LEARNING FROM PEERS' PRIVATE INFORMATION: EVIDENCE FROM FAILED M&A

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I investigate the effects of private information acquisition from M&A due diligence on bidders' subsequent actions. Using a sample of negotiated and announced M&A deals that fail to close, I find that, following the failed transactions, bidders achieve higher investment efficiency and higher innovation outputs. Cross-sectional cuts demonstrate that the effects are more pronounced when a bidder has greater opportunities to learn from the target firms' proprietary information. While bidders benefit through M&A negotiations, target firms bear costs from sharing proprietary information, as shown by a modest decline in their innovation and product outcomes. Overall, my study contributes to the understanding of the real effects of learning from peers' proprietary information.

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INTRODUCTION

I investigate an unexplored benefit of acquisitions, specifically, whether the M&A process helps aspiring acquirers gain valuable information, even from their failed acquisition attempts. Acquisitions are conventionally seen as a means for acquirers to gain a strategic advantage in product markets or expand their investment opportunities, benefits that should accrue to successful acquirers. However, if acquisition attempts also represent a learning opportunity for bidders, because of the insights they gain from target firms, including proprietary strategic information (Raman et al., 2013), aspiring acquirers will benefit even when their bids fail. Studying the implications of this form of learning illuminates how managers incorporate peer firms' *proprietary* information into their decision-making, which is an important but underexplored question in the literature (Roychowdhury et al., 2019).

Empirically it is challenging to identify when and how peer-to-peer proprietary information transfers occur or whether managers acquire peer firms' private information. The due diligence phase of M&A is a unique setting in which substantial private information is exchanged between participating firms. An example is the failed 2014 merger between Eagleview Technologies (EVT) and Verisk Analytics. A year after Verisk ended its attempt, EVT sued Verisk, alleging patent infringement. EVT's complaint argued that Verisk had knowledge of EVT's patents because Verisk had performed due diligence prior to withdrawing its bid.[1]

During due diligence, the acquirer's team of experts assesses not only the target's financial records and business model but its customer list, intellectual property, and newly developed technologies, patents, products, and services. Due diligence often begins long before the acquisition is publicly announced and continues until it is closed or withdrawn (Wangerin, 2019). During due diligence, the acquirers' experts visit key sites and interact with employees intimately familiar with the target's R&D, its contract negotiations with key customers, and its development of new products and services. This process helps the acquiring managers understand what they are buying and enables them to evaluate potential synergies.

My central prediction is that the information exchanged during M&A negotiations improves the bidder's subsequent investment decisions. I use as my setting M&A deals that bidders negotiate and announce but do not consummate. I employ this sample because there are no physical assets transferred, yet the public announcement ensures that due diligence was conducted. Hence I can test my central prediction while mitigating concerns that my findings result from the merger per se and not from the information transferred during due diligence. Deals can fail for several reasons—regulatory decisions, unexpected legal action, or changes in market conditions (Seru, 2014), all of which are largely exogenous to the bidder's learning opportunities during due diligence.

[1] The formal complaint alleged seven patent infringements. For each alleged infringement, the complaint has a paragraph stating: "On information and belief, Xactware [a subsidiary of Verisk] has had knowledge of the [patent #] Patent since at least as early December 2014 in connection with Verisk's intended acquisition of EVT. *Verisk performed due diligence related to its intended acquisition of EVT, including with respect to Eagle View's patent holdings. EVT personnel had discussions with representatives of Verisk concerning Eagle View's patents, including the* [patent #] *Patent, prior to the termination of the EVT acquisition in December 2014*." Emphasis added. See https://www.eagleview.com/wp-content/uploads/2019/03/2015-09-23-001-Complaint.pdf

I expect learning to improve the quality of bidders' subsequent investment decisions because, when evaluating and executing a firm's investment options, managers have imperfect and incomplete knowledge. If interactions between bidders and potential targets alleviate uncertainty regarding investment payoffs and timing, mitigate adjustment costs, or reveal new opportunities, these interactions should improve the quality of bidders' investment decisions. I measure the impact of managerial learning in two ways. First, I test for changes in the sensitivity of investment to the availability of investment options (Shroff et al., 2014; Jayaraman and Wu, 2018). An increase in investment sensitivity suggests greater knowledge of industry prospects and better project choices. Second, I focus on changes in knowledge-oriented investment outputs, measured by new-patent grants and patent citations (Zong, 2018). An increase in bidders' innovation outputs shows that learning via M&A due diligence enhances bidders' competitive advantage in their product markets.

I test my main prediction using a difference-in-differences approach that compares changes in investment efficiency and innovation outputs before versus after failed bids for treated firms, relative to control (i.e., unaffected) firms. Treated firms are bidders that conducted due diligence for announced M&A but whose deals failed to close. I only consider failed bids that targets initially welcomed (no hostile ones), thus increasing the likelihood that the target cooperated during due diligence. To construct my sample of matched control firms, I begin with all firms that did not publicly announce acquisitions during my sample period; these firms never enter the treatment sample.[2] Then I match treatment firms to similar nonbidders within the same industry on the the likelihood of making a bid, based on a determinant model of acquisition.[3,4]

In my main tests, I find that learning through due diligence improves bidders' investment efficiency. The effect is present with respect to both of my primary proxies for investment (i.e. aggregate capital investment and innovation expenditure) and is economically significant—a one standard deviation increase in investment opportunities leads to a 3.36% higher investment expenditure for a bidder of a failed M&A deal, relative to a matched control firm in the post period.[5] Next, I find that the bidder of a failed deal generates 1.41 more patents (37.49 citations), relative to the control group, a 9.72% (15.44%) increase over the sample means.[6] These results are robust to different combinations of firm and year fixed effects and controlling for a variety of firm characteristics. I also plot and find no trending differences in the coefficient estimates of investment sensitivity and innovativeness among treatment and control firms in the years prior to acquisition announcements. This evidence assuages concerns that the findings simply reflect differential trends for the treatment and control firms.

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[2] Using firms that do not publicly announce any acquisitions ensures that the control sample is imperfect, since the treatment firms make at least one bid. While I cannot fully mitigate this concern, I follow the literature and select control firms from within this set based on characteristics that predict bid likelihood (e.g. Bena and Li, 2014). Note that I cannot use successful acquirers as my control group because the real effects of mergers confound these observations.

[3] I ensure that neither the control nor treatment firm makes any successful acquisition in the event year.

[4] One caveat of my sample construction is that I do not observe bidders that only partially complete due diligence and withdraw their purchase offers before making any public announcements. These unobservable bidders are thus excluded from the treatment sample and instead are included in the pool of potential control firms. Further, the unobservable failed bidders are conceivably present in the final matched control sample, if their propensity score is close enough to treatment firms. However, their presence likely works against finding results to the extent that these unobservable failed bidders resemble observable bidders and learn similar information.

[5] This represents a 20% increase relative to the unconditional sample mean of total investment.

[6] Prior studies (e.g. Glaeser 2018) have used a word count based measure of trade secrecy as a proxy for innovation outcome. However, only 2% of firms in my sample adopted or ceased to report a trade secrecy within t-5 to t+5 of the event year. Thus it is highly sticky over time for firms in my sample. Moreover, because, such a measure cannot indicate the change in the amount of the innovation, I do not use trade secrecy as an innovation outcome for my tests.

To validate my inference that *learning* drives the observed efficiencies in investment and innovation, I run several additional analyses. First, I perform a placebo test in which I examine whether similar effects exist in a sample of failed bids with limited scope for learning. I use a sample of failed bids that were hostile or unsolicited, where information-sharing between acquirer and target is unlikely. Consistent with my expectations, I fail to find evidence of greater investment efficiency and improved innovation. This finding helps mitigate concerns that the observed effects occur not because bidders learn during M&A negotiations but because bidders who launch acquisition attempts are better-informed by selection. Second, in a robustness test, I find that the learning effects exist in a sample of bids that failed due to exogenous reasons such as regulatory intervention. This test mitigates concerns that the bidders in my sample are unique such that they abandon the deals due to the availability of better outside opportunities.

I perform several cross-sectional tests, exploiting variations in the bidder's willingness and opportunities to learn. Prior studies (e.g. Harford 2002; Erik, Kadapakkam, and Krishnamurthy 2009) suggest that the motive of an acquisition can be driven by agency costs, synergies etc. Thus I explore whether the learning effects are more pronounced when the bidder is seeking a knowledge-based acquisition, where I measure bidders' knowledge seeking by its level of R&D spending. I find that the innovation effects are concentrated among bidders with above-median levels of R&D spending.[7] Next, I explore whether the effects are more pronounced when innovation is highly important at the industry level. I find that innovation outcomes of the bidder predominantly improve in industries with high patenting. Finally, I investigate the effects in the presence of agency costs measured with excess cash holding. I predict and find that innovation

[7] One may have a concern that higher innovation output is a direct consequence of higher R&D. However, that is true for both bidders and their control firms. I still observe a differential when I compare the innovation of the bidder firms, relative to control firms within a high R&D group, and, in fact, the differential is larger than that in the low R&D group.

effects are weaker in acquisitions with higher agency costs in which bidder managers are more likely to seek their own personal benefits (e.g. greater scope of authority, personal risk diversification, etc.) rather than aiming to improve the bidder firms' innovation portfolio. I also explore whether the effects are more pronounced when learning opportunities are greater. To capture learning opportunities, I use three measures: the form of the target (i.e., private versus public), business similarity, and patent-class similarity. I find that learning is more pronounced when the target is a private firm—supporting the intuition that, given the lack of regulatory filings, private firms have significant undisclosed proprietary information that becomes accessible through M&A due diligence. Moreover, bidders that share similar industries and patent classes with their targets achieve higher investment efficiency and generate more new patents. Taken together, these cross-sectional tests strengthen my interpretation that bidders' improved investment outcomes result from learning.

In supplementary tests, I study the consequences of private information transfer on the target firm's outcomes. I find that the target firm's responsiveness to investment opportunities does not change significantly. However, innovation outcomes, as measured with patents, decline significantly following the failed bid, suggesting a wealth transfer from the target to the bidder as a result of proprietary information exchange. Moreover, I find that the target firms lose market share and face higher competition in the product market relative to their matched control firms in the period after the failure. While targets of friendly bids suffer negative consequences, those of hostile bids do not, which mitigate concerns that the consequences are not entirely driven by the overall poor condition of the targets that fail to close the deal.

My study contributes primarily to three areas of research. First, I add to the literature on the effects of peer learning (Badertscher et al., 2013) by illuminating a new channel: learning potentially proprietary information through M&A due diligence. In my setting, the potential acquirer possesses an exclusive right to access a target's *private* information. In contrast, much of the existing literature focuses on learning from public disclosures (Beatty et al., 2013; Durnev and Mangen, 2009) and is generally vague about the means of information acquisition (Veldkamp, 2011). Note, too, that my research design sidesteps a typical confounding factor in studies examining spillovers from public disclosures: the possibility that common shocks (such as growth) affect both the peer firms' public disclosures and focal firms' investment decisions. Finally, the potential for transfer of proprietary information in my setting also provides an opportunity to examine its effects on innovation. I thus contribute to the understanding of how firms learn from peers' proprietary information.

Second, my findings add to the literature on the economic gains from M&A. Most studies suggest that almost all acquisition gains are captured by targets (Bruner, 2021). Zero announcement returns to the buyers and post-merger underperformance raise questions about why managers chase acquisitions, aside from agency considerations. My study suggests an undocumented and unexamined benefit to acquiring firms: acquisitions help managers improve decisions because of the opportunities to gain information otherwise difficult to access. My finding complements the work of Harford and Schonlau (2013), who document that acquisition experiences, both value-destroying and value-increasing, boost a CEO's prospects in the director labor market. By doing so, I also document a potentially unintended cost to an M&A target: the divulgence of proprietary information during due diligence.

Third, my findings enhance our understanding of how organizations learn from failure. Organizational behavior studies focus on conditions and traits under which employees learn from their failures (Thornhill and Amit, 2003; Willhelm et al., 2019). My study complements this literature in two ways. First, I show that due diligence during M&A negotiations improves top management's experience with certain products or markets, enabling them to invest more efficiently even when a deal fails. Second, I find that certain organizations, such as firms seeking knowledge-based acquisitions from an innovative industry, are more likely to learn via experience.

1.0 LITERATURE AND HYPOTHESES DEVELOPMENT

1.1 LEARNING FROM PEERS

Managers face significant uncertainties when investing. Payoffs are uncertain and depend on macro-, industry-, and firm-level factors. Moreover, the optimal timing of an investment is unclear, and the option value of waiting is higher when managers expect the arrival of new information (Dixit and Pindyck, 1994). Since firms within a peer group (e.g., industry, geographic region, supply chain, etc.) have similar assets-in-place and growth options, peer information can help managers reduce or resolve uncertainties about payoffs as well as the optimal timing of investments (Roychowdhury et al., 2019). Peer information can also help managers identify new markets, products, and customers, facilitating additional investments.

Several studies provide evidence that managers rely on peer firms' information in making investment decisions. A common feature of these studies is their focus on publicly available financial disclosures by peers, such as earnings announcements, financial reports, or restatements (Durnev and Mangen, 2009; Baderstcher et al., 2013; Breuer, 2021). In contrast, my study focuses on managers' private interactions with peers, which permit the transfer of proprietary information regarding not only finances but also otherwise unobservable, detailed information about products, customers, and technologies. Although the primary goal of the information acquisition is to value the peer in the context of an M&A decision, an unintended benefit is deep learning about the target firm.

Evidence on managerial learning from peers focuses on indirect learning, such as learning from price movements or knowledge spillovers from publicly available disclosures, and is generally vague about the means of information acquisition (Veldkamp, 2011). In contrast, I illuminate a more direct learning channel, that is, firms learning potentially proprietary information during due diligence. In my setting, the potential acquirer possesses an *exclusive* right to access a target's private information, which is likely proprietary. The source and the nature of this information also provide an opportunity to examine the effect of managerial learning on innovation. Previously, studies have not examined the effect on innovation, perhaps because they have relied on public disclosures, which are unlikely to contain significant proprietary information (Glaeser and Omartian, 2019; Jayaraman and Wu, 2018; Jayaraman and Wu, 2020).

One concern with prior studies relying on public disclosures is that the observed effects on peer actions may either be due to learning or due to an industry-level growth opportunity shock, both of which can drive the disclosing firm's disclosure choices and peers' actions (Manski, 1993). An advantage of my setting is that it allows for one-to-one proprietary information exchange, specifically, information that is not necessarily disclosed to an outside audience. This allows me to compare the potential acquirer's actions with those of a matched control firm from the same industry-year that did not gain access to the target's information. Thus, a growth opportunity shock cannot be driving an observed difference between the acquirer and the control, since such a shock would impact both firms similarly.

1.2 M&A DUE DILIGENCE

When purchasing a company, managers face an information disadvantage, as the target managers hold valuable private information about their business (products and customers), economic resources and know-how, and underlying risks. Due diligence provides an acquirer an opportunity to gain and verify valuation-relevant information about the target. Acquirers assess the costs and benefits of a proposed acquisition by making inquiries "into all relevant aspects of the past, present, and predictable future of the business to be purchased" (Lajoux and Elson, 2000). Thus due diligence helps the acquirer to reduce its information and business risk.

Due diligence occurs in several phases. Figure 1 shows the typical sequence in acquisitions involving public bidders. The buyer begins learning about the target company by holding private meetings with the target's management. The buyer attempts to understand the target's product markets, key customers, and innovative technologies and to verify proofs of concept, especially if the target is a private startup developing new products or technologies. Next, a nondisclosure agreement (NDA) is signed between the buyer and the target. The NDA grants the buyer permission to delve deeply into the inner workings of the target. In an effort to sell the company for the best price, target personnel often share highly sensitive, nonpublic information. Generally, the NDA prohibits the buyer from revealing any proprietary information received to a third party or using it to reverse engineer products or services offered by the target. However, NDAs are silent about information and knowledge retained in acquirer employees' memory. Once a particular trade secret, product strategy, or patent is seen and learned, it cannot be unlearned and thus can be used in a similar (but not exactly in the same) way to benefit the bidder.

Next, the signing of a letter of intent (LOI) marks the start of confirmatory due diligence. At the time of signing, the bidder provides a range of potential acquisition prices to the target. A letter of intent also often includes an exclusivity clause, which prevents the target from talking to other buyers during due diligence. During this phase, human resources, compliance, tax, and accounting personnel get involved to ensure that the target's business has been properly presented and understood by the acquisition team. Revenue, cost, production information, and sales pipeline information are examined in detail. The business development team often speaks directly with key customers to understand better the depth of their commitment to target. Financial due diligence is performed to review financial performance and verify accounting processes. Legal due diligence reviews the seller's contracts with suppliers and customers. After financial and legal due diligence, the acquisition team often pushes the target for additional details on technology, such as pending and existing patents. Members of the acquisition team also often visit key production sites and observe product demonstrations, and engineers from both firms meet to review technical specifications. Operational due diligence reviews the target's back office systems. Finally, a sales and purchase agreement (SPA) is signed, and the deal is publicly announced within a few days of the signing.

Although a major portion of due diligence happens before the announcement, the process continues post announcement up to the consummation or termination of the deal. This phase is known as transactional due diligence. Some extraneous factors (e.g., regulatory approval and tender offer rules) may even make the due diligence lengthier by affecting the time to termination or completion.

Studies have focused on gains to targets' valuation from due diligence (Skaife and Wangerin, 2013; Wangerin, 2019). I build on this research by showing that benefits from due diligence extend beyond simply the higher valuation of target firms: these benefits also include information acquisition for future investment decisions by the acquirer. In fact, it is likely that one of the major motives for deal-making is to gather information about product markets, new technologies, and key competitors.[8]

[8] However, it is difficult to test this motive because I only observe deals that are announced. Sometimes, deals are abandoned before the announcement but after completion of a portion of the due diligence (Wangerin, 2019).

1.3 ECONOMIC GAINS FROM M&A

While some recent evidence indicates that completed mergers can reduce overlapping R&D projects and increase the scale of R&D expenditure, more often than not, unexpected integration costs exceed realized synergies, resulting in nearly zero gains to the bidder's shareholders. In fact, the weight of evidence indicates that, in the long run, mergers underperform (Rau and Vermaelen, 1998; Eckbo, 1992)[9], which raises questions of why managers still pursue them, aside from agency considerations. My study suggests an undocumented benefit to acquiring firms: helping managers improve decisions through the acquisition of otherwise-difficult-to-obtain information. My finding complements the work of Harford and Schonlau (2013), who document that acquisition experiences, both value-destroying and value-increasing, boost a CEO's prospects in the director labor market. I also document a potentially unintended cost of M&A, that is, the divulgence of proprietary information during due diligence.

1.4 HYPOTHESES DEVELOPMENT

When investment is at least partially irreversible, the impact on investment spending of a given firm's demand shocks (i.e., investment opportunities) tends to be weaker for firms that are subject to more uncertainty (Bloom, 2007). To the extent that knowledge acquired through due diligence reduces the degree of uncertainty regarding the payoffs and the timing of an investment

[9] Denes, Duchin, and Harford (2018) find that, when an industry experiences a wave of patent expirations, its firms are more likely to pursue M&A. However, this M&A generates lower announcement returns and worse long-term performance for acquirers.

and helps the bidder learn about new opportunities, such interactions will improve investment sensitivity. Thus, my hypothesis is as follows:

***H*$_1$**: *The investment efficiency of a potential acquirer improves following a failed M&A transaction, relative to a matched control firm.*

Notwithstanding the above discussion, there are reasons I may not observe the predicted outcome. Studies allude to the fact that acquirers face time and resource constraints in due diligence (Wangerin, 2019). The presence of NDAs, which may pose litigation risk, also limits the benefits of direct learning. Hence it is an open empirical question whether acquirers learn significant new information during due diligence.

Note that my prediction relates to the sensitivity of investment to opportunities, rather than the level of investment. Firms with higher investment opportunities likely have higher investment, but they do not necessarily respond to those opportunities faster. In contrast, possessing greater knowledge and certainty need not per se increase investment; it could instead increase the speed with which the firm adjusts to its growth opportunity set. Hence I am interested in investment sensitivity and control for the main effect of the treatment on the level of investment.

While my first prediction is about an input-based test of learning, my second hypothesis relates to the impact of knowledge spillover on innovativeness, that is, an output-based test of learning. The bidder learns about a specific strategy, technology, product pipeline, etc., during due diligence. Spillovers from peers' proprietary disclosures can help firms 1) innovate, potentially via greenfield projects; 2) enhance their existing innovation projects; and 3) improve their project selection and continuation decisions by facilitating access to useful information (Kim and Valentine, 2021).[10]

[10] There are several ways in which better investment decisions may result in innovation outputs. Some firms may choose not to patent their innovations and instead keep them as trade secrets. Trade secrets are information that derives future economic value from not being appropriable by competitors (e.g., unpatented innovations). Harabi (1995)

The creation of patents requires precise technological information, which is unlikely to be present in public peer information but can conceivably be gleaned from private disclosures. Since most studies examine learning in pure public-disclosure settings, which are intrinsically nonproprietary, the findings are not easily generalizable to innovation outcomes.[11] For example, Beatty et al. (2013) show that firms overinvest when their peers overstate earnings. This is because overstated earnings make the industry prospects seem unrealistically rosy. Li et al. (2016) show that the distortions that result from peers' misreporting also extend to choices firms make with respect to R&D, advertising, and pricing. The underlying channel in both Beatty et al. (2013) and Li et al. (2016) is that firms rely on peers' disclosures to learn about macroeconomic trends and industry prospects. These findings are not generalizable to innovation outcomes because it is unclear that publicly disclosed peer information can affect innovation outcomes.[12] My second hypothesis is as follows.

H_2: *The potential acquirer (or bidder) in a failed M&A transaction experiences increased innovation following the failure of the deal, compared to a matched control firm.*

Innovation and technology are key drivers of M&A decisions (Cunningham, Ederer, and Ma, 2021; Bena and Li, 2014). Innovation helps firms gain competitive advantages and sometimes even monopolies. Bena and Li (2014) find that acquirers produce more patents post-merger if they have ex ante technological overlap with the target. Bidders seeking to develop intellectual property are expected to be keener about learning from even their failed bids. They are also more likely to have in-house experts to mimic the target's technology portfolio. Hence I expect that they will be

surveys 358 Swiss R&D experts and finds that "the ability of competitors to 'invent around' patented innovations constraints them from patenting innovations."

[11] Also, public disclosures are influenced by strategic disclosure motives of managers, such as preserving proprietary information or appeasing shareholders.

[12] The intuition comports with the finding of Shroff, Verdi, and Yost (2017) that the public peer information is a noisier signal than peer firm-specific information.

the ones experiencing a higher impact on their innovation after a failed acquisition bid. My third hypothesis is as follows.

H_{3a}: *The effect of a failed acquisition bid on the bidder's innovation output is stronger when the bidder has high R&D expenditure.*

Because bidders in innovation-rich industries are more likely to exploit the opportunity to learn from innovative targets, I further predict the following.

H_{3b}: *The effect of a failed acquisition bid on the bidder's innovation output is stronger when the bidder belongs to an industry with high patenting activity.*

Prior studies find that managers' desire to reduce their personal undiversified risk or increase the scope of their authority may lead them to make value-destroying acquisitions. Hence, it is important to delve into the motive behind a merger. Harford (2002) finds that bidders with high agency costs: proxied by excessive cash reserves tend to choose lower quality deals and thus will learn less through the M&A. Based on this, I test the following prediction:

H_{3c}: *The effect of a failed acquisition bid on the bidder's innovation output is weaker when the bidder has higher agency costs ex ante.*

Bidders are more likely to learn *proprietary* information from those targets about which public information is sparse. This would allow bidders to gain exclusive knowledge during due diligence. Thus I predict the following.

H_{3d}: *The effect of a failed acquisition bid on the bidder's investment efficiency is stronger when the target is a private firm.*

The likelihood of a bidder learning from a target through information spillovers is higher when the bidder and target are more similar in their operations and in the overlap of their technology and pre-bid innovation. Based on this, I test the following two predictions.

H_{3e}: *The effect of a failed acquisition bid on the bidder's investment efficiency is stronger when the bidder belongs to the same industry as the target.*

H_{3f}: *The effect of a failed acquisition bid on the bidder's innovation output is stronger when the bidder shares patent similarity with the target ex ante.*

2.0 SAMPLE AND DATA

2.1 SAMPLE

Table 1 outlines the sample selection process to obtain a sample of failed friendly bids.[13] I started with all publicly traded bidders in the United States in the Securities Data Company Platinum database (SDC) that announced but failed to complete an acquisition between 1986 and 2015. I impose the following restrictions. (1) The transaction must have reached an M&A agreement. (2) The attitude must be coded as friendly. (3) The bidder must be an US firm.[14] I exclude bidders that have had a successful acquisition in the same year to ensure that the results are not confounded by successful acquisitions. I further exclude transactions in which the bidder firm operates in the energy or financial industries (SIC codes 4900–4999 and 6000–7099) or seeks to acquire less than 50% of the target. After merging with Compustat/CRSP, the final sample consists of 860 firm years with failed bids.

For the control sample, I obtain the entire Compustat universe of firm-year observations from 1985 to 2014. I exclude a firm year from the control group if the firm has made a successful acquisition, operates in the energy or financial industries. If a firm is ever treated, I also exclude all firm-year observations related to the treated firm, from the control group to avoid any confounding effects from treatment. These filters leave 107,754 firm-years available as the pool of potential control firms.

[13] A merger is generally considered friendly when negotiation occurs between the target's management and the bidder's management.
[14] I manually searched for deal synopsis to ensure that the deals reached a merger agreement.

To construct the primary sample for this study, I perform the following matching procedure. In relative year = −1 (one year prior to the M&A), I match each treatment firm with replacement to non-treated firms (firms from the above control pool) within the same two-digit SIC code, in the same year, with an absolute difference in the predicted probability of launching an acquisition attempt of less than 0.05. [15] The final matched sample consists of 532 failed bidders (for whom a match exists) and their matched control firms, totaling 1506 firms.[16] To create an annual proxy for innovation for each firm in the matched sample, I match the firms to firm-level assignees from Kogan, Papanikolaou, Seru, and Stoffman (2019). Next, I collect necessary financial statement data to create control variables from Compustat. My final sample consists of 11,505 (8,520) firm-year observations with non-missing values for dependent, independent, and control variables after accounting for fixed effects for innovation (investment sensitivity) tests.

2.2 VARIABLE MEASUREMENT

2.2.1 Investment Sensitivity

In the classical theory of investment, investment sensitivity is defined as the co-movement of investment expenditure and investment opportunities. It is captured by the coefficient β_1 in the following investment-q regression (e.g., Fazzari et al., 1988; Kaplan and Zingales, 1997; Rauh, 2006; Chava and Roberts, 2008):

$$Investment_{it+1} = \beta_0 + \beta_1 * IndustryQ_{it} + \varepsilon_{it}.$$

[15] I limit the matched control firms to two with the closest match per treatment firm. However, the primary result of the study is robust to including three, four, or five matched control firms per treatment firm.
[16] I describe the matching technique in detail in the research design section.

I augment the classical investment-q regression with additional interaction terms for failed bids in Section 4.1.2. To capture each firm's investment opportunities, I use *Industry Q,* defined as the sum of aggregate market value of equity and aggregate book value of debt in an industry, divided by aggregate total assets in that industry (e.g., Nini et al., 2009; Badertscher et al., 2013). Following the literature, I measure *Investment* in two ways: aggregate investment expenditure and innovation expenditure.

2.2.2 Innovation

My innovation measures aim to capture improvement in innovation outcomes. I construct two patent-based measures to capture innovative output: *Patents* and *Citations Weighted Patents* (Acharya et al., 2013; Hsu et al., 2014). *Patents* is the logarithm of the number of patents a firm applies for in a given year. Following Trajtenberg (1990), *Citations Weighted Patents* is measured as the logarithm of the sum of patents applied for by a firm in a given year, weighted by the actual number of citations that they subsequently receive over their lifetime:

$$Citation\ Weighted\ Patents_t = \sum_{i=1}^{n_t} (1 + C_i),$$

where n_t is the number of patents issued during year t. This linear weighted scheme then assigns a value of one to all citations and all patents.

I obtain data on patents and patent citations from Kogan, Papanikolaou, Seru, and Stoffman (2019). The authors download the entire history of U.S. patent documents from the Google Patents database and match the patent assignee to CRSP. Following prior work, I use the patent's file date instead of its grant date, as there is typically at least a year's lag between file and grant dates. I address the truncation bias in patent data in two ways. First, I use year-fixed effects in all tests.

Second, I follow Hall, Jaffe, Trajtenberg (2001) and adjust the observations that occur prior to the last three years of the patent database with historical growth in patents and citations.

2.2.3 Control Variables

I use separate control variables for the analyses of investment sensitivity and innovation outcomes. For the sensitivity analysis, I control for a number of firm characteristics documented by the literature to affect a firm's ability to exploit investment opportunities: size (*Firm Size*), past performance (*Return on Assets*), leverage (*Leverage*), and liquidity (*Cash*). I also control for the Herfindahl-Hirschman index of competition with *Herfindahl* and *Herfindahl***Industry Q* to allow for the possibility that industry competition affects firms' investment efficiency (Biddle et al., 2009; Baderstcher et al., 2013).

For my tests of innovation outcomes, I control for firm age (Firm Age) and size (Firm Size), as they are correlated with innovativeness (Glaeser, 2018). I also include return on assets (Return on Assets) and market-to-book ratio (Market to Book) to capture growth opportunity and profitability; leverage ratio (Leverage) and internally generated cash (Liquidity) to account for the effect of capital structure; the Herfindahl-Hirschman index (Herfindahl) and its square term (Herfindahl2) to control for product market competition (Aghion et al., 2005); the percentage of shares held by institutional investors (Institutional Ownership) as a proxy for ownership structure; and R&D expenditure (R&D) to capture innovation effort. I control for firms' access to external financing (Finance), calculated as the sum of net equity issuance over a five-year rolling window ending with the current year, assuming that all equity financing raised during the past five years contributes to current R&D investment (Brown et al., 2013).

2.3 DESCRIPTIVE STATISTICS

Table 2 Panel A reports descriptive statistics for bidders and their control firms at the firm-year level. The mean *Total Investment* (*Innovation Investment*) is 17% (6%) of total assets. The average number of patents filed is 14.47 and of forward citations is 242.85. Because these two variables have a highly skewed distribution, I follow the literature and use the log transformation. My sample firms have a median *Industry Q* of 1.86, in line with that of prior studies (e.g., Jayaraman and Wu, 2018). On average, the sample firms are profitable, as evidenced by the mean (median) value of *Return on Assets* of 0.11 (0.05). The average age of a sample firm is 19.79 years. The firms have an average cash holding of 10% (of assets) and finance 20% of their assets with debt.

Figure 2 graphs the percentage of failed M&As and patents for the top ten industries (three-digit SIC) by the prevalence of failed M&As. The top four industries are drugs, computer programming, data processing, air transportation, and measuring and controlling devices, consistent with much of M&A activities concentrated in hi-tech and pharmaceutical sectors. Also represented are healthcare-related fields such as medical instruments, and supplies and drugs. The top 10 industries represent approximately 36% of total failed M&As and the remaining 102 industries represent about 64% of total failed M&A deals, demonstrating that while there is some concentration of the failure of M&A deals in certain sector, a variety of industries experience significant failed M&A deals.

3.0 MAIN ANALYSIS

3.1 RESEARCH DESIGN

3.1.1 Controlling for determinants of M&A

The focus of this study is to examine whether investment sensitivity and innovation outcome changes after the bidder went through the due diligence process in an M&A. Launching an M&A attempt precedes a due diligence process. However, launching an acquisition is not a random event. It is possible that correlated omitted variables that affect firms' investments also influence a firm's propensity to launch an acquisition attempt. Failure to account for this possibility could lead to spurious inferences. One of the first steps I take to address the nonrandom nature of launching an M&A bid is that I match bidder firms with similar firms who did not make a bid but have a similar probability of making a bid.[17]

To determine the probability of making a bid, I estimate a firm-level probit model with a pooled sample of for all treatment (the failed bidders) and potential control firms:

$$P\{bid_{it} = 1|X_{it-1}\} = G(\beta' X_{it-1}). \qquad (1)$$

Where, $bid_{it} = 1$ is an indicator variable equal to one if a firm enters into an acquisition attempt and zero otherwise. X_{it-1} is a list of observable characteristics: firm size, return on assets, sales growth, capital expenditure, and cash, following Petrova and Shafer (2010) and Bena and Li

[17] My ideal control sample would be those who were interested in the target initially but have not gotten far enough through the negotiation process and did not get past M&A diligence. However, that is not observable. But I want to approximate this ideal control sample- those who would have made a bid but did not end up making one. I approximate this sample by getting matched control firms based on the probability that they would make a bid.

(2014). Sales growth capture growth opportunities (Andrade, Mitchell, and Stafford, (2001). Cash captures financial constraints, which is another important driver of M&A. Return on assets and capital expenditure captures attractiveness as an M&A partner while firm size captures overvaluation (Shleifer and Vishny, 2003), Rhodes-Kropf and Viswanathan, 2004)). The pool of potential control firms consist of firms who did not make a bid- either successful or failed. Moreover, I limit the pool of potential control firms to ones who never had a failed bid to reduce any confounding effect of the treatment.

Using the estimates from the prediction model, I assign a score that represents the predicted probability of making an M&A bid to every firm-level observations in the pooled sample. Next, for each bidder of a deal announced in year *t*, I identify the no-bidding firms in the same industry with predicted values within 0.05 in score difference in the year *t-1*. Thus, while one concern is that my control firms make no bid, whereas my treatment firms make at least one failed bid, by using propensity score matching, I find firms closest to the nature of my treatment firm.[18] I force the matched control firm-years for each treatment firm-year to have the exact same two-digit SIC code to account for similar industry characteristics and limit the number of matched control firm-years to two per treatment firm-year. Because I match firms at the same point in time, I reduce the confounding effects of macroeconomic conditions, such that these conditions will not differ between the treatment firm and the matched control firms. Overall, my technique helps reduce selection bias in choosing a control. Panel C of Table 2 shows the results of the matching procedure for the sample. The matched treatment and control groups display no significant differences in any of the matching variables.

[18] I cannot use successful bids in my control group because they are going to show the effect of mergers. As mentioned earlier, they are also absent in my treatment group.

3.1.2 Difference-in-Differences

To empirically investigate whether learning through failed bids leads to better investment decisions, I employ a staggered difference-in-differences research design.

$$\begin{aligned} Investment_{it+1} = \beta_0 + \beta_1 * \ Treat_{it} * Post_{it} * IndustryQ_{it} + \beta_2 Post_{it} * \ Treat_{it} \\ +\beta_3 Post_{it} * IndustryQ_{it} + \ \beta_4 \ Treat_{it} * IndustryQ_{it} + \beta_5 \ Post_{it} \\ + \beta_6 \ Treat_{it} + \beta_7 \ IndustryQ_{it} \ + \sum \beta_j X_{it} \\ +Year \ FE + Firm \ FE + \varepsilon_{it}. \qquad (2) \end{aligned}$$

In the equation above, *i* and *t* index firms and year, respectively. The dependent variable $Investment_{it+1}$ has two different proxies—Total Investment and innovation investment. $Post_{it}$ is defined as 0 for three years before the acquisition announcement (*t-3 to t-1*) and as 1 for three years afterward (*t+1 to t+3*).[19] $Treat_{it}$ is an indicator variable equal to one if a firm made a friendly bid but failed to complete the acquisition and 1) zero for their matched control pair. $IndustryQ_{it}$ is the proxy for investment opportunities a year prior to the investment.[20] The triple interaction among these three variables is the triple difference estimator of interest. The coefficient β_1 gives the marginal impact of a change in the investment opportunities for the treatment firm, compared to a control firm, in the post-period, relative to the prior years. If β_1 is positive, I interpret this as evidence that bidders learn from targets through due diligence. X_{it} represents the vector of control variables described above. I include year fixed effects, which account for potential time-series variation in learning, perhaps due to changing nature of due diligence over the years or other macroeconomic factors. Moreover, I include firm fixed effects to control for time-invariant sources

[19] I exclude the year *t* from my analysis, which is the year of the announcement, as the observable changes in investment sensitivity are impacted by resources spent on the acquisition and price impact of the deal announcement.
[20] The literature shows that investment takes some time to respond to investment opportunities. Hence I use the one-year lag between when investment opportunities become available and when the investment is made. Additionally, my primary results are robust to using Tobin's Q as the measure of investment opportunities.

of unobservable heterogeneity unique to each firm. Under this regression framework, *Treat* itself is unidentified (and thus dropped from the regressions) because its effect is fully absorbed by the firm fixed effects. Post is still identified because the events occur at different points in time. Finally, I cluster standard errors by two-digit SIC code, because these are coarser than firm-level clustering. My results are, however, robust to clustering by firm.

To test my main predictions on innovation outcomes, I use the following difference-in-differences regression.

$$Innovation\ Output_{it+1} = \beta_0 + \beta_1 * Treat_{it} * Post_{it} + \beta_2 Post_{it} + \beta_3\, Treat_{\ it} + \sum \beta_j X_{it} + Year\ FE + Firm\ FE + \varepsilon_{it}. \qquad (3)$$

Post$_{it}$ is defined as 0 for five years before the acquisition announcement and as 1 for four years afterward. I use a longer time horizon to capture the effects of learning on innovation outcomes because, unlike investment expenditure, innovation outcomes, such as patents, require a gestation period.[21] The coefficient β_1 is the difference-in-differences estimate that I am interested in and indicates the change in the innovation outcome for the treatment firm, compared to a control firm, in the post-period, relative to the prior years. I expect β_1 to be positive.

3.2 EFFECT OF FAILURE ON SUBSEQUENT INVESTMENT SENSITIVITY

Table 3 provides the results from estimating Equation (2). The table shows the changes in investment sensitivity post failed bid for the treatment firms, relative to the control group. Results are shown using two proxies for investment expenditure: *Total Investment* (columns 1–4) and

[21]Allowing a longer time horizon increases the power of my tests since decisions on innovation need long gestation periods to generate outcomes (Glaeser and Glaeser (2020)).

Innovation Investment (columns 5–8). In the first column for each proxy, I only include year fixed effect while in the second column I include firm fixed effect but no year fixed effect. In the third column, I include both year and firm fixed effects but omit firm characteristics. Finally, in the fourth column, I include firm and year fixed effects as well as firm characteristics.

In column 3, the positive coefficient on *Post*Treat*Industry Q* (coef. = 0.026; t-stat = 1.91) indicates that treatment firms respond more to investment opportunities during the three years after an acquisition announcement, relative to control firms. Column 4 shows a similar result after controlling for firm characteristics. The magnitude of the coefficient indicates that, on average, a one standard deviation increase in *Industry Q* leads to a 3.36% higher investment expenditure for a bidder of a failed M&A deal, compared to a matched control firm in the post-period.[22]

The remaining columns of Table 4 show results consistent with those in the first four columns after replacing the *Total Investment* proxy with *Innovation Investment* (columns 5–8). For each proxy, the results indicate a higher investment sensitivity for the treatment firms, relative to control firms, in the post-period. In terms of economic magnitude, a one standard deviation increase in *Industry Q* leads to 1.57% higher *Innovation Investment* during the three years post announcement, compared to the matched control group.[23]

3.3 EFFECT OF FAILURE ON SUBSEQUENT INNOVATION OUTCOMES

Table 4 provides the results from estimating equation (3). The table shows the changes in innovation outcomes post failed bid for the treatment firms, relative to the control group. Results

[22] This represents a 20% increase relative to the unconditional sample mean of total investment.
[23] This represents a 28.04% increase relative to the unconditional mean of R&D investment.

are shown using two different proxies for innovation: log number of *patents* (columns 1–4), log number of patents weighted by forward citations, *Citations* (columns 5–8).

In the first column, the positive coefficient on *Post*Treat* (coef. = 0.087; t-stat = 2.02) indicates that treatment firms file more patents during the five years after an acquisition announcement year, relative to control firms. The magnitude of the coefficient indicates that, on average, the treatment firm files 1.41 more patents, relative to a matched control firm, in the post-period, which is a 9.72% increase, relative to the mean.[24] In the first column for citations, the positive coefficient on *Post*Treat* (coef. = 0.189; t-stat = 2.01) indicates that treatment firms also gather more citations, which suggests the patents they file are more impactful, during the post-period, relative to control firms. In columns 4 and 8, I use both firm and year fixed effects as well as firm characteristics. Results are consistent across all specifications.

3.4 PARALLEL TRENDS BEFORE BID FAILURE

A key identifying assumption for my main tests is parallel trends. Though there may be differences between firms of interest, the parallel trends assumption requires that those differences be constant in the pre-period and that they would have continued absent treatment. Thus, to investigate whether there are any differences in the investment sensitivity (innovation outcomes) between the treatment and control groups on a year-by-year basis from *t-3* to *t+3* (*t-5* to *t+5*), I estimate a modified version of equation (2) (equation (3)) in which I replace the post variable with

[24] Specifically, I first multiply the regression coefficient (e.g., 0.087 in Column (1) of Table 5) to the change in my independent variable: 0.063*1= 0.063). I use this value to derive an implied change in our dependent variable relative to its untransformed mean value (i.e., 14.47) in the following way: I solve for r such that 0.087 = ln(1+14.47*(1+r))-ln(1+14.47) to assess the economic effect of my regression coefficient relative to the mean value of my dependent variable. In this example, r = 9.72%.

a separate indicator variable for each event year. Next, from the modified version of Equation (2), I plot the coefficients of the interaction terms *t-3* × *Treatment* through *t+3* × *Treatment* in Figure 3 Panel A.[25] The coefficients are plotted along with a 90% confidence interval, calculated based on standard errors clustered at the industry level. The interaction terms *t-3* × *Treatment* through *t+3* × *Treatment* aim to capture any differential trends in the investment sensitivity between treatment and control firms in the periods prior to the acquisition announcement. Figure 3 shows that the investment sensitivity differential is insignificant in the pre-event period and becomes significant only from *t+2*. Hence treatment firms start altering their investments shortly after their failed bids.

Next, from the modified version of Equation (3) with *Patents (Citations)* as the dependent variable, I plot the coefficients of the interaction terms *t-5* × *Treatment* through *t+5* × *Treatment* in Panel B (Panel C). The coefficients are plotted along with a 90% confidence interval, calculated based on standard errors clustered at the firm level. Panel B (Panel C) demonstrates the effect of information transfer on *Patents* (*Citations*) of bid failure are absent in the pre-bid years, whereas significant effects begin to appear in the years after the announcement. Panels B and C also demonstrate that the effects of *Patents* and *Citations* are gradual and begin predominantly from *t+3*. This is consistent with the notion that, although firms may start altering their research investments immediately, their innovative output changes more slowly. It is possible that learning helps improve their existing innovations and that information spillover largely helps with the development of new ones. Glaeser, Glaeser, and Labro (2020) suggest that the average incubation period for an innovation is three to four years, which resembles the timing of the effects I

[25] I don't interact the relative year *t =0* as it is not included in the main analysis.

document.[26] Overall, Figure 3 supports my main hypothesis and provides reassurance that the results are not due to differential trends between treatment and control firms.

3.5 CORROBORATING THE MAIN FINDINGS

In this section, I provide a falsification test to validate my inferences about the *learning* channel. I also run several cross sectional tests to solidify the interpretation of my findings.

3.5.1 Falsification Test

A plausible alternative explanation for my main finding is that the effects are driven by a change in bidders' information set that occurred prior to deal negotiations, rather than by learning during the deal negotiations. In other words, a bidder may want to acquire a particular target because it has better information about its industry and thus would have expanded its investments into that market, regardless of the acquisition attempt. To mitigate this concern, in a placebo test, I use bidders that initiate hostile or unsolicited bids but fail to acquire the target as treatment firms. Thus, they have the same feature that the outcomes were not confounded by the actual take over. Moreover, both kinds of bidders likely possess similar initial information about the target's industry. However, one important difference is, in a hostile tender offer, the bidder does not

[26] Year *t+2 (t+3)* can be interpreted as the third (fourth) year in the development timeline of a patent if the decision to start the project was taken in year *t=0*, the year of the failed bid.

generally negotiate with the target's board and management (Raman et al., 2013). Because due diligence is usually absent in a hostile bid, learning from the target is expected to be muted.[27, 28]

I construct a new sample from SDC of treatment firms by identifying hostile or unsolicited bids that failed in 1986–2015. I only retain the deals that involved a U.S. bidder that does not operate in the energy or financial industries (SIC codes 4900–4999 and 6000–7099) and seeks to acquire at least 50% of the target.[29] Next, I match the hostile bids to control firms using the matching technique mentioned in section 4.1.1. The final sample for the falsification test consists of 2,512 observations for 153 treatment firms (with 869 observations) and 294 matched control firms (with 1643 observations). I re-estimate Equations 2 and 3 by using the hostile bids sample and report the results in Tables 5 and 6. In Table 5, for two investment expenditure proxies, the coefficient on the interaction term *Post*Treat*Industry Q* is insignificantly different from zero, indicating no change in investment sensitivity of the hostile bidders during the post-period, compared to the control firms. Results are consistent in Table 6, where changes in patents and citations are either negative or insignificantly different from zero. These results provide assurance that the main findings in Tables 3 and 4 with regard to effects of learning do not simply reflect the bidder's better ex ante information or ex post pressure to perform well.

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[27] Bidders may become more productive due to elevated market pressure—which is learning from its failure per se but not from the target's information. If so, I should observe improved outcomes for the hostile bidders too.
[28] There could be deals that start out as friendly and turn hostile. I am double-checking that my sample does not contain these deals.
[29] By law, in some jurisdictions (e.g., United Kingdom) even a hostile bidder gets on-demand access to information that the target has shared with friendly bidders.

3.5.2 The Effect of Learning Conditional on the Ability to Learn

In this section, I exploit the heterogeneity across the type of bidder to solidify the interpretation of my main findings on innovation outcomes. The type of the bidder is relevant because there must be a readiness on the part of the bidder to learn. A bidder with high R&D is likely eager to learn and to innovate after a deal. Such a firm is more likely to have experts who can understand and mimic the target's technologies. To test my conjecture, I partition the matched sample based on whether the firm's R&D expenditure in the pre-period (t-5 to t-1) is above (High R&D) or below (Low R&D) the median and re-estimate Equation (2) for each subsample. I expect that the differential in innovation output that the bidder experiences as a result of learning, relative to the control firm, is higher (lower) in the high (low) R&D bin. One concern may be that firms with historically high (low) R&D expenditures are likely to have high (low) innovation output. Note that, in the high (low) R&D bin, like the bidder firms, control firms are high (low) in R&D. Thus the baseline effect of R&D on innovation should be homogenous across bidder and control firms within a bin. The *incremental* effect of learning on bidder firms, *relative* to control firms across the two bins, is what matters here.

In Table 7 panel A, column (1), the coefficient on the difference-in-differences estimator, *Post* × *Treat*, is significantly positive (coef. = 0.137; t-stat. = 3.15), indicating that bidders have higher innovation outputs, relative to the control firms, in the high R&D sample. The coefficient differs insignificantly from zero (coef. = -0.002; t-stat. = -0.08) in the low R&D sample in column (2). An F-test shows that the difference between the coefficients in the two columns is statistically significant (p-value = 0.01), suggesting that the learning effects are concentrated among bidders with higher R&D. Columns (3) and (4) show similar results for forward citations weighted patents as the dependent variable.

The importance of having a robust product and technology portfolio likely also depends on the industry type. There is substantial heterogeneity across industries in patenting. While some industries, such as electronic equipment, require much innovation, others, such as real estate, do not. I predict that a bidder is more likely to pursue a target in part to acquire private information if innovation matters more in the bidder's industry. To test this hypothesis, I define high patenting industries as those with above-median aggregate patenting activity. The remaining industries are classified as low patenting.

Table 7 panel B examines the role of patenting intensity in the bidder's industry. In column (1), the coefficient on the difference-in-differences estimator, *Post* × *Treat*, is significantly positive (coef. = 0.104; t-stat. = 2.54), indicating that bidders have higher innovation outputs, relative to the control firms, in the high patenting industries bin. Economically, the log number of patents filed by the treatment firm increases by 13.87% following a bid failure in high patenting industries. Column 2 shows that this strong effect is absent in the subsample of bidders from low patenting industries (coef. = -0.004; t-stat. = -0.14). An F-test shows that the difference between the coefficients in the two columns is statistically significant (p-value = 0.02), which suggests that firms in high patenting industries are more likely to pursue knowledge-based acquisitions.

It is important to delve into the motive behind the acquisition because a bidder manager with high agency costs tends to seek her own benefits (e.g. greater scope of authority, personal wealth diversification, etc.) rather than aiming to improve the bidder firm's innovative capabilities. A bidder manager with high agency costs is less likely to seek knowledge-based acquisitions and thus will learn less through the M&A. Following Harford (2002) I measure agency costs using bidder's excess cash reserves in the year prior to the acquisition. Excess cash reserves is the actual cash holding less the predicted level of normal cash holding. The predicted level is determined by running a baseline regression model by industry and year.[30] The baseline regression model is developed on inventory management and buffer-stock theories of cash management (Harford 2002). I partition the matched sample based on whether the firm's excess cash is above (High Excess Cash) or below (Low Excess Cash) the median and re-estimate Equation (2) for each subsample. I expect that the differential in innovation output that the bidder experiences as a result of learning, relative to the control firm, is lower (higher) in the high (low) excess cash bin.

In Table 7 panel C, columns (2) represents that the coefficient on the difference-in-differences estimator, *Post* × *Treat*, is significantly positive (coef. = 0.073; t-stat. = 2.27), indicating that bidders have significantly higher innovation outputs, relative to the control firms, in the low ex ante excess cash sample. The coefficient differs insignificantly from zero (coef. = 0.041; t-stat. = 0.59) in the high excess cash sample in column (1). Columns (3) and (4) show similar results for forward citations weighted patents as the dependent variable. Although an F-test shows that the difference between the coefficients in the two columns is statistically insignificant (p-value = 0.30), the magnitude of the coefficient on *Post* × *Treat* is much bigger in the low ex ante excess cash sample suggesting that the learning effects are concentrated among bidders with lower ex ante excess cash.

3.5.3 The Effect of Learning Conditional on the Scope to Learn

The effects of learning should depend on available opportunities to learn, which I proxy with target-specific characteristics. Because target-specific information is only present for firms

[30] The actual cash holding and all the variables in the model are scaled by sales.

that actually bid and I am investigating variation in learning across bidders over time, I exclude control firms from the sample. The modified research design is the following.

$$Investment_{it+1} = \beta_0 + \beta_1 Post_{it} * IndustryQ_{it} + \beta_2 Post_{it} + \beta_3\, IndustryQ_{it} + \sum \beta_j X_{it} + Year\ FE + Firm\ FE + \varepsilon_{it}. \qquad (5)$$

The first characteristic I examine is whether the target is a private entity. About 35% of the bidders in my full sample have a private counterparty. I partition the bidders into two bins, depending on whether their counterparty is a private or public firm. Since private firms possess significant amounts of private information, I expect bidders that target them to have more opportunities to learn and thus a greater investment sensitivity effect. Table 8 Panel A presents the results of estimating equation (5) in each subsample. Results are shown using two different proxies for investment expenditure: *Total Investment* (columns 1 and 2) and *Innovation Investment* (columns 3 and 4). In column 3, in the private target sample, the coefficient on *Post* × *Industry Q* is significantly positive (coef. = 0.025; t-stat. = 2.03), but it is insignificantly different from zero (coef. = -0.005; t-stat. = -1.16) in column 4, in the public target sample. An F-test shows that the difference between the coefficients in the two columns is statistically significant (p-value = 0.02). Although, the coefficient on *Post* × *Industry Q* is slightly lower in magnitude in the private target subsample than that in the public subsample for the other proxy for investment expenditure but the coefficients are not significantly different from each other.

The second characteristic I examine is whether the target belongs to the same industry as the bidder. For this analysis, I partition the bidders into two bins, depending on whether the target belongs to the same industry, using the macro industry classification data from Thomson SDC.[31] I conjecture that bidders who share an industry with their targets show greater investment efficiency post bid failure. Table 8 Panel B presents the results of estimating equation (5) in each

[31] Thompson SDC has an industry classification available for private target firms as well.

subsample. Consistent with expectations, the improvement in investment efficiency is mostly concentrated in the same-industry subsample for both proxies for investment.

Finally, I investigate whether the bidder has higher innovation outputs when it shares the same patent class as the target. I collect patent class information from the Patent View dataset but can only able observe patent classes of public entities. I proxy for same patent class with an indicator variable that equals to one if in any of the pre-bid years the bidder and target share a common patent class and zero otherwise. I partition the bidders into two bins, depending on whether the target shares a same patent class pre-bid. Table 8 Panel C represents the results of estimating the following equation in each subsample.

$$Innovation\ Output_{it+1} = \beta_0 + \beta_1 Post_{it} + \sum \beta_j X_{it} + Year\ FE + Firm\ pair\ FE + \varepsilon_{it}. \quad (6)$$

In column (1), in the same patent class sample, the coefficient on *Post* is significantly positive (coef. = 0.169; t-stat. = 1.86), but it is insignificantly different from zero (coef. = 0.007; t-stat. = 0.04) in column (2), in the different patent class sample suggesting that the innovation effects are stronger when the bidder and target possess similar patents. An F-test however shows that the difference between the coefficients in the two columns is not statistically significant (p-value = 0.89). Results are consistent using citation weighted patents as the dependent variable across column (3) and (4).

3.6 CONSEQUENCES TO THE DISCLOSING (TARGET) FIRM

In this section, I investigate the consequences to the *target* firm as a result of the divulgence of proprietary information. According to the Pareto improvement hypothesis, improvement in peers' actions as a result of learning does not occur at the expense of the disclosing firm. On the other hand, the resource relocation hypothesis posits that disclosure leads to a wealth transfer from the disclosing firm to its peers.

To investigate costs to the target firms, I construct a sample of firms by identifying targets of friendly bids that failed in 1986–2015. The final sample for the consequence tests consists of 2,402 observations for 120 treatment firms (with 669 observations) and 231 matched control firms (with 1733 observations). I re-estimate equations 2 and 3 using this sample. I report the results in Table 9. In Table 9 Panel A, for both the investment expenditure proxies, the coefficient on the interaction term *Post* Treat*Industry Q* differs insignificantly from zero, indicating no change in investment sensitivity for the targets during the post-period, compared to the control firms. However, in Table 9 panel B columns (1-4), the results are consistent with the resource relocation hypothesis: changes in patents are significantly negative in the post-period (coef. = -0.057; t-stat. = -2.10). Moreover, in columns (5-8), I find that changes in patents are insignificantly different from zero when the bidder is a hostile one that suggest that targets do not exhibit similar negative consequences.[32]

Additionally, I investigate two more outcome variables related to target's product market dynamics to further investigate their consequences. I estimate the following regression using the sample of targets and their matched control firms:

$$Product\ Market\ Output_{it+1} = \beta_0 + \beta_1 * \ Treat_{it} * Post_{it} + \beta_2 Post_{it} + \beta_3\, Treat_{\ it} + \sum \beta_j X_{it} + Year\ FE + Firm\ FE + \varepsilon_{it}. \qquad (7)$$

Where *Product Market Output*$_{it+1}$ is measured with two proxies: market share and product market competitiveness. Market share is defined as the sales of a sample firm divided by the total sales in four digit SIC code a given year. Product market competitiveness is defined as the

[32] The sample consists of 103 targets of failed hostile bids and their matched pairs.

similarity in product portfolio of a sample firm with its top 20 rivals. If β_1 is negative (positive) for the test on market share (product market competitiveness), I interpret it as an evidence that target firms lose market share (face higher competition) relative to matched control firms in the post-period. Table 9 panel C reports the corresponding results. I find that target firms' market share significantly declines (coef. = -0.021; t-stat. = -2.17) and overall product market competitiveness significantly increases (coef. = 0.006; t-stat. = 1.90).[33,34] Overall, I provide multiple evidence that information spillover harms future innovation and market dynamics for the disclosing firm, whereas it can improve the net investment efficiency of firms in the economy.

3.7 ROBUSTNESS TESTS

Although theoretically, it is likely that the bid failed because the target is a poor choice relative to outside options of the bidder, I find that similar evidence of learning exists even in a sample where the deals fail for exogenous reasons. To this end, I investigate a sub-sample of friendly deals that failed due to exogenous reasons such as regulatory intervention. The sample consists of 2,635 observations for 76 treatment firms (with 520 observations) and 294 matched control firms (with 2,115 observations). I re-estimate Equation 3 and report the corresponding results in Table 10. In column (4), the coefficient on *Post* × *Treat*, is significantly positive (coef. = 0.176; t-stat. = 2.10), indicating that bidders have higher newly granted patents, relative to the control firms. In column (8), the coefficient on *Post* × *Treat*, is significantly positive (coef. = 0.280; t-stat. = 1.73), indicating that bidders receive higher citations per patents, relative to the

[33] For the test on product similarity, I cluster standard errors by year. While clustering by industry or firm generates similar results qualitatively, they are weaker.
[34] In untabulated tests, I find that targets do not exhibit similar negative consequences in hostile failed deals.

control firms. This test mitigates concerns that the bidders in my sample are unique such that they abandon the deals due to the availability of better outside opportunities. Moreover, such evidence also indicates that perhaps not all the time the information acquisition attempt is intentionally planned.

4.0 CONCLUSION

I investigate the effects of learning during due diligence on the subsequent actions of the bidders. I construct a sample by matching bidding firms that negotiated, announced but failed to close deals with non-bidding firms on the probability of entering into a bid, based on a determinants model of acquisition likelihood. I find that bidders make better investment decisions and innovate more, relative to control firms, following a failed M&A. My estimates indicate that a one standard deviation change in investment growth opportunity leads to a 3.36% change in the investment level for a bidder in a failed M&A deal, relative to a matched control firm in the post-period. I also find that the bidder of a failed deal generates 1.41 more patents (37.49 citations), relative to the control group, a 9.72% (15.44%) increase over the sample means. In a sample of failed hostile bids, where no learning likely occurs, I fail to find similar effects, which supports my argument that the explanation is indeed learning from peers. Moreover, the bidder's intensity of learning depends on the types of target and its own purpose of the acquisition, which further emphasizes the learning channel. Lastly, I find that the target bears the costs of divulging its proprietary information.

I contribute to the literature by documenting that proprietary information spillover has significant implications for both peers and the disclosing firm. Second, I document an unexplored economic benefit of acquisition attempts that accrues to acquirers: access to a rival's strategies. Third, I uncover the industry- and firm-specific conditions under which organizational learning happens.

The idea that the bidder may acquire important information from due diligence is an underexplored—but potentially important—concept in the M&A literature. Investigating whether targets price-protect against information leakage would be an interesting extension of my study. Relatedly, studying whether bidder-firm managers trade more profitably on the stock of the target or target's peers after due diligence could also extend my findings. I leave these considerations for future research.

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Figure 1

M&A Due Diligence Process

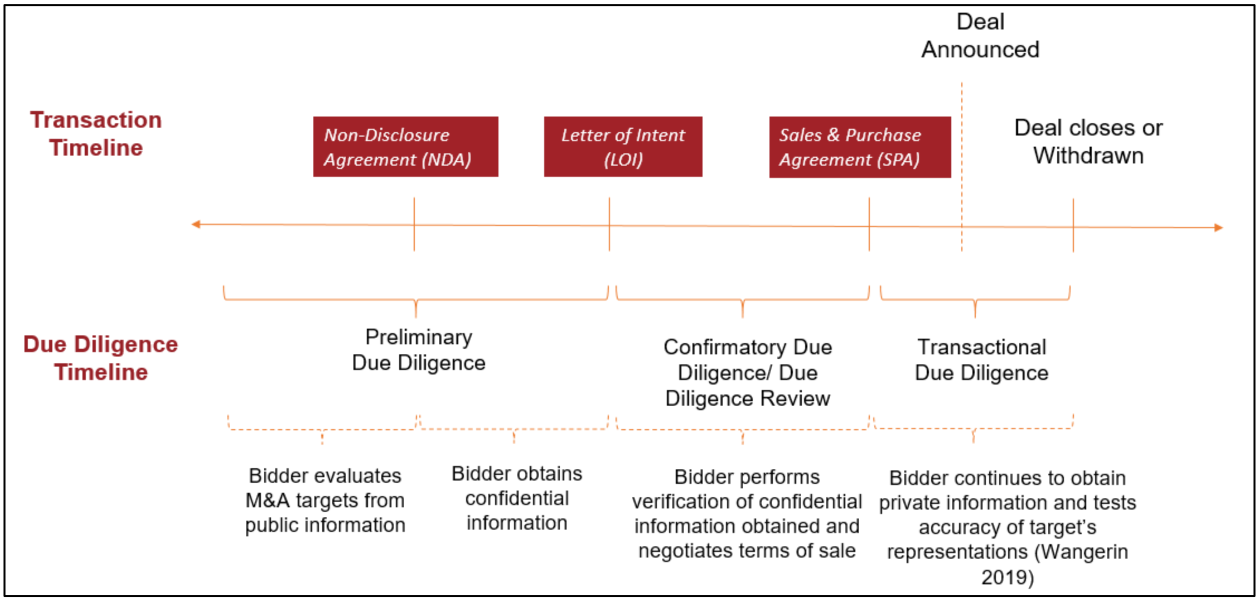


Figure 2

Top Ten Industries by the Number of Failed M&As

This figure graphs the number of failed M&As and patents filed firm as a percent of totals by industry sectors for the top ten industries by failed M&A. Industries are based on three-digit SIC codes. Detailed definitions of all variables are provided in Appendix A.

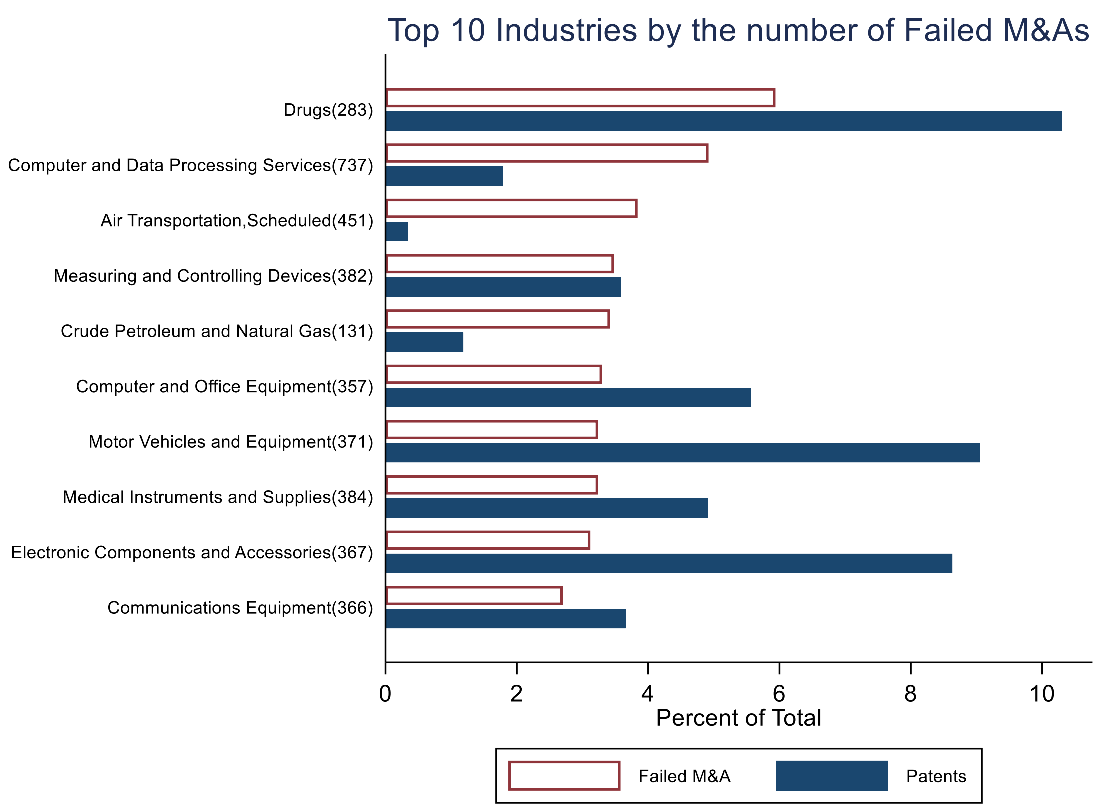


Figure 3

Parallel Trends in Investment Sensitivity, Patents, and Citations

This figure provides a visual representation of changes in investment sensitivity, patents, and citations around bid failure. The x-axis represents time by event year and the y-axis represents the treatment firm's changes relative to the control firm during any given period. For Panel A (B & C), a version of Equation (2) (Equation (3)) is estimated but the *Post* indicator variable is replaced by separate indicator variables for each event year *t-3* to *t+3* (*t-5* to *t+5*). The coefficients are plotted along with a 90% confidence interval, calculated based on standard errors clustered at the industry level. Note that t-3 has a coefficient of zero and no confidence interval because it serves as the benchmark period.

Panel A: Investment Efficiency

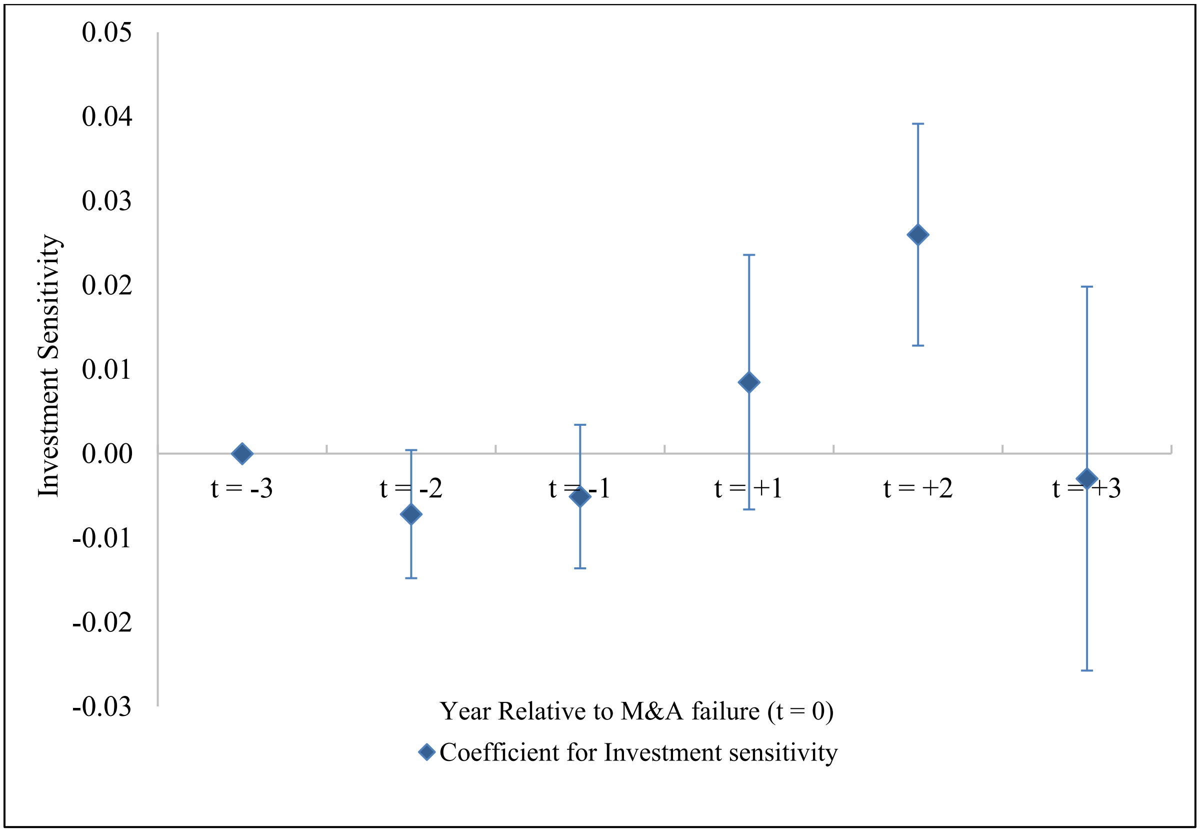
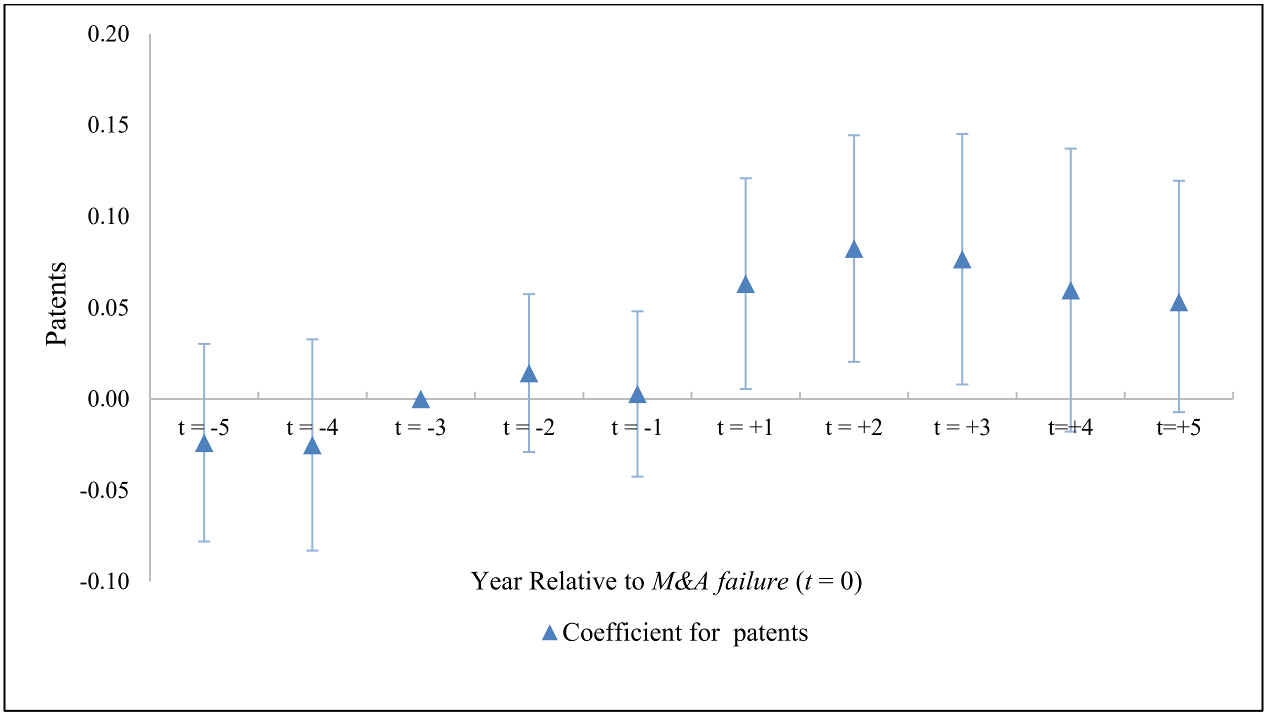


Figure 3 [Continued]

Panel B: Patents



Panel C: Citation Weighted Patents

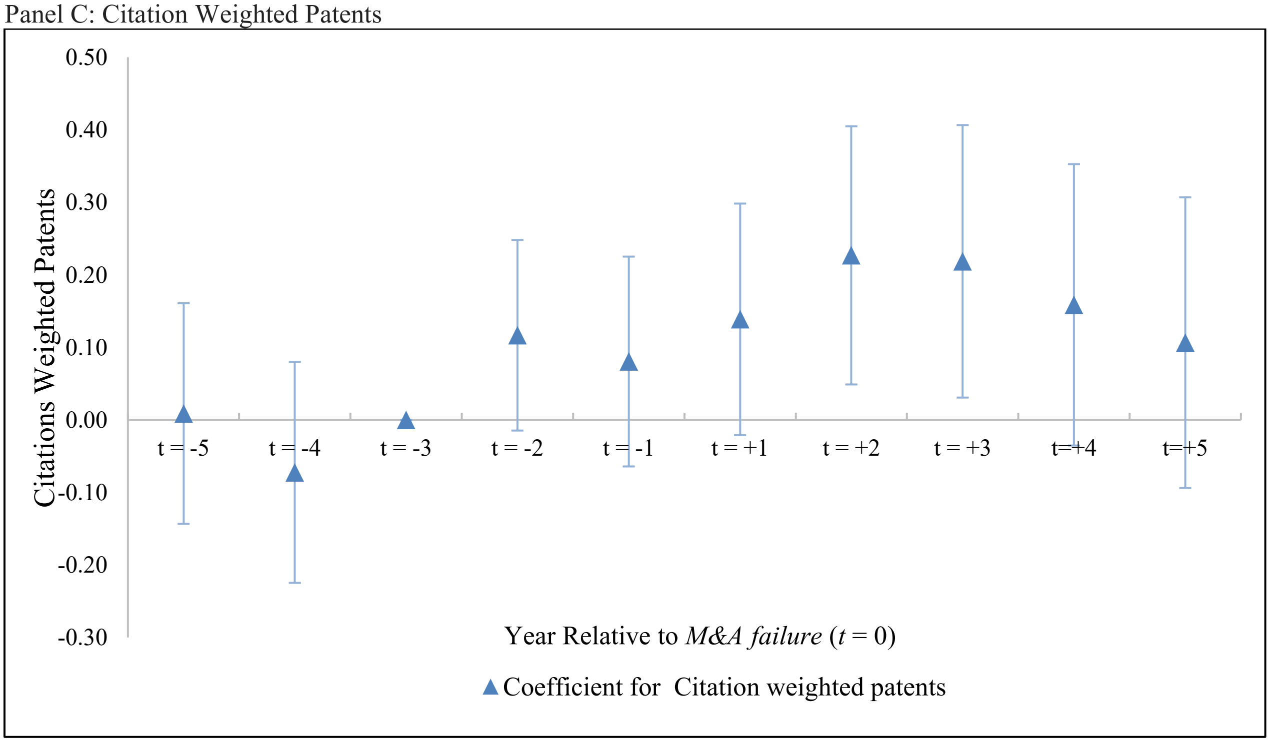


Table 1

Sample Selection
This table reports the sample selection procedure and the number of firm-year observations used in my empirical analyses.

	No. of obs.
Number of withdrawn (friendly) bids from SDC (1986-2015)	5,900
Drop: Failed bids that do not have a matching identifier for the bidder in COMPUSTAT/CRSP	*-3,217*
	2683
Drop: Failed bids with the bidder in SIC code 4900-4999 or 6000-7099	*-675*
	2008
Drop: Failed bids where percentage sought < 50%	*-378*
	1630
Drop: Failed bidders that had successful acquisition in the same year	*-770*
	860
Drop: Failed bidders for which a matched control not found	*-132*
	728
Drop: Firms with less than two years of financial data in each of the pre and post period	-196
	532
Total number of failed bidders and control firms in the matched sample	1506
Firm-years with non missing data in the pre and post period (-5,+5) [Sample for Tests on Innovation Outcomes]	11505
Firm-years with non missing data in the pre and post period (-3,+3) [Sample for Tests on Investment Sensitivity]	8,520

Table 2

This table presents descriptive information for the sample and variables of interest. Panel A reflects the summary statistics for the variables. Panel B reflects the matching variables. Details of variable construction are contained in Appendix A.

Panel A: Descriptive Statistics

	Obs.	Mean	SD	P10	P25	Median	P75	P90
Investment Outcomes								
Capital Investment	8,435	0.17	0.28	0.02	0.05	0.10	0.20	0.36
Innovation Investment	8,435	0.06	0.14	0.00	0.00	0.00	0.06	0.16
Innovation Outcomes								
Patents Raw	11,505	14.47	58.24	0	0.00	0.00	2.00	16
Citation Weighted Patents Raw	11,505	242.85	967.37	0.00	0.00	0.00	22.00	278.00
Patents	11,505	0.77	1.42	0.00	0.00	0.00	1.10	2.83
Citation Weighted Patents	11,505	1.54	2.49	0.00	0.00	0.00	3.09	5.63
Other Variables								
Industry Q	8,435	1.86	1.12	1.05	1.21	1.53	2.12	2.96
Firm Size	11,505	5.43	2.30	2.51	3.64	5.27	7.07	8.65
Tangibility	11,505	0.31	0.23	0.06	0.13	0.25	0.45	0.68
Institutional Ownership	11,505	0.27	0.57	0.00	0.00	0.11	0.51	0.77
Market to Book	11,505	1.86	1.47	0.87	1.05	1.37	2.05	3.41
Return on Assets	11,505	0.11	0.18	-0.05	0.05	0.11	0.19	0.29
Leverage	11,505	0.20	0.23	0.00	0.01	0.12	0.32	0.55
Liquidity	11,505	0.10	0.13	0.00	0.01	0.05	0.14	0.27
Herfindahl	11,505	0.29	0.19	0.09	0.14	0.24	0.41	0.60
Firm Age (Raw)	11,505	19.79	12.91	6.00	10.00	16.00	28.00	40.00
Finance	11,505	0.62	2.34	0.00	0.00	0.00	0.27	1.12
R&D	11,505	0.05	0.10	0.00	0.00	0.00	0.05	0.15

Panel B: Difference in Treat and Control in the Matched Sample

	Treat	Control		t-test	
Matching Variables	Mean	Mean	Diff	t value	pr>|t|
Size	4.97	5.00	0.03	0.33	0.74
Sales Growth	0.32	0.30	-0.01	-0.36	0.71
Return on Assets	0.02	0.02	0.00	0.07	0.94
Cash Flow	0.00	0.00	0.00	0.23	0.81
Capital Expenditure	0.19	0.19	-0.00	-0.40	0.68

Table 3

The Effect of Failure on Investment Sensitivity

This table presents results examining the effects on investment sensitivity following a bid failure. The sample consists of all friendly bids that failed and their matched control firms in between 1986-2015. The dependent variable is investment expenditure measured with two different proxies: *Total Investment* (*Innovation Investment*) in columns 1-4 (5-8). *Post* is an indicator variable equal to one for years *t+1* to *t+3* and zero for years *t-1* to *t-3*. *Treat* an indicator variable equal to one if a firm made a friendly bid but failed to complete an acquisition and zero for their matched control pair. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent Variable:	*Total Investment*				*Innovation Investment*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*IndustryQ*	0.020	0.028*	0.026*	0.030*	0.016	0.014**	0.013**	0.014**
	(1.37)	(1.73)	(1.91)	(1.84)	(1.28)	(2.05)	(2.13)	(2.13)
*Post*Treat*	-0.031	-0.044	-0.046	-0.048	-0.023	-0.024*	-0.022*	-0.024**
	(-0.99)	(-1.36)	(-1.44)	(-1.46)	(-1.11)	(-1.99)	(-1.99)	(-2.05)
*Post*IndustryQ*	0.000	-0.001	0.001	-0.003	-0.002	-0.007	-0.006	-0.007
	(0.06)	(-0.20)	(0.12)	(-0.41)	(-0.43)	(-1.62)	(-1.38)	(-1.62)
*Treat*IndustryQ*	-0.005	-0.011	-0.003	-0.010	-0.002	-0.013	-0.012	-0.013
	(-0.54)	(-0.57)	(-0.16)	(-0.52)	(-0.26)	(-1.08)	(-1.03)	(-1.07)
IndustryQ	0.027***	0.008	0.007	0.002	0.051***	0.003	0.004*	0.002
	(2.67)	(1.02)	(0.85)	(0.20)	(4.41)	(0.87)	(1.72)	(0.62)
Post	-0.011	-0.026*	-0.011	0.005	0.003	0.010*	0.014**	0.016**
	(-0.66)	(-1.80)	(-0.83)	(0.42)	(0.38)	(1.67)	(2.13)	(2.34)
Treat	0.021				-0.008			
	(0.84)				(-0.71)			
Return on Assets	-0.043	-0.038		-0.048	-0.051*	-0.031		-0.036*
	(-1.03)	(-0.78)		(-0.99)	(-1.68)	(-1.63)		(-1.86)
Leverage	-0.086***	-0.297***		-0.264***	-0.062***	-0.011		-0.006
	(-5.20)	(-6.06)		(-5.83)	(-3.95)	(-1.36)		(-0.70)
Firm size	0.004**	0.039***		0.043***	-0.001	0.007*		0.009*
	(2.08)	(4.78)		(4.94)	(-0.79)	(1.90)		(1.81)
Herfindahl	-0.101**	-0.074		-0.044	0.071	0.021		0.019
	(-2.22)	(-0.90)		(-0.56)	(1.62)	(0.87)		(0.78)
*Herfindahl*IndustryQ*	-0.020	-0.031		-0.024	-0.072**	0.004		0.004
	(-0.85)	(-1.61)		(-1.22)	(-2.38)	(0.38)		(0.39)
Liquidity	0.274***	0.151***		0.199***	0.261***	0.020		0.023
	(3.44)	(3.11)		(3.81)	(3.35)	(0.54)		(0.63)
Obs.	8,435	8,435	8,435	8,435	8,435	8,435	8,435	8,435
Adj. R-Square	0.055	0.209	0.190	0.214	0.213	0.674	0.674	0.676
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 4

The Effect of Failure on Innovation Outcomes
This table presents results examining the effects on innovation following a bid failure. The sample consists of all friendly bids that failed and their matched control firms in between 1986-2015. The dependent variable is innovation measured with two different proxies. *Post* is an indicator variable equal to one for years *t+1* to *t+5* and zero for years *t-1* to *t-5*. *Treat* an indicator variable equal to one if a firm made a friendly bid but failed to complete an acquisition and zero for their matched control pair. Columns 1-4 (5-8) show the results using *Patents* (*Citation Weighted Patents*) as the innovation proxy. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent Variable:		*Patents*				*Citation weighted patents*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*	0.087**	0.064**	0.047*	0.063**	0.189**	0.141*	0.108	0.143*
	(2.02)	(2.31)	(1.89)	(2.38)	(2.01)	(1.79)	(1.61)	(1.92)
Post	-0.106**	-0.119***	-0.107*	-0.109**	-0.179**	-0.252***	-0.091	-0.107*
	(-2.46)	(-3.79)	(-1.99)	(-2.33)	(-2.21)	(-4.63)	(-1.35)	(-1.77)
Treat	-0.052				-0.032			
	(-1.16)				(-0.33)			
Firm size	0.346***	0.087***		0.096***	0.540***	0.122***		0.157***
	(5.60)	(3.25)		(3.62)	(6.65)	(3.86)		(4.16)
Tangibility	-0.973***	0.013		-0.005	-1.510***	0.240		0.065
	(-4.14)	(0.13)		(-0.05)	(-3.71)	(1.37)		(0.37)
Institutional Ownership	-0.003	0.014		0.026	0.078	0.010		0.047
	(-0.04)	(0.69)		(1.20)	(0.69)	(0.40)		(1.41)
Market to Book	-0.103***	-0.000		-0.002	-0.134***	0.021		0.011
	(-4.31)	(-0.04)		(-0.31)	(-4.03)	(1.09)		(0.61)
Return on Assets	0.116	0.016		0.016	0.364	0.124		0.099
	(0.78)	(0.26)		(0.27)	(1.40)	(1.05)		(0.82)
Leverage	-0.012	-0.085		-0.076	-0.296	-0.370**		-0.304*
	(-0.06)	(-1.04)		(-0.95)	(-0.88)	(-2.09)		(-1.76)
Liquidity	-0.306	-0.074		-0.060	-0.552*	-0.178		-0.135
	(-1.50)	(-0.88)		(-0.68)	(-1.72)	(-0.73)		(-0.55)
Herfindahl	1.382	0.192		0.342	3.587**	1.228		1.860**
	(1.42)	(0.67)		(1.12)	(2.37)	(1.25)		(2.18)
Firm Age	0.257***	0.168*		0.188**	0.445***	0.059		0.503***
	(3.30)	(1.86)		(2.43)	(3.65)	(0.37)		(3.08)
Finance	0.003	-0.010*		-0.006	-0.008	-0.041***		-0.011
	(0.28)	(-1.71)		(-0.86)	(-0.42)	(-3.25)		(-1.04)
Herfindahl2	-1.815	-0.101		-0.233	-4.684**	-1.468		-1.934**
	(-1.53)	(-0.26)		(-0.61)	(-2.47)	(-1.30)		(-2.03)
R&D	3.631***	0.167		0.132	7.265***	0.737***		0.569*
	(5.33)	(1.13)		(0.97)	(5.47)	(3.09)		(1.89)
Obs.	11,505	11,505	11,505	11,505	11,505	11,505	11,505	11,505
Adj. R-Square	0.365	0.881	0.879	0.882	0.334	0.791	0.793	0.797
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 5

Falsification Test: The Effect of Failure on Investment Sensitivity in a Sample of Hostile Bids
This table presents results examining the effects on investment sensitivity following a bid failure. The sample consists of all hostile and unsolicited bids that failed and their matched control firms in between 1986-2015. The dependent variable is investment expenditure measured with two different proxies: *Total Investment* (*Innovation Investment*) in columns 1-4 (5-8). *Post* is an indicator variable equal to one for years *t+1* to *t+3* and zero for years *t-1* to *t-3*. *Treat* an indicator variable equal to one if a firm made a hostile or unsolicited bid but failed to complete an acquisition and zero for their matched control pair. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent Variable:		*Capital Investment*				*Innovation Investment*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*IndustryQ*	0.017	0.007	0.046	-0.005	0.010	-0.009	-0.007	-0.008
	(0.31)	(0.07)	(0.44)	(-0.05)	(1.20)	(-1.05)	(-0.94)	(-1.01)
*Post*Treat*	-0.014	0.003	-0.064	0.027	-0.003	0.020	0.017	0.018
	(-0.10)	(0.02)	(-0.30)	(0.14)	(-0.29)	(1.55)	(1.53)	(1.65)
*Post*IndustryQ*	-0.032*	-0.017	-0.030	-0.037*	-0.009	-0.005	-0.002	-0.003
	(-1.94)	(-0.91)	(-1.26)	(-1.70)	(-1.52)	(-1.15)	(-0.53)	(-0.63)
*Treat*IndustryQ*	-0.026	0.001	0.009	0.008	-0.000	0.016*	0.013*	0.014
	(-1.22)	(0.02)	(0.25)	(0.19)	(-0.04)	(1.92)	(1.77)	(1.65)
IndustryQ	0.028	0.017	0.033	0.014	0.049***	-0.000	-0.001	-0.003
	(1.16)	(0.34)	(1.68)	(0.32)	(7.12)	(-0.02)	(-0.34)	(-0.67)
Post	0.054	-0.009	0.031	0.052	0.010	0.003	-0.005	-0.005
	(1.57)	(-0.26)	(0.72)	(1.35)	(1.07)	(0.38)	(-0.68)	(-0.60)
Treat	0.084				-0.012			
	(1.08)				(-0.91)			
Return on Assets	-0.056	-0.154		-0.184	0.045	-0.019		-0.015
	(-0.30)	(-0.71)		(-0.83)	(1.18)	(-0.42)		(-0.34)
Leverage	-0.117**	-0.569**		-0.559**	-0.040***	-0.016**		-0.017*
	(-2.04)	(-2.56)		(-2.52)	(-3.15)	(-2.07)		(-1.75)
Firm size	0.001	0.035**		0.030*	-0.004***	0.002		0.003
	(0.11)	(2.06)		(1.71)	(-3.50)	(0.98)		(1.19)
Herfindahl	-0.065	0.037		0.058	0.103***	-0.033		-0.033
	(-0.41)	(0.08)		(0.14)	(3.10)	(-1.49)		(-1.57)
*Herfindahl*IndustryQ*	-0.010	-0.042		-0.048	-0.095***	0.003		0.002
	(-0.15)	(-0.26)		(-0.35)	(-6.54)	(0.40)		(0.25)
Liquidity	0.535*	0.923		1.083	0.120***	-0.038*		-0.041
	(1.82)	(1.46)		(1.61)	(3.44)	(-1.70)		(-1.56)
Obs.	1,790	1,790	1,790	1,790	1,790	1,790	1,790	1,790
Adj. R-Square	0.031	0.083	0.038	0.091	0.283	0.791	0.791	0.794
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 6

Falsification Test: The Effect of Failure on Innovation in a Sample of Hostile Bids

This table presents results examining the effects on innovation following a bid failure. The sample consists of all failed hostile and unsolicited bids and their matched control firms in between 1986-2015. The dependent variable is innovation measured with two different proxies: *Patents* (*Citation Weighted Patents*) in columns 1-4 (5-8). *Post* is an indicator variable equal to one for years *t+1* to *t+5* and zero for years *t-1* to *t-5*. *Treat* an indicator variable equal to one if a firm made a hostile or unsolicited bid but failed to complete an acquisition and zero for their matched control pair. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent Variable:	*Patents*				*Citation Weighted Patents*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*	-0.224*	-0.137*	-0.153**	-0.127*	-0.293	-0.167	-0.173	-0.131
	(-1.80)	(-1.90)	(-2.09)	(-1.69)	(-1.49)	(-1.05)	(-1.15)	(-0.82)
Post	-0.013	-0.024	0.101	0.061	-0.068	-0.153	0.197	0.129
	(-0.13)	(-0.45)	(1.27)	(1.10)	(-0.47)	(-1.24)	(1.27)	(1.12)
Treat	-0.175				-0.209			
	(-1.55)				(-1.06)			
Firm size	0.315***	0.047		0.060*	0.458***	0.022		0.051
	(5.99)	(1.57)		(1.71)	(5.93)	(0.45)		(0.80)
Tangibility	-1.187***	0.110		0.071	-1.709***	0.633		0.347
	(-4.06)	(0.43)		(0.28)	(-3.38)	(1.07)		(0.59)
Institutional Ownership	0.241	-0.093		-0.028	0.633**	-0.095		0.158
	(1.13)	(-0.89)		(-0.28)	(2.10)	(-0.50)		(0.84)
Market to Book	-0.006	-0.004		-0.010	0.034	0.031		0.019
	(-0.11)	(-0.28)		(-0.50)	(0.26)	(0.84)		(0.51)
Return on Assets	0.017	0.076		0.075	0.093	0.205		0.280
	(0.04)	(0.49)		(0.49)	(0.16)	(0.51)		(0.75)
Leverage	0.201	-0.151		-0.069	0.248	-0.456		-0.213
	(0.97)	(-1.17)		(-0.55)	(0.67)	(-1.36)		(-0.70)
Liquidity	-0.483	0.250		0.297	-0.506	0.662		0.469
	(-1.07)	(1.18)		(1.47)	(-0.58)	(1.48)		(1.30)
Herfindahl	0.283	-0.249		-0.286	0.024	-0.081		-0.103
	(0.23)	(-0.33)		(-0.35)	(0.01)	(-0.04)		(-0.05)
Firm Age	0.436***	0.270**		0.491***	0.722***	0.380		1.063***
	(3.15)	(2.21)		(3.35)	(3.75)	(1.54)		(4.35)
Finance	0.100	-0.020		0.008	0.185**	-0.115		-0.016
	(1.41)	(-0.69)		(0.29)	(2.20)	(-1.05)		(-0.21)
Herfindahl2	-0.208	-0.384		-0.204	0.836	-1.093		-0.390
	(-0.14)	(-0.39)		(-0.19)	(0.29)	(-0.47)		(-0.17)
R&D	10.462***	-0.456		-0.403	19.061***	1.956		1.942
	(7.14)	(-0.57)		(-0.48)	(7.99)	(0.86)		(0.83)
Obs.	2,512	2,512	2,512	2,512	2,512	2,512	2,512	2,512
Adj. R-Square	0.440	0.895	0.893	0.896	0.411	0.799	0.801	0.804
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 7

The Effect of Learning Conditional on the Ability to Learn

This table presents results examining the effects on innovation following a bid failure, conditional on the ability to learn. The sample consists of all failed friendly bids and their matched control firms in between 1986-2015. The dependent variable is innovation measured with two different proxies. *Post* is an indicator variable equal to one for years *t+1* to *t+5* and zero for years *t-1* to *t-5*. *Treat* an indicator variable equal to one if a firm made a friendly bid but failed to complete an acquisition and zero for their matched control pair. Columns 1-2 (3-4) show the results using *Patents* (*Citation Weighted Patents*) as the innovation proxy. In Panel A, the sample is bifurcated into those with R&D levels above-median (High R&D) and below-median (Low R&D). In Panel B, the sample is bifurcated into those with industry patenting activities above-median (High Patenting) and below-median (Low Patenting). In Panel C, the sample is bifurcated into those with excess cash reserves above-median (High Excess Cash) and below-median (Low Excess Cash). All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Conditional on Bidder's Ex ante R&D Expenditure

Dependent Variable:	*Patents*		*Citation weighted patents*	
	High R&D	Low R&D	High R&D	Low R&D
	(1)	(2)	(3)	(4)
*Post*Treat*	0.137***	-0.002	0.258**	0.023
	(3.15)	(-0.08)	(2.40)	(0.28)
Post	-0.233***	0.018	-0.271**	0.036
	(-2.94)	(1.08)	(-2.47)	(0.63)
Firm size	0.191***	0.009	0.306***	0.031
	(5.19)	(1.36)	(5.56)	(1.50)
Tangibility	0.041	0.012	0.081	0.061
	(0.15)	(0.24)	(0.15)	(0.48)
Institutional Ownership	0.032	-0.019	0.064*	-0.112
	(1.54)	(-0.31)	(1.90)	(-0.73)
Market to Book	-0.013	-0.001	-0.002	0.001
	(-1.17)	(-0.11)	(-0.06)	(0.06)
Return on Assets	0.045	-0.014	0.138	0.005
	(0.40)	(-0.64)	(0.63)	(0.09)
Leverage	-0.101	-0.064**	-0.603	-0.158*
	(-0.50)	(-2.36)	(-1.45)	(-1.73)
Liquidity	-0.071	-0.014	-0.075	-0.048
	(-0.48)	(-0.26)	(-0.21)	(-0.27)
Herfindahl	0.265	0.074	2.149	0.687
	(0.46)	(0.26)	(1.56)	(0.78)
Firm Age	0.392**	0.032	0.910***	0.155
	(2.49)	(0.66)	(3.30)	(1.13)
Finance	-0.005	-0.003	0.004	-0.001
	(-0.54)	(-1.26)	(0.31)	(-0.15)
Herfindahl2	0.000	-0.104	-2.254	-0.796
	(0.00)	(-0.31)	(-1.36)	(-0.80)
R&D	0.131	0.072	0.332	2.304
	(1.02)	(0.08)	(0.94)	(0.55)
p-value for difference in coefficients	0.01		0.05	
Obs.	5,749	5,756	5,749	5,756
Adj. R-Square	0.869	0.736	0.780	0.589
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 7 [Continued]

Panel B: Conditional on Ex ante Patenting Activities in Bidder's Industry

Dependent Variable:	*Patents*		*Citation weighted patents*	
	High Patenting	Low Patenting	High Patenting	Low Patenting
	(1)	(2)	(3)	(4)
*Post*Treat*	0.104**	-0.004	0.219*	-0.012
	(2.54)	(-0.14)	(1.96)	(-0.14)
Post	-0.186***	-0.004	-0.246***	0.055
	(-3.01)	(-0.09)	(-3.41)	(0.64)
Firm size	0.171***	0.017	0.274***	0.041
	(4.08)	(1.41)	(3.76)	(1.14)
Tangibility	0.032	-0.035	-0.131	0.123
	(0.12)	(-0.54)	(-0.29)	(0.98)
Institutional Ownership	0.224	0.002	0.245	0.006
	(0.97)	(0.33)	(0.58)	(0.60)
Market to Book	-0.011	-0.004	0.003	0.002
	(-0.84)	(-0.59)	(0.09)	(0.15)
Return on Assets	-0.022	0.041	0.004	0.103
	(-0.17)	(1.33)	(0.01)	(1.32)
Leverage	-0.133	-0.076***	-0.569	-0.204*
	(-0.67)	(-3.00)	(-1.47)	(-1.99)
Liquidity	-0.035	-0.060	-0.072	-0.039
	(-0.22)	(-0.95)	(-0.19)	(-0.21)
Herfindahl	0.601	-0.142	2.460**	0.611
	(1.16)	(-0.67)	(2.10)	(0.76)
Firm Age	0.363**	0.049	0.819***	0.112
	(2.29)	(0.74)	(2.80)	(0.67)
Finance	-0.006	-0.002	-0.008	0.002
	(-0.55)	(-0.85)	(-0.47)	(0.36)
Herfindahl2	-0.511	0.175	-2.682**	-0.626
	(-0.70)	(0.66)	(-2.05)	(-0.63)
R&D	0.175	0.170	0.535	0.569
	(1.25)	(1.31)	(1.43)	(0.76)
p-value for difference in coefficients	0.02		0.07	
Obs.	5,741	5,764	5,741	5,764
Adj. R-Square	0.869	0.797	0.781	0.647
Year FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes

Table 7 [Continued]

Panel C: The Effect of Learning Conditional on Bidder's Ex ante Agency Costs (Excess Cash)

Dependent Variable:	*Patents*		*Citation weighted patents*	
	High Excess	Low Excess	High Excess	Low Excess
	(1)	(2)	(3)	(4)
*Post*Treat*	0.041	0.073**	0.016	0.178**
	(0.59)	(2.27)	(0.10)	(2.23)
Post	-0.089*	-0.039	-0.154	-0.060
	(-1.77)	(-1.06)	(-1.37)	(-0.85)
Firm size	0.066***	0.078***	0.125**	0.150***
	(3.61)	(2.66)	(2.43)	(2.97)
Tangibility	0.116	-0.020	0.064	0.124
	(0.91)	(-0.18)	(0.21)	(0.60)
Institutional Ownership	0.033*	0.205	0.075**	0.210
	(1.91)	(1.31)	(2.54)	(0.83)
Market to Book	-0.002	0.003	0.022	0.007
	(-0.18)	(0.32)	(0.90)	(0.42)
Return on Assets	-0.029	0.086	0.080	0.149
	(-0.44)	(1.16)	(0.48)	(1.01)
Leverage	-0.194**	-0.023	-0.660***	-0.145
	(-2.33)	(-0.22)	(-3.06)	(-0.63)
Liquidity	-0.035	-0.164	-0.108	-0.227
	(-0.40)	(-1.47)	(-0.31)	(-1.11)
Herfindahl	0.781	0.289	3.159*	1.463*
	(0.92)	(0.97)	(1.90)	(1.92)
Firm Age	0.165**	0.202**	0.387*	0.559***
	(2.08)	(2.58)	(1.81)	(3.43)
Finance	-0.003	-0.003	-0.004	-0.004
	(-0.90)	(-0.40)	(-0.31)	(-0.41)
Herfindahl2	-1.318	-0.014	-4.278**	-1.220
	(-1.12)	(-0.04)	(-2.03)	(-1.45)
R&D	0.205	0.246	0.623	0.580
	(0.92)	(1.13)	(0.91)	(0.94)
p-value for difference in coefficients	0.66		0.30	
Obs.	4,030	7,437	4,030	7,437
Adj. R-Square	0.894	0.886	0.811	0.795
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 8

The Effect of Learning Conditional on the Scope to Learn
This table presents results examining the effects on outcomes following a bid failure, conditional on the scope to learn. The sample consists of all friendly bids that failed and their matched control firms in between 1986-2015. In Panel A and B, the dependent variable is investment expenditure measured with two different proxies: *Total Investment* (*Innovation Investment*) in columns 1-2 (3-4). In Panel C, the dependent variable is innovation measured with two different proxies: *Patents* (*Citation Weighted Patents*) in columns 1-2 (3-4). *Post* is an indicator variable equal to one for years *t+1* to *t+3* and zero for years *t-1* to *t-3*. In Panel A, the sample is bifurcated into those with private target (Private target) and public target (Public target). In Panel B, the sample is bifurcated into those with the target operating in the same industry (Same Industry) and different industry (Different Industry). In Panel C, same patent class is an indicator variable that equals to one if in any of the pre-bid years the bidder and target share a common patent class and zero otherwise. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.
Panel A: Conditional on the Form of the Target

Dependent Variable:	*Total Investment*		*Innovation Investment*	
	Private target	Public target	Private target	Public target
	(1)	(2)	(3)	(4)
*Post*IndustryQ*	0.018	0.027*	0.025**	-0.005
	(1.27)	(1.87)	(2.03)	(-1.16)
IndustryQ	-0.040	0.015	-0.039	0.006
	(-1.34)	(0.65)	(-1.50)	(1.00)
Post	-0.082*	-0.033	-0.064	0.010
	(-1.83)	(-1.22)	(-1.62)	(1.45)
Return on Assets	-0.026	-0.042	-0.087	-0.004
	(-0.36)	(-0.36)	(-1.29)	(-0.14)
Leverage	-0.149**	-0.374**	-0.007	-0.002
	(-2.34)	(-2.43)	(-0.28)	(-0.26)
Firm size	0.077***	0.041**	0.031**	0.004
	(4.56)	(2.51)	(2.60)	(1.23)
Herfindahl	0.085	-0.208	-0.063	-0.012
	(0.43)	(-1.16)	(-0.81)	(-0.41)
*Herfindahl*IndustryQ*	0.019	-0.068	0.026	-0.006
	(0.34)	(-1.17)	(0.65)	(-0.55)
Liquidity	0.114	0.450*	0.023	-0.000
	(1.03)	(1.67)	(0.22)	(-0.00)
p-value for difference in coefficients	0.63		0.02	
Obs.	942	1,940	942	1,940
Adj. R-Square	0.440	0.098	0.680	0.791
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 8 [Continued]

Panel B: Conditional on the Type of the Industry of the Target

Dependent Variable:	*Total Investment*		*Innovation Investment*	
	Same Industry	Different Industry	Same Industry	Different Industry
	(1)	(2)	(3)	(4)
*Post*IndustryQ*	0.023**	0.014	0.019**	-0.003
	(2.13)	(0.63)	(2.71)	(-0.53)
IndustryQ	-0.029	0.007	-0.010	-0.002
	(-1.34)	(0.34)	(-0.85)	(-0.15)
Post	-0.037	-0.028	-0.022**	0.007
	(-1.12)	(-0.69)	(-2.05)	(0.69)
Return on Assets	-0.331*	0.054	-0.040	-0.030
	(-1.88)	(0.48)	(-0.80)	(-0.63)
Leverage	-0.550***	-0.125	0.007	-0.018
	(-2.78)	(-1.00)	(0.51)	(-1.16)
Firm size	0.047***	0.073***	0.015*	0.012
	(2.78)	(3.30)	(1.94)	(1.69)
Herfindahl	0.430	-0.458	-0.045	-0.023
	(0.70)	(-1.53)	(-1.11)	(-0.59)
*Herfindahl*IndustryQ*	0.016	-0.032	0.004	0.001
	(0.29)	(-0.58)	(0.20)	(0.04)
Liquidity	0.461*	-0.036	0.018	-0.088
	(1.99)	(-0.38)	(0.38)	(-1.63)
p-value for difference in coefficients	0.69		0.01	
Obs.	1,969	1,015	1,969	1,015
Adj. R-Square	0.157	0.099	0.682	0.780
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 8 [Continued]

Panel C: Conditional on the Type of Patent Class of the Target

Dependent Variable:	*Patents*		*Citation Weighted Patents*	
	Same Patent Class	Different Patent Class	Same Patent Class	Different Patent Class
	(1)	(2)	(3)	(4)
Post	0.169*	0.007	0.334**	0.019
	(1.86)	(0.04)	(2.35)	(0.06)
Firm size	0.256*	0.196***	0.348**	0.354***
	(1.99)	(3.60)	(2.33)	(3.37)
Tangibility	0.543	0.122	-0.636	0.751
	(0.51)	(0.41)	(-0.40)	(0.81)
Institutional Ownership	-0.052	-0.304	0.325	-0.589
	(-0.11)	(-1.33)	(0.56)	(-0.90)
Market to Book	0.007	0.008	0.046	0.002
	(0.17)	(0.77)	(0.84)	(0.08)
Return on Assets	-0.042	0.027	-0.043	0.117*
	(-1.06)	(0.82)	(-0.79)	(1.85)
Leverage	-1.545***	-0.113	-3.468***	-0.530
	(-3.29)	(-0.78)	(-4.00)	(-1.55)
Liquidity	-0.561	-0.519	-1.114	-1.371
	(-0.96)	(-1.07)	(-1.37)	(-1.20)
Herfindahl	1.287*	1.084	1.741*	4.297
	(1.92)	(0.59)	(2.14)	(1.16)
Firm Age	1.278*	0.033	2.145**	-0.108
	(1.85)	(0.14)	(2.64)	(-0.23)
Finance	-0.062**	-0.129***	-0.066**	-0.307***
	(-2.49)	(-2.97)	(-2.55)	(-3.63)
Herfindahl2	-4.706**	-0.727	-3.511***	-4.154
	(-2.23)	(-0.28)	(-3.01)	(-0.81)
R&D	0.426	0.066	0.412	-0.176
	(1.01)	(0.42)	(0.68)	(-0.45)
p-value for difference in coefficients	0.87		0.73	
Obs.	619	1,076	619	1,076
Adj. R-Square	0.810	0.737	0.770	0.606
Year FE	Yes	Yes	Yes	Yes
Firm-Pair FE	Yes	Yes	Yes	Yes

Table 9

Consequences to the Disclosing (Target) Firm

This table presents results examining the effects on the target's outcomes following a bid failure. The sample consists of targets of all friendly bids that failed and their matched control firms in between 1986-2015. In Panel A, the dependent variable is investment expenditure measured with two different proxies: *Total Investment* (*Innovation Investment*) in columns 1-4 (5-8). In Panel B, the dependent variable is innovation measured with *Patents*. Columns 1-4 (5-8) represent target's innovation outcomes in the main sample (failed hostile sample). In Panel C, the dependent variable is market outcomes measured with two proxies: market share and competition. *Post* is an indicator variable equal to one for years *t+1* to *t+3 (t+1 to t+5*) and zero for years *t-1* to *t-3* (*t-1* to *t-5*) for investment efficiency (innovation and market) outcomes. *Treat* an indicator variable equal to one if a firm made a friendly (hostile) bid but failed to complete an acquisition and zero for their matched control pair in the main sample (hostile sample). All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Target's Investment Efficiency Post Bid Failure (Main Sample)

Dependent Variable:	*Capital Investment*				*Innovation Investment*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*IndustryQ*	-0.065	-0.071	-0.074	-0.080	-0.044	-0.045	-0.041	-0.049
	(-1.25)	(-1.30)	(-1.55)	(-1.43)	(-1.25)	(-1.28)	(-1.31)	(-1.29)
*Post*Treat*	0.137	0.162*	0.151*	0.172*	0.079	0.081	0.075	0.086
	(1.57)	(1.74)	(1.88)	(1.85)	(1.24)	(1.36)	(1.39)	(1.35)
*Post*IndustryQ*	0.076*	0.079*	0.077*	0.087*	0.044	0.047	0.042	0.051
	(1.91)	(1.95)	(2.01)	(1.97)	(1.36)	(1.33)	(1.31)	(1.33)
*Treat*IndustryQ*	0.072	0.097*	0.112**	0.107*	0.043	0.059	0.057	0.064
	(1.51)	(1.77)	(2.27)	(1.89)	(1.21)	(1.41)	(1.44)	(1.38)
IndustryQ	-0.074	-0.099*	-0.084*	-0.099	-0.039	-0.059	-0.052	-0.062
	(-1.39)	(-1.75)	(-1.69)	(-1.63)	(-0.88)	(-1.26)	(-1.29)	(-1.23)
Post	-0.182**	-0.217***	-0.179**	-0.200**	-0.076	-0.089	-0.081	-0.095
	(-2.54)	(-3.10)	(-2.50)	(-2.43)	(-1.20)	(-1.41)	(-1.26)	(-1.27)
Treat	-0.148*				-0.080			
	(-1.76)				(-1.20)			
Return on Assets	0.029	0.001		-0.009	-0.186	-0.155		-0.163
	(0.11)	(0.00)		(-0.06)	(-1.02)	(-1.38)		(-1.36)
Leverage	-0.019	-0.071		-0.054	-0.042	-0.025		-0.026
	(-0.36)	(-0.95)		(-0.72)	(-1.20)	(-0.70)		(-0.70)
Firm size	0.009**	0.028*		0.023	0.003	-0.005		-0.008
	(2.08)	(1.69)		(1.26)	(1.34)	(-0.58)		(-0.73)
Herfindahl	-0.038	-0.127		-0.014	-0.027	-0.053		-0.018
	(-0.33)	(-0.75)		(-0.08)	(-0.50)	(-0.83)		(-0.34)
*Herfindahl*IndustryQ*	0.009	0.034		0.009	0.002	0.009		0.003
	(0.19)	(0.47)		(0.12)	(0.09)	(0.45)		(0.15)
Liquidity	0.427**	0.439**		0.445**	0.341*	0.276*		0.272*
	(2.19)	(2.18)		(2.23)	(1.90)	(1.86)		(1.85)
Obs.	2,402	2,402	2,402	2,402	2,402	2,402	2,402	2,402
Adj. R-Square	0.040	0.186	0.184	0.196	0.033	0.220	0.205	0.217
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 9 [Continued]

Panel B: Target's Innovation Outcomes Post Bid Failure

Dependent Variable:	*Patents*							
	Main Sample				Hostile Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*	-0.038	-0.067**	-0.064**	-0.057**	-0.128	-0.119	-0.131	-0.111
	(-0.92)	(-2.28)	(-2.05)	(-2.10)	(-0.70)	(-0.73)	(-0.81)	(-0.77)
Post	0.015	0.048	0.028	0.023	0.057	-0.040	0.018	0.021
	(0.23)	(1.65)	(0.80)	(0.65)	(0.62)	(-0.75)	(0.33)	(0.41)
Treat	-0.083				0.202			
	(-1.41)				(1.56)			
Firm size	0.161***	0.023**		0.024**	0.262***	0.136***		0.151***
	(3.74)	(2.09)		(2.07)	(3.58)	(2.74)		(2.86)
Tangibility	-0.193	-0.028		-0.046	-0.426*	0.208		0.023
	(-1.57)	(-0.32)		(-0.57)	(-1.73)	(0.84)		(0.10)
Institutional Ownership	0.099	0.082*		0.119**	0.156	-0.185**		-0.131*
	(0.65)	(1.99)		(2.50)	(0.60)	(-2.08)		(-1.75)
Market to Book	-0.094***	0.001		0.000	-0.099	0.057		0.038
	(-3.39)	(0.08)		(0.05)	(-1.38)	(1.67)		(1.15)
Return on Assets	-0.170	-0.009		0.015	0.460	0.103		0.131
	(-1.25)	(-0.17)		(0.27)	(1.54)	(0.99)		(1.30)
Leverage	0.203	-0.042		-0.044	-0.185	-0.086		-0.060
	(1.54)	(-1.11)		(-1.11)	(-1.20)	(-0.48)		(-0.32)
Liquidity	-0.281	-0.286		-0.351**	-0.304	-0.399		-0.275
	(-1.15)	(-1.64)		(-2.02)	(-1.02)	(-1.38)		(-1.02)
Herfindahl	-0.506	0.192		0.269	-2.181	-2.613		-2.325
	(-0.43)	(0.54)		(0.70)	(-0.71)	(-1.59)		(-1.52)
Firm Age	0.251***	0.027		0.027	0.332***	0.188*		0.341
	(3.06)	(0.90)		(0.63)	(4.57)	(1.76)		(1.49)
Finance	0.043	-0.028*		-0.017	0.000***	0.000		0.000
	(0.89)	(-1.70)		(-1.15)	(3.02)	(0.40)		(0.62)
Herfindahl2	0.761	-0.231		-0.276	2.057	2.683		2.395
	(0.49)	(-0.49)		(-0.57)	(0.56)	(1.54)		(1.38)
R&D	11.679***	1.710***		1.648***	5.643***	-0.295		-0.442*
	(8.51)	(4.04)		(3.59)	(5.27)	(-1.39)		(-1.97)
Obs.	2,402	2,402	2,402	2,402	2,402	2,402	2,402	2,402
Adj. R-Square	0.344	0.895	0.893	0.895	0.359	0.802	0.799	0.802
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 9 [Continued]

Panel C: Target's Product Market Outcomes Post Bid Failure (Main Sample)

Dependent Variable:	*Market Share*				*Product Competitiveness*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*	-0.019*	-0.023	-0.024**	-0.021**	0.006	0.008	0.005	0.006*
	(-1.94)	(-1.36)	(-2.40)	(-2.17)	(1.60)	(1.37)	(1.42)	(1.90)
Post	-0.008	-0.002	-0.015	-0.016	0.005**	-0.001	0.010***	0.009***
	(-1.53)	(-0.11)	(-1.40)	(-1.53)	(2.35)	(-0.23)	(3.31)	(3.04)
Treat		-0.013				-0.002		
		(-1.08)				(-0.49)		
Firm size	0.020***	0.056***		0.020***	0.004***	0.007***		0.005**
	(6.12)	(19.70)		(5.75)	(2.86)	(8.11)		(2.63)
Institutional Ownership	0.066***	0.018		0.068**	-0.001	-0.002		0.000
	(2.83)	(0.66)		(2.64)	(-0.21)	(-0.56)		(0.07)
Market to Book	-0.006**	0.011		-0.005**	0.001**	0.002***		0.001*
	(-2.31)	(1.62)		(-2.09)	(2.33)	(2.94)		(1.71)
Return on Assets	0.006	-0.082***		0.004	0.002	0.003		0.000
	(0.47)	(-3.24)		(0.29)	(0.23)	(0.47)		(0.02)
Leverage	0.015	-0.013		0.010	-0.017***	0.023***		-0.013***
	(0.88)	(-0.38)		(0.60)	(-3.75)	(4.51)		(-2.89)
Liquidity	0.004	-0.183***		-0.005	-0.009	0.030***		-0.003
	(0.12)	(-4.18)		(-0.17)	(-1.02)	(2.98)		(-0.36)
R&D	0.007	-0.622***		0.051	0.036	-0.038		0.020
	(0.03)	(-3.86)		(0.21)	(0.84)	(-0.79)		(0.40)
Obs.	2,402	2,402	2,402	2,402	2,402	2,402	2,402	2,402
Adj. R-Square	0.881	0.125	0.878	0.881	0.724	0.084	0.725	0.728
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 10

Robustness Test: The Effect of Failure on Innovation Outcomes

This table presents results examining the effects on innovation following a bid failure. The sample consists of all friendly bids that supposedly failed due to regulatory intervention and their matched control firms in between 1986-2015. The dependent variable is innovation measured with two different proxies. *Post* is an indicator variable equal to one for years *t+1* to *t+5* and zero for years *t-1* to *t-5*. *Treat* an indicator variable equal to one if a firm made a friendly bid but failed to complete an acquisition and zero for their matched control pair. Columns 1-4 (5-8) show the results using *Patents* (*Citation Weighted Patents*) as the innovation proxy. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent Variable:	*Patents*				*Citation Weighted Patents*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Post*Treat*	0.195*	0.164**	0.141	0.176**	0.303	0.244	0.216	0.280*
	(1.77)	(2.01)	(1.65)	(2.10)	(1.41)	(1.44)	(1.31)	(1.73)
Post	-0.386***	-0.178***	-0.133*	-0.138**	-0.549***	-0.451***	-0.176	-0.210*
	(-3.50)	(-3.85)	(-1.83)	(-2.29)	(-2.98)	(-5.46)	(-1.24)	(-1.82)
Treat	0.101				0.252			
	(0.58)				(0.85)			
Firm size	0.359***	0.136***		0.133***	0.573***	0.239***		0.230***
	(7.55)	(4.01)		(3.69)	(8.03)	(4.03)		(3.69)
Tangibility	-0.622**	0.243		0.177	-1.143**	0.879*		0.559
	(-2.05)	(0.94)		(0.74)	(-2.30)	(1.79)		(1.19)
Institutional Ownership	0.335	-0.133		-0.083	0.900**	-0.445		-0.185
	(1.21)	(-0.83)		(-0.50)	(2.00)	(-1.40)		(-0.55)
Market to Book	-0.079	0.001		0.003	-0.072	0.020		0.028
	(-1.11)	(0.04)		(0.10)	(-0.48)	(0.30)		(0.42)
Return on Assets	-1.130***	0.024		0.032	-2.118***	-0.037		-0.034
	(-4.71)	(0.40)		(0.54)	(-4.86)	(-0.38)		(-0.34)
Leverage	-0.132	-0.179*		-0.194*	-0.595	-0.493**		-0.451**
	(-0.59)	(-1.67)		(-1.71)	(-1.48)	(-2.25)		(-1.98)
Liquidity	0.056	-0.183		-0.109	0.270	0.151		0.358
	(0.12)	(-0.60)		(-0.38)	(0.32)	(0.24)		(0.63)
Herfindahl	3.052**	1.221		1.594	6.446**	2.760		3.603*
	(2.04)	(1.11)		(1.48)	(2.57)	(1.44)		(1.88)
Firm Age	0.522***	0.451***		0.528***	0.815***	0.954***		1.407***
	(5.03)	(3.80)		(3.23)	(4.81)	(4.28)		(4.93)
Finance	-0.036	-0.094***		-0.055*	-0.020	-0.225**		-0.096
	(-0.72)	(-2.79)		(-1.72)	(-0.26)	(-2.17)		(-1.15)
Herfindahl2	-2.949	-1.504		-1.884	-6.743**	-3.526		-4.256*
	(-1.38)	(-1.06)		(-1.35)	(-1.98)	(-1.49)		(-1.80)
R&D	8.325***	-0.062		-0.119	15.474***	0.350		0.372
	(4.81)	(-0.15)		(-0.29)	(4.90)	(0.50)		(0.52)
Obs.	2,635	2,635	2,635	2,635	2,635	2,635	2,635	2,635
Adj. R-Square	0.398	0.897	0.892	0.898	0.391	0.861	0.856	0.866
Year FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Appendix A. Variable Definitions

Variable	Definition	Sources
Post	An indicator variable equal to one for years t+1 to t+3 (t+1 to t+5) and zero for years t-1 to t-3 (t-1 to t-5) for the investment sensitivity (innovation outcome) tests.	
Treat	An indicator variable equal to one if a firm made a friendly bid but failed to complete an acquisition and zero for their matched control pair.	Thompson SDC
Total Investment	The sum of research and development expenditure, capital expenditure, and acquisition expenditure scaled by lagged assets.	Compustat
Innovation Investment	Research and development expenditure scaled by lagged assets.	Compustat
Patents	The log of one plus total number of patents applied by a firm in a given year t. I correct for truncation bias using Hall, Jaffe, Trajtenberg (2005).	Kogan et al. (2017)
Citation Weighted Patents	The sum of patents applied by a firm in a given year t, weighted by the actual number of citations that they subsequently received, Trajtenberg (1990).	Kogan et al. (2017)
Industry Q	The sum of aggregate market value of equity and aggregate book value of debt in an industry, divided by aggregate total assets in the same four-digit NAICS industry code.	Compustat
Return on Assets	Earnings before extraordinary items, depreciation, and R&D expense, divided by average total assets.	Compustat
Firm Size	The natural log of one plus total assets.	Compustat
Industry Concentration	The natural log of one plus the sum of the squared market share of each firm in a six-digit NAICS code in a year. Market share is a firm's sales divided by the total sales of the NAICS code.	Compustat
Market to Book	Market capitalization divided by book value of equity.	Compustat
Leverage	The ratio of long-term debt to the sum of long-term debt and the market value of equity.	Compustat
Liquidity	The ratio of cash and cash equivalent to total assets.	Compustat
Institutional Ownership	Total number of shares held by institutions as a percentage of the total number of shares outstanding.	Thompson, Compustat
Finance	The sum of a firm's net equity issues (scaled by total assets) over a rolling seven-year window ending in the current fiscal year.	Compustat
Firm Age	Natural log of the number of years listed on Compustat.	Compustat
Tangibility	The ratio of property plant equipment to total assets	Compustat
R&D Expenditure	R&D expenditure scaled by total assets	Compustat

Same Industry	An indicator variable equal to one if the bidder's industry description (macro industry description) matches that of the target.	SDC
Private Target	An indicator variable equal to one if the target is listed as a private entity and zero if it is a public or subsidiary of a public entity.	SDC
High R&D	An indicator variable equal to one if the bidder's sum of the preceding five years R&D expenditure in between t-3 to t+1 is above-median and zero otherwise.	Compustat
High Patenting	An indicator variable equal to one for industries (4 digit SIC) with aggregate historical (preceeding three years) patenting activity in the above median group of the distribution and zero otherwise.	KPSS, Compustat
Same Patent Class	An indicator variable that equals to one if in any of the pre-bid years the bidder and target share a common patent class and zero otherwise.	KPSS, Patent view
Excess Cash	Equal to the actual cash holding less the predicted level of normal cash holding. The predicted level is determined by running a baseline regression model by industry and year. The baseline regression model is developed on inventory management and buffer-stock theories of cash management (Harford 2002).	Compustat
Market Share	The ratio of sales to total sales in the same four-digit NAICS industry code.	Compustat
Product Competitiveness	The average product similarity with top twenty rivals. Product similarity is measured with Hoberg and Phillips firm pair-wise similarity score.	Hoberg and Phillips (2010a, 2016)

Appendix B. Relevant Anecdotes

This appendix provides two anecdotal evidences in support of the narrative of this paper. The main narrative of this paper is that the bidders learn valuable private information from the due diligence process that it then incorporates into its future investment decisions. The presence of non-disclosure agreements (NDAs) provides significant empirical tension in the story. An NDA usually states that "Recipient shall not attempt to reverse-engineer any Evaluation Material and/or tangible objects containing the Evaluation Material." However, it may not be possible to foresee various cases of information leakage contingencies and have every possible detail written into the contract. For example, although an NDA governed the due diligence process between L'Oreal USA, Inc. and Olaplex, Olaplex found it difficult to enforce the NDA in court. The case arose as a result of L'Oreal and Olaplex entering into negotiations regarding a potential acquisition, pursuant to which Olaplex shared with L'Oreal its confidential information, including asserted trade secrets. L'Oreal subsequently walked away from the deal and launched competing products of its own. Though the parties' negotiations were governed by a non-disclosure agreement, the Federal Circuit found Olaplex failed to prove that either its asserted trade secrets were actually trade secrets, or that L'Oreal had misappropriated them. In a significant recent decision, the Federal Circuit reversed a $66 million judgment against L'Oreal USA, Inc. for patent infringement and trade secret misappropriation asserted by Olaplex, Inc.[35]

The case of Verisk Analytics green fielding Eagle View's product pipeline after a failed merger talk in 2014, is yet another example of learning through the M&A negotiation

[35] Source: https://www.natlawreview.com/article/secret-hair-don-t-care-when-ndas-fail-to-protect-trade-secrets

process. Verisk was eager to buy Eagle View due to its cutting edge aerial devices. The merger talks eventually failed due to anti-competitive concerns of the deal. Shortly afterwards, in 2015, Eagle View initiated lawsuit against Verisk Analytics. The formal complaint alleged seven patent infringements. For each alleged infringement, the complaint has a paragraph stating: "On information and belief, Xactware [a subsidiary of Verisk] has had knowledge of the [patent #] Patent since at least as early December 2014 in connection with Verisk's intended acquisition of EVT. Verisk performed due diligence related to its intended acquisition of EVT, including with respect to Eagle View's patent holdings. EVT personnel had discussions with representatives of Verisk concerning Eagle View's patents, including the [patent #] Patent, prior to the termination of the EVT acquisition in December 2014."