition
Acquisition Vulnerability	The ex-ante likelihood that a technology peer is acquired, estimated using a binomial logistic model
Acquirer-Target Same Technology-Space Dummy	A binary variable that equals one if the acquirer and target are in the same technology space (source: Kogan et al. (2017))
Age	The natural logarithm of a firm's age in years based on the Compustat IPO year, if available; otherwise on the beginning date in CRSP, if available; otherwise on the first fiscal year available in Compustat
Age Squared	The square of *Age*
Blockholder Dummy	A binary variable that equals one when there is at least one institutional blockholder with a 5% or higher ownership stake in the firm (source: Thomson/CDA Spectrum)
Cash Ratio	The natural logarithm of cash and short-term investments over total assets (source: Compustat)
Closely Held Shares	The fraction of shares held by long-term shareholders such as insiders, corporations, and blockholders (source: Datastream)
Customer Dummy	A binary variable that equals one if a peer candidate is in the downstream industry of the target firm's industry with a Customer Input Coefficient (CIC) greater than 1%. The CIC is the value of an upstream industry's output sold to the downstream industry divided by the value of the downstream industry's total output (source: Bureau of Economic Analysis)
Dividend-Payment Dummy	A binary variable which equals one if a firm pays dividends in a year and zero otherwise (source: Compustat)
HHI	Sales-based Herfindahl-Hirschman index for the SIC-3 industry in which a peer operates (source: Compustat).
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. The premium is measured using the five-day (-2, $+2$) market-model abnormal returns of the target firm at the deal announcement (source: CRSP)
Hostile Takeover Index	A variable reflecting the probability that a firm receives a hostile takeover threat (Cain et al., 2017, p.474). Source: Prof. Stephen McKeon's website, https://pages.uoregon.edu/smckeon/.
High Patent-Value Dummy	A binary variable that equals one if the ratio of the total value of patents a peer candidate received over the previous five years (source: Kogan et al. (2017)) to the candidate's total assets minus the book value of equity plus the market value of equity (source: Compustat) is higher than the median value for all peer candidates in the same year
High R&D Dummy	A binary variable that equals one if the research and development expense scaled by sales of a peer candidate is higher than the median for all peer candidates in the same year (source: Compustat)
Institutional Ownership	The proportion of stock owned by institutional investors (source: Thomson Reuters Institutional (13f) Holdings)
Knowledge-Base Overlap Ratio	The number of patents in the *Common Knowledge Space* scaled by the total number of patents that receive at least one citation from either the target or the peer candidate over the past 60 months. For each acquisition target and peer candidate pairing, the *Common Knowledge Space* is the set of prior patents cited by both the patents that the target issued and the patents that the peer candidate issued over the past 60 months (source: Kogan et al. (2017))
Knowledge-Base Peer Dummy	A binary variable that is one for firms that, in the month of an acquisition, have a *Knowledge-Base Overlap Ratio* with the target firm greater than the 98th percentile of the values of this variable across all the possible peers in the same month
Lagged R&D	The lagged R&D expenditures scaled by sales (source: Compustat)
Large-Size Dummy	A binary variable that equals one if the logarithm of a firm's market capitalization is higher than the sample median in a year (source: Compustat)
Leverage	Debt in current liabilities plus long-term debt, scaled by total assets (source: Compustat)
M/B Ratio	The market-to-book ratio which is total assets minus the book value of equity plus the market value of equity, scaled by total assets (source: Compustat)
Mahalanobis Distance	The Mahalanobis extension, by Bloom et al. (2013), of the *Technology Proximity Score* that accounts for the distance between every two technology classes measured by the co-location of technology classes within firms (source: Kogan et al. (2017))
Mahalanobis Peer Dummy	A binary variable that is set to one for firms that, in the month of an acquisition, have a *Mahalanobis Distance* with the target greater than the 98th percentile of the values of this variable across all the possible firm pairs in the same month
Market Cap	The natural logarithm of the market value of equity (source: Compustat), inflation-adjusted using the CPI. The base year is 1983 (source: FRED)
Net Working Capital	Net working capital divided by sales (source: Compustat)
P/E Ratio	The price-earnings ratio which is the ratio of a firm's stock price to its earnings per share (source: Compustat)
PPE	The net value of property, plant, and equipment over total assets (source: Compustat)

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 (source: Thomson SDC Platinum M&A database; Kogan et al. (2017))
Product Market Dummy	A binary variable that is one for firms that, in the year preceding an acquisition, have a *Product Proximity Score* with the target greater than the 98th percentile of this score across all the possible firm pairs in the same year
Product Proximity Score	A score constructed following Bloom et al. (2013) which is analogous to the *Technology Proximity Score* but based on the distribution of a firm's sales across SIC-3 segments (source: Compustat)
R&D	R&D expenditures scaled by sales (source: Compustat)
R&D Increase	The change in R&D expenditures scaled by sales from the year before to the year after an acquisition (source: Thomson SDC Platinum M&A database; Compustat)
ROA	The return on assets which is measured by earnings before interest and taxes over total assets (source: Compustat)
Sales Increase	The change in sales relative to the previous year (source: Compustat)
Same FF-48 Industry Dummy	A binary variable that equals one if a peer candidate and the corresponding acquisition target are in the same Fama-French 48 industry (source: Prof. Kenneth French's website; CRSP)
Same SIC-3 Industry Dummy	A binary variable that equals one if a peer candidate and the corresponding acquisition target are in the same SIC-3 industry (source: CRSP)
Same State Dummy	A binary variable that equals one if the headquarters of a peer candidate and those of the acquisition target are in the same state (source: Compustat and Augmented 10-X Header Data from Prof. Bill McDonald's website)
Same TNIC-3 Dummy	A binary variable that equals one if a peer candidate and the corresponding acquisition target are in the same TNIC-3 industry (Hoberg and Phillips, 2010) (source: website of Prof. Gerard Hoberg and Prof. Gordon Phillips)
Supplier Dummy	A binary variable that equals one if a peer candidate is in the upstream industry of the corresponding target firm's industry with a Customer Input Coefficient (CIC) greater than 1%. The CIC is the value of an upstream industry's output sold to the downstream industry divided by the value of the downstream industry's total output (source: Bureau of Economic Analysis)
Technology Proximity Score	A score calculated each month based on the cosine similarity between the technology of two firms (Jaffe, 1986). A firm's technology is proxied by a vector whose elements are the values of patents in the USPC technology classes granted to the firm in the previous 60 months scaled by the value of all patents the firm received in the same period (source: Kogan et al. (2017))
Technology-Peer Dummy	A binary variable that is one for firms that, in the month of an acquisition, have a *Technology Proximity Score* with the target greater than the 98th percentile of the score for all the possible firm pairs
Vdshock	The detrended annual percentage change in the size of the downstream industry using the input-output matrix (source: Bureau of Economic Analysis) calculated following Phillips and Zhdanov (2013)

Table 2: **The Abnormal Returns on the Target Firms and the Portfolios of Their Technology Peers**

This table reports the abnormal returns on the target firms and the portfolios of their technology peers. Panels A, B, and C report the cumulative average abnormal returns (CAARs) on the equal-weighted portfolios of target technology peers during the deal announcement of their respective targets. We describe the samples of acquisitions and peers in Table OAT5 of the Online Appendix. 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 with the value-weighted market index of all CRSP firms. 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 over the five-day window (-2, $+2$) centered on the acquisition announcement day. We estimate each firm's CAR based on the market model, 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. Panel C reports the market-model CAARs on the technology-peer portfolios where target technology peers are defined based on alternative technology proximity measures (defined in Table 1). Panel D reports the market-model CARs on the target firms during the deal announcement. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. CAAR on the Portfolios of Target Technology Peers 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, $+2$) on the Portfolios of Target Technology Peers 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	n/a	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***

Panel C. CAAR (-2, $+2$) on the Portfolios of Target Technology Peers Using Alternative Definitions of Target Technology Peers (Market-Model-Adjusted)

Technology Proximity Measures	Number of Portfolios	CAAR	StdCsect Z
Mahalanobis Distance	1254	0.29%	4.466***
Knowledge-Base Overlap Ratio	1202	0.20%	3.403***

Panel D. CAAR on the Target Firms Over the Acquisition Announcement Period (Market-Model-Adjusted))

Day	Number of Firms	CAR	StdCsect Z
CAAR (-2, 0)	1252	19.99%	26.568***
CAAR (0, $+2$)	1252	23.27%	29.051***
CAAR (-2, $+2$)	1252	25.85%	32.098***
CAAR (-5, $+5$)	1252	27.82%	32.822***

Table 3: **Comparison Between the Technology and Alternative Spillover Effects**

This table reports the cumulative average abnormal returns (CAARs) on the equal-weighted portfolios of technology-peer candidates. Different peer-candidate portfolios are formed based on their relations to their corresponding target firms and the intersections of such relations. A peer candidate is considered as being in its corresponding target's technology space if it is a technology peer (i.e., the variable *Technology Peer Dummy* takes a value of one). Peer-candidate portfolios are also built in consideration of product-market (based on the variables *Product Market Dummy*, *Same SIC-3 Industry Dummy*, *Same FF-48 Industry Dummy*, and *Same TNIC-3 Industry Dummy*), geographic (based on the variable *Same State Dummy*), and supply-chain relations (based on the variables *Supplier Dummy* and *Customer Dummy*) between targets and peer candidates. Detailed variable definitions can be found in Table 1. The cumulative abnormal returns (CARs) of each firm, which are measured over the window (−2, +2), are estimated using the market model with the value-weighted market index of all CRSP firms. 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. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

	Technology Peer Dummy=0			*Technology Peer Dummy*=1		
	Number of Portfolios	CAAR	StdCsect Z	Number of Portfolios	CAAR	StdCsect Z
Product Market Dummy=0	1185	0.05%	0.323	1176	0.24%	3.226***
Product Market Dummy=1	940	0.25%	2.786***	715	0.46%	3.359***
Same SIC-3 Industry Dummy=0	1264	0.04%	0.391	1249	0.18%	2.864***
Same SIC-3 Industry Dummy=1	1210	0.22%	2.930***	903	0.37%	3.437***
Same FF-48 Industry Dummy=0	1257	0.04%	0.387	1237	0.18%	2.756***
Same FF-48 Industry Dummy=1	1251	0.17%	2.519***	1023	0.33%	3.764***
Same TNIC-3 Industry Dummy=0	813	0.08%	1.035	805	0.32%	3.029***
Same TNIC-3 Industry Dummy=1	750	0.18%	2.089**	599	0.37%	2.940***
Same State Dummy=0	1191	0.05%	0.306	1181	0.26%	3.852***
Same State Dummy=1	1186	0.11%	0.967	797	0.50%	2.705***
Supplier Dummy=0	1264	0.04%	0.488	1254	0.28%	4.119***
Supplier Dummy=1	876	0.11%	0.926	605	0.14%	1.146
Customer Dummy=0	1264	0.06%	0.65	1251	0.26%	4.101***
Customer Dummy=1	669	0.12%	0.665	443	0.36%	1.316*

Table 4: **The Determinants of the Abnormal Returns on Peer Candidates**

This table reports the estimates of 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 with the value-weighted market index of all CRSP firms. In Panel A, we regress a peer candidate's CAR on the *Technology Proximity Score* or the *Technology-Peer Dummy*, controlling for the *Product Proximity Score* between a peer candidate and its corresponding acquisition target, the spillover effects through geographical channels (*Same State Dummy*) and supply chains (*Supplier Dummy* and *Customer Dummy*), and other firm characteristics. In Panel B, we regress a peer candidate's CAR on alternatives to the *Technology-Peer Dummy* (namely *Mahalanobis Peer Dummy* and *Knowledge-Base Peer Dummy*), controlling for *Product Proximity Score* and other firm characteristics. In Panel C, we add several interaction terms built using the *Technology Proximity Score* with the *High Acquisition-Premium Dummy*, the *High Patent-Value Dummy*, the *High R&D Dummy*, and the *Acquirer-Target Same Technology-Space Dummy*. Other control variables in Panel C include *Product Proximity Score*, *Sales Increase*, *Closely Held Shares*, *Leverage*, *Market Cap*, *ROA*, *M/B Ratio*, and *HHI*. All the variables in this table are defined in Table 1. The t-statistics, clustered by deal, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels respectively.

Panel A. CARs of Peer Candidates–Effects of Technology Relations

	(1)	(2)	(3)	(4)	(5)	(6)
Technology Proximity Score	0.486***		0.435***		0.449***	
	(3.78)		(3.63)		(3.63)	
Technology-Peer Dummy		0.281***		0.238***		0.237***
		(3.69)		(3.26)		(3.15)
Sales Increase	0.000	−0.000	0.024	0.024	0.025	0.024
	(0.00)	(−0.01)	(0.76)	(0.75)	(0.77)	(0.75)
Closely Held Shares	−0.035	−0.036	−0.045	−0.046	−0.065	−0.066
	(−0.94)	(−0.97)	(−1.11)	(−1.13)	(−1.49)	(−1.52)
Leverage	−0.010	−0.012	0.013	0.013	0.049	0.049
	(−0.16)	(−0.18)	(0.20)	(0.20)	(0.73)	(0.73)
Market Cap	−0.003	−0.002	−0.008	−0.006	−0.006	−0.005
	(−0.30)	(−0.18)	(−0.69)	(−0.58)	(−0.52)	(−0.42)
ROA	−0.166*	−0.171*	−0.136	−0.140	−0.135	−0.139
	(−1.76)	(−1.81)	(−1.40)	(−1.44)	(−1.40)	(−1.44)
M/B Ratio	−0.138***	−0.139***	−0.136***	−0.137***	−0.142***	−0.143***
	(−10.38)	(−10.38)	(−9.84)	(−9.85)	(−10.32)	(−10.33)
HHI	−0.141*	−0.147*	−0.137	−0.139*	−0.123	−0.126
	(−1.80)	(−1.87)	(−1.62)	(−1.65)	(−1.44)	(−1.46)
Product Proximity Score			0.135*	0.164**	0.114	0.143**
			(1.90)	(2.25)	(1.60)	(1.96)
Same State Dummy					0.053	0.055
					(1.01)	(1.04)
Supplier Dummy					0.100	0.102
					(1.39)	(1.43)
Customer Dummy					−0.059	−0.056
					(−0.76)	(−0.72)
Joint Significant Wald Test of Same State Dummy, Supplier Dummy, and Customer Dummy (p-value)					0.412	0.399
Deal Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.036	0.036	0.038	0.038	0.039	0.039
Observations	1543391	1543391	1334932	1334932	1188322	1188322

Panel B. CARs of Peer Candidates–Alternative Definitions of Target Technology Peers

	(1)	(2)	(3)	(4)
Mahalanobis Peer Dummy	0.308***		0.260***	
	(3.76)		(3.32)	
Knowledge-Base Peer Dummy		0.153**		0.119*
		(2.48)		(1.87)
Sales Increase	−0.000	0.000	0.024	0.024
	(−0.01)	(0.01)	(0.75)	(0.77)
Closely Held Shares	−0.036	−0.036	−0.046	−0.046
	(−0.96)	(−0.96)	(−1.13)	(−1.12)
Leverage	−0.012	−0.012	0.013	0.015
	(−0.18)	(−0.18)	(0.19)	(0.22)
Market Cap	−0.002	−0.003	−0.007	−0.007
	(−0.22)	(−0.30)	(−0.61)	(−0.67)
ROA	−0.169*	−0.174*	−0.138	−0.142
	(−1.79)	(−1.85)	(−1.42)	(−1.46)
M/B Ratio	−0.139***	−0.138***	−0.136***	−0.136***
	(−10.39)	(−10.34)	(−9.85)	(−9.83)
HHI	−0.146*	−0.153*	−0.139*	−0.141*
	(−1.86)	(−1.94)	(−1.65)	(−1.67)
Product Proximity Score			0.158**	0.191***
			(2.19)	(2.59)
Deal Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.036	0.036	0.038	0.038
Observations	1543391	1543391	1334932	1334932

Panel C. CARs of Peer Candidates–Technology Proximity and Interactions Terms

	(1)	(2)	(3)	(4)
High Acquisition-Premium Dummy*	0.653**			
Technology Proximity Score	(2.50)			
High Patent-Value Dummy*		0.328**		
Technology Proximity Score		(2.07)		
High R&D Dummy*			0.490**	
Technology Proximity Score			(2.53)	
Acquirer-Target Same Technology-Space Dummy*				0.593*
Technology Proximity Score				(1.89)
Technology Proximity Score	0.093	0.210*	0.080	0.126
	(0.56)	(1.70)	(0.62)	(0.73)
High Patent-Value Dummy		0.112***		
		(5.67)		
High R&D Dummy			0.100**	
			(2.40)	
Product Proximity Score	0.122*	0.131*	0.108	0.113
	(1.72)	(1.85)	(1.52)	(1.43)
Other Control Variables	Yes	Yes	Yes	Yes
Deal Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.038	0.038	0.038	0.038
Observations	1324826	1334932	1334932	1016665

Table 5: **The Determinants of a Firm's Likelihood of Being an Acquisition Target**

This table reports the estimates from linear probability models 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 utilities sectors) in the Compustat-CRSP merged database and all the acquisitions from the Thomson SDC Platinum M&A database over the 1984–2010 period. The 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. 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. All the independent variables are measured in the previous year (year t–1) and defined in Table 1. The industry fixed effects are based on the Fama-French 48 industry definitions. t-statistics, clustered by firm, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Previous-Acquisition Dummy	0.009***	0.010***	0.010***	0.007***	0.008***	0.007**
	(3.55)	(3.62)	(3.47)	(2.67)	(2.74)	(2.32)
M/B Ratio	−0.006***	−0.006***	−0.007***	−0.006***	−0.006***	−0.007***
	(−8.47)	(−8.43)	(−8.90)	(−8.09)	(−8.04)	(−8.49)
PPE	−0.027***	−0.026***	−0.027***	−0.025***	−0.025***	−0.027**
	(−2.84)	(−2.78)	(−2.63)	(−2.65)	(−2.58)	(−2.52)
Cash Ratio	−0.001	−0.001	0.001	−0.001	−0.001	−0.000
	(−0.57)	(−0.64)	(0.55)	(−1.16)	(−1.24)	(−0.10)
Blockholder Dummy	0.017***	0.017***	0.013***	0.017***	0.018***	0.013***
	(6.63)	(6.71)	(4.64)	(6.72)	(6.83)	(4.67)
Market Cap	−0.004***	−0.004***	−0.003***	−0.004***	−0.004***	−0.003***
	(−5.35)	(−5.33)	(−3.47)	(−5.32)	(−5.34)	(−3.44)
Leverage	0.027***	0.027***	0.032***	0.028***	0.028***	0.033***
	(3.43)	(3.46)	(3.82)	(3.57)	(3.60)	(3.91)
ROA	−0.015**	−0.013**	−0.017**	−0.013**	−0.011*	−0.015**
	(−2.29)	(−2.05)	(−2.51)	(−2.00)	(−1.71)	(−2.12)
Age		−0.011**			−0.014**	
		(−2.13)			(−2.57)	
Age Squared		0.002**			0.003**	
		(2.02)			(2.43)	
Hostile Takeover Index			0.011			0.006
			(0.65)			(0.38)
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
R^2	0.016	0.016	0.016	0.040	0.041	0.043
Observations	41562	41562	36755	41562	41562	36755

Table 6: **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. The sample contains the technology peers of columns (7) and (8) of Panel A Table OAT5 of the Online Appendix. The dependent variable (i.e., the CAR on each firm), measured over the window (−2, +2), is estimated using the market model with the value-weighted market index of all CRSP firms. 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 Table OAT17 of the Online Appendix for columns (1)-(2), (3)-(4), and (5)-(6) respectively. The other independent variables are defined in Table 1. All the independent variables are measured in the year t–1 and defined in Table 1. t-statistics, clustered by deal, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Acquisition Vulnerability	22.050***	16.584**	19.727***	11.692*	22.325***	16.252*
	(5.86)	(2.11)	(5.80)	(1.74)	(5.46)	(1.93)
Product Proximity Score		0.261		0.263		0.194
		(1.59)		(1.60)		(1.17)
Sales Increase		0.207		0.196		0.173
		(1.28)		(1.22)		(1.05)
Closely Held Shares		−0.488		−0.529		−0.530
		(−1.47)		(−1.59)		(−1.47)
Leverage		−0.426		−0.318		−0.488
		(−1.00)		(−0.74)		(−1.07)
Market Cap		−0.022		−0.049		−0.042
		(−0.42)		(−1.01)		(−0.87)
ROA		−0.472		−0.477		−0.259
		(−1.22)		(−1.22)		(−0.67)
M/B Ratio		−0.060		−0.074*		−0.048
		(−1.36)		(−1.68)		(−0.96)
HHI		−0.306		−0.295		−0.293
		(−0.65)		(−0.63)		(−0.63)
Deal Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.068	0.080	0.068	0.080	0.072	0.083
Observations	41401	28433	41401	28433	36655	26343

Table 7: **The Previous Acquisition of Technology Peers and Firms' R&D Investment**

This table reports the estimate of the impact of acquisition activities on the R&D investments of targets' technology peers. The dependent variable is a firm's R&D expenditure divided by sales in a year (year t). The sample comprises all the firm-years (excluding firms from the financial and utilities sectors) in the Compustat-CRSP merged database and all the acquisitions from the Thomson SDC Platinum M&A database over the 1984–2010 period. Firm-years that do not obtain any patents in the past five years are excluded because, for them, neither the technology space nor the technology peers can be identified. The variable *Previous-Acquisition Dummy* is set to 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. All the independent variables are measured in the previous year and defined in Table 1. The industry fixed effects are based on the Fama-French 48 industry definitions. t-statistics, clustered by firm, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Previous Acquisition Dummy	0.011	0.059***	0.121***	0.006	0.054***	0.123***
	(1.43)	(4.18)	(5.21)	(0.76)	(3.72)	(5.03)
Previous-Acquisition Dummy*		−0.101***			−0.103***	
Large-Size Dummy		(−5.66)			(−5.52)	
Previous-Acquisition Dummy*			−0.021***			−0.023***
Market Cap			(−5.94)			(−5.98)
Large-Size Dummy		0.006			0.008	
		(0.63)			(0.77)	
Market Cap	−0.016***		−0.001	−0.016***		0.000
	(−4.90)		(−0.46)	(−4.76)		(0.17)
Lagged R&D	0.663***	0.662***	0.662***	0.660***	0.659***	0.659***
	(30.36)	(30.31)	(30.28)	(29.81)	(29.78)	(29.75)
Vdshock	−0.046	−0.050	−0.050	−0.096	−0.089	−0.088
	(−0.35)	(−0.37)	(−0.38)	(−0.77)	(−0.72)	(−0.71)
Age	−0.018***	−0.019***	−0.017**	−0.020***	−0.021***	−0.019***
	(−2.64)	(−2.85)	(−2.51)	(−2.78)	(−3.00)	(−2.67)
PPE	−0.144***	−0.148***	−0.145***	−0.140***	−0.143***	−0.140***
	(−3.16)	(−3.24)	(−3.16)	(−2.99)	(−3.06)	(−2.99)
Cash Ratio	0.035***	0.034***	0.035***	0.036***	0.036***	0.036***
	(9.03)	(8.86)	(9.02)	(9.04)	(8.88)	(9.02)
Net Working Capital	−0.090	−0.090	−0.091*	−0.092	−0.091	−0.092
	(−1.64)	(−1.64)	(−1.65)	(−1.63)	(−1.63)	(−1.64)
P/E Ratio	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(−5.49)	(−5.61)	(−5.42)	(−5.48)	(−5.60)	(−5.42)
Dividend-Payment Dummy	−0.007	−0.016*	−0.009	−0.007	−0.015	−0.008
	(−0.86)	(−1.77)	(−1.08)	(−0.76)	(−1.61)	(−0.98)
Institutional Ownership	−0.069***	−0.067***	−0.069***	−0.069***	−0.066***	−0.070***
	(−3.49)	(−3.36)	(−3.53)	(−3.42)	(−3.26)	(−3.46)
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
R^2	0.633	0.633	0.633	0.637	0.637	0.637
Observations	37961	37961	37961	37909	37909	37909

Table 8: **The Abnormal Returns on Technology Peers and R&D Increase**

This table reports the regression estimates of how a technology peer's cumulative abnormal return (CAR) at the acquisition announcement varies according to the peer's change in R&D expenditures. The sample contains the technology peers of columns (7) and (8) of Panel A Table OAT5 of the Online Appendix. The dependent variable, measured over the window (−2, +2), is estimated using the market model with the value-weighted market index of all CRSP firms. The variable *R&D Increase* is the change in R&D expenditures scaled by sales from the year before the acquisition to the year after. All the independent variables are defined in Table 1. t-statistics, clustered by deal, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
R&D Increase	0.0023	−0.0365	0.0167	−0.0162
	(0.09)	(−1.13)	(0.56)	(−0.43)
R&D Increase* Large-Size Dummy			−0.0447	−0.0599
			(−0.91)	(−0.96)
Large-Size Dummy			−0.2747**	−0.2966**
			(−2.49)	(−2.12)
Product Proximity Score		0.2996**		0.2993**
		(2.03)		(2.03)
Sales Increase		0.2020		0.2050
		(1.37)		(1.39)
Closely Held Shares		−0.3783		−0.2943
		(−1.40)		(−1.11)
Leverage		−0.0591		−0.1024
		(−0.20)		(−0.34)
Market Cap		−0.0846**		
		(−2.52)		
ROA		−0.1397		−0.2496
		(−0.47)		(−0.85)
M/B Ratio		−0.0957***		−0.1021***
		(−3.16)		(−3.39)
HHI		0.4382		0.4456
		(1.01)		(1.02)
Deal Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.080	0.102	0.081	0.102
Observations	39335	25837	39278	25837

Table 9: **The 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 with the value-weighted market index of all CRSP firms. For each acquiring firm, we form equal-weighted portfolios of several types of potential customers. The sample of acquisitions and peers are described in Table OAT5 of the Online Appendix. *Generic customers* are firms that belong to an industry in the downstream of the acquiring-firm industry with a 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 regions as their corresponding acquiring firms. In Panel A, we report the abnormal returns on the customer portfolios for the full sample of deals and sub-samples by industry competition level. A deal is classified as being in a high or low competition industry according to the sales-based Herfindahl-Hirschman Index (HHI) of the acquiring firm's four-digit SIC industry. If, in the year before the deal announcement, this variable is lower (greater) than the sample median of the same year, the deal is classified as taking place in a high (low) competition industry. In Panel B, we report the abnormal returns on the customer portfolios for deals that fall in the ranges of [5%, 0] ([10%, 0]) below and [0, 5%] ([0, 10%]) above the Federal Trade Commission (FTC) review threshold (HSR threshold), which is constructed in the spirit of Cunningham et al. (2021). 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. We report the t-statistics from a t-test of the equality of means of sub-samples between high and low competition industries in Panel A, and similar t-statistics for the sub-samples of deals just below and just above the HSR threshold in Panel B. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. CAAR on the Portfolios of Customers of Acquiring Firms

		Generic Customers	Main Customers	Reliant Customers	Small Customers	Regional Customers
	N	737	726	728	710	682
Full Sample	CAAR	0.12%	0.10%	0.17%	0.35%	0.42%
	StdCsect Z	0.792	0.827	1.327*	3.197***	2.307**
	N	394	390	390	386	378
High-Competition Industry	CAAR	0.24%	0.20%	0.28%	0.51%	0.50%
	StdCsect Z	1.445*	1.337*	1.973**	3.357***	2.544***
	N	343	336	338	324	304
Low-Competition Industry	CAAR	−0.02%	−0.02%	0.04%	0.16%	0.33%
	StdCsect Z	−0.465	−0.562	−0.365	0.998	0.739
Difference	CAAR	0.26%	0.21%	0.25%	0.34%	0.17%
	t-statistics	1.428	0.795	0.862	1.175	0.549

Panel B. CAAR on the Portfolios of Customers of Acquiring Firms around FTC Review Threshold

		Generic Customers	Main Customers	Reliant Customers	Small Customers	Regional Customers
	N	8	8	8	8	8
5% Below Threshold	CAAR	1.07%	0.47%	−0.14%	1.88%	1.49%
	StdCsect Z	1.409*	1.081	−0.235	1.039**	1.726**
	N	10	10	10	9	9
5% Above Threshold	CAAR	0.87%	0.01%	0.09%	1.00%	1.94%
	StdCsect Z	0.68	0.184	0.136	0.437	1.696**
Difference	CAAR	−0.20%	−0.46%	0.23%	−0.87%	0.45%
	t-statistics	−0.197	−0.604	0.198	−0.612	0.321
	N	26	26	25	24	23
10% Below Threshold	CAAR	−0.17%	0.05%	1.02%	0.48%	0.18%
	StdCsect Z	0.625	0.911	1.624*	2.350***	1.811**
	N	22	21	22	21	21
10% Above Threshold	CAAR	−0.26%	−1.18%	−0.77%	−0.18%	−0.21%
	StdCsect Z	−1.076	−1.787**	−1.767**	−0.655	−0.428
Difference	CAAR	−0.09%	−1.23%	−1.79%	−0.67%	−0.39%
	t-statistics	−0.123	−1.419	−1.671	−0.649	−0.354

Online Appendix for “Acquisitions and Technology Value Revision”

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Online Appendix for "Acquisitions and Technology Value Revision"

I. Overview of the Online Appendix

While we describe all the main variables in Table 1 of the main body, some details of variable construction are left out for brevity, for example the details for the *Technology Proximity Score* and the *Knowledge-Base Overlap Ratio*. In this Online Appendix we provide more details of variable descriptions and construction, where necessary.

We also provide information on the tests mentioned in the main body that either complement our main analysis or demonstrate the robustness of our findings.

List of Content

II. Definitions of the Variables Used Only in the Online Appendix

In Table OAT1, we define the variables that appear only in the Online Appendix.

III. The *Technology Proximity Score* of Firm Pairs and the Technology Peers of Acquisition Targets

For a calendar month, we assume that a firm's technology can be represented by the classes of patents granted to the firm in the previous 60 months. For example, a firm's technology in February 1991 can be represented by the 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 given 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 a pair of firms if any of them has no patent granted in the previous 60 months. We rely on 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 peer-candidate firm is higher than the 98$^{\text{th}}$ percentile of the distribution of the pairwise *Technology Proximity Score* among all candidates 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. The technology spaces based on the 98$^{\text{th}}$ percentile are similar in granularity to the three-digit SIC industries. For the technology peers, the value of the binary variable *Technology-Peer Dummy* is set to one.

IV. Alternative Measures of Technology Closeness

We consider two alternative measures of technology closeness starting from a proximity score that considers the spillovers among patents belonging to different technology classes. Bloom et al. (2013) argue that an important limitation of the proximity score advocated by Jaffe (1986) is its underlying assumption that technology spillovers can only occur within the same technology class. The authors propose a Mahalanobis extension of the *Technology Proximity Score* that reflects the distance between each pair of technology classes based on the distribution of a firm's patents across all possible technology classes. The logic behind this approach is that if firms tend to obtain patents across a sub-set of patent classes then these classes can be considered more proximate to one another than other classes. For each month and pair of firms, we closely follow Bloom et al. (2013) to calculate the *Mahalanobis Distance* measure using patent data over the past 60 months. Specifically, we compute the *Mahalanobis Distance* between two generic firms A and B as follows

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

, where the vectors S_a and S_b are defined in Section III of the Online Appendix, which denote the technology of firms A and B, respectively. Ω is a weighting matrix, and element $\Omega_{i,j}$ of the matrix measures the closeness of patents in patent classes i and j. If patent classes i and j coincide frequently within the same firm, then $\Omega_{i,j}$ will be close to one. The Online Appendix of Bloom et al. (2013, pp.1358–1359) provides the technical details of the definition of $\Omega_{i,j}$. We compute the share of a firm's patents in a particular class based on the patents' market values. The value of each patent is measured using the stock market response to the announcement of the granting of a new patent (Kogan et al., 2017).

Following Bena and Li (2014) and Ma (2020), we also measure technology closeness by evaluating whether, and to what extent, the patents of two firms cite common prior patents. This alternative measure complements the *Technology Proximity Score* in that 1) it relies on the knowledge input for innovation activities rather than innovation output and 2) it is less subject to the concern that patented innovation outputs cluster disproportionally in certain popular patent classes, as we discuss in Section 2.1 of the main body of our paper. Specifically, for each month, we build a citation-based measure that aims to capture overlaps in firms' knowledge bases. For an acquisition target and a peer candidate, we define their *Common Knowledge Space* as the set of patents that are cited at least once by both the target's patents and the candidate's patents issued over the past 60 months. The *Knowledge-Base Overlap Ratio* between the target and the peer candidate is the number of patents in the *Common Knowledge Space* between the two firms scaled by the total number of patents that receive at least one citation from either the target or the candidate (or both) over the same period.

In each calendar month, we obtain the distributions of the two alternative measures of technology closeness for all possible pairs of firms in our sample and obtain the values of the 98^{th} percentiles. A target firm's technology peers are then defined as those peer candidates with proximity scores above these thresholds. The binary variables *Mahalanobis-Peer Dummy* and *Knowledge-Base Peer Dummy* take a value of one for these firms and zero otherwise.

V. The *Technology Proximity Score*: Complements or Substitutes

It is intriguing to ask whether technology closeness reflects substitution or complementarity. The previous literature does not provide a clear indication of this, as far as we know. However, it is possible that technology overlap between firms represents both complementary and substitutionary opportunities. In this regard, our *Technology Proximity Score* measure assumes that the set of innovation categories corresponds to the pool of patent classes formally defined by the USPTO. On the one hand, patents in the same patent class could represent complementary opportunities. For example, both patent US8472410 (Rake Receiver Architecture within a WCDMA Terminal) and patent US6990091 (Method and Apparatus for Fast WCDMA Acquisition) are in the United States Patent Class 370 (Multiplex Communications). These two patents represent complementary technology, as both patents are used in WCDMA, a standard for the third generation of wireless mobile telecommunications technology. On the other hand, patents in the same patent class could represent substitutionary opportunities. For example, both patent US6990091 (Method and Apparatus for Fast WCDMA Acquisition) and patent US7778225 (Method and Apparatus for Dynamic Packet Transport in CDMA2000 Networks) are in the United States Patent Class 370 (Multiplex Communications). These two patents represent substitutionary technology, as the two patents are used in WCDMA and CDMA2000, respectively. CDMA2000 is a technology standard that competes against WCDMA in the third generation of wireless mobile telecommunications technology market.

Innovation activities in the same technology field inevitably rely on, consolidate, and improve existing technologies and, at the same time, generate new technologies that potentially displace existing ones, as is postulated by Schumpeter (1942) and Aghion and Howitt (1992). Importantly, an acquisition announcement should have value implications for both substitutes and complements. Specifically, the acquisition announcement attaches a high value to the synergies obtained from acquiring and integrating a certain technology. Upon observing the acquisition, the stock market realizes that equivalent synergies are likely to be achievable through acquiring similar and substitutionary technologies, which leads to the higher valuation of these substitutes. Regarding complementary technologies, to the extent that they contribute to a package of technology resources that produce synergies now deemed to be worth more, their value should also be higher following the acquisition announcement.

From the perspectives of future acquirers, if they receive a signal that potential technology synergies are greater than previously expected, either from acquiring the substitutes or the complements of the targets' technology, they will be incentivized to investigate and tap such opportunities through acquisitions.

It would be informative to conduct further empirical analyses based on substitutes or complements. However, the interactions among technologies are complex and, to the best of our knowledge, there is a lack of suitable data and methods for us to measure and study such complexity.

The above discussions relate to substitutes/complements from a technical point of view. Similar technologies may also lead to the emergence of substitutes/complements in the product markets. Previous literature primarily focuses on the substitution effect, i.e., the competition effect or the 'business stealing' effect (see, e.g., Bloom et al., 2013; Aghion and Howitt, 1992). The product-market substitution effect predicts that technology peers who compete in the same product market as the acquisition targets should have lower abnormal returns at the acquisition announcement (Bena and Li, 2014), which is opposite to what we find in Table 3 of the main body.

VI. The Summary Statistics of the Technology Closeness Measures

In Tables OAT2, OAT3, and OAT4 of the Online Appendix, we report the summary statistics of the *Technology Proximity Score*, the *Mahalanobis Distance*, and the *Knowledge-Base Overlap Ratio* respectively. Specifically, included in these tables are the monthly number of firm pairs, the monthly average across firm pairs of these measures, and the 98^{th} percentile of their distribution in a month which we use to define technology peers.

VII. Sample Description

Table OAT5 of the Online Appendix reports the sample distribution and attrition of the acquisition targets and their technology peers, by year and by industry.

VIII. Difference between Technology Space and Other Economic Relations

In Table OAT6 of the Online Appendix, we report the overlap between technology space and other measured economic relations, namely several measures of target firms' product market (segment-based product market (Bloom et al., 2013), three-digit SIC industries (SIC-3), Fama-French 48 industries (FF-48), text-based TNIC-3 industries (Hoberg and Phillips, 2010)), customers or suppliers of the target firms, and firms with headquarters in the same states as where target firms' headquarters are located.

IX. Firm and Deal Characteristics

In Table OAT7 of the Online Appendix, we report the characteristics of acquiring firms, target firms, technology peer candidates, technology peers, and acquisition transactions.

X. CAAR of Individual Technology Peers

In Table OAT8 of the Online Appendix, we report the CAARs for the individual technology peers.

XI. Abnormal Returns across Technology Proximity Deciles

In Table OAT9 of the Online Appendix, we report how the peer candidates' CAARs change across the deciles formed according to the candidates' technology proximity to their respective acquisition targets.

XII. Comparison between Technology and the Other Spillover Channels

In Table 3 of the main body, we formally test the robustness of the technology spillover effect with respect to alternative economic relations.

In this section, we provide more details of the various economic relations analyzed in Section 3.2 of the main body.

XII.A. Identifying a Firm's State

The state of a firm's headquarters is identified using information taken from the dataset created by Prof. Bill McDonald.[1] Since this dataset does not cover our early sample period of 1983–1994, we backfill these early years using information from the first year available in the above dataset, unless a firm is not covered by this dataset. In such a case, we use the headquarters information from Compustat. Companies are further classified into the following six geographical regions based on the state in which their headquarters is based: Northeast, Southeast, Southwest, Mideast, Midwest, and West.

XII.B. Identifying Customers and Suppliers

We identify the potential customers and suppliers of target firms following Shahrur (2005). Specifically, we use the benchmark input-output tables from the Bureau of Economic Analysis (BEA) to find the suppliers/customers in the upstream/downstream of the supply chain. The input-output tables report the estimate of the dollar value of the output of a specific supplier

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

industry used as an input by a given 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 complicated by information from irrelevant industries (Cen et al., 2013). Moreover, some of the multi-segment customer firms even contain segments in the industries of the acquiring firm or the target firm.

XIII. Placebo Tests

In Table OAT10 of the Online Appendix, we further strengthen our baseline finding using placebo tests based on the empirical distribution of CAAR (-2,$+2$) estimated using randomly-selected portfolios of peer candidates. We find that the CAAR on actual technology peer portfolios (i.e., 0.26%) is larger than the 99$^{\text{th}}$ percentile of the empirical distribution of CAAR simulated from 1,000 randomly selected samples of peer candidates who reside outside of their respective acquisition targets' technology spaces. This finding shows that it is unlikely that our baseline result in Table 2, i.e., peers' positive value revision upon acquisition announcement, is obtained by chance.

In Table OAT10, we also consider four alternative industry (i.e., product market) classifications and draw similar conclusions for technology peers in or not in the same industry. For example, the CAAR for the peer portfolios in (not in) the same SIC-3 industry as that of their respective targets, which is 0.37% (0.18%), is no less than the 95$^{\text{th}}$ (99$^{\text{th}}$) percentile of the distribution of CAAR estimated from 1,000 randomly drawn samples of peer candidates that are not in their corresponding targets' technology spaces and operate in a SIC-3 industry that is the same as (different from) that of the acquisition targets. The findings are similarly significant for the other definitions of industry, except for the TNIC-3 industry classification. The CAAR for the technology peers in the same TNIC-3 industry as that of their targets' is slightly below the 90th percentile for the corresponding randomly drawn sample. For technology peers not in their corresponding targets' TNIC-3 industries, we, again, find their CAAR lies above the 99$^{\text{th}}$ percentile of the simulated distribution.

In the same table, we also repeat the above analysis based on supply-chain relations and geographical locations. It is notable here that the CAAR for peers from and not from the target firms' states are greater than the 99$^{\text{th}}$ percentile of the CAAR distribution for the corresponding randomly drawn portfolios of peer candidates. Results of similar statistical strength are reported for portfolios of peers not in the upstream (suppliers') or downstream (customers') industries. In contrast, the CAARs for peers in the upstream (downstream) industry is well below (around) the 90$^{\text{th}}$ percentile of the distribution of the respective benchmark portfolio.

Overall, the results in Table OAT10 show that our baseline finding is unlikely to be due to chance. However, the statistical weakness of some of the results in this section may raise some concerns about the importance of overlaps between a firm's technology and other types of economic link, which could inflate the significance of the technology peer effect. In our regression analyses, we include a range of variables that capture inter-firm economic relations beyond technology links. We find that the CAAR being greater for technology peers than non-peer candidates is robust to the inclusion of these controls.

XIV. Robustness: The Determinants of the Abnormal Returns on Peer Candidates – Standard Errors Clustered by Year or by Patent Class

In Table OAT11 and Table OAT12 of the Online Appendix, we estimate several multivariate models to evaluate the effect of technology closeness on peer candidates' abnormal returns around acquisition announcements, with the standard errors adjusted for clustering by year and patent class, respectively.

XV. Robustness: The Determinants of the Abnormal Returns on Peer Candidates – Controlling for Alternative Measures of the Industry Relations

In Columns (3) and (4) of Panel A of Table 4 in the main body, we find our baseline result is robust when we control for industry overlap through the inclusion of the *Product Proximity Score*. In Table OAT13 of the Online Appendix, we control for alternative measures of product-market overlap using SIC-3, TNIC-3, and the segment-based *Product Market Dummy.* Our baseline result remains qualitatively the same.

XVI. Robustness: The Determinants of the Abnormal Returns on Peer Candidates – Excluding Acquirers' Technology Peers

In Table OAT14 of the Online Appendix, we estimate several multivariate models to evaluate how technology closeness relates to peer candidates' abnormal returns around acquisition announcements, using a sample that excludes the acquirers' technology peers.

XVII. Boundaries of the Main Finding

In Section 3.6 of the main body, we discuss the boundaries of our main finding based on the results reported in Table OAT15 of the Online Appendix. The objective is to understand whether our main finding represents a robust economic phenomenon or just a byproduct of merger waves, technology waves, or certain industry structures or technology features.

XVIII. *Previous-Acquisition Proximity Score* and a Firm's Likelihood of Being an Acquisition Target

In Table 5 of the main body, we estimate the effect of the *Previous-Acquisition Dummy* on a firm's likelihood of being an acquisition target. In Table OAT16 of the Online Appendix, as a robustness test, we estimate the effect of the *Previous-Acquisition Proximity Score* on a firm's likelihood of being an acquisition target. The result remains qualitatively the same.

XIX. Estimating Acquisition Vulnerability

In Table 6 of the main body, we estimate how a technology peer's *Acquisition Vulnerability* affects its CAR at acquisition announcement. In Table OAT17 of the Online Appendix, we report the results of the regressions that we use to estimate firms' *Acquisition Vulnerability.*

XX. Abnormal Returns for Withdrawn Deals

In Table OAT18 of the Online Appendix, we report firms' CAAR for withdrawn transactions. Panel A contains the CAARs at the acquisition announcement on target firms and their technology peers. Panel B reports the target firms' CAAR up to 48 months after the deal announcement. In Panel C, we repeat the analysis in Panel B, using a cleaned sample of withdrawn deals. We clean the sample by removing the transactions where the withdrawals were undertaken because the deal price was deemed excessive by the acquirer or because the fundamentals of the target firm and/business environment deteriorated.

In Table OAT19 of the Online Appendix, we repeat our analysis in Panels B and C of Table OAT18 of the Online Appendix and report the target abnormal returns for withdrawn deals measured using the Buy-and-Hold Abnormal Return (BHAR).

XXI. Abnormal Returns on Technology Peers and Acquisition Intensity

In Table OAT20 of the Online Appendix, we estimate how the technology peers' CARs relate to the change of acquisition intensity in a target firm's technology field.

XXII. Who Later Acquires the Peers?

If peers' revaluation is driven by the increased expectation of technology synergies and merger prospects, it would be natural to ask who acquires the peers in subsequent periods. In other words, which companies are likely to benefit from the technology synergies common to the peers?

The previous literature suggests that the answer is likely to rest with economically related firms. Several predictions are therefore in place. First, as Bena and Li (2014) postulate, companies with closer technologies are more likely to benefit from technology synergies. We, therefore, predict that companies with a higher *Technology Proximity Score* with the peer firms are more likely to acquire those peers. Second, geographically closer companies are more likely to benefit from technology spillover and technology synergies because knowledge spillovers are notably localized (e.g. Jaffe et al., 1993). The prediction is, therefore, that companies located in peers' states are more likely to be subsequent acquirers, especially when they are also technologically close. Third, a substantial literature finds that horizontal mergers are often motivated by efficiency gains (Eckbo, 1983; Hoberg and Phillips, 2010). Along this line of reasoning, we predict that peers are more likely to be acquired by companies in the same industry. However, companies overlapping in both technology and product market could have limited synergies due to the "business stealing" effect (see Bloom et al., 2013). Along these lines, the coexistence of technology closeness and product-market overlap should reduce a company's intention to acquire the peers. Fourth, vertical integration generates notable gains for the acquiring firms (Fan and Goyal, 2006). Theoretical work on this front is extensive (see the survey of Lafontaine and Slade, 2007). Importantly, in their recent study, Frésard et al. (2020) find firms are more likely to be the acquisition targets of supply-chain partners when their innovation is realized and already protected by legally enforceable patents, while less likely when their innovation is still at the unrealized stage of R&D. Their findings are consistent with the prediction of the property rights theory (Grossman and Hart, 1986; Hart and Moore, 1990) because, with realized innovations, the incentive to commercialize the innovation becomes important relative to the incentive to innovate. In such a context, vertical integration optimally allocates control to firms that are good at commercializing. According to this line of reasoning, we predict that suppliers and/or customers of peers are more likely to be acquirers, especially when they are technologically close.

Our empirical strategy is analogous to that of Bena and Li (2014, p.1930) and Bouwman (2011, pp. 2374–2375). Specifically, we follow two steps. First, we limit our samples to the peers that subsequently receive an acquisition proposal in the year following the current acquisition (454 subsequent acquisitions). Second, for each subsequent acquirer, we randomly draw five pseudo acquirers out of all firms that do not acquire in the same year (2270 firms). We then compute the *Technology Proximity Score*, *Product Proximity Score*, *Same State Dummy*, *Customer Dummy*, and *Supplier Dummy* for these actual and pseudo acquirers with respect to the peers and include them as independent variables of interest in conditional logit regressions that estimate the probability of a firm being an actual acquirer of target firms' technology peers. We perform the random draw of pseudo acquirers 1000 times to generate the empirical distribution of each coefficient and report the critical percentiles in Panel A of Table OAT21 of the Online Appendix. The result shows that the *Technology Proximity Score*, *Product Proximity Score*, *Same State Dummy*, and *Supplier Dummy* all have their 5^{th} percentiles above zero, while the *Customer Dummy* has its 5^{th} percentile below zero (i.e.,-0.627). These findings show that future acquirers are more likely to be companies that are close to peers in terms of technology, products, and geographical locations, or companies that are from the upstream of the supply chain. Customers are unlikely to be future acquirers, however. Moreover, in Panel C, we find that the interaction term *Technology Proximity Score* $\times$ *Product Market Dummy* has a negative 95^{th} percentile of -2.385, suggesting product-market rivals who have close technologies are less likely to be acquirers, consistent with the view that "business stealing" reduces expected technology synergies (Bena and Li, 2014; Bloom et al., 2013). Furthermore, we find the interaction terms *Technology Proximity Score* $\times$ *Same State Dummy*, *Technology Proximity Score* $\times$ *Customer Dummy*, and *Technology Proximity Score* $\times$ *Supplier Dummy* have intervals of $[-1.741, 1.691]$, $[-4.319, 0.737]$, and $[-2.237, 3.032]$ between their 5^{th} and 95^{th} percentiles, respectively, showing that local firms, customers, or suppliers that have closer technology are not more likely to acquire the peers, contrary to the predictions.

In Panels B and D of Table OAT21 of the Online Appendix, we evaluate the robustness of the findings in Panels A and C by replacing the *Technology Proximity Score* with the *Technology-Peer Dummy*. Our findings remain robust.

XXIII. Customers of Acquiring Firms

In Table 9 of the main body, we report the CAARs of the portfolios of the acquiring firms' potential customers following Shahrur (2005), as explained in Section XII.B of the Online Appendix. We form portfolios of several types of customer as described 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 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 states in which they are headquartered: Northeast, Southeast, Southwest, Mideast, Midwest, and West. Firms' headquarters are obtained as explained in Section XII.A of the Online Appendix.

XXIV. ***Previous-Acquisition Proximity Score*** and Firms' R&D Investment

In Table 7 of the main body, we estimate the effect of the *Previous Acquisition Dummy* on firms' R&D investment. In Table OAT22 of the Online Appendix, as a robustness test, we estimate the effect of the *Previous-Acquisition Proximity Score* on firms' R&D investment. The result remains qualitatively the same.

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Table OAT1: **Definitions of Variables Used Only in the Online Appendix**

Name	Definition
Capital Liquidity	For each year, capital liquidity is defined as the four-quarter average of the spread between the rate on commercial & industrial loans minus the federal funds rate (source: Prof. Stephen McKeon's website)
Completed-Deal Dummy	A binary variable that equals one for completed deals (source: Thomson SDC Platinum M&A database)
Deal Value	The natural logarithm of the deal's value (source: Thomson SDC Platinum M&A database) inflation-adjusted using the CPI. The base year is 1983 (source: FRED)
Declining Acquisition-Intensity Dummy	A binary variable that equals one if the number of a target firm's technology peers acquired in the 12 months before an acquisition is not lower than the number of the target firm's technology peers acquired in the following 12 months (source: Thomson SDC Platinum M&A database; Kogan et al. (2017))
Dormant Period	The natural logarithm of the number of days since a previous acquisition announcement in the same technology space (source: Thomson SDC Platinum M&A database; Kogan et al. (2017))
Dot-Com Bubble Dummy	A binary variable that equals one if a deal is announced during the Dot-Com bubble period of 1998-2001 (source: Thomson SDC Platinum M&A database)
High Capital Liquidity Dummy	A binary variable that equals one if a deal is announced during a period when capital liquidity is higher than the sample median. For each year, capital liquidity is defined as the four-quarter average of the spread between the rate on commercial & industrial loans and the federal funds rate (source: Thomson SDC Platinum M&A database and Prof. Stephen McKeon's website)
Horizontal-Merger Dummy	A binary variable that equals one if the target and the acquirer share the same three-digit SIC code(source: CRSP)
Industry Innovation-Wave Dummy	A binary variable that equals one if the SIC-3 industry of the target firm experiences an innovation wave in the year of the acquisition. A SIC-3 industry's innovation wave occurs if the per capita (source: FRED) number of breakthrough patents (source: Kelly et al. (2021)) issued by the USPTO in the SIC-3 industry in a year is higher than the 90^{th} percentile of the yearly per capita number in the same SIC-3 industry over the entire sample period. Patents are attributed to industries using the USPC to NAICS crosswalk constructed by Goldschlag et al. (2016) and the concordance between NAICS and SIC codes from the Census Bureau
Industry Merger-Wave Dummy	A binary variable that equals one if a deal is announced during an industry merger wave period defined following Harford (2005) (source: Thomson SDC Platinum M&A database)
IT Industry Dummy: Target (Candidate)	A binary variable that equals one if a target (candidate) firm is in the information technology industry as defined in Kim et al. (2016) (source: CRSP)
Later Sample-Period Dummy	A binary variable that equals one if a deal is announced after 1997 (source: Thomson SDC Platinum M&A database)
Low Product-Concentration Dummy: Target (Candidate)	A binary variable that equals one if the sales-based Herfindahl-Hirschman index for the SIC-3 industry in which the target (peer candidate) operates is lower than the median value of the same variable for all of the targets (peer candidates) in the same year (source: Compustat)
Low Technology-Concentration Dummy: Target (Candidate)	A binary variable that equals one if the patent-based Herfindahl-Hirschman index (based on the number of patents issued over the past 60 months) for the SIC-3 industry in which the target (peer candidate) operates is lower than the median value of the same variable for all targets (peer candidates) in the same year (source: CRSP; Kogan et al. (2017))
Patent-Class Innovation-Wave Dummy	A binary variable that equals one if the patent-value-weighted proportion of a target firm's patent classes experiencing innovation waves is greater than the median across all target firms in a year. A patent class experiences an innovation wave when the per capita (source: FRED) number of breakthrough patents (source: Kelly et al. (2021)) issued by the USPTO in the patent class in a year is higher than the 90^{th} percentile of the yearly per capita number in this class over the entire sample period
Pharmaceutical Industry Dummy: Target (Candidate)	A binary variable that equals one if a target (candidate) firm is in the pharmaceutical industry as defined in Bloom et al. (2013) (source: CRSP)
Previous-Acquisition Proximity Score	The value-weighted average of the *Technology Proximity Score* between a firm and all of the acquisition targets in the previous year (source: Thomson SDC Platinum M&A database; Kogan et al. (2017))
Relative Patent Value	The ratio of the total value of a firm's patents received by the firm over the previous five years (source: Kogan et al. (2017)) to its enterprise value (i.e., total assets minus the book value of equity plus the market value of equity) (source: Compustat)

Table OAT2: **Summary Statistics for the Firm-Pair *Technology Proximity Score***

This table contains the descriptive statistics of the firm-pair *Technology Proximity Scores* for our baseline dataset during the 1984–2010 period. The *Technology Proximity Score* is computed following Jaffe (1986), using the patent dataset of Kogan et al. (2017) for US-listed firms. The *Technology Proximity Score* for a specific pair of firms measures the closeness of these two firms' technology. For each calendar month over our 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 Table 1. 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$^{\text{th}}$ percentile of the proximity scores of all firm-pairs. The 98$^{\text{th}}$ percentile 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
2002	2920	2924	2927	2923	2921	2925	2916	2919	2917	2915	2913	2913
2003	2904	2906	2911	2910	2898	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	0.019	0.020	0.019	0.020
1985	0.020	0.020	0.020	0.020	0.019	0.020	0.019	0.019	0.019	0.020	0.020	0.020
1986	0.020	0.020	0.020	0.019	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	0.018	0.018	0.018	0.019	0.018	0.018	0.018	0.018	0.018	0.018
1989	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
1990	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
1991	0.019	0.019	0.019	0.019	0.019	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	0.020	0.021	0.021	0.021
1998	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.022	0.022	0.021	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	0.022	0.022	0.022	0.022	0.022
2001	0.022	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
2002	0.023	0.023	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	0.024	0.025	0.025	0.025	0.025	0.025	0.025	0.025
2005	0.025	0.025	0.025	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.027
2006	0.027	0.027	0.027	0.027	0.028	0.027	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	0.034	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	0.251	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	0.258	0.259	0.261	0.262	0.263	0.264	0.267	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	0.268	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	0.288	0.286	0.286	0.285	0.288	0.290	0.289	0.289	0.290
1995	0.290	0.289	0.289	0.291	0.290	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	0.296	0.299	0.301	0.304
1997	0.306	0.309	0.310	0.312	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	0.342	0.342	0.347	0.345	0.347	0.349
1999	0.351	0.354	0.353	0.352	0.353	0.354	0.357	0.356	0.358	0.361	0.360	0.362
2000	0.364	0.364	0.367	0.367	0.367	0.367	0.370	0.370	0.367	0.369	0.369	0.368
2001	0.370	0.373	0.374	0.375	0.378	0.381	0.383	0.383	0.382	0.386	0.388	0.388
2002	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	0.400	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	0.460	0.459	0.461	0.468	0.469	0.469	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	0.596

Table OAT3: **Summary Statistics for the Firm-Pair *Mahalanobis Distance***

This table contains the descriptive statistics of the firm-pair *Mahalanobis Distance* for our dataset during the 1984–2010 period. The *Mahalanobis Distance* is computed following Bloom et al. (2013) and using the patent dataset of Kogan et al. (2017) for US-listed firms. The *Mahalanobis Distance* for a specific pair of firms measures 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 *Mahalanobis Distance* of all possible firm-pairs in the patent dataset. We exclude from the computation the firms that do not receive any patent over the selected 60 months. A detailed definition of the *Mahalanobis Distance* can be found in Table 1. Panel A reports the number of firms in the firm-pair *Mahalanobis Distance* dataset by calendar month. Panel B contains the average *Mahalanobis Distance* of all the firm-pairs for each calendar month. Panel C reports, for each month, the 98$^{\text{th}}$ percentile of the *Mahalanobis Distance* of all firm-pairs. The 98$^{\text{th}}$ percentile is important because we require the *Mahalanobis Distance* of a technology peer to be higher than this threshold.

Panel A. The Number of Firms in the Firm-Pair *Mahalanobis Distance* 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
2002	2920	2924	2927	2923	2921	2925	2916	2919	2917	2915	2913	2913
2003	2904	2906	2911	2910	2898	2888	2872	2865	2857	2834	2820	2808
2004	2801	2802	2797	2778	2774	2761	2754	2737	2726	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	2322	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 *Mahalanobis Distance* by Calendar Month

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	0.043	0.042	0.043	0.043	0.042	0.042	0.042	0.042	0.041	0.041	0.041	0.041
1985	0.041	0.042	0.041	0.041	0.041	0.042	0.042	0.041	0.041	0.042	0.043	0.042
1986	0.043	0.042	0.042	0.042	0.041	0.041	0.040	0.040	0.040	0.039	0.039	0.039
1987	0.039	0.038	0.037	0.036	0.037	0.037	0.038	0.038	0.038	0.038	0.038	0.037
1988	0.037	0.037	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036
1989	0.037	0.037	0.037	0.037	0.037	0.038	0.038	0.038	0.038	0.039	0.038	0.038
1990	0.039	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038
1991	0.038	0.038	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.040	0.039	0.040
1992	0.039	0.039	0.039	0.039	0.039	0.039	0.038	0.038	0.038	0.039	0.039	0.039
1993	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
1994	0.039	0.038	0.038	0.038	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037
1995	0.038	0.038	0.037	0.037	0.037	0.038	0.037	0.037	0.037	0.038	0.037	0.037
1996	0.037	0.037	0.037	0.037	0.037	0.036	0.037	0.036	0.036	0.037	0.036	0.037
1997	0.037	0.037	0.036	0.037	0.036	0.036	0.036	0.036	0.036	0.036	0.037	0.037
1998	0.037	0.037	0.037	0.037	0.037	0.037	0.038	0.038	0.038	0.038	0.038	0.038
1999	0.039	0.039	0.038	0.039	0.039	0.039	0.039	0.039	0.039	0.040	0.039	0.040
2000	0.040	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
2001	0.039	0.039	0.039	0.039	0.040	0.040	0.040	0.040	0.040	0.040	0.041	0.040
2002	0.041	0.040	0.040	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
2003	0.041	0.041	0.041	0.041	0.042	0.042	0.041	0.041	0.041	0.042	0.042	0.042
2004	0.042	0.042	0.042	0.042	0.042	0.043	0.044	0.044	0.044	0.044	0.044	0.044
2005	0.045	0.044	0.045	0.045	0.045	0.045	0.046	0.046	0.046	0.047	0.047	0.048
2006	0.048	0.048	0.048	0.049	0.049	0.049	0.050	0.050	0.051	0.051	0.052	0.052
2007	0.052	0.052	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.054	0.054	0.054
2008	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.056	0.056	0.056	0.056	0.056
2009	0.057	0.058	0.058	0.058	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.060
2010	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.061	0.061	0.061	0.061	0.061

Panel C. The 98th Percentile of the *Mahalanobis Distance*

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	0.387	0.385	0.385	0.386	0.386	0.384	0.383	0.382	0.376	0.378	0.377	0.377
1985	0.377	0.380	0.380	0.379	0.380	0.383	0.381	0.382	0.380	0.383	0.388	0.385
1986	0.388	0.389	0.384	0.385	0.381	0.383	0.378	0.375	0.372	0.372	0.372	0.369
1987	0.367	0.363	0.359	0.353	0.357	0.357	0.361	0.362	0.360	0.363	0.363	0.360
1988	0.357	0.356	0.355	0.357	0.356	0.358	0.354	0.353	0.354	0.354	0.354	0.355
1989	0.358	0.363	0.365	0.365	0.367	0.371	0.372	0.374	0.377	0.383	0.379	0.379
1990	0.384	0.380	0.378	0.379	0.379	0.381	0.380	0.381	0.379	0.379	0.381	0.379
1991	0.381	0.382	0.384	0.386	0.388	0.388	0.387	0.389	0.389	0.393	0.392	0.395
1992	0.395	0.393	0.393	0.396	0.396	0.396	0.395	0.398	0.397	0.402	0.404	0.405
1993	0.409	0.408	0.406	0.413	0.415	0.413	0.415	0.414	0.413	0.414	0.413	0.413
1994	0.416	0.409	0.409	0.407	0.401	0.402	0.402	0.402	0.403	0.403	0.402	0.405
1995	0.408	0.408	0.407	0.409	0.411	0.412	0.406	0.406	0.412	0.412	0.409	0.410
1996	0.408	0.404	0.402	0.403	0.406	0.406	0.406	0.406	0.407	0.410	0.411	0.417
1997	0.420	0.420	0.421	0.424	0.423	0.422	0.423	0.422	0.425	0.429	0.437	0.439
1998	0.441	0.443	0.439	0.445	0.447	0.446	0.459	0.457	0.465	0.465	0.466	0.470
1999	0.472	0.476	0.474	0.476	0.477	0.477	0.481	0.482	0.487	0.492	0.489	0.493
2000	0.494	0.489	0.490	0.489	0.488	0.488	0.490	0.494	0.488	0.491	0.494	0.493
2001	0.495	0.497	0.499	0.501	0.506	0.510	0.511	0.512	0.510	0.514	0.519	0.518
2002	0.520	0.521	0.523	0.527	0.527	0.527	0.531	0.529	0.531	0.532	0.533	0.535
2003	0.534	0.535	0.536	0.540	0.542	0.541	0.537	0.538	0.538	0.541	0.541	0.543
2004	0.546	0.547	0.547	0.544	0.552	0.558	0.568	0.565	0.572	0.573	0.574	0.573
2005	0.576	0.573	0.572	0.575	0.576	0.580	0.582	0.580	0.591	0.593	0.599	0.604
2006	0.608	0.609	0.610	0.611	0.619	0.619	0.623	0.631	0.635	0.635	0.640	0.639
2007	0.643	0.649	0.648	0.654	0.656	0.660	0.664	0.661	0.664	0.665	0.666	0.672
2008	0.674	0.679	0.676	0.675	0.673	0.670	0.676	0.684	0.684	0.681	0.684	0.689
2009	0.696	0.700	0.701	0.707	0.714	0.721	0.721	0.721	0.717	0.716	0.719	0.731
2010	0.733	0.735	0.736	0.743	0.745	0.749	0.749	0.752	0.759	0.762	0.762	0.761

Table OAT4: **Summary Statistics for the Firm-Pair *Knowledge-Base Overlap Ratio***

This table contains the descriptive statistics of the firm-pair *Knowledge-Base Overlap Ratio* for our dataset during the 1984–2010 period. The *Knowledge-Base Overlap Ratio* is computed following Bena and Li (2014) and Ma (2020) and using the patent dataset of Kogan et al. (2017) for US-listed firms. The *Knowledge-Base Overlap Ratio* for a specific pair of firms measures 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 *Knowledge-Base Overlap Ratio* of all possible firm-pairs in the patent dataset. We exclude from the computation the firms that do not receive any patent over the selected 60 months. A detailed definition of the *Knowledge-Base Overlap Ratio* can be found in Table 1. Panel A reports the number of firms in the firm-pair *Knowledge-Base Overlap Ratio* dataset by calendar month. Panel B contains the average *Knowledge-Base Overlap Ratio* of all the firm-pairs for each calendar month. Panel C reports, for each month, the 98^{th} percentile of the *Knowledge-Base Overlap Ratio* of all firm pairs. The 98^{th} percentile is important because we require the *Knowledge-Base Overlap Ratio* of a technology peer to be higher than this threshold.

Panel A. The Number of Firms in the *Knowledge-Base Overlap Ratio* Dataset by Calendar Month

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	1699	1702	1698	1701	1701	1703	1708	1716	1726	1727	1732	1738
1985	1741	1742	1745	1752	1752	1748	1751	1755	1755	1740	1737	1735
1986	1730	1730	1740	1742	1754	1758	1761	1776	1775	1779	1777	1785
1987	1788	1798	1811	1833	1837	1839	1851	1859	1859	1868	1877	1889
1988	1897	1902	1908	1918	1929	1936	1943	1949	1950	1954	1950	1953
1989	1946	1945	1945	1948	1953	1951	1951	1956	1966	1961	1972	1972
1990	1966	1966	1963	1962	1955	1955	1964	1955	1960	1962	1947	1951
1991	1951	1950	1946	1945	1936	1924	1926	1923	1922	1918	1929	1926
1992	1933	1934	1933	1937	1935	1943	1945	1943	1946	1940	1939	1939
1993	1946	1942	1946	1944	1942	1944	1947	1952	1952	1945	1956	1956
1994	1949	1957	1959	1978	1988	2000	2011	2012	2020	2021	2027	2033
1995	2031	2030	2037	2038	2051	2053	2059	2073	2084	2081	2102	2107
1996	2117	2128	2137	2143	2163	2181	2194	2213	2231	2238	2247	2258
1997	2281	2293	2309	2323	2351	2356	2361	2376	2386	2404	2415	2424
1998	2437	2448	2463	2472	2488	2509	2522	2546	2551	2563	2583	2595
1999	2611	2629	2651	2653	2654	2651	2657	2672	2679	2683	2692	2722
2000	2741	2754	2769	2775	2778	2788	2804	2802	2838	2856	2871	2883
2001	2899	2910	2912	2936	2940	2953	2955	2958	2974	2976	2986	2990
2002	2994	2993	2994	2990	2988	2991	2982	2985	2982	2982	2980	2984
2003	2978	2977	2981	2980	2969	2957	2939	2931	2923	2904	2890	2881
2004	2876	2867	2857	2837	2833	2818	2811	2793	2782	2762	2749	2718
2005	2701	2712	2712	2723	2720	2711	2697	2684	2677	2668	2647	2645
2006	2633	2637	2629	2623	2612	2607	2596	2586	2585	2579	2564	2560
2007	2555	2555	2556	2542	2528	2522	2517	2514	2508	2504	2501	2491
2008	2483	2485	2479	2468	2462	2459	2457	2453	2450	2442	2438	2436
2009	2419	2409	2402	2395	2388	2379	2378	2378	2366	2361	2361	2352
2010	2352	2346	2342	2332	2326	2315	2310	2298	2288	2272	2269	2253

Panel B. The Average Value of the *Knowledge-Base Overlap Ratio* by Calendar Month

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	4.37E-05	4.38E-05	4.41E-05	4.39E-05	4.40E-05	4.39E-05	4.39E-05	4.39E-05	4.36E-05	4.39E-05	4.40E-05	4.44E-05
1985	4.42E-05	4.45E-05	4.45E-05	4.44E-05	4.49E-05	4.51E-05	4.52E-05	4.53E-05	4.53E-05	4.57E-05	4.58E-05	4.56E-05
1986	4.55E-05	4.51E-05	4.46E-05	4.45E-05	4.45E-05	4.44E-05	4.44E-05	4.43E-05	4.43E-05	4.44E-05	4.45E-05	4.40E-05
1987	4.38E-05	4.39E-05	4.35E-05	4.30E-05	4.33E-05	4.36E-05	4.43E-05	4.42E-05	4.44E-05	4.47E-05	4.47E-05	4.42E-05
1988	4.42E-05	4.42E-05	4.43E-05	4.43E-05	4.41E-05	4.48E-05	4.49E-05	4.49E-05	4.50E-05	4.55E-05	4.58E-05	4.55E-05
1989	4.60E-05	4.66E-05	4.74E-05	4.78E-05	4.80E-05	4.86E-05	4.91E-05	4.93E-05	4.95E-05	5.01E-05	4.94E-05	4.95E-05
1990	5.01E-05	5.02E-05	5.07E-05	5.09E-05	5.11E-05	5.16E-05	5.16E-05	5.20E-05	5.16E-05	5.14E-05	5.22E-05	5.20E-05
1991	5.22E-05	5.26E-05	5.30E-05	5.29E-05	5.34E-05	5.39E-05	5.36E-05	5.37E-05	5.36E-05	5.39E-05	5.38E-05	5.38E-05
1992	5.38E-05	5.38E-05	5.40E-05	5.41E-05	5.39E-05	5.35E-05	5.40E-05	5.42E-05	5.42E-05	5.44E-05	5.45E-05	5.48E-05
1993	5.48E-05	5.50E-05	5.51E-05	5.52E-05	5.59E-05	5.58E-05	5.60E-05	5.57E-05	5.65E-05	5.67E-05	5.66E-05	5.73E-05
1994	5.82E-05	5.78E-05	5.69E-05	5.62E-05	5.61E-05	5.60E-05	5.58E-05	5.61E-05	5.62E-05	5.60E-05	5.65E-05	5.69E-05
1995	5.73E-05	5.76E-05	5.80E-05	5.82E-05	5.78E-05	5.85E-05	5.89E-05	5.89E-05	5.93E-05	6.04E-05	6.02E-05	6.05E-05
1996	6.06E-05	6.05E-05	6.05E-05	6.06E-05	6.00E-05	5.97E-05	5.97E-05	6.00E-05	6.09E-05	6.14E-05	6.15E-05	6.15E-05
1997	6.18E-05	6.22E-05	6.22E-05	6.23E-05	6.22E-05	6.23E-05	6.25E-05	6.26E-05	6.34E-05	6.32E-05	6.34E-05	6.38E-05
1998	6.37E-05	6.39E-05	6.41E-05	6.44E-05	6.47E-05	6.54E-05	6.65E-05	6.63E-05	6.71E-05	6.78E-05	6.82E-05	6.88E-05
1999	6.89E-05	6.91E-05	6.98E-05	7.05E-05	7.08E-05	7.11E-05	7.15E-05	7.16E-05	7.17E-05	7.23E-05	7.27E-05	7.33E-05
2000	7.38E-05	7.37E-05	7.37E-05	7.40E-05	7.45E-05	7.50E-05	7.51E-05	7.57E-05	7.51E-05	7.50E-05	7.58E-05	7.62E-05
2001	7.60E-05	7.64E-05	7.72E-05	7.73E-05	7.79E-05	7.93E-05	7.99E-05	8.02E-05	7.97E-05	8.05E-05	8.13E-05	8.20E-05
2002	8.21E-05	8.23E-05	8.23E-05	8.29E-05	8.35E-05	8.37E-05	8.47E-05	8.47E-05	8.55E-05	8.58E-05	8.66E-05	8.65E-05
2003	8.73E-05	8.78E-05	8.76E-05	8.78E-05	8.77E-05	8.84E-05	8.88E-05	8.89E-05	8.88E-05	8.98E-05	8.97E-05	9.01E-05
2004	9.05E-05	9.04E-05	9.06E-05	9.11E-05	9.16E-05	9.21E-05	9.24E-05	9.33E-05	9.38E-05	9.49E-05	9.50E-05	9.54E-05
2005	9.54E-05	9.48E-05	9.50E-05	9.50E-05	9.54E-05	9.67E-05	9.78E-05	9.85E-05	9.84E-05	9.89E-05	9.96E-05	9.98E-05
2006	1.00E-04	1.01E-04	1.01E-04	1.01E-04	1.01E-04	1.02E-04	1.03E-04	1.03E-04	1.05E-04	1.05E-04	1.07E-04	1.07E-04
2007	1.08E-04	1.09E-04	1.09E-04	1.10E-04	1.11E-04	1.11E-04	1.11E-04	1.10E-04	1.10E-04	1.10E-04	1.11E-04	1.12E-04
2008	1.12E-04	1.13E-04	1.13E-04	1.13E-04	1.14E-04	1.14E-04	1.14E-04	1.16E-04	1.16E-04	1.16E-04	1.17E-04	1.17E-04
2009	1.18E-04	1.19E-04	1.18E-04	1.19E-04	1.19E-04	1.19E-04	1.19E-04	1.19E-04	1.20E-04	1.21E-04	1.21E-04	1.22E-04
2010	1.22E-04	1.22E-04	1.23E-04	1.24E-04	1.24E-04	1.24E-04	1.25E-04	1.26E-04	1.27E-04	1.27E-04	1.27E-04	1.26E-04

Panel C. The 98th Percentile of the Firm-pair *Knowledge-Base Overlap Ratio*

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
1984	9.81E-05	9.71E-05	1.03E-04	1.02E-04	1.02E-04	1.02E-04	1.02E-04	1.09E-04	1.07E-04	1.09E-04	1.10E-04	1.13E-04
1985	1.10E-04	1.29E-04	1.29E-04	1.23E-04	1.27E-04	1.29E-04	1.28E-04	1.28E-04	1.40E-04	1.59E-04	1.61E-04	1.61E-04
1986	1.61E-04	1.60E-04	1.55E-04	1.51E-04	1.43E-04	1.43E-04	1.34E-04	1.23E-04	1.26E-04	1.24E-04	1.27E-04	1.14E-04
1987	1.19E-04	1.12E-04	1.07E-04	9.49E-05	9.51E-05	9.72E-05	1.03E-04	1.01E-04	1.07E-04	1.01E-04	9.87E-05	8.94E-05
1988	8.78E-05	8.78E-05	8.73E-05	8.63E-05	8.47E-05	8.99E-05	8.87E-05	9.59E-05	9.65E-05	1.03E-04	1.06E-04	1.07E-04
1989	1.13E-04	1.16E-04	1.22E-04	1.31E-04	1.34E-04	1.37E-04	1.43E-04	1.42E-04	1.43E-04	1.50E-04	1.42E-04	1.43E-04
1990	1.47E-04	1.45E-04	1.47E-04	1.49E-04	1.52E-04	1.68E-04	1.63E-04	1.72E-04	1.69E-04	1.67E-04	1.75E-04	1.71E-04
1991	1.70E-04	1.71E-04	1.73E-04	1.72E-04	1.80E-04	1.88E-04	1.85E-04	1.91E-04	1.88E-04	1.96E-04	1.95E-04	2.01E-04
1992	1.89E-04	1.85E-04	1.88E-04	1.85E-04	1.85E-04	1.78E-04	1.72E-04	1.71E-04	1.71E-04	1.74E-04	1.74E-04	1.79E-04
1993	1.73E-04	1.78E-04	1.78E-04	1.83E-04	1.91E-04	1.84E-04	1.87E-04	1.84E-04	1.92E-04	1.99E-04	1.96E-04	2.01E-04
1994	2.12E-04	2.02E-04	1.99E-04	1.89E-04	1.78E-04	1.74E-04	1.66E-04	1.63E-04	1.64E-04	1.67E-04	1.69E-04	1.75E-04
1995	1.83E-04	1.89E-04	1.88E-04	1.93E-04	1.85E-04	1.91E-04	1.91E-04	1.85E-04	1.91E-04	2.00E-04	1.92E-04	1.98E-04
1996	1.97E-04	1.99E-04	1.99E-04	1.99E-04	1.91E-04	1.84E-04	1.84E-04	1.80E-04	1.84E-04	1.87E-04	1.85E-04	1.83E-04
1997	1.77E-04	1.79E-04	1.77E-04	1.75E-04	1.59E-04	1.62E-04	1.62E-04	1.62E-04	1.62E-04	1.62E-04	1.61E-04	1.64E-04
1998	1.66E-04	1.64E-04	1.64E-04	1.68E-04	1.68E-04	1.72E-04	1.86E-04	1.83E-04	1.91E-04	1.96E-04	1.98E-04	2.03E-04
1999	2.04E-04	1.99E-04	2.00E-04	2.08E-04	2.08E-04	2.10E-04	2.13E-04	2.13E-04	2.14E-04	2.21E-04	2.25E-04	2.28E-04
2000	2.31E-04	2.28E-04	2.28E-04	2.32E-04	2.36E-04	2.39E-04	2.37E-04	2.44E-04	2.37E-04	2.36E-04	2.41E-04	2.43E-04
2001	2.42E-04	2.46E-04	2.57E-04	2.59E-04	2.66E-04	2.74E-04	2.80E-04	2.85E-04	2.82E-04	2.87E-04	2.95E-04	3.01E-04
2002	3.02E-04	3.03E-04	3.01E-04	3.12E-04	3.24E-04	3.28E-04	3.41E-04	3.46E-04	3.57E-04	3.64E-04	3.76E-04	3.75E-04
2003	3.90E-04	3.97E-04	3.97E-04	3.99E-04	4.10E-04	4.18E-04	4.25E-04	4.32E-04	4.32E-04	4.46E-04	4.48E-04	4.54E-04
2004	4.61E-04	4.63E-04	4.72E-04	4.85E-04	4.95E-04	5.13E-04	5.23E-04	5.46E-04	5.57E-04	5.72E-04	5.78E-04	5.96E-04
2005	6.01E-04	5.99E-04	6.04E-04	6.05E-04	6.14E-04	6.34E-04	6.48E-04	6.56E-04	6.71E-04	6.81E-04	6.93E-04	7.00E-04
2006	7.14E-04	7.23E-04	7.32E-04	7.45E-04	7.56E-04	7.68E-04	7.93E-04	8.08E-04	8.27E-04	8.41E-04	8.70E-04	8.73E-04
2007	8.88E-04	9.00E-04	9.07E-04	9.25E-04	9.39E-04	9.43E-04	9.38E-04	9.26E-04	9.32E-04	9.35E-04	9.34E-04	9.53E-04
2008	9.56E-04	9.62E-04	9.63E-04	9.81E-04	9.90E-04	9.90E-04	9.93E-04	1.01E-03	1.02E-03	1.02E-03	1.03E-03	1.03E-03
2009	1.05E-03	1.07E-03	1.06E-03	1.07E-03	1.07E-03	1.08E-03	1.07E-03	1.07E-03	1.08E-03	1.10E-03	1.10E-03	1.10E-03
2010	1.11E-03	1.11E-03	1.12E-03	1.12E-03	1.12E-03	1.13E-03	1.14E-03	1.16E-03	1.16E-03	1.17E-03	1.17E-03	1.15E-03

Table OAT5: **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 calendar year and industry. Panel A reports the sample distribution and attrition by year. Column 1 contains the number of targets in all the acquisitions announced between January 1, 1984 and December 31, 2010, covered by the Thomson Reuters SDC Platinum M&A database. Column 2 reports the number of targets with patent data. Column 3 reports the average number of technology-peer candidates per target. Column 4 reports the average monthly 98^{th} percentiles of the *Technology Proximity Score* (defined in Table 1), i.e., the threshold values used to define the technology peers by month. Column 5 reports the number of targets that have technology peers. Column 6 reports the number of peers averaged across the acquisition targets. Column 7 reports the number of targets that have technology peers which have the required stock return data from CRSP. Column 8 reports the number of technology peers with valid stock return data averaged across the target firms. Panel B reports the sample distribution across the Fama-French 48 industries.

Panel A. Sample Distribution by Year

Year	Number of Acquisition Targets Covered by SDC	Number of Acquisition Targets with Valid Patent Data	Number of Technology-Peer Candidates per Acquisition Target	Average *Technology Proximity Score* Threshold Value	Number of Acquisition Targets Having Technology Peers	Number of Technology Peers per Acquisition Target	Number of Targets with Technology Peers that Have Valid Stock-Return Data	Number of Peers with Valid Stock-Return Data per Acquisition Target
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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 Covered by SDC	Number of Acquisition Targets with Valid Patent Data	Number of Technology Peer Candidates per Target	Average *Technology Proximity Score* Threshold Value	Number of Acquisition Targets Having Technology Peers	Number of Technology Peers per Acquisition Target	Number of Targets with Technology Peers that Have Valid Stock-Return Data	Number of Peers with Valid 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 48 Industries

Fama-French 48 Industry	Number of Acquisition Targets Having Technology Peers	Percentage of Acquisition Targets having Technology Peers	Number of Technology Peers	Percentage of Technology Peers
Agriculture	3	0.24%	65	0.14%
Food Products	10	0.80%	474	1.01%
Candy & Soda	2	0.16%	77	0.16%
Beer & Liquor	1	0.08%	145	0.31%
Tobacco Products	0	0.00%	21	0.04%
Recreation	16	1.27%	282	0.60%
Entertainment	11	0.88%	116	0.25%
Printing and Publishing	3	0.24%	111	0.24%
Consumer Goods	31	2.47%	982	2.08%
Apparel	6	0.48%	146	0.31%
Healthcare	11	0.88%	545	1.16%
Medical Equipment	138	10.98%	4439	9.42%
Pharmaceutical Products	111	8.83%	11751	24.93%
Chemicals	34	2.70%	1584	3.36%
Rubber and Plastic Products	27	2.15%	437	0.93%
Textiles	5	0.40%	271	0.57%
Construction Materials	32	2.55%	900	1.91%
Construction	5	0.40%	120	0.25%
Steel Works Etc.	15	1.19%	419	0.89%
Fabricated Products	5	0.40%	99	0.21%
Machinery	73	5.81%	1455	3.09%
Electrical Equipment	26	2.07%	1825	3.87%
Automobiles and Trucks	22	1.75%	608	1.29%
Aircraft	17	1.35%	266	0.56%
Shipbuilding, Railroad Equipment	1	0.08%	59	0.13%
Defense	9	0.72%	86	0.18%
Precious Metals	3	0.24%	53	0.11%
Non-Metallic and Industrial Metal Mining	3	0.24%	134	0.28%
Coal	0	0.00%	22	0.05%
Petroleum and Natural Gas	19	1.51%	659	1.40%
Communication	25	1.99%	895	1.90%
Personal Services	0	0.00%	160	0.34%
Business Services	184	14.64%	6662	14.13%
Computers	121	9.63%	2480	5.26%
Electronic Equipment	171	13.60%	4386	9.31%
Measuring and Control Equipment	58	4.61%	1934	4.10%
Business Supplies	24	1.91%	610	1.29%
Shipping Containers	6	0.48%	337	0.71%
Transportation	4	0.32%	171	0.36%
Wholesale	14	1.11%	803	1.70%
Retail	6	0.48%	238	0.50%
Restaurants, Hotels, Motels	4	0.32%	60	0.13%
Others	1	0.08%	248	0.53%
Total	1257	100.00%	47135	100.00%

Table OAT6: **Difference between Technology Space and Other Spaces**

This table compares the number of technology peers (percentage in parentheses) that belong to their corresponding target firms' product markets (Bloom et al., 2013), three-digit SIC industries, FF-48 industries, text-based TNIC-3 industry spaces (Hoberg and Phillips, 2010), downstream industries, upstream industries, and states to the number of technology peers (percentage in parentheses) that do not.

Year	Number of Acquisition Targets	Number of Technology Peers	Number of Technology Peers in the Targets' Product Markets	Number of Technology Peers NOT in the Targets' Product Markets	Number of Technology Peers in the Targets' SIC-3 Industries	Number of Technology Peers NOT in the Targets' SIC-3 Industries	Number of Technology Peers in the Targets' FF-48 Industries	Number of Technology Peers NOT in the Targets' FF-48 Industries
1984	26	820	80	633	82	738	173	647
1985	45	1560	170	1209	199	1361	310	1250
1986	51	1610	174	1117	174	1436	319	1291
1987	38	839	137	593	137	702	193	646
1988	43	1279	101	911	98	1181	199	1080
1989	31	879	147	618	178	701	206	673
1990	14	368	52	273	39	329	58	310
1991	16	477	184	262	96	381	112	365
1992	15	461	140	279	116	345	129	332
1993	16	672	43	559	75	597	107	565
1994	43	1838	495	1144	556	1282	600	1238
1995	54	1783	462	1106	529	1254	627	1156
1996	54	1534	225	1171	360	1174	451	1083
1997	70	2362	406	1644	693	1669	745	1617
1998	101	3504	734	2327	1253	2251	1360	2144
1999	100	4796	1071	3100	1750	3046	1883	2913
2000	79	2604	410	1542	1001	1603	1087	1517
2001	56	2800	537	1821	1347	1453	1391	1409
2002	43	1903	315	1229	764	1139	807	1096
2003	44	2645	498	1538	1558	1087	1617	1028
2004	40	1744	280	1212	803	941	872	872
2005	52	2464	402	1530	1148	1316	1315	1149
2006	46	1468	213	1036	702	766	761	707
2007	51	1644	357	1036	682	962	785	859
2008	48	2173	422	1256	1078	1095	1136	1037
2009	48	2203	319	1162	1200	1003	1299	904
2010	33	705	92	491	255	450	282	423
Total	1257	47135	8466 (22%)	30799 (78%)	16873 (36%)	30262 (64%)	18824 (40%)	28311 (60%)

Year	Number of Technology Peers in the Targets' TNIC-3 Industries	Number of Technology Peers NOT in the Targets' TNIC-3 Industries	Number of Technology Peers in the Downstream of the Target	Number of Technology Peers NOT in the Downstream of the Target	Number of Technology Peers in the Upstream of the Target	Number of Technology Peers NOT in the Upstream of the Target	Number of Technology Peers in the Targets' States	Number of Technology Peers NOT in the Targets' States
1984			0	815	0	815	58	668
1985			9	1535	14	1530	98	1309
1986			137	1466	141	1462	94	1412
1987			4	829	5	828	48	724
1988			43	1234	67	1210	116	1002
1989			103	775	129	749	103	730
1990			18	349	49	318	33	320
1991			90	384	120	354	36	408
1992			16	442	22	436	38	375
1993			68	600	81	587	67	560
1994			138	1696	235	1599	181	1441
1995			186	1592	335	1443	158	1489
1996			81	1452	202	1331	142	1253
1997	470	1892	8	2352	13	2347	332	1773
1998	819	2685	511	2989	624	2876	415	2557
1999	1625	3171	1042	3752	1147	3647	594	3239
2000	646	1958	557	2047	653	1951	191	1798
2001	1144	1656	751	2049	834	1966	357	1623
2002	519	1384	20	1883	29	1874	237	1054
2003	1115	1530	526	2119	602	2043	333	1662
2004	664	1080	305	1439	385	1359	352	932
2005	907	1557	618	1846	709	1755	338	1493
2006	485	983	430	1038	423	1045	135	1044
2007	514	1130	0	1644	0	1644	211	919
2008	1010	1163	0	2170	0	2170	356	1393
2009	969	1234	0	2202	0	2202	297	1286
2010	199	506	0	703	0	703	98	470
Total	11086 (34%)	21929 (66%)	5661 (12%)	41402 (88%)	6819 (14%)	40244 (86%)	5418 (14%)	32934 (86%)

Table OAT7: **Summary Statistics of Firm and Deal Characteristics**

This table contains the summary statistics of the characteristics of acquiring firms (Panel A), target firms (Panel B), technology-peer candidates (Panel C), technology peers (Panel D), and M&A deals (Panel E). Detailed definitions of these variables are in Table 1 and Table OAT1 of the Online Appendix. The samples of acquisitions and technology peers are described in Table OAT5 of the Online Appendix.

Panel A. Acquiring Firms

Variable	Obs.	Mean	Median	Std.
Sales Increase	1,116	0.1138	0.1073	0.2109
Closely Held Shares	1,053	0.1570	0.1110	0.1880
Leverage	1,152	0.1832	0.1618	0.1610
Market Cap	1,159	7.1889	7.1306	2.1761
ROA	1,158	0.0948	0.1091	0.1256
M/B 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	0.1800	0.2000
Leverage	1,230	0.1797	0.1312	0.1893
Market Cap	1,234	4.9744	4.8397	1.7986
ROA	1,238	−0.0119	0.0591	0.2496
M/B 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
Market Cap	2,307,661	5.2248	5.0360	2.1869
ROA	2,311,579	−0.0209	0.0650	0.2828
M/B 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	0.0360	0.0908	0.4723
Closely Held Shares	38,694	0.2188	0.1667	0.2012
Leverage	49,993	0.1712	0.1111	0.1969
Market Cap	50,069	5.2888	5.0068	2.2265
ROA	50,130	−0.0935	0.0394	0.3474
M/B Ratio	50,065	2.8245	1.9345	2.4820
HHI	48,773	0.1112	0.0641	0.1077

Panel E. Deals

Variable	Obs.	Mean	Median	Std.
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
Dormant Period	1,307	5.1032	4.8828	2.0677

Table OAT8: **The Abnormal Returns on Technology Peers – Firm-Level Evidence**

This table reports the cumulative average abnormal returns (CAARs) on technology peers during the deal announcement of their respective targets. We describe the samples of acquisitions and peers in Table OAT5 of the Online Appendix. In Panel A, the cumulative abnormal return (CAR) of each firm, measured over different windows (day 0 being the deal announcement day), is estimated using the market model with the value-weighted market index of all CRSP firms. 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 peers, estimated using different models. The CAARs are measured over a five-day window (−2, +2) centered on the acquisition announcement day. In particular, we estimate each firm's CAR based on the market model (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. Panel C reports the market-model CAARs on the technology peers where target technology peers are defined based on alternative technology proximity measures (defined in Table 1). *, **, 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 Peers	CAAR	StdCsect Z
CAAR (−2, 0)	47121	0.15%	4.238***
CAAR (0, +2)	47123	0.23%	6.698***
CAAR (−2, +2)	47123	0.33%	7.284***
CAAR (−5, +5)	47124	0.55%	7.893***

Panel B. CAAR (−2, +2) Using Alternative Estimation Methods and Test Statistics

Estimation Method	Number of Peers	CAAR	Positive : Negative ARs	StdCsect Z	Time-series (CDA) t	Generalized Sign Z
Market-Model-Adjusted Return	47123	0.33%	22962:24161	7.284***	3.667***	7.936***
Market-Adjusted Return	47123	0.55%	23532:23591	11.103***	6.022***	10.238***
Market Model with GARCH (1,1)	47123	0.49%	23370:23753	n/a	5.474***	8.987***
Scholes-Williams Abnormal Return	47123	0.32%	22990:24133	7.063***	3.497***	7.595***
Fama-French-Model-Adjusted Return	47123	0.23%	22757:24366	5.664***	3.321***	4.788***

Panel C. CAAR (−2, +2) Using Alternative Definitions of Target Technology Peers (Market-Model-Adjusted)

Technology Proximity Measures	Number of Peers	CAAR	StdCsect Z
Mahalanobis Distance	47222	0.39%	9.045***
Knowledge-Base Overlap Ratio	50580	0.22%	6.537***

Table OAT9: **Abnormal Returns on the Portfolios of Technology-Peer Candidates 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) values of the *Technology Proximity Score*, 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 values of the *Technology Proximity Score* 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 with the value-weighted market index of all CRSP firms. 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. *, **, 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 OAT10: **Placebo Tests Based on the CAAR Distribution of the Portfolios of Randomly-Selected Peer Candidates**

This table compares the cumulative average abnormal returns (CAARs) on different technology-peer portfolios to the distribution of CAARs on non-peer portfolios containing the randomly-selected peer candidates that are not technology peers of their corresponding acquisition targets. In the first column, we report the CAARs on different equal-weighted portfolios of the actual technology peers. We form the technology-peer portfolios based on the peers' relation to their corresponding target firms considering the following binary variables: *Product Market Dummy*, *Same SIC-3 Industry Dummy*, *Same FF-48 Industry Dummy*, *Same TNIC-3 Industry Dummy*, *Same State Dummy*, *Customer Dummy*, and *Supplier Dummy*. Detailed variable definitions can be found in Table 1. In each draw of non-peer candidates (i.e., candidates that are not peers), we randomly select a number of non-peer candidates equal to the number 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. For example, when a peer is not in the corresponding target's product market, neither is the randomly-selected non-peer candidate. We replicate this process 1000 times to determine the empirical CAAR distribution. The cumulative abnormal returns (CARs) of each firm, measured over the window (−2, +2), are estimated using the market model with the value-weighted market index of all CRSP firms.

The CAARs on Actual Technology-Peer Portfolios	The CAAR Distributions of Randomly-Selected Non-Peer Portfolios					
	Mean	Median	75th	90th	95th	99th
All Firms:						
0.26%	0.05%	0.05%	0.08%	0.10%	0.12%	0.15%
Product Market Dummy=1:						
0.46%	0.24%	0.24%	0.32%	0.40%	0.45%	0.55%
Product Market Dummy=0:						
0.24%	0.05%	0.05%	0.08%	0.11%	0.13%	0.17%
Same SIC-3 Industry Dummy=1:						
0.37%	0.20%	0.20%	0.27%	0.34%	0.37%	0.42%
Same SIC-3 Industry Dummy=0:						
0.18%	0.04%	0.04%	0.08%	0.11%	0.13%	0.17%
Same FF-48 Industry Dummy=1:						
0.33%	0.15%	0.15%	0.20%	0.25%	0.29%	0.33%
Same FF-48 Industry Dummy=0:						
0.18%	0.04%	0.04%	0.08%	0.11%	0.13%	0.17%
Same TNIC-3 Industry Dummy=1:						
0.37%	0.24%	0.24%	0.32%	0.40%	0.45%	0.55%
Same TNIC-3 Industry Dummy=0:						
0.32%	0.07%	0.07%	0.12%	0.16%	0.19%	0.23%
Same State Dummy=1:						
0.50%	0.09%	0.09%	0.19%	0.30%	0.37%	0.48%
Same State Dummy=0:						
0.26%	0.05%	0.05%	0.08%	0.11%	0.12%	0.16%
Customer Dummy=1:						
0.36%	0.11%	0.10%	0.26%	0.41%	0.50%	0.64%
Customer Dummy=0:						
0.26%	0.05%	0.05%	0.08%	0.11%	0.12%	0.16%
Supplier Dummy=1:						
0.14%	0.11%	0.10%	0.20%	0.29%	0.33%	0.46%
Supplier Dummy=0:						
0.28%	0.04%	0.04%	0.07%	0.10%	0.12%	0.14%

Table OAT11: **The Determinants of Abnormal Returns on Peer Candidates – Standard Errors Clustered by Year**

This table reports the estimates of the determinants of technology-peer candidates' cumulative abnormal returns (CARs). The sample includes all of the peer candidates with valid data. The dependent variable is a peer candidate's CAR. Moreover, the CAR on each firm, measured over the window (−2, +2), is estimated using the market model with the value-weighted market index of all CRSP firms. We regress a peer candidate's CAR on the *Technology Proximity Score* or the *Technology-Peer Dummy*, controlling for the *Product Proximity Score* between a peer candidate and its corresponding acquisition target, the spillover effects through geographical channels (*Same State Dummy*) and supply chains (*Supplier Dummy* and *Customer Dummy*), and other firm characteristics (these variables are defined in Table 1). The t-statistics, clustered by year, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Technology Proximity Score	0.486***		0.435***		0.449***	
	(5.51)		(3.87)		(4.29)	
Technology-Peer Dummy		0.281***		0.238***		0.237***
		(5.36)		(3.37)		(3.34)
Sales Increase	0.000	−0.000	0.024	0.024	0.025	0.024
	(0.00)	(−0.01)	(0.50)	(0.49)	(0.52)	(0.51)
Closely Held Shares	−0.035	−0.036	−0.045	−0.046	−0.065	−0.066
	(−0.61)	(−0.63)	(−0.72)	(−0.73)	(−1.01)	(−1.03)
Leverage	−0.010	−0.012	0.013	0.013	0.049	0.049
	(−0.07)	(−0.08)	(0.08)	(0.08)	(0.30)	(0.30)
Market Cap	−0.003	−0.002	−0.008	−0.006	−0.006	−0.005
	(−0.12)	(−0.08)	(−0.30)	(−0.26)	(−0.23)	(−0.19)
ROA	−0.166	−0.171	−0.136	−0.140	−0.135	−0.139
	(−0.97)	(−1.00)	(−0.89)	(−0.91)	(−0.85)	(−0.87)
M/B Ratio	−0.138***	−0.139***	−0.136***	−0.137***	−0.142***	−0.143***
	(−8.24)	(−8.27)	(−7.48)	(−7.51)	(−8.02)	(−8.05)
HHI	−0.141	−0.147	−0.137	−0.139	−0.123	−0.126
	(−0.82)	(−0.85)	(−0.84)	(−0.86)	(−0.80)	(−0.81)
Product Proximity Score			0.135*	0.164**	0.114**	0.143**
			(1.94)	(2.41)	(2.06)	(2.70)
Same State Dummy					0.053	0.055
					(0.92)	(0.95)
Supplier Dummy					0.100	0.102
					(0.97)	(0.99)
Customer Dummy					−0.059	−0.056
					(−0.87)	(−0.82)
Joint Significant Wald Test of Same State Dummy, Supplier Dummy, and Customer Dummy (p-value)					0.473	0.475
Deal Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.036	0.036	0.038	0.038	0.039	0.039
Observations	1543391	1543391	1334932	1334932	1188322	1188322

Table OAT12: **The Determinants of Abnormal Returns on Peer Candidates – Standard Errors Clustered by Patent Class**

This table reports the estimates of the determinants of target technology-peer candidates' cumulative abnormal returns (CARs). The sample includes all target peer candidates with valid data. The dependent variable is a target peer candidate's CAR. The CAR on each firm, measured over the window (−2, +2), is estimated using the market model with the value-weighted market index of all CRSP firms. We regress a target peer candidate's CAR on the *Technology Proximity Score* or the *Technology-Peer Dummy*, controlling for the *Product Proximity Score* and other firm characteristics. All the variables are defined in Table 1. The t-statistics, clustered by deal and the primary patent class, are in parentheses. A peer candidate's primary patent class is the class in which the peer candidate has received the highest cumulative value of patents over the previous 60 months. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)
Technology Proximity Score	0.435***	
	(3.70)	
Technology-Peer Dummy		0.238***
		(3.50)
Product Proximity Score	0.135**	0.164**
	(2.01)	(2.33)
Sales Increase	0.024	0.024
	(0.60)	(0.58)
Closely Held Shares	−0.045	−0.046
	(−0.92)	(−0.94)
Leverage	0.013	0.013
	(0.17)	(0.16)
Market Cap	−0.008	−0.006
	(−0.65)	(−0.56)
ROA	−0.136	−0.140
	(−1.09)	(−1.12)
M/B Ratio	−0.136***	−0.137***
	(−9.24)	(−9.25)
HHI	−0.137	−0.139
	(−1.46)	(−1.48)
Deal Fixed Effects	Yes	Yes
R^2	0.038	0.038
Observations	1334932	1334932

Table OAT13: **The Determinants of Abnormal Returns on Peer Candidates – Alternative Measures of Product-Market Relations**

This table reports the estimates of 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 with the value-weighted market index of all CRSP firms. We regress a peer candidate's CAR on the *Technology Proximity Score* or the *Technology-Peer Dummy*, controlling for several alternative measures of the industry relations between the peer candidates and the corresponding acquisition targets (*Same SIC-3 Industry Dummy*, *Same TNIC-3 Industry Dummy* or *Product Market Dummy*), and other firm characteristics. All of the variables are defined in Table 1. The t-statistics, clustered by deal, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Technology Proximity Score	0.414***		0.444***		0.467***	
	(3.46)		(3.29)		(3.73)	
Technology-Peer Dummy		0.234***		0.254***		0.260***
		(3.29)		(2.92)		(3.44)
Same SIC-3 Industry Dummy	0.129*	0.153**				
	(1.83)	(2.12)				
Same TNIC-3 Industry Dummy			0.105	0.137		
			(1.05)	(1.35)		
Product Market Dummy					0.184**	0.210***
					(2.42)	(2.68)
Sales Increase	−0.001	−0.001	0.043	0.043	0.024	0.024
	(−0.02)	(−0.04)	(1.35)	(1.33)	(0.77)	(0.75)
Closely Held Shares	−0.034	−0.035	−0.052	−0.053	−0.046	−0.047
	(−0.92)	(−0.94)	(−1.20)	(−1.22)	(−1.12)	(−1.15)
Leverage	−0.004	−0.005	0.001	0.001	0.012	0.011
	(−0.07)	(−0.07)	(0.02)	(0.01)	(0.18)	(0.16)
Market Cap	−0.003	−0.002	−0.001	−0.000	−0.008	−0.006
	(−0.26)	(−0.16)	(−0.09)	(−0.00)	(−0.69)	(−0.57)
ROA	−0.164*	−0.168*	−0.154	−0.157	−0.136	−0.140
	(−1.75)	(−1.79)	(−1.54)	(−1.57)	(−1.40)	(−1.45)
M/B Ratio	−0.139***	−0.139***	−0.144***	−0.144***	−0.136***	−0.136***
	(−10.41)	(−10.42)	(−9.57)	(−9.58)	(−9.84)	(−9.85)
HHI	−0.123	−0.125	−0.200**	−0.204**	−0.142*	−0.146*
	(−1.57)	(−1.59)	(−2.09)	(−2.13)	(−1.68)	(−1.73)
Deal Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.036	0.036	0.038	0.038	0.038	0.038
Observations	1543391	1543391	1201980	1201980	1334932	1334932

Table OAT14: **The Determinants of Abnormal Returns on Peer Candidates – Excluding Acquirers' Technology Peers**

This table reports the estimates of the determinants of target technology-peer candidates' cumulative abnormal returns (CARs). The dependent variable is a target peer candidate's CAR. The CAR on each firm, measured over the window (−2, +2), is estimated using the market model with the value-weighted market index of all CRSP firms. We regress a target peer candidate's CAR on the *Technology Proximity Score* or the *Technology-Peer Dummy*, controlling for the *Product Proximity Score* and other firm characteristics. All the variables are defined in the Table 1. The sample includes the target peer candidates with valid data except those that are technology peers of the corresponding acquirers. The *t*-statistics, clustered by deal, are in parentheses. *, **, and *** denote the statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)
Technology Proximity Score	0.395***	
	(3.01)	
Technology-Peer Dummy		0.198**
		(2.49)
Product Proximity Score	0.095	0.119
	(1.30)	(1.60)
Sales Increase	0.020	0.020
	(0.64)	(0.62)
Closely Held Shares	−0.043	−0.044
	(−1.03)	(−1.05)
Leverage	−0.003	−0.004
	(−0.05)	(−0.05)
Market Cap	−0.007	−0.006
	(−0.67)	(−0.58)
ROA	−0.128	−0.131
	(−1.30)	(−1.33)
M/B Ratio	−0.137***	−0.137***
	(−9.73)	(−9.75)
HHI	−0.134	−0.136
	(−1.59)	(−1.61)
Deal Fixed Effects	Yes	Yes
R^2	0.038	0.038
Observations	1307905	1307905

Table OAT15: **Boundaries of the Main Finding**

This table reports the cross-sectional variation of the effect of the *Technology Proximity Score* on the target firms' technology-peer candidates' value revision. 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 with the value-weighted market index of all CRSP firms. We regress this variable on the *Technology Proximity Score* and several interaction terms built using the *Technology Proximity Score* with dummy variables for specific sub-periods (*Later Sample-Period Dummy* and *Dot-Com Bubble Dummy*), merger waves (*High Capital Liquidity Dummy* and *Industry Merger-Wave Dummy*), innovation waves (*Industry (Patent-Class) Innovation-Wave Dummy*), industry-level technological concentration (*Low Technology-Concentration Dummy: Target (Candidate)*), product market concentration (*Low Product-Concentration Dummy: Target (Candidate)*), and specific industries (*Pharmaceutical Industry Dummy: Target (Candidate)* and *IT Industry Dummy: Target (Candidate)*). The control variables are the same as those in Panel C of 4. All of the variables are defined in Table 1 and Table OAT1 of the Online Appendix. The t-statistics, clustered by deal, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Dummy Variable	(1) Later Sample-Period	(2) Dot-Com Bubble	(3) High Capital Liquidity	(4) Industry Merger-Wave	(5) Industry Innovation-Wave
Dummy Variable * Technology Proximity Score	0.053	0.230	−0.169	0.483	0.588
	(0.25)	(0.74)	(−0.70)	(1.54)	(1.46)
Technology Proximity Score	0.393***	0.365***	0.538***	0.349**	0.460**
	(2.62)	(2.58)	(3.62)	(2.54)	(2.22)
Other Control Variables	Yes	Yes	Yes	Yes	Yes
Deal Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.038	0.038	0.038	0.038	0.038
Observations	1334932	1334932	1334932	1334932	848673

Dummy Variable	(6) Patent-Class Innovation-wave	(7) Low Technology-Concentration: Target	(8) Low Technology-Concentration: Candidate	(9) Low Product-Concentration: Target	(10) Low Product-Concentration: Candidate
Dummy Variable * Technology Proximity Score	−0.105	0.037	0.223	−0.059	0.083
	(−0.28)	(0.15)	(1.29)	(−0.23)	(0.53)
Technology Proximity Score	0.620***	0.412**	0.284**	0.473***	0.382***
	(2.91)	(2.57)	(2.15)	(3.16)	(2.80)
Other Control Variables	Yes	Yes	Yes	Yes	Yes
Deal Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.039	0.038	0.038	0.038	0.038
Observations	904260	1334932	1334932	1292701	1334932

Dummy Variable	(11) Pharmaceutical Industry (Target)	(12) Pharmaceutical Industry (Candidate)	(13) IT Industry (Target)	(14) IT Industry (Candidate)
Dummy Variable * Technology Proximity Score	0.497	−0.018	−0.190	−0.156
	(0.69)	(−0.07)	(−0.75)	(−0.69)
Technology Proximity Score	0.400***	0.432***	0.483***	0.471***
	(3.28)	(3.59)	(3.19)	(3.29)
Other Control Variables	Yes	Yes	Yes	Yes
Deal Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.038	0.038	0.038	0.038
Observations	1334932	1334932	1334932	1334932

Table OAT16: **The Determinants of a Firm's Likelihood of Being an Acquisition Target—*Previous-Acquisition Proximity Score***

This table reports the linear probability model estimates of the determinants of the likelihood a firm being an acquisition target in a given 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 utilities sectors) in the Compustat-CRSP merged database and all the acquisitions from the Thomson SDC Platinum M&A database over the 1984–2010 period. 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. The variable *Previous-Acquisition Proximity Score* is the value-weighted average of the technology proximity scores measured 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 Table 1 and Table OAT1 of the Online Appendix. The industry fixed effects are based on the Fama-French 48 industry definitions. t-statistics, clustered by year, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Previous-Acquisition Proximity Score	0.069***	0.071***	0.078***	0.082**	0.084**	0.082**
	(2.60)	(2.66)	(2.65)	(2.50)	(2.54)	(2.28)
M/B Ratio	−0.006***	−0.006***	−0.007***	−0.006***	−0.006***	−0.007***
	(−8.44)	(−8.43)	(−8.93)	(−7.99)	(−7.99)	(−8.47)
PPE	−0.029***	−0.029***	−0.031***	−0.028***	−0.027***	−0.030***
	(−3.06)	(−3.01)	(−2.91)	(−2.84)	(−2.78)	(−2.77)
Cash Ratio	−0.001	−0.001	0.001	−0.001	−0.002	−0.000
	(−0.64)	(−0.72)	(0.42)	(−1.26)	(−1.37)	(−0.25)
Blockholder Dummy	0.017***	0.018***	0.014***	0.018***	0.018***	0.014***
	(6.67)	(6.77)	(4.73)	(6.76)	(6.88)	(4.74)
Market Cap	−0.004***	−0.004***	−0.003***	−0.004***	−0.004***	−0.003***
	(−5.25)	(−5.20)	(−3.41)	(−5.30)	(−5.29)	(−3.43)
Leverage	0.027***	0.027***	0.033***	0.028***	0.029***	0.034***
	(3.39)	(3.42)	(3.81)	(3.54)	(3.57)	(3.92)
ROA	−0.015**	−0.013**	−0.017**	−0.013**	−0.011*	−0.015**
	(−2.27)	(−2.03)	(−2.48)	(−1.96)	(−1.67)	(−2.08)
Age		−0.012**			−0.014**	
		(−2.07)			(−2.53)	
Age Squared		0.002*			0.003**	
		(1.92)			(2.34)	
Hostile Takeover Index			0.008			0.003
			(0.48)			(0.19)
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
R^2	0.015	0.015	0.015	0.040	0.040	0.042
Observations	40190	40190	35509	40190	40190	35509

Table OAT17: **Acquisition Vulnerability Estimation**

This table reports the logistic regression estimates of the likelihood of a firm being an acquisition target in a year (year t), used in Table 6 as the variable of interest. The sample comprises all the firm-years (excluding firms from the financial and utilities sectors) in the Compustat-CRSP merged database over the 1984–2010 period. 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 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 Table 1 and Table OAT1 of the Online Appendix. t-statistics, clustered by year, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)
Constant	−2.302***	−1.868***	−2.313***
	(−27.84)	(−13.90)	(−26.21)
M/B Ratio	−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 Ratio	0.007	0.011	0.030
	(0.41)	(0.59)	(1.58)
Blockholder Dummy	0.298***	0.318***	0.238***
	(6.43)	(6.83)	(4.82)
Market Cap	−0.066***	−0.053***	−0.030**
	(−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)
Age		−0.114	
		(−1.26)	
Age Squared		0.013	
		(0.68)	
Capital Liquidity		−0.186***	
		(−5.36)	
Hostile Takeover Index			−0.156
			(−0.56)
Pseudo R^2	0.013	0.015	0.011
Observations	41562	41562	36755

Table OAT18: **Abnormal Returns on Target Firms and their Technology Peers for Withdrawn Deals**

This table reports the cumulative average abnormal returns (CAARs) on the targets and their technology peers. In Panel A, we divide the deals in our sample into two groups based on whether a deal is completed or withdrawn, and calculate the CAARs on target firms and on the portfolios of their technology peers during the deal announcement period. The CAARs are measured over a five-day window (−2, +2) centered on the acquisition announcement day. The cumulative abnormal return (CAR) of each firm is estimated using the market model with the value-weighted market index of all CRSP firms. 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 and Panel C report 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 month in which the deal is announced (month zero), requiring valid data for at least six months over the estimation window. Panel B reports the CAARs for several windows relative to month zero, the announcement month. For example, (−1, +24) means the CAR on each firm is measured over the window from one month before to 24 months after the month of the announcement. In Panel C, we further clean up the sample of targets that are not subsequently acquired, by removing the deals withdrawn because the 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 cleaned sample for the same time windows as in Panel B. The time-series (CDA) t-test is a time-series standard deviation test that uses the entire sample for variance estimation. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. CAARs over the Acquisition Announcement Period

		Completed Deals			Withdrawn Deals		
	Event Time Period (in days)	N	CAAR	StdCsect Z	N	CAAR	StdCsect Z
Target Firms	(−2,+2)	1001	27.01%	29.895***	219	21.15%	11.925***
Portfolios of Technology-Peers	(−2,+2)	1010	0.25%	3.569***	222	0.28%	1.552*

Panel B. 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 C. 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 OAT19: **Abnormal Returns on Target Firms for Withdrawn Deals – Buy-and-Hold Abnormal Returns (BHAR)**

This table reports the average buy-and-hold abnormal returns (ABHARs) on the targets of withdrawn deals for various time windows. The BHAR on each firm is estimated using the DGTW benchmarks (see Daniel et al., 1997; Wermers, 2003) based on monthly data. Panel A reports the BHARs on target firms for several windows relative to the month of the acquisition announcement (month zero). For example, (−1, +24) means the ABHAR on each firm is measured over the window from one month before to 24 months after month zero. A target is classified as subsequently acquired if it is acquired within the five years after month zero. Otherwise, a target is deemed to have not been subsequently acquired. In Panel B, we further clean up the sample of targets of withdrawn deals that are not subsequently acquired, by removing the deals withdrawn because the 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 ABHARs of this cleaned sample for the same time windows. The time-series (CDA) t-test is a time-series standard deviation test that uses the entire sample for variance estimation. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. Target ABHARs of Withdrawn Deals

Event Time Period		Total Sample			Subsequently Acquired			Not Subsequently Acquired	
(in Months)	N	ABHAR	Time-Series t	N	ABHAR	Time-Series t	N	ABHAR	Time-Series t
(−1, 0)	204	26.48%	9.340***	98	29.58%	7.250***	106	23.61%	5.993***
(−1,1)	204	27.41%	8.130***	98	35.25%	6.840***	106	20.15%	4.679***
(−1,6)	204	23.04%	4.991***	98	33.76%	5.731***	106	13.12%	1.900*
(−1,12)	204	22.20%	4.012***	98	35.94%	5.541***	106	9.50%	1.099
(−1,24)	204	27.02%	3.452***	98	40.57%	5.913***	106	14.49%	1.067
(−1,48)	204	24.47%	1.826*	98	37.24%	5.133***	106	12.67%	0.508
(1,6)	196	−4.87%	−1.850*	93	0.71%	0.212	103	−9.91%	−2.522**
(1,12)	196	−7.18%	−2.231**	93	1.65%	0.427	103	−15.14%	−3.078***
(1,24)	196	−5.76%	−1.201	93	4.54%	1.08	103	−15.06%	−1.834*
(1,48)	196	−15.41%	−2.550**	93	1.47%	0.306	103	−30.64%	−2.932***

Panel B. Target ABHARs of the Deals Withdrawn due to Non-Price Reasons (for Targets not Subsequently Acquired)

Event Time Period (in Months)	N	ABHAR	Time-Series t
(−1, 0)	65	28.20%	5.891***
(−1,1)	65	23.85%	6.021***
(−1,6)	65	27.88%	2.892***
(−1,12)	65	24.62%	2.011**
(−1,24)	65	24.79%	1.244
(−1,48)	65	22.24%	0.595
(1,6)	62	−3.23%	−0.771
(1,12)	62	−8.17%	−1.496
(1,24)	62	−13.64%	−1.335
(1,48)	62	−31.40%	−2.415**

Table OAT20: **The Abnormal Returns on Technology Peers and Acquisition Intensity**

This table reports the regression estimates of how a target's technology peer's cumulative abnormal return (CAR) at the time of the acquisition announcement varies according to the change in acquisition intensity targeted at a firm's technology peers. The sample contains the technology peers described in columns (7) and (8) of Panel A Table OAT5 of the Online Appendix with valid data. The dependent variable (the CAR on each firm), measured over the window (−2, +2), is estimated using the market model with the value-weighted market index of all CRSP firms. The variable *Declining Acquisition-Intensity Dummy* equals one if the number of a target firm's technology peers acquired in the 12 months before the acquisition announcement month is not lower than the number of the target firm's technology peers acquired in the 12 months following this month and zero otherwise. The other independent variables are defined in Table 1 and Table OAT1 of the Online Appendix. The industry fixed effects are based on the Fama-French 48 industry definitions. *t*-statistics, clustered by deal, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
Declining Acquisition-Intensity Dummy	−0.446***	−0.353**	−0.354*	−0.368**
	(−2.69)	(−2.33)	(−1.95)	(−2.01)
Product Proximity Score			0.230	0.231
			(1.18)	(1.19)
Sales Increase			0.150	0.150
			(1.08)	(1.08)
Closely Held Shares			−0.355	−0.360
			(−1.33)	(−1.35)
Leverage			−0.130	−0.127
			(−0.43)	(−0.42)
Market Cap			−0.051	−0.051
			(−1.55)	(−1.56)
ROA			−0.226	−0.229
			(−0.73)	(−0.74)
M/B Ratio			−0.111***	−0.111***
			(−3.61)	(−3.61)
HHI			0.222	0.229
			(0.42)	(0.43)
Deal Value				0.014
				(0.23)
Horizontal-Merger Dummy				−0.027
				(−0.15)
Completed-Deal Dummy				0.429**
				(1.96)
Dormant Period				0.026
				(0.52)
Constant	0.432***			
	(3.68)			
Industry Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
R^2	0.001	0.005	0.006	0.007
Observations	47135	47135	29491	29491

Table OAT21: **The Future Acquirers of Technology Peers**

This table reports the percentiles, the mean, and the standard deviation of the empirical distributions of the coefficients on the determinants of the likelihood that a firm acquires a technology peer in the year following the acquisition, estimated using 1,000 iterations. The acquirer sample is constructed based on the peers that receive an actual bid in the year following an acquisition. In each iteration, the coefficients are obtained by estimating a conditional logit regression using a dataset that includes both the actual acquirers of the technology peers and, for each peer, a control group of five randomly-chosen pseudo acquirers. The dependent variable in the conditional logit specification is one for the actual future acquirers and zero for the pseudo acquirers. Deal fixed effects are included in all estimations. The variables *Technology Proximity Score*, *Technology-Peer Dummy*, *Product Proximity Score*, *Product Market Dummy*, *Same State Dummy*, *Customer Dummy*, and *Supplier Dummy* are constructed using information on the relations between each technology peer and the respective acquirers. All the variables are defined in Table 1 and Table OAT1 of the Online Appendix.

Panel A. The Future Acquirers of Technology Peers – Technology Proximity Score

	1%	5%	10%	50%	90%	95%	99%	mean	Std.
Technology Proximity Score	3.502	3.754	3.913	4.477	5.145	5.420	5.701	4.513	0.490
Product Proximity Score	2.677	2.829	2.898	3.167	3.513	3.606	3.827	3.192	0.243
Same State Dummy	0.107	0.241	0.316	0.576	0.829	0.891	1.015	0.575	0.197
Customer Dummy	−0.929	−0.627	−0.466	0.008	0.451	0.568	0.902	−0.005	0.372
Supplier Dummy	−0.143	0.061	0.156	0.488	0.821	0.927	1.153	0.487	0.266
Sales Increase	−0.243	−0.095	−0.015	0.297	0.634	0.741	0.968	0.312	0.259
M/B Ratio	−0.166	−0.137	−0.124	−0.073	−0.024	−0.009	0.020	−0.074	0.039
ROA	−0.691	−0.400	−0.256	0.276	0.878	1.025	1.304	0.288	0.441
Leverage	−2.006	−1.735	−1.584	−1.034	−0.525	−0.347	−0.112	−1.042	0.418
R&D	−0.146	−0.096	−0.070	−0.005	0.053	0.072	0.099	−0.007	0.050
Market Cap	0.439	0.471	0.479	0.533	0.586	0.597	0.628	0.533	0.040
Relative Patent Value	−0.205	−0.016	0.097	0.497	0.931	1.069	1.284	0.507	0.328
Pseudo R^2	0.663	0.673	0.679	0.698	0.719	0.724	0.737	0.698	0.016
Observations	2724	2724	2724	2724	2724	2724	2724	2724	0

Panel B. The Future Acquirers of Technology Peers – Technology-Peer Dummy

	1%	5%	10%	50%	90%	95%	99%	Mean	Std.
Technology-Peer Dummy	1.715	1.864	1.966	2.294	2.660	2.768	3.067	2.304	0.280
Product Proximity Score	2.888	3.039	3.097	3.373	3.699	3.792	4.006	3.387	0.230
Same State Dummy	0.148	0.281	0.352	0.597	0.830	0.893	0.987	0.593	0.184
Customer Dummy	−0.864	−0.632	−0.498	−0.034	0.376	0.510	0.782	−0.044	0.349
Supplier Dummy	−0.019	0.149	0.230	0.543	0.856	0.964	1.130	0.544	0.247
Sales Increase	−0.174	−0.060	0.014	0.303	0.589	0.673	0.831	0.303	0.221
M/B Ratio	−0.160	−0.133	−0.120	−0.077	−0.030	−0.015	0.011	−0.076	0.036
ROA	−0.582	−0.393	−0.267	0.218	0.734	0.886	1.118	0.224	0.388
Leverage	−1.947	−1.731	−1.581	−1.097	−0.613	−0.488	−0.215	−1.098	0.376
R&D	−0.121	−0.085	−0.065	−0.009	0.043	0.057	0.079	−0.011	0.042
Market Cap	0.461	0.486	0.497	0.545	0.592	0.606	0.634	0.545	0.037
Relative Patent Value	0.060	0.233	0.328	0.710	1.114	1.219	1.464	0.716	0.305
Pseudo R^2	0.635	0.643	0.649	0.668	0.687	0.693	0.705	0.668	0.015
Observations	2724	2724	2724	2724	2724	2724	2724	2724	0

Panel C. The Future Acquirers of Technology Peers – Technology Proximity Score and Interactions Terms

	1%	5%	10%	50%	90%	95%	99%	mean	Std.
Technology Proximity Score * Product Market Dummy	−6.081	−5.302	−4.928	−3.884	−2.717	−2.385	−1.580	−3.855	0.889
Technology Proximity Score * Same State Dummy	−2.307	−1.741	−1.412	−0.225	1.262	1.691	3.037	−0.125	1.088
Technology Proximity Score * Customer Dummy	−5.154	−4.319	−3.886	−2.055	0.084	0.737	2.286	−1.970	1.583
Technology Proximity Score * Supplier Dummy	−3.137	−2.237	−1.678	0.247	2.438	3.032	4.025	0.317	1.621
Technology Proximity Score	5.256	5.622	5.798	6.514	7.338	7.639	8.276	6.550	0.618
Product Market Dummy	2.168	2.346	2.439	2.788	3.194	3.317	3.499	2.806	0.294
Same State Dummy	0.249	0.392	0.450	0.692	0.930	0.998	1.116	0.691	0.184
Customer Dummy	0.017	0.251	0.366	0.755	1.166	1.295	1.494	0.764	0.321
Supplier Dummy	0.138	0.288	0.386	0.737	1.071	1.184	1.382	0.734	0.270
Sales Increase	−0.223	−0.094	−0.006	0.242	0.511	0.586	0.788	0.243	0.207
M/B Ratio	−0.146	−0.122	−0.108	−0.064	−0.022	−0.008	0.010	−0.065	0.034
ROA	−0.759	−0.530	−0.401	0.055	0.548	0.687	0.925	0.074	0.366
Leverage	−2.173	−1.942	−1.821	−1.355	−0.879	−0.787	−0.522	−1.351	0.361
R&D	−0.089	−0.062	−0.047	0.001	0.048	0.060	0.060	0.000	0.038
Market Cap	0.456	0.481	0.491	0.537	0.586	0.599	0.624	0.538	0.037
Relative Patent Value	−0.261	−0.098	−0.004	0.343	0.748	0.869	1.006	0.358	0.289
Pseudo R^2	0.608	0.615	0.621	0.639	0.659	0.666	0.673	0.640	0.015
Observations	2724	2724	2724	2724	2724	2724	2724	2724	0

Panel D. The Future Acquirers of Technology Peers – Technology-Peer Dummy and Interactions Terms

	1%	5%	10%	50%	90%	95%	99%	Mean	Std.
Technology-Peer Dummy * Product Market Dummy	−3.038	−2.788	−2.593	−1.978	−1.300	−1.102	−0.602	−1.956	0.513
Technology-Peer Dummy * Same State Dummy	−1.253	−0.996	−0.844	−0.192	0.533	0.763	1.390	−0.154	0.689
Technology-Peer Dummy * Customer Dummy	−2.615	−1.930	−1.697	−0.498	0.863	1.267	2.039	−0.445	1.000
Technology-Peer Dummy * Supplier Dummy	−2.160	−1.809	−1.502	−0.438	0.899	1.263	2.012	−0.362	0.929
Technology-Peer Dummy	2.773	2.947	3.021	3.359	3.748	3.879	4.090	3.373	0.287
Product Market Dummy	2.130	2.298	2.382	2.676	3.037	3.133	3.331	2.689	0.254
Same State Dummy	0.312	0.426	0.483	0.682	0.885	0.927	1.039	0.683	0.155
Customer Dummy	−0.068	0.141	0.245	0.607	0.973	1.098	1.304	0.611	0.292
Supplier Dummy	0.340	0.500	0.566	0.853	1.146	1.248	1.409	0.854	0.225
Sales Increase	−0.156	−0.052	0.016	0.220	0.433	0.487	0.606	0.223	0.163
M/B Ratio	−0.133	−0.112	−0.103	−0.065	−0.024	−0.015	0.005	−0.065	0.030
ROA	−0.702	−0.502	−0.400	−0.019	0.397	0.496	0.666	−0.015	0.301
Leverage	−2.134	−1.877	−1.794	−1.400	−0.989	−0.881	−0.722	−1.399	0.308
R&D	−0.077	−0.056	−0.045	−0.008	0.030	0.042	0.064	−0.007	0.030
Market Cap	0.490	0.507	0.518	0.556	0.602	0.613	0.636	0.559	0.033
Relative Patent Value	0.058	0.227	0.315	0.616	0.984	1.095	1.219	0.633	0.261
Pseudo R^2	0.549	0.557	0.562	0.579	0.598	0.602	0.613	0.579	0.014
Observations	2724	2724	2724	2724	2724	2724	2724	2724	0

Table OAT22: **The Previous Acquisition of Technology Peers and Firms' R&D Investment**—***Previous-Acquisition Proximity Score***

This table reports the estimates of the impact of acquisition activities on the R&D investments of targets' technology peers. The dependent variable is a firm's R&D expenditure divided by sales in a year (year t). The sample comprises all the firm-years (excluding firms from the financial and utilities sectors) in the Compustat-CRSP merged database and all the acquisitions from the Thomson SDC Platinum M&A database over the 1984-2010 period. Firm-years in which no patents were obtained in the past five years are excluded because, for them, neither the technology space nor the technology peers can be identified. The variable *Previous-Acquisition Proximity Score* is the value-weighted average of the technology proximity scores between the firm and all the acquisition targets in the previous year. All the independent variables are measured in the previous year and defined in Table 1 and Table OAT1 of the Online Appendix. The industry fixed effects are based on the Fama-French 48 industry definitions. t-statistics, clustered by firm, are in parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Previous-Acquisition Proximity Score	0.337	1.447***	2.589***	0.245	1.347***	2.445***
	(1.60)	(3.43)	(4.26)	(1.32)	(3.53)	(4.34)
Previous-Acquisition Proximity Score *		−2.021***			−2.011***	
Large-Size Dummy		(−4.58)			(−4.61)	
Previous-Acquisition Proximity Score *			−0.378***			−0.371***
Market Cap			(−5.12)			(−5.02)
Large-Size Dummy		−0.005			−0.004	
		(−0.35)			(−0.25)	
Market Cap	−0.018***		−0.003	−0.017***		−0.003
	(−5.23)		(−1.02)	(−4.99)		(−0.77)
Lagged R&D	0.660***	0.658***	0.658***	0.656***	0.654***	0.655***
	(30.62)	(30.55)	(30.51)	(30.10)	(30.04)	(29.99)
Vdshock	−0.019	−0.027	−0.027	−0.077	−0.064	−0.063
	(−0.14)	(−0.20)	(−0.20)	(−0.62)	(−0.51)	(−0.50)
Age	−0.019***	−0.018***	−0.016**	−0.020***	−0.020***	−0.018**
	(−2.66)	(−2.58)	(−2.30)	(−2.81)	(−2.73)	(−2.47)
PPE	−0.148***	−0.157***	−0.157***	−0.144***	−0.153***	−0.154***
	(−3.26)	(−3.46)	(−3.44)	(−3.10)	(−3.31)	(−3.30)
Cash Ratio	0.035***	0.033***	0.034***	0.036***	0.034***	0.035***
	(8.88)	(8.44)	(8.52)	(8.89)	(8.42)	(8.51)
Net Working Capital	−0.093*	−0.093*	−0.093*	−0.094*	−0.094*	−0.094*
	(−1.69)	(−1.69)	(−1.70)	(−1.67)	(−1.68)	(−1.68)
P/E Ratio	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(−5.16)	(−5.14)	(−4.99)	(−5.13)	(−5.07)	(−4.95)
Dividend-Payment Dummy	−0.004	−0.013	−0.006	−0.003	−0.011	−0.005
	(−0.44)	(−1.43)	(−0.71)	(−0.34)	(−1.19)	(−0.57)
Institutional Ownership	−0.071***	−0.072***	−0.082***	−0.072***	−0.073***	−0.083***
	(−3.53)	(−3.61)	(−4.05)	(−3.50)	(−3.55)	(−4.00)
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
R^2	0.633	0.634	0.634	0.637	0.637	0.637
Observations	36667	36667	36667	36618	36618	36618