M&As and innovation: Evidence from acquiring private firms

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Abstract

We show that acquisitions of private targets increase the quantity, quality, and value of the acquiring firms' patents significantly more than acquisitions of public targets. Moreover, private target acquisitions foster significantly greater innovation synergies, increase total number of inventors, and promote new collaborations among inventors. These outcomes are not driven by the target's existing patent portfolios and are most pronounced in breakthrough industries. The patenting increases link to the acquirers' expertise in identifying innovative private targets. Finally, the patenting increases explain away the higher announcement returns for private versus public target acquisitions. Our findings underscore the role of complementary innovative capabilities in driving value creation through private target acquisitions.

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1 Introduction

Innovation reflects firm efforts to develop and accumulate knowledge and it has long been recognized as a key factor of firm growth in today's knowledge economy (see for example, Hall, 1993; Cockburn, Henderson, and Stern, 2000; Gao, Hsu, and Li, 2018). Innovation is also an important motivation for mergers and acquisitions (M&As) through which companies gain rather than develop new ideas or technologies (Bena and Li, 2014; Sevilir and Tian, 2012; Phillips and Zhdanov, 2013). Empirical analyses of innovation have so far not explored the heterogeneity in acquisitions of private versus public firms. Nevertheless, private firms are economically important players both for innovation activity and as acquisition targets.[1] Past research shows that private targets are associated with better announcement returns of M&As (Faccio, McConnell, and Stolin, 2006), but little is known about whether innovation plays a role in the value creation in private target acquisitions. In this paper, we ask how acquisitions of private versus public targets influence the patent quantity, quality, value, and synergies at publicly listed acquirers post acquisitions. We focus on patenting as a measurable innovation outcome.

Our aim is to contrast acquisitions of private versus public targets by publicly listed acquirers. Public and private firms may have complementary capabilities to innovate, which would motivate acquisitions of private firms by public companies. Private firms have a comparative advantage for developing new technologies due to their higher tolerance for failure and long-term orientation of their owners, whereas public firms, under the pressure of capital markets, are more short-termist and less failure-tolerant (Holmstrom, 1989; Ferreira, Manso, and Silva, 2014). In contrast, public firms, as potential acquirers, have a comparative advantage for commercializing and scaling up new technologies due to their commercial expertise, professional resources, and better access to capital markets (Gans and Stern, 2003). On the buyer's side of the M&A transaction, public firms benefit from acquiring private firms with newly developed technologies when the innovation uncertainty is

[1]For example, Google's patent portfolio has increased from 38 patents in 2007 to over 50,000 patents by 2013, with many of these patents purchased from the start-up market rather than produced in-house (Wang, 2018).

to a large extent resolved. Hence, they avoid developing risky new technologies themselves, which is in line with their low tolerance to failure. The bought-in breakthrough ideas and new inventor teams, which are at that point independent of firm private ownership, then spur additional follow-on innovation that may be less risky. On the seller's side, private firms are willing to sell because it is otherwise costly for them to gain access to complementary assets and external capital that are necessary to commercialize their newly developed technologies (Gans and Stern, 2003). It is also beneficial to private targets that acquirers can smooth the patenting process, which is usually troublesome for inexperienced firms and firms with higher information asymmetry (Jia and Tian, 2018). Hence, the combination of innovation capabilities, which results in innovation synergies, potentially brings value to both public acquirers and private targets. It also helps to overcome challenges associated with the targets' transition from private to public ownership.

In contrast, acquisitions of public targets by public companies lack these complementary capabilities in innovation; targets and acquirers face similar innovation incentives and environment and do not differ much in access to assets and finances necessary for commercialization.[2] Therefore, we hypothesize that acquisitions of private versus public targets are associated with a larger increase in patent quantity, quality, value, and innovation synergies after acquisitions.

Our baseline sample of 43,660 firm-year observations, which consists of matched acquisitions of US private and public targets by US public firms from 5 years before to 5 years after acquisition announcements, runs from 1990 until 2020 due to data availability across different data sources. Our results show that patent quantity, quality, and value, measured through patent count, forward cites, and patent value (due to Kogan, Papanikolaou, Seru, and Stoffman, 2017), respectively, increase significantly more after acquisitions of private targets than after acquisitions of public

[2] To illustrate patenting outcome differences when acquiring private versus public targets, Apendix A shows two acquisitions by HP, one of a private and one of a public target. The first one is of a private Persist Technologies Inc undertaken in 2003 that pursued high growth prospects in the particular market of e-mail archiving. The second acquisition is of public target Pregrine Systems Inc completed in 2005. Pregrine experienced financial difficulties since 2002. HP saw the potential of becoming a market leader in the segment and of operational synergies through cross-selling to different groups of customers.

targets. The additional increase is economically significant: it ranges between 8 and 9 percentage points. This result pertains when we consider innovation synergies and when comparing successful acquisitions to withdrawn deals. Further robustness tests include alternative matching between private and public target acquisitions, shorter event window, checking how the patenting effect depends on the target size, adding extra technological class fixed effects, and controlling for a wider range of post-acquisition effects. Our baseline results hold.

We also explore potential sources of the increased innovation and innovation synergies. We examine three mechanisms: (i) target's patenting activity, (ii) breakthrough technology sectors, and (iii) acquirer expertise. We establish that the existence of granted patents in target firms is not a necessary condition for increased patenting post acquisition. Only 25 percent of the private targets own any granted patents when they are acquired. Furthermore, the higher patenting effects for private targets concentrate in sectors that are dominated by breakthrough technologies, consistent with unique advantages of private firms (tolerance for failure and long-term orientation) shining through more in sectors with higher innovation progress. We also show that the patenting effect is present for managers with higher ability and when acquirers own corporate venture capital divisions. Altogether, these additional results suggest that the acquirer's ability to pick suitable private targets with new innovative technologies that fit acquirer's own commercializing capabilities is an important factor.

The final part of our analysis focuses on acquirer announcement abnormal returns. We test if stock prices incorporate information on innovation. Complementing results in the literature (Faccio et al., 2006; Jaffe, Jindra, Pedersen, and Voetmann, 2015), we show that the 5-day announcement abnormal returns are significantly higher for private target acquirers that increase innovation post-acquisition the most. Importantly, the higher expectation of innovation improvement and the corresponding larger market reaction explain away the higher announcement returns when firms acquire private targets.

Our paper contributes to the important literature on how boundaries of the firm and M&As

affect innovation. First, we contribute to the literature on the relationship between M&As and subsequent innovation. Sevilir and Tian (2012) show that M&As are positively associated with contemporaneous and future innovative outcomes, measured by the number of acquirers' patents and citations. Bena and Li (2014) highlight the importance of both ex-ante selection and ex-post treatment effects of M&A on corporate innovation outputs. Tian and Wang (2014) find that IPO firms backed by failure tolerant venture capitalists are more innovative. In contrast, Rajan, Servaes, and Zingales (2000) and Scharfstein and Stein (2000) argue that M&As are associated with lower innovation because post-acquisition employees tend to have less incentive to generate valuable ideas.

So far, the M&A and innovation literature has not distinguished between public versus private target deals. The closest is perhaps Phillips and Zhdanov (2013) who analyze the effect of M&As on innovation in large versus small firms. Even if one thinks of firm size as being correlated with private versus public status, Phillips and Zhdanov (2013) focus on incentives to innovate that come from the possibility of future acquisitions. Thus, while they focus on the selection effect and pre-acquisition innovation, we complement their study by examining treatment effects and post-acquisition patenting. We add to this literature by arguing that because private firms are better suited for new risky innovation activity, acquiring these targets is associated with larger subsequent innovation increases for their public acquirers than when acquiring public targets. As private firms are incubators of new innovative technologies that are risky to develop, public firms gain synergies from acquiring private targets once the risky ideas have matured.

Second, we contribute to the literature on innovation in public versus private firms. Ferreira et al. (2014) model managers' incentives to innovate in private versus public firms and highlight the higher tolerance for failure of private firms that motivates their higher innovation rates. Gao et al. (2018) show that public firms' patents rely more on existing knowledge, while private firms' patents are more exploratory. They conclude that these differences are mostly due to shorter investment horizon in public equity markets. The literature on innovation in private versus public firms has not investigated the M&A market. Our analysis highlights the crucial role of private firms for patenting of publicly listed firms. Publicly listed firms acquire rather than develop risky new technologies and profit from follow-on increase in innovation. Our analysis also emphasizes the M&A exit potential for innovative private firms as analyzed in Wang (2018).

Third, we contribute to the literature on value consequences when acquiring public versus private targets, which has not reached a consensus yet (Chang, 1998; Fuller, Netter, and Stegemoller, 2002; Moeller, Schlingemann, and Stulz, 2004; Faccio et al., 2006; Jaffe et al., 2015). We show that the market reacts more positively to acquisitions of private targets with higher expected increases in quantity, quality, and value of patents. Importantly, the well-known result of higher announcement returns when acquiring private targets is explained away by expected differences in innovation outcomes. Taken together, our paper contributes to explaining the value creation when firms acquire public versus private targets.

The remainder of the paper is organized as follows. Section 2 reviews the literature and explains our main hypothesis. Section 3 describes the data and statistics. Section 4 presents and discusses our baseline results. Section 5 explores sources of patenting outcome increases. Section 6 analyzes announcement abnormal returns and Section 7 concludes.

2 Hypothesis development

Innovation is risky, unpredictable, long-term, multistage, labor intensive and idiosyncratic (Holmstrom, 1989). Even though innovative projects have low probability of success, they are very profitable when successful (Robinson, 2008; Ferreira et al., 2014). Fostering of innovation requires strong risk-taking incentives, tolerance for failure, and rewards for long-term success (Manso, 2011). The literature has provided ample evidence that private and small firms are more innovative (see, among others, Holmstrom, 1989; Lerner, Sorensen, and Strömberg, 2011; Phillips and Zhdanov, 2013; Aggarwal and Hsu, 2014; Ferreira et al., 2014; Bernstein, 2015).

On the contrary, the literature lists several reasons for why publicly listed firms are at a comparative disadvantage to conduct highly innovative research. Holmstrom (1989), modeling innovation as the outcome of an optimal assignment of tasks across firms, highlights concerns for reputation in the capital market that induces large firms to act more cautiously in taking risks. Holmstrom (1989) also points out that because mixing hard-to-measure activities (innovation) with easy-to-measure activities (routine) is associated with high costs, large firms prefer serving production and marketing goals, tasks they are better at, rather than innovation. The same logic also applies to public firms as they are more complex organizations that incur higher costs for hard-to-measure activities. Further, Ferreira et al. (2014) stress a lower tolerance for failure in publicly listed firms and their preference for projects with higher probability of early success. They model managers' incentives to innovate under public versus private ownership and show that private ownership creates incentives for innovation, whereas public ownership disincentivizes innovation. In their model, the tolerance for failure is the key determinant of innovation in private companies. For public companies, stock prices react quickly to good news, which creates incentives for short-termism. It promotes projects with a higher probability of early success and discourages innovation in the long term. In addition, He and Tian (2013) argue that analysts exert pressure on managers of public firms to meet short-term goals, impeding firms' investment in long-term innovative projects. Hence, incentivizing managers to innovate is a challenge for most public firms (Manso, 2011).

In this paper, we explore the effect of acquiring private targets on ex-post innovation in public firms relative to acquiring public targets. The literature suggests that while public firms are less prone to innovate because of their low tolerance for failure and short-termism, private firms with higher tolerance for failure and long-term horizon are better at developing new technologies. However, public firms can acquire newly developed technologies externally through acquisitions of private targets (Phillips and Zhdanov, 2013; Bernstein, 2015).

From the perspective of the private target, once a new technology is ready for commercialization, start-up firms may either bring the innovation to commercial applications, or trade their ideas in the external markets via licensing, strategic partnership, or selling the company (Gans and Stern, 2003). They may prefer to sell the company rather than commercialize the new ideas (Cefis and Marsili, 2011). A lack of experience and financial resources makes commercialization difficult for private firms, and access to specialized complementary assets (such as distribution, manufacturing capabilities, marketing know-how, or vast body of potential customers) requires significant investments which are often not possible due to financial constraints of private firms (Acharya and Xu, 2017). Established public firms have a comparative advantage at getting innovative products to extensive clienteles and better access to capital. Importantly, private firms initiate a sale at a point when technological uncertainty is sufficiently resolved but the technology is still hard to imitate (Gans and Stern, 2003). The newly developed ideas and inquisitive inventor teams are transferable across firms and do not depend on firm private ownership. In addition, private start-ups are also less experienced at filing new patents (Jia and Tian, 2018). All these aspects increase potential takeover innovation synergies and serve as incentives to sell.

From a public acquirer's point of view, acquiring newly developed technologies is less risky than starting from scratch.[3] Importantly, these acquisitions create innovation synergies even though targets change from private to public ownership. For example, they create opportunities for inventors from private targets to cooperate closely with acquirers' established inventors and motivate future follow-on innovation with less risk involved. Gao et al. (2018) argue that publicly listed firms are better suited for exploitative innovation, while private firms for more risky exploratory innovation. Acquiring firms enhance their innovation because of the acquired complementary innovative capabilities – i.e., newly developed technologies, future innovation potential, and new teams of inquisitive inventors – rather than because of any change in their tolerance for failure or investment horizon. These innovation synergies when combining private targets with public acquirers help to overcome challenges associated with the targets' transition from private to public ownership. Both

[3]Note that engaging in acquisitions to kill potential innovatory competition as in Cunningham, Ederer, and Ma (2021) is not in the scope of our analysis. We do not think that private versus public ownership of the target would make much difference when killing new ideas. Ignoring this potential effect should result in lower patenting outcomes but not serve as an alternative explanation.

sides of the deal benefit from the combination.

Acquisitions of public targets by public companies, in contrast, lack complementary capabilities in innovation. Targets and acquirers are both publicly listed and face similar innovation incentives and environment. Neither do they differ much in access to assets and finances necessary for commercialization of new technologies.

Alternatively, private target acquisitions could also disrupt innovation processes of public companies. Innovation quality declines after firms go public and IPO firms experience an exodus of skilled inventors and a decline in the productivity of the remaining inventors (Bernstein, 2015). Wu, Lou, and Hitt (2025) argue that employee incentives deteriorate post IPO because of dilution of ownership. Acquisition integration could be disruptive, leading to the most severe productivity drops for inventors who have lost the most social status and centrality in the combined firm (Paruchuri, Nerkar, and Hambrick, 2006). The disruption effect may be stronger for private than public targets as inventors in private firms enjoy more freedom and influence which may be lost post acquisition. Nevertheless, we conjecture that the combination of a private target with a public acquirer creates innovation synergies that outweigh any disruptions associated with the acquisition and transfer from private to public ownership. Under this premise, acquisitions of private targets are associated with a higher increase in patent quantity, quality, value, and synergies post acquisition than acquisitions of public targets.

3 Data

To measure innovation output, we primarily use patent and citation data from the KPSS database (due to Kogan et al., 2017) covering the period between 1926 and 2020.[4] In addition, we use the Kelly, Papanikolaou, Seru, and Taddy (2021) patent data (KPST), which covers the period between 1839 and 2015, to source technological classifications and patents by private firms.[5] The M&A data

[4]https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data

[5]KPST is at https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Replication-Kit. We match by company name and state of incorporation, and perform a fuzzy match. Appendix B describes

come from SDC Platinum and meet the following requirements: (i) the acquirer is a publicly listed US firm; (ii) the target is a US stand-alone private or publicly listed firm; (iii) the deal is not a leveraged buyout, spinoff, recapitalization, exchange offer, self-tender, repurchase acquisition, or privatization; (iv) the deal is completed; and (v) the transaction is reported as equity rather than asset sale. Finally, financial information comes from Compustat with relatively poor coverage before 1990, and stock returns from CRSP. Constraints of the data sources define our time frame: our sample starts in 1990 (Compustat restriction) and extends to 2020 (KPSS restriction). Note that because we are comparing innovation before versus after acquisitions, we cover acquisitions between 1995 and 2015 to allow for 5 years of patent data at both ends.

We require that all firms in our main sample file at least one patent over the period between 1990 and 2020. Our research question in essence concerns only innovative firms with patents as firms without any patents would by definition have a zero change in innovation variables from before to after acquisitions and would not be interesting for our research question (Bena and Li, 2014, have a similar restriction). All the data requirements result in 13,453 acquisitions, of which 11,291 are with private and 2,162 with public targets.

Our analysis relies on variables measuring quantity, quality, and value of patents, three complementary patent attributes (following, for example, Trajtenberg, Henderson, and Jaffe, 1997; Kogan et al., 2017; He and Hirshleifer, 2022). The literature refers to the patent count as a measure of innovation quantity, while forward citations measure innovation quality – they reflect how a focal patent is important for future ideas. The *patent count* equals the number of new filed patents scaled by all new patents filed in the given year to account for truncation issues (Lerner and Seru, 2022). The *forward cites* variable measures quality of patents filed by a focal firm in a given year. It equals the sum of all citations made to the patents filed by the focal firm in the year scaled by the total citations to patents filed in the given year in the same technological class (following, for example, Dong, Hirshleifer, and Teoh, 2021). We round up the set of innovation variables by

the matching procedure.

including the *patent value* reported in Kogan et al. (2017). It is the cumulative dollar abnormal value at the announcement (and two following days) of a patent approval of all patents filed by the focal firm in the year, scaled by firm market capitalization for better comparison across firms.

In addition, we employ data on inventors that is derived from patent data (we follow the procedure due to Li and Wang, 2023, which is fully described in Appendix C) and create two new inventor variables that we use to measure patent synergies. The number of all inventors shows the development in the overall inventor numbers. The second variable, the number of new inventors collaborating, takes into account only 'new' inventors who file their first patent in the given year and we count only new inventors who coauthor patents with acquirer's incumbent inventors. All variable definitions are provided in Appendix D.

Acquirers of public targets are larger firms with a higher book to market ratio (Faccio et al., 2006) and larger firms have more patents (Bena and Li, 2014). To account for differences between acquirers of public versus private targets and avoid biases in our estimated effects, we match the two sets of acquirers based on year, industry, size, and book to market ratio (following Bena and Li, 2014). In particular, we run a propensity score matching procedure predicting acquisitions of public targets using the acquirer's total assets and book to market ratio as reported in Panel A of Table 1. Given the sample of public deals is smaller, we match each acquirer of a public deal to one acquirer of a private deal with the closest propensity score within the same FF 30 industry and calendar year. We end up with a final sample of 2,143 public target deals and 2,143 private target deals. Panel B in Table 1 shows means across public versus private target acquirers before and after matching. The two groups of acquirers are statistically significantly different before matching, but fall in line after the matching procedure. Note that we report log transformations for the patenting variables as described in Section 4.1 below with $x = 0$. As a robustness test, we identify up to five matched private target deals within the same FF 30 industry and calendar year and report matching statistics in Table I.1 in the Internet Appendix. We can see that matching is less precise.

Insert Table 1 about here.

Table 2 shows distribution of of private and public target acquisitions before and after 1:1 matching across years and FF 30 industries. Then, Panel A in Table 3 shows summary statistics for the 1:1 matched sample across the whole panel spanning five years before and after the acquisition announcement year, which contains 43,660 firm-year observations. We can see the mean and standard deviation in the first two columns and then an extended set of percentiles. The patenting and inventor variables are reported in their logarithmic transformation with both $x = 0$ and $x = 1$.

Insert Tables 2 and 3 about here.

Panel B in Table 3 shows univariate statistics for our patenting and inventor variables across private versus public target acquisitions. For simplicity, we include only the log transformations. We start with means for the whole event period (Columns 1 and 2) and then separately for the pre- versus post-acquisition period (Columns 3 to 6). The pre- (post-) acquisition figures correspond to the average from year -5 to year -1 (year 0 to year $+5$). We report the change for the post- relatively to the pre-acquisition period in Columns 7 and 8. Except for the patent value, we see an increasing trend in innovation over time for acquirers of private targets. The double differences in Column 9 are all positive suggesting that innovation increases more after private than after public target acquisitions, but they are lacking conventional statistical significance.

4 Results

4.1 Baseline results

Our main research question aims to test the impact of private versus public target acquisitions on innovation outcomes of public acquirers. We use data from 5 years before to 5 years after announcements of acquisitions and estimate the following regression:

$$\begin{aligned} log(Inn)_{i,t} = \alpha_1\ Private_i + \alpha_2\ Post_t + \beta\ Private_i \times Post_t + \\ + Controls_{i,t-1}\ \lambda + PairFE_i + YearFE_y + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

where i runs across all private and public target deals, t is the event year ($t = -5, -4, \ldots, 4, 5$) corresponding to a calendar year y. $Inn_{i,t}$ is one of the three patent variables for acquirer of deal i in event year t; $Private_i$ is a dummy variable equal to 1 in all event years for completed private target deals and 0 for their matched pubic target deals; $Post_t$ is equal to 1 in the post-deal period for all deals including the deal announcement year ($t = 0$) and 0 otherwise; $Controls_{i,t-1}$ represents a matrix of lagged control variables that contains size (total sales), R&D expenditures, leverage, net income, and industry concentration; $PairFE_i$ is the fixed effect for each private-public matched pair; $YearFE_y$ is the calendar year fixed effect; and $\varepsilon_{i,t}$ is the error term. Coefficients β for the interaction term $Private_i$ x $Post_t$ are the coefficients of interests. Standard errors are clustered by private-public matched pairs.

Table 4 shows coefficient estimates for Regression (1) with patent count, forward cites, and patent value as the dependent variable Inn while using the 1:1 matched sample. We rely on a log transformation of the Inn variables following Chen and Roth (2023) to account for the concavity of the outcome which also allows to interpret the estimated coefficients as percentage changes. In particular, we normalize the minimum nonzero value of Inn to 1 by dividing all observations by the minimum nonzero value and then take $log(Inn)$. We set $log(Inn) = -x$ for zero values of Inn. We opt for $x = 1$ and $x = 0$ in Columns 1–3 and 4–6, respectively. Following Chen and Roth (2023), x specifies how much a firm values a change in patenting from 0 to 1 (after the normalization) relative to a percentage change in patenting when it is nonzero. In essence, it defines the extensive relative to intensive margin.[6]

Insert Table 4 about here.

The beta coefficients across the three innovation measures in Panel A in Table 4 show that

[6]Setting $x = 1$ implies that firms value the extensive margin effect of moving patenting from 0 to 1 the same as a 100% increase in patenting with nonzero values. The average effect for this transformation can be interpreted as an approximate percentage (log point) effect, where an increase from 0 to 1 is valued at 100 x log points. When $x = 0$, the extensive margin is zero and the whole average effect comes from patenting increases on the intensive margin (from nonzero values).

private target acquisitions increase quantity, quality, and value of innovation for their acquirers post- versus pre-deal more than public target acquisitions. Due to the log transformation of the patenting variables, the interpretation of a β coefficient is as additional change in percentage points. For example, focusing on the patent count in Column 4 with $x = 0$, when the extensive margin is assumed to be zero, the average increase in patent count after private target acquisitions is by 7.2 percentage points larger than for public target acquisitions. The corresponding average effect for private versus public target acquisitions is and additional increase of 8.2 percentage points in Column 1, when we assume a 100% increase in patenting on the extensive margin when moving from 0 to 1 in the normalized patent count. We see a small increase $(1 = 8.2 - 7.2)$ in the average effect coming from the extensive margin, but importantly we have an economically significant effect also exclusively on the intensive margin.[7] Regardless what we assume concerning the extensive margin, i.e. value of x, the average effect is significantly positive. The remaining beta coefficient estimates suggest similar average effects for forward cites and patent value. We conclude that patenting quantity, quality, and value are higher after acquisitions of private targets than after acquisitions of publicly listed targets.

Panel B in Table 4 shows parallel trend statistics for log transformations with both $x = 1$ and $x = 0$. We show average yearly changes in the three innovation variables from 5 years to 1 year before the acquisition for private versus public target acquirers. We can see that in most cases, the changes are always with the same sign for the two groups, indicating similar trends. Importantly, the differences in the mean changes for private versus public target acquisitions in Columns 3 and 8 are statistically insignificant. Figure 1 shows the yearly changes graphically. This confirms the main assumption of the difference-in-differences approach that absent acquisitions the average change in the treated versus control groups would have been the same.

We perform five additional robustness tests in Table I.2 in the Internet Appendix that confirm our baseline result that acquisitions of private versus public targets are associated with larger

[7]Untabulated results with $x = 3$ gain still larger beta coefficients.

increases in patenting activities. The first test increases the number of matched private target deals to closer reflect the realized ratio of private to public target acquisitions of 5:1. We match acquirers of public targets to at least five acquirers of private targets. The resulting matching is less precise; the propensity score difference increases and becomes statistically significant, but this matching accounts for the fact that private target acquisitions are more frequent than acquisitions of publicly listed targets. The beta coefficients in Panel A in Table I.2 are also in this case all positive, showing a larger increase in patenting after private target acquisitions. However, the beta coefficients for forward cites are now markedly smaller and statistically insignificant. Less precise matching is associated with increases for patent quantity and value, but not for patent quality.

The second robustness test in Panel B in Table I.2 explores target size effects as the literature often takes firm size and private ownership status interchangeably. We want to show that our baseline results above are not driven by the target size instead of private ownership. Panel B splits all targets from the baseline data set by transaction size. For private targets, this is the only measure of target size we have available and the coverage is still low; the number observations drops by 35 percent. We confirm that private targets are smaller than their public counterparts. We use the median value across all targets to split the private an public targets into small versus large and to introduce triple interaction terms γ^s and γ^l reflecting the patenting outcomes in small versus large targets, respectively. We can see that only the γ^l coefficients are statistically significant, indicating that private target acquisitions are associated with better patenting outcomes when it comes to large rather than small targets. These results are inconsistent with target size driving the differences in patenting outcomes. If the results were driven by target size instead of target ownership type, we would expect that private targets would show better results for small sizes.

Panel C includes additional fixed effects for cooperative patent classification (CPC) to assure that the increase in patenting is not driven by acquirers who are active in patent classes with a generally high numbers and citations. Panel D modifies the baseline regressions in Table 4 by adding interaction terms between the post dummy and all control variables to make sure that the

β coefficients do not pick up some trend entrenched in control variables. Finally, Panel E covers a shorter event window including 3 instead of 5 years before and after the acquisition. This way we avoid using the last 2 years of data that suffer from truncation issues the most (Lerner and Seru, 2022). Our conclusions hold.

In summary, we show that acquirers of private targets increase their patenting activity post-acquisition relatively to the pre-acquisition period and the corresponding change for public target acquisitions. Figure 2 shows the development of the average effect over time since the deal announcement year $t = 0$ for the 1:1 matched sample. The reference category includes all lags from -5 to -1, thus the coefficients estimate the increase in the corresponding year relatively to the pre-acquisition period and relative to the same change for the counterfactual. The increase in innovation outcomes is insignificant in the year of acquisition and then gradual over the next two/three years. This suggests that acquirers may submit some patents developed by targets before the acquisition as larger public acquirers may have more resources to file patents or may be more aggressive in their patenting strategy.

4.2 Withdrawn deals

Our baseline regressions in Table 4 compare patenting outcomes for acquirers of private target versus acquirers of public target. Both types of acquirers decide for an acquisition, but of a different type of target company. One may argue that the results are driven by different innovation inertia of acquirers of private versus public targets. The argument is that acquirers of private targets have high innovation drive and aspirations and they would increase innovation relative to acquirers of public targets anyway even without the acquisitions. In other words, the effects we see in Table 4 are not due to the acquisitions of private targets but rather due to internal drive for innovation inherent within the firms that chose to acquire private targets. To test for this possibility, we follow Seru (2014) and Bena and Li (2014) and for private target acquisitions form a control group with firms that attempted private target acquisitions but failed due to exogenous reasons. As this control group includes firms that intend to acquire a private target but are eventually not successful, we have a suitable counterfactual with similar inertia to innovate. Moreover, Seru (2014) argues that selection into the successful versus withdrawn groups is random. To get a full picture, we also compare public target acquisitions to withdrawn public target deals.

We use all withdrawn deals of private and public targets due to exogenous reasons.[8] The frequency of withdrawing is relatively low, so this group is significantly smaller than the group of successful deals. We match each withdrawn private (public) target acquisition with a successful private (public) target acquisition based on year, industry, size, and book to market ratio using propensity score matching.[9] Table 5 shows results for private and public target acquisitions in Panels A and B, respectively.

Insert Table 5 about here.

Comparing the beta coefficients for private target acquisitions in Panel A with public target acquisitions in Panel B, we can see that the patenting effects pertain for private target acquisitions but not for public target acquisitions. In Columns 1 to 3 accounting for extensive margin in patenting with $x = 1$, all three beta coefficients for private target acquirers in Panel A are positive and significant. In contrast, the corresponding beta coefficients for public acquirers in Panel B are insignificant. Beta coefficients in Columns 4 to 6 follow a similar pattern. We conclude that it is not the inertia to innovate that drives the differences in patenting outcomes between acquisitions of private versus public targets.

To round-up our analysis, Table I.5 in the Internet Appendix compares patenting outcomes of private target acquirers to matched firms without any acquisitions in Panel A and of public target acquirers to their matched counterparts without any acquisitions. Even though these comparisons

[8]Table I.3 in the Internet Appendix lists withdrawal reasons from news articles for 30 randomly picked deals. We do not find that these reasons relate to innovation. Similar to Savor and Lu (2009), the main reasons for deal failures are targets' rejection of the offer, failure in negotiations, objection by regulatory bodies, competing offer, or general market conditions.

[9]We estimate 2 probit models using (i) all withdrawn and successful private target deals and (ii) all withdrawn and successful public target deals in our sample. Table I.4 in the Internet Appendix reports the matching statistics.

may suffer a selection bias due to innovation inertia of acquirers, they still provide some extra information and include all available acquisitions. We find, similar to the analysis with withdrawn deals, that private target acquisitions are associated with larger increases in patent quantity, quality, and value than firms that do not engage in acquisitions. In contrast, acquirers of public targets do not show insignificant increases.

4.3 Innovation synergies

Our results so far confirm the hypothesis that acquiring private targets, which pertain the advantage of engaging in development of new innovative technologies due to their higher tolerance for failure and longer-term orientation, is associated with a significantly larger increase in quantity, quality, and value of patents for the acquiring firms than when acquiring publicly listed targets. To round-up the analysis, Table 6 tests whether acquiring private versus public targets is associated with extra patenting synergies. We hypothesize that private firms with developed new technologies may decide for a sale instead of commercialization due to a lack of experience or resources to commercialize and a lack of resources to invest in manufacturing or distribution capabilities. Acquiring firms enhance their innovation because of the acquired complementary innovative capabilities; newly developed breakthrough technologies, future innovation potential, and new teams of inquisitive inventors. Acquiring firms with more patenting know-how can also help with filing new patents. These synergistic effects are not present when acquiring public targets.

To test for synergistic effects coming from a combination of acquirers and targets, we create for each private and public deal in the baseline data set with 1:1 matching a new variable $CombInn$ (combined innovation) following the Patent Index measure in Bena and Li (2014). For patent count (forward cites), it equals the sum of values of the patent count (forward cites) for the acquirer and the target in each pre-acquisition event year and the acquirer innovation values in each post-acquisition event year. Note that $CombInn$ is not defined for patent value for private targets. We run the following regression with the logarithmic transformation of the dependent variable due to

Chen and Roth (2023) as in Section 4.1:

$$
\begin{aligned}
log(CombInn)_{i,t} &= \alpha_1 \ Private_i + \alpha_2 \ Post_t + \beta \ Private_i \times Post_t + \\
&+ Controls_{i,t-1} \ \lambda + PairFE_i + YearFE_y + \varepsilon_{i,t},
\end{aligned} \tag{2}
$$

where all explanatory variables are defined as in Regression (1).

In addition, we want to examine more directly whether new inventors coming from targets cooperate with acquirers' inventors and create new patents that would not be possible without combining the two firms. Put it differently, we explore whether the increases in patenting outcomes from acquisitions come from innovation synergies and are not mechanistic due to patents that would have been filed anyway by private targets without any acquisitions. The data on inventors is described in Appendix C. We create two inventor variables and use their logarithmic transformations (Chen and Roth, 2023) in the following regression:

$$
\begin{aligned}
log(Inventor)_{i,t} &= \alpha_1 \ Private_i + \alpha_2 \ Post_t + \beta \ Private_i \times Post_t + \\
&+ Controls_{i,t-1} \ \lambda + PairFE_i + YearFE_y + \varepsilon_{i,t},
\end{aligned} \tag{3}
$$

where all explanatory variables are again defined as in Regression (1).

Table 6 shows results for Regression (2) with the combined patent count and combined forward cites and Regression (3) with the number of all inventors and number of new inventors collaborating. Again, we report results with varying values on the extensive margin; x takes values of 1 and 0 in Columns 1 to 4 and Columns 5 to 8, respectively. The β coefficients are all significant and positive showing that acquisitions of private targets are associated with higher synergies than acquisitions of public targets. New filed patents and forward cites increase by 19 and 32 percentage points more, respectively, when accounting for extensive margin ($x = 1$). These effects are somewhat smaller but still statistically significant when we assume zero extensive margin ($x = 0$). The combined firm produces higher quantity and quality of patents even compared to the sum of patenting in the target-acquirer pair before the combination.

Insert Table 6 about here.

In Column 3, the number of inventors in the acquiring company increases by 7 percentage points more when taking over a private than a public target. Column 4 then takes into account only 'new' inventors who file their first patent in the given year. Moreover, we count only new inventors who coauthor patents with acquirer's incumbent inventors. The β coefficient in Column 4 shows that acquirers of private targets increase the number of new inventors who collaborate with their inventors by 8 percentage points more than acquirers of public targets. These significant inventor effects suggest synergies; the acquiring firm increases its inventor numbers and numbers of inventors who file a patent for the first time and coauthor patents with incumbent inventors from the acquiring firm.

5 Sources of positive patenting outcomes

In this section, we examine potential sources of patenting increases, namely, target's patenting activity, breakthrough technology sectors, and acquirer expertise to select targets.

5.1 Target patenting activity

We first consider whether acquirers' patenting increases post acquisition depend on existing patents of target firms. The literature usually restricts analyses to acquirers and targets with patents (Sevilir and Tian, 2012; Bena and Li, 2014), but only around 25 percent of the private targets in our sample own granted patents at the time of the acquisition. For public targets, the fraction is 46 percent. This raises the question of how important private targets' granted patents are in the context of the patenting effects documented in the previous section. Hence, we run the following regression that splits the overall patenting effect of private target acquisitions into two effects; for deals involving a target with versus without an existing patent:

$$
\begin{aligned}
log(Y_{i,t}) = {} & \alpha_1^{wp}\ Private_i \times Target\text{WP}_i + \alpha_1^{wop}\ Private_i \times Target\text{WoP}_i + \\
& + \alpha_2^{wp}\ Post_t \times Target\text{WP}_i + \alpha_2^{wop}\ Post_t \times Target\text{WoP}_i + \\
& + \gamma^{wp}\ Private_i \times Post_t \times Target\text{WP}_i + \gamma^{wop}\ Private_i \times Post_t \times Target\text{WoP}_i + \\
& + Controls_{i,t-1}\ \lambda + PairFE_i + YearFE_y + \varepsilon_{i,t},
\end{aligned} \tag{4}
$$

where $Y_{i,t}$ is $Inn_{i,t}$, $CombInn_{i,t}$, or $Inventor_{i,t}$ and $Target\text{WP}$ ($Target\text{WoP}$) is a dummy variable equal to 1 in all event years if the target has at least 1 granted patent (has no granted patents) before the acquisition, and 0 otherwise. The triple interaction terms with coefficients γ^{wp} and γ^{wop} measure the patenting or synergistic effects when acquiring private targets that own and do not own patents, respectively.

Panel A in Table 7 with the three baseline patenting measures of quantity, quality, and value shows that only the γ^{wop} coefficients are positive and significant at the one-percent level. The γ^{wp} coefficients for targets with patents before the acquisition are negative and, in fact, the γ^{wp} coefficient for forward cites is negative and statistically significant on the five-percent level. The differences between the corresponding coefficients are statistically significant on the one-percent level (not reported). This means that private target acquisitions are associated with higher patenting outcomes (in terms of quantity, quality, and value) post-acquisition than public target acquisitions, but only when they acquire firms without patents. When acquiring firms with patents, private target acquisitions show disadvantage in forward citations when compared to their public target counterparts. Panel B splits the overall synergistic effect into two parts depending on existing patents of target firms. The pattern of results is similar to Panel A. Coefficients γ^{wop} are all positive and statistically significant on the one-percent level. Coefficients γ^{wp} are now all insignificant.

Insert Table 7 about here.

In our view, these results suggest that a part of the patenting outcomes after acquiring private targets without patents is due to post-acquisition filing of patents that are ready to be filed by the private target before the acquisition, but the target prefers to have it conducted by the more experienced public acquirer. Public acquirers have a comparative advantage in patenting and on average may file patents sooner, faster, and more frequently. Filing patent applications seems to be relatively more costly for private than for public firms as private targets are less likely to have filed patents. Furthermore, once private targets have filed patents, their patenting outcomes are not better than outcomes of public targets as γ^{wp} are mostly insignificant, which suggests that innovative ideas of private targets are on average in earlier stages of development and have more potential for further exploitation. In this vein, Panel B shows that innovators from both parties collaborate with each other and come up with new innovations for private targets without patents but not when targets filed for patents already before the acquisition.

Results in Table 7 imply that acquired private targets own innovative ideas even when they do not file them as patents. To provide supporting evidence, in Appendix E we perform a small-scale in-depth analysis of a random sample of 21 acquisitions of private targets that do not own any existing granted patents. We make three observations from the anecdotal evidence. First, we confirm that 18 out of the 21 private targets are acquired because of their innovative activities. The second observation is that the target's employees often join the acquirer company. Third, we observe that the target founder or CEO in some instances features as an innovator on patents filed by the acquirer after the acquisition. All of these observations are in line with the notion that acquired private targets may not need existing patents and still increase patenting post acquisition.

5.2 Breakthrough technologies

The innovation effects for private firms should be stronger in sectors that are dominated by breakthrough technologies where the advantages of private ownership (tolerance for failure and long-term orientation) have more space to manifest fully. We explore private targets' comparative innovation advantages by comparing patenting outcomes across sectors that are dominated by breakthrough technologies versus sectors that are more traditional. We create a time-varying dummy for breakthrough sectors following Kelly et al. (2021). First, we identify all breakthrough patents each year across Fama-French 30 industries and define a breakthrough patent as falling within the top 10% of patents in our Compustat sample in the year of filing based on patent importance. A patent is classified as important if it meets two criteria: (i) it is novel – it significantly differs from previous inventions, and (ii) it is impactful for future inventions. Relying on KPST data (Kelly et al., 2021), we use backward similarity to measure (i) and forward similarity to measure (ii). Patent importance is then calculated as the ratio between forward similarity and backward similarity over a 5-year period. As the last step, we compute the ratio of breakthrough patents within all filed patents for each sector-year. Breakthrough versus traditional sectors are defined based on the median value across all sector-years.

Table 8 splits the patenting and synergistic effects (in Panels A and B, respectively) for breakthrough versus traditional sectors. In line with our hypothesis, the significant patenting and synergistic outcomes for private targets are concentrated in breakthrough sectors.

Insert Table 8 about here.

5.3 Expertise to identify targets

Table 9 explores acquirers' expertise to identify suitable private targets. First, following Bertrand and Schoar (2003) we conjecture that acquirers with high patenting gains are run by managers with higher than average ability and skills. We borrow the measure of managerial ability due to Demerjian, Lev, and McVay (2012), which is based on the efficiency with which managers convert resource inputs into outputs relative to their industry peers. According to Demerjian et al. (2012), this measure detects managers who better understand technology and industry trends, reliably predict product demand, invest in higher value projects, and manage their employees more efficiently than less able managers. They find that firms with more able managers are associated with future improvements in firm performance. Moreover, managerial ability is also associated with a higher patent rate and patent value in a general cross-section of publicly listed firms (Chen, Podolski, and Veeraraghavan, 2015) and with higher acquirer announcement returns and post-acquisition accounting performance (Doukas and Zhang, 2020).

Insert Table 9 about here.

Table 9 splits all observations into high versus low managerial ability (MA), which is set based on the top quartile. We can see that the patenting and synergistic effects (in Panels A and B, respectively) are positive and statistically significant only for acquirers with high managerial ability which suggests that it is the acquirers with better expertise that pick private targets with higher potential in patenting increases. This ability is not essential when acquiring public targets as public firms are less informationally opaque.

Second, we explore innovation outcomes for acquirers with versus without corporate venture capital divisions (CVCs). CVCs are stand-alone corporate subsidiaries that invest in new ventures on behalf of their corporate parents. Chemmanur, Loutskina, and Tian (2014) find that CVC-backed entrepreneurial firms produce more and higher quality patents than firms backed by independent VCs. Generally, the main strategic mission of CVCs is to enhance the competitive advantage of their parents by gathering and testing new ideas and technologies (Chemmanur et al., 2014). CVCs possess superior industry and technology expertise for nurturing innovation, which flows back to their corporate parents. We collect information on CVCs from a list of venture capital funds active over the period 1984-2020 provided by Prequin. We manually determine the parent company of CVC funds in the list and match to our acquirer names coming from Compustat. The CVC dummy is set to 1 if an acquirer is classified as a CVC parent company in the announcement year. Overall, only around 4 percent of our deals are by acquirers that have a CVC unit.

Again in line with the acquirer expertise idea, Table 9 shows that acquirers with CVC units are associated with significant and markedly higher patenting and synergistic effects for private versus public targets. Acquirers with CVC units are especially good in identifying suitable private targets with high future innovation potential.

Third, we explore expertise through acquirers' prior experience in acquiring private targets (Field and Mkrtchyan, 2017). Firms with such experience may build expertise in identifying and selecting innovative private targets. We split the sample according whether acquiring firms have had at least one acquisition of a private target before the current deal. Table 9 shows that it is the acquirers with past acquisition experience (with AE) that are associated with significantly higher patenting and synergistic outcomes.

6 Acquirer announcement returns

Our last set of tests examines whether investors anticipate the differences in innovation outcomes. More specifically, we analyze whether the differences in acquirer announcement abnormal returns between private versus public targets are related to the significant patenting improvements after private target acquisitions. Table 10 shows results when we regresses acquirer 5-day cumulative abnormal returns around deal announcements, adjusted by the value-weighted market index return, on a dummy for private targets and a set of control variables following the M&A literature (Faccio et al., 2006; Fuller et al., 2002).[10] All specifications include the matched 1:1 sample and year and FF 30 industry fixed effects. Column 1 with a baseline specification shows, in line with the literature, that the private target dummy is significantly positive; acquisitions of private versus public targets create more value for the acquiring firm shareholders.

Insert Table 10 about here.

In Columns 2 to 4, we add three dummy variables indicating quartiles by improvement in the three patent variables from before to after the acquisition, respectively. The first quartile with the lowest change is dropped and constitutes the reference category. Using the set of dummy variables, we assume that the market is able to sort out acquirers into those that are going to improve

[10]Table I.6 in the Internet Appendix provides summary statistics.

innovation more versus those that do not do it much.[11] We also add interaction terms between the patenting change quartiles and the private target dummy to separate the valuation effect of innovation improvements between private versus public targets.

We can see that the inclusion of the patent change dummies and the interaction terms is important. The three interaction terms are always positive and for the highest quartile they are statistically significant. The market reaction is significantly higher for acquisitions of private targets in the highest quartile than in the lowest quartile. This is not the case for acquirers of public targets – the plain quartile dummies are negative and sometimes significant. Importantly, the stand-alone private target dummy decreases in size and becomes statistically insignificant. These results suggest that the value differences between private and public firms are explained by acquiring private targets with more patenting and innovation potential. The results do not change when we match up to five private target acquisitions for each public target one (Table I.7 in the Internet Appendix).[12] In summary, private target acquirers with larger changes in quantity, quality, or value of patents are associated with higher announcement market reactions. In contrast, we do not observe such an effect for public target acquisitions.

7 Conclusions

This paper studies how acquiring private targets influences innovation outcomes and synergies of public acquirers. Existing empirical studies on innovation have largely overlooked the distinction between acquisitions of private versus public targets. We address this gap by showing that publicly listed firms, often characterized by short-termism and low tolerance for failure, experience a larger increase in patent count, forward cites, and patent value after acquiring private targets than acquisitions of public targets. These private target acquisitions drive follow-on innovation which

[11] We are using future information concerning patenting that the market participants do not have available at the time of a deal announcement and therefore we do not use a continuous variable.

[12] Untabulated results show that controlling for the change in profitability and industry competition from before to after acquisitions does not affect the innovation coefficients.

may be less risky. We also find evidence of innovation synergies as private target acquisitions are linked to higher increases in target-acquirer combined patenting, number of total inventors, and new collaborations among them.

Notably, these positive impacts are concentrated in breakthrough sectors and for acquirers with expertise in identifying innovative targets – with higher managerial ability, corporate venture capital divisions, and prior experience in acquiring private firms. Interestingly, the positive innovation outcomes occur regardless of whether the acquired private targets already hold patents, suggesting that some public acquirers excel in selecting innovative ideas, patented or not, from private firms that ultimately help them to generate patenting synergies. The increase in innovation persists over time, aligning with the notion that private target acquisitions drive sustained follow-on innovation.

Importantly, differences in innovation outcomes also explain away the well documented empirical pattern of higher announcement returns for acquiring private targets. Taken together, our results suggest that complementary capabilities of innovation play a key role in the value creation of private target M&As.

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Tables

Table 1. Matching acquirers with private versus public targets
This table reports coefficient estimates and standard errors (in parentheses) for a logit model predicting the probability of acquiring public versus private targets, with FF 30 industry fixed effects and data over 1995-2015 in Panel A. *Public* equals to 1 for firms acquiring public targets in the given year and 0 for firms acquiring private targets; its sample mean is 0.16. The explanatory variables are lagged 1 year. In Panel B, Columns 1 to 3 (Columns 4 to 6) show means for acquirers of private and public targets before (after) matching. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. Patenting variables are in their log transformation. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $x = 0$. ***, ** and * indicate significance at the one-, five- and ten-percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Predicting public target acquisitions					
Dependent variable	Constant	Total assets	BM	FF30 FE	χ^2	# obs.
Public	-6.244***	0.207***	0.044***	yes	677.18	13,453
	(0.304)	(0.011)	(0.009)			
	Panel B: Means for acquirers of private versus public targets					
	Before matching			After matching		
	Private	Public	Mean diff.	Private	Public	Mean diff.
# of observations	11,291	2,162		2,143	2,143	
Total assets	20.77	21.92	-1.15***	21.86	21.92	-0.06
Book to market ratio	0.39	0.41	-0.01	0.39	0.41	-0.02
Propensity score	0.15	0.21	-0.06***	0.20	0.21	0.00
Size (log of sales)	20.42	21.44	-1.02***	21.44	21.43	0.01
R&D expenditure	12.06	13.19	-1.13***	13.16	13.26	-0.10
Leverage	0.15	0.15	0.00	0.15	0.15	0.00
Net income	-0.01	0.02	-0.03	0.03	0.02	0.01***
Industry concentration	0.24	0.20	0.04 ***	0.21	0.20	0.01
Patent count	1.79	2.43	-0.65***	2.46	2.44	0.02
Forward cites	4.41	5.82	-1.42***	5.91	5.83	0.08
Patent value	4.10	4.96	-0.86***	4.54	4.48	0.06
# all inventors	3.54	4.27	-0.73***	4.28	4.28	0.01
New inv. collaborating	1.64	2.19	-0.55***	2.23	2.19	0.04

Table 2. Distribution of acquisitions of private and public targets by year and industry
This table reports frequencies of private and public target acquisitions by year in Panel A and by FF 30 industry in Panel B. Columns 1–2 include all transactions while Columns 3–4 cover only the 1:1 matched sample.

	(1)	(2)	(3)	(4)
	Before matching		After matching	
	Private	Public	Private	Public
Total count	11,291	2,162	2,143	2,143
Panel A: Frequencies by year				
1995	501	120	120	120
1996	610	138	138	138
1997	803	138	138	138
1998	873	204	204	204
1999	900	243	243	243
2000	838	190	188	188
2001	485	145	144	144
2002	434	89	88	88
2003	426	84	84	84
2004	528	76	75	75
2005	506	95	94	94
2006	565	100	99	99
2007	586	92	92	92
2008	486	72	72	72
2009	295	66	61	61
2010	405	71	71	71
2011	433	38	38	38
2012	443	55	51	51
2013	348	39	38	38
2014	445	45	44	44
2015	381	62	61	61
Panel B: Frequencies by industry				
Food Products	184	34	34	34
Beer & Liquor	13	6	2	2
Recreation	152	36	35	35
Printing and Publishing	133	15	15	15
Consumer Goods	143	24	24	24
Apparel	61	17	16	16
Healthcare, Med. Equipment, Pharma. Products	1182	379	379	379
Chemicals	192	35	35	35
Textiles	47	2	2	2
Construction and Construction Materials	318	26	26	26
Steel Works Etc	118	17	16	16
Fabricated Products and Machinery	638	89	89	89
Electrical Equipment	221	13	13	13
Automobiles and Trucks	131	22	20	20
Aircraft, ships, and railroad equipment	232	39	39	39
Precious Metals, Non-Met., and Ind. Metal Mining	27	11	7	7
Petroleum and Natural Gas	237	55	53	53
Utilities	74	26	26	26
Communication	223	93	93	93
Personal and Business Services	2591	341	341	341
Business Equipment	2500	495	495	495
Business Supplies and Shipping Containers	159	34	34	34
Transportation	39	19	16	16
Wholesale	475	37	37	37

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	(1)	(2)	(3)	(4)
	Before matching		After matching	
	Private	Public	Private	Public
Retail	160	34	34	34
Restaurants, Hotels, Motels	20	6	5	5
Banking, Insurance, Real Estate, Trading	661	184	184	184
Everything Else	360	73	73	73

Table 3. Summary and univariate statistics

Panel A reports means and standard deviations in Columns 1 and 2, respectively, for the 1:1 matched sample covering 5 years before and 5 years after acquisitions. Columns 3 to 9 provide the minimum, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th} percentiles, and maximum, respectively. Panel B shows patent and inventor variable means separately for private and public target acquirers; Columns 1–2 for the whole event period and Columns 3–4 (5–6) for the pre- (post-) activism period. Column 7 (8) reports differences for private (public) target acquirers between the post- versus pre-acquisition. Column 9 shows the difference-in-differences. We use simple OLS regressions to test for the mean difference significance. All variables are defined in Appendix D and winsorized at the 1^{st} and 99^{th} percentiles. Patent and inventor variables are reported in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 0$ and $x = 1$. ***, ** and * indicate significance at the one-, five- and ten-percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Matched panel sample summary stats								
	Mean	St.dev.	Min	P10	P25	P50	P75	P90	Max
Size (log of sales)	21.50	2.42	0.00	18.44	20.15	21.77	23.36	24.18	25.13
R&D expenditure	13.19	8.44	0.00	0.00	0.00	17.55	19.54	20.37	21.13
Leverage	0.160	0.162	0.000	0.000	0.027	0.134	0.237	0.355	1.512
Net income	0.016	0.232	-14.614	-0.063	0.012	0.044	0.083	0.124	0.509
Industry concentration	0.207	0.180	0.011	0.055	0.083	0.154	0.262	0.407	1.000
x=1									
Patent count	2.46	2.80	-1.00	-1.00	-1.00	2.34	4.79	6.35	9.18
Forward cites	2.81	3.33	-1.00	-1.00	-1.00	2.61	5.70	7.58	9.88
Patent value	4.29	3.41	-1.00	-1.00	-1.00	5.51	6.91	7.82	10.09
# all inventors	3.91	2.91	-1.00	0.00	1.61	3.99	6.27	7.81	10.66
New inv. collaborating	1.73	2.64	-1.00	-1.00	-1.00	1.39	3.95	5.55	8.23
x=0									
Patent count	2.72	2.50	0.00	0.00	0.00	2.34	4.79	6.35	9.18
Forward cites	3.11	3.01	0.00	0.00	0.00	2.61	5.70	7.58	9.88
Patent value	4.55	3.01	0.00	0.00	0.00	5.51	6.91	7.82	10.09
# all inventors	4.00	2.76	0.00	0.00	1.61	3.99	6.27	7.81	10.66
New inv. collaborating	2.11	2.27	0.00	0.00	0.00	1.39	3.95	5.55	8.23

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Panel B: Univariate statistics

	Full sample		Pre-acquisition		Post-acquisition		Differences		
	Private	Public	Private	Public	Private	Public	(5)–(3)	(6)–(4)	(7)–(8)
x=1									
Patent count	2.496	2.427	2.428	2.399	2.555	2.451	0.127***	0.052	0.075
Forward cites	2.847	2.777	2.843	2.806	2.851	2.752	0.008	-0.054	0.063
Patent value	4.316	4.259	4.334	4.324	4.300	4.202	-0.034	-0.122***	0.088
# all inventors	3.935	3.875	3.735	3.708	4.108	4.020	0.373***	0.312***	0.061
New inv. collaborating	1.762	1.697	1.593	1.564	1.910	1.812	0.317***	0.248***	0.069
x=0									
Patent count	2.748	2.686	2.682	2.655	2.805	2.712	0.123***	0.058*	0.065
Forward cites	3.137	3.077	3.126	3.096	3.146	3.061	0.020	-0.035	0.056
Patent value	4.571	4.521	4.596	4.588	4.550	4.464	-0.045	-0.124***	0.079
# all inventors	4.030	3.974	3.833	3.807	4.202	4.119	0.369***	0.312***	0.057
New inv. collaborating	2.136	2.082	1.980	1.959	2.271	2.190	0.291***	0.231***	0.060

Table 4. Patenting when acquiring private versus public targets
This table shows estimation results for Regression (1) with patent count, forward cites, and patent value as dependent variables, which are in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–3 and 4–6, respectively, in Panel A. Private and public target acquirers are 1:1 matched based on year, industry, size, and book to market ratio and covered for years -5 to $+5$ around the acquisition announcement year ($t = 0$). Panel B shows average annual change rates for private and public target acquirers during the pre-acquisition years -5 to -1. *Private* is a dummy variable indicating an acquisition of a private target and is set to 0 for acquisitions of a public target. *Post* is a dummy variable set to 1 for all event years between 0 and +5 and 0 otherwise. All regressions include calendar year and private-public matched pair fixed effects. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Extensive margin		$x = 1$			$x = 0$	
		Panel A: Coefficient estimates				
	Patent count	Forward cites	Patent value	Patent count	Forward cites	Patent value
Private x post (β)	0.082***	0.079***	0.092**	0.072***	0.072***	0.083**
	(0.023)	(0.030)	(0.040)	(0.019)	(0.027)	(0.035)
Private	0.029	0.030	0.016	0.026	0.022	0.013
	(0.032)	(0.044)	(0.048)	(0.028)	(0.039)	(0.042)
Post	-0.101***	-0.161***	-0.194***	-0.080***	-0.137***	-0.177***
	(0.022)	(0.032)	(0.045)	(0.018)	(0.028)	(0.038)
Size	0.160***	0.177***	0.132***	0.149***	0.164***	0.115***
	(0.024)	(0.029)	(0.034)	(0.021)	(0.026)	(0.030)
R&D expenditure	0.097***	0.115***	0.123***	0.083***	0.100***	0.109***
	(0.008)	(0.010)	(0.010)	(0.007)	(0.008)	(0.009)
Leverage	-0.691***	-0.726***	-0.655***	-0.612***	-0.642***	-0.568***
	(0.123)	(0.155)	(0.197)	(0.105)	(0.137)	(0.172)
Net income	-0.114***	-0.077	-0.085	-0.105***	-0.079**	-0.083
	(0.041)	(0.047)	(0.084)	(0.033)	(0.039)	(0.073)
Industry concentration	0.209	0.685**	0.032	0.209	0.693**	0.036
	(0.231)	(0.311)	(0.309)	(0.201)	(0.279)	(0.271)
Constant	-2.181***	-2.490***	0.001	-1.514***	-1.726***	0.787
	(0.529)	(0.637)	(0.736)	(0.457)	(0.561)	(0.645)
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.84	0.78	0.66	0.86	0.79	0.67
# of observations	43,650	43,650	43,650	43,660	43,660	43,660
		Panel B: Parallel trend tests				
	Change for private	Change for public	Change difference	Change for private	Change for public	Change difference
Patent count	0.053	0.048	0.005	0.042	0.040	0.002
Forward cites	0.025	0.022	0.004	0.017	0.015	0.002
Patent value	0.123	0.113	0.010	0.105	0.098	0.007

Table 5. Withdrawn deals as counterfactuals

This table shows estimation results for Regression (1) with patent count, forward cites, and patent value as dependent variables, which are in logarithmic transformation. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–3 and 4–6, respectively. The sample covers successful and withdrawn acquisitions of private (public) targets in Panel A (Panel B). Both panels cover years -5 to $+5$ around the acquisition announcement year ($t = 0$). *Private* (*Public*) is a dummy variable indicating an acquisition of a private (pubic) target and is set to 0 for withdrawn private (public) target acquisitions. *Post* is a dummy variable set to 1 for all event years between 0 and +5 and 0 otherwise. All regressions include calendar year and private-public matched pair fixed effects and the following control variables: acquirer size, R&D expenditure, leverage, net income and industry concentration. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	$x = 1$			$x = 0$		
	Patent count	Forward cites	Patent value	Patent count	Forward cites	Patent value
Panel A: Private target acquisitions						
Private x post (β^{pr})	0.235**	0.378**	0.399*	0.156**	0.275**	0.319
	(0.104)	(0.150)	(0.242)	(0.076)	(0.123)	(0.205)
Private	-0.032	0.069	-0.112	0.005	0.094	-0.072
	(0.078)	(0.112)	(0.180)	(0.056)	(0.092)	(0.153)
Post	-0.160	-0.176	-0.275	-0.102	-0.083	-0.223
	(0.114)	(0.165)	(0.265)	(0.083)	(0.135)	(0.224)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.49	0.40	0.37	0.52	0.40	0.38
# of observations	1,803	1,803	1,803	1,803	1,803	1,803
Panel B: Public target acquisitions						
Public x post (β^{pu})	0.005	-0.072	0.055	-0.001	-0.069	0.045
	(0.078)	(0.103)	(0.110)	(0.063)	(0.089)	(0.090)
Public	0.444***	0.590***	0.474***	0.371***	0.509***	0.406***
	(0.058)	(0.077)	(0.082)	(0.047)	(0.066)	(0.067)
Post	-0.135	-0.187	-0.166	-0.117*	-0.168*	-0.153
	(0.086)	(0.115)	(0.122)	(0.070)	(0.099)	(0.100)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.69	0.62	0.55	0.71	0.63	0.57
# of observations	4,740	4,740	4,740	4,740	4,740	4,740

Table 6. Innovation synergies

This table shows estimation results for Regressions (2) and (3) with 4 alternative dependent variables, which are in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–4 and 5–8, respectively. Private and public target acquirers are 1:1 matched based on year, industry, size, and book to market ratio and covered for years -5 to $+5$ around the acquisition announcement year ($t = 0$). *Private* is a dummy variable indicating an acquisition of a private target and is set to 0 for acquisitions of a public target. *Post* is a dummy variable set to 1 for all event years between 0 and +5 and 0 otherwise. All regressions include calendar year and private-public matched pair fixed effects. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$x = 1$				$x = 0$			
	Patent count	Forward cites	# all inventors	new invent. collaborating	Patent count	Forward cites	# all inventors	new invent. collaborating
Private x post (β)	0.191***	0.315***	0.068***	0.078***	0.161***	0.290***	0.065***	0.069***
	(0.025)	(0.047)	(0.021)	(0.022)	(0.021)	(0.042)	(0.019)	(0.018)
Private	-0.079**	-0.164***	0.027	0.027	-0.062**	-0.154***	0.025	0.019
	(0.032)	(0.061)	(0.034)	(0.029)	(0.028)	(0.055)	(0.031)	(0.024)
Post	-0.215***	-0.452***	-0.069***	-0.064***	-0.169***	-0.407***	-0.064***	-0.051***
	(0.024)	(0.052)	(0.018)	(0.023)	(0.020)	(0.046)	(0.016)	(0.018)
Size	0.157***	0.205***	0.150***	0.142***	0.146***	0.192***	0.141***	0.123***
	(0.024)	(0.040)	(0.024)	(0.021)	(0.021)	(0.036)	(0.022)	(0.017)
R&D expenditure	0.095***	0.156***	0.114***	0.086***	0.082***	0.141***	0.106***	0.069***
	(0.008)	(0.013)	(0.008)	(0.007)	(0.007)	(0.012)	(0.008)	(0.006)
Leverage	-0.690***	-0.974***	-0.828***	-0.664***	-0.606***	-0.891***	-0.777***	-0.566***
	(0.124)	(0.224)	(0.140)	(0.115)	(0.106)	(0.201)	(0.127)	(0.095)
Net income	-0.107**	-0.042	-0.178***	-0.124***	-0.100***	-0.047	-0.165***	-0.104***
	(0.042)	(0.078)	(0.061)	(0.040)	(0.033)	(0.067)	(0.052)	(0.032)
Industry concentration	0.197	0.610	0.272	0.254	0.194	0.617*	0.285	0.258
	(0.225)	(0.408)	(0.252)	(0.207)	(0.198)	(0.372)	(0.232)	(0.176)
Constant	-1.940***	-1.182	-0.744	-2.398***	-1.317***	-0.475	-0.349	-1.409***
	(0.522)	(0.869)	(0.526)	(0.452)	(0.455)	(0.784)	(0.484)	(0.375)
Pair fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.83	0.72	0.87	0.82	0.85	0.74	0.88	0.84
# of observations	43,660	43,660	43,660	43,660	43,660	43,660	43,660	43,660

Table 7. Targets with and without patents
This table shows estimation results for Regression (4) with 3 patenting measures as the dependent variable in Panel A and 4 patent synergy measures in Panel B. The patent variables are in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–4 and 5–8, respectively. We split the innovation effect by targets with patents (*targetWP*) versus targets without patents (*targetWoP*). Both panels cover the 1:1 matched sample over years -5 to $+5$ around the acquisition announcement year ($t = 0$). *Private* is a dummy variable indicating an acquisition of a private target and is set to 0 for acquisitions of a public target. *Post* is a dummy variable set to 1 for all event years between 0 and +5 and 0 otherwise. All specifications include corresponding double interaction terms, calendar year and private-public matched pair fixed effects, and the following control variables: acquirer size, R&D expenditure, leverage, net income, and industry concentration. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		$x = 1$				$x = 0$		
				Panel A: Patenting effects				
	Patent count	Forward cites	Patent value		Patent count	Forward cites	Patent value	
Private x post x targetWP	-0.053	-0.152**	-0.122		-0.042	-0.133**	-0.107	
(γ^{wp})	(0.051)	(0.065)	(0.079)		(0.044)	(0.058)	(0.069)	
Private x post x targetWoP	0.153***	0.207***	0.216***		0.130***	0.182***	0.193***	
(γ^{wop})	(0.036)	(0.048)	(0.058)		(0.031)	(0.043)	(0.050)	
Controls	yes	yes	yes		yes	yes	yes	
Pair fixed effects	yes	yes	yes		yes	yes	yes	
Calendar time fixed effects	yes	yes	yes		yes	yes	yes	
Adjusted R^2	0.84	0.78	0.66		0.86	0.79	0.67	
# of observations	43,660	43,660	43,660		43,660	43,660	43,660	
				Panel B: Synergistic effects				
	Patent count	Forward cites	# all inventors	new inv. collaborating	Patent count	Forward cites	# all inventors	new inv. collaborating
Private x post x targetWP	-0.005	-0.105	-0.056	-0.015	0.013	-0.084	-0.060	-0.006
(γ^{wp})	(0.053)	(0.096)	(0.047)	(0.048)	(0.046)	(0.086)	(0.042)	(0.040)
Private x post x targetWoP	0.251***	0.473***	0.148***	0.132***	0.207***	0.429***	0.142***	0.112***
(γ^{wop})	(0.037)	(0.069)	(0.037)	(0.034)	(0.031)	(0.062)	(0.033)	(0.028)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.83	0.72	0.87	0.82	0.85	0.74	0.88	0.84
# of observations	43,660	43,660	43,660	43,660	43,660	43,660	43,660	43,660

Table 8. Breakthrough sectors

This table shows estimation results for Regression (4) with 3 patenting measures as the dependent variable in Panel A and 4 patent synergy measures in Panel B. The patent variables are in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–4 and 5–8, respectively. We split the innovation effect by acquirers in *breakthrough* versus *traditional* sectors. Both panels cover the 1:1 matches sample over years -5 to $+5$ around the acquisition announcement year ($t = 0$). *Private* is a dummy variable indicating an acquisition of a private target and is set to 0 for acquisitions of a public target. *Post* is a dummy variable set to 1 for all event years between 0 and +5 and 0 otherwise. All specifications include calendar year and private-public matched pair fixed effects, and the following control variables: acquirer size, R&D expenditure, leverage, net income, and industry concentration. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$x = 1$				$x = 0$			
Panel A: Patenting effects								
	Patent count	Forward cites	Patent value		Patent count	Forward cites	Patent value	
Private x post x traditional	-0.018	-0.036	-0.026		-0.019	-0.043	-0.025	
(γ^t)	(0.069)	(0.101)	(0.099)		(0.060)	(0.091)	(0.087)	
Private x post x breakthrough	0.128***	0.162***	0.114*		0.115***	0.151***	0.101*	
(γ^b)	(0.042)	(0.051)	(0.060)		(0.036)	(0.045)	(0.053)	
Controls	yes	yes	yes		yes	yes	yes	
Pair fixed effects	yes	yes	yes		yes	yes	yes	
Calendar time fixed effects	yes	yes	yes		yes	yes	yes	
Adjusted R^2	0.84	0.79	0.66		0.86	0.80	0.68	
# of observations	38,838	38,838	38,838		38,838	38,838	38,838	
Panel B: Synergistic effects								
	Patent count	Forward cites	# all inventors	new inv. collaborating	Patent count	Forward cites	# all inventors	new inv. collaborating
Private x post x traditional	-0.021	-0.021	-0.046	-0.063	-0.020	-0.027	-0.055	-0.056
(γ^t)	(0.070)	(0.135)	(0.077)	(0.065)	(0.061)	(0.123)	(0.071)	(0.055)
Private x post x breakthrough	0.129***	0.198***	0.102**	0.144***	0.116***	0.186***	0.104**	0.127***
(γ^b)	(0.042)	(0.072)	(0.046)	(0.038)	(0.036)	(0.064)	(0.042)	(0.032)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.84	0.73	0.87	0.83	0.86	0.74	0.88	0.85
# of observations	38,849	38,849	38,849	38,849	38,849	38,849	38,849	38,849

Table 9. Acquirer expertise

This table shows estimation results for Regression (4) with 3 patenting measures as the dependent variable in Panel A and 4 patent synergy measures in Panel B. The patent variables are in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–4 and 5–8, respectively. We split the innovation effect by acquirers' managerial ability (high MA is the top quartile), CVC, and acquisition experience (AE). Both panels cover the 1:1 matched sample over years -5 to $+5$ around the acquisition announcement year ($t = 0$). *Private* is a dummy variable indicating an acquisition of a private target and is set to 0 for acquisitions of a public target. *Post* is a dummy variable set to 1 for all event years between 0 and +5 and 0 otherwise. All specifications include corresponding double interaction terms, calendar year and private-public matched pair fixed effects, and the following control variables: acquirer size, R&D expenditure, leverage, net income, and industry concentration. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		$x = 1$				$x = 0$		
				Panel A: Patenting effects				
	Patent count	Forward cites	Patent value		Patent count	Forward cites	Patent value	
Private x post x low MA	0.078*	0.061	0.085		0.068*	0.047	0.076	
(γ^l)	(0.044)	(0.058)	(0.062)		(0.038)	(0.052)	(0.054)	
Private x post x high MA	0.211***	0.216***	0.140**		0.196***	0.199***	0.124**	
(γ^h)	(0.059)	(0.076)	(0.070)		(0.053)	(0.070)	(0.062)	
Controls	yes	yes	yes		yes	yes	yes	
Pair fixed effects	yes	yes	yes		yes	yes	yes	
Calendar time fixed effects	yes	yes	yes		yes	yes	yes	
Adjusted R^2	0.838	0.773	0.655		0.857	0.783	0.673	
# of observations	38,465	38,465	38,465		38,465	38,465	38,465	
Private x post x with CVC	0.348***	0.427***	0.285***		0.326***	0.412***	0.263***	
(γ^{cvc})	(0.094)	(0.126)	(0.081)		(0.089)	(0.120)	(0.074)	
Private x post x without CVC	0.088**	0.080*	0.090*		0.077**	0.066	0.079*	
(γ^{novc})	(0.037)	(0.048)	(0.053)		(0.032)	(0.042)	(0.046)	
Controls	yes	yes	yes		yes	yes	yes	
Pair fixed effects	yes	yes	yes		yes	yes	yes	
Calendar time fixed effects	yes	yes	yes		yes	yes	yes	
Adjusted R^2	0.838	0.776	0.656		0.857	0.786	0.675	
# of observations	43,660	43,660	43,660		43,660	43,660	43,660	
Private x post x with AE	0.137***	0.131***	0.135***		0.121***	0.112**	0.119***	
(γ^{wae})	(0.038)	(0.049)	(0.050)		(0.033)	(0.044)	(0.044)	
Private x post x without AE	-0.033	-0.022	0.030		-0.034	-0.013	0.027	
(γ^{woae})	(0.090)	(0.116)	(0.151)		(0.075)	(0.101)	(0.130)	
Controls	yes	yes	yes		yes	yes	yes	
Pair fixed effects	yes	yes	yes		yes	yes	yes	
Calendar time fixed effects	yes	yes	yes		yes	yes	yes	
Adjusted R^2	0.837	0.776	0.656		0.856	0.786	0.674	
# of observations	43,660	43,660	43,660		43,660	43,660	43,660	
				Panel B: Synergistic effects				
	Patent count	Forward cites	# all inventors	new inv. collaborating	Patent count	Forward cites	# all inventors	new inv. collaborating
Private x post x low MA	0.076*	0.101	0.059	0.074*	0.067*	0.086	0.054	0.059*
(γ^l)	(0.044)	(0.079)	(0.048)	(0.040)	(0.039)	(0.072)	(0.044)	(0.034)
Private x post x high MA	0.221***	0.276***	0.180***	0.193***	0.205***	0.258***	0.174***	0.181***
(γ^h)	(0.060)	(0.097)	(0.059)	(0.057)	(0.054)	(0.090)	(0.056)	(0.050)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.834	0.719	0.872	0.823	0.853	0.735	0.882	0.841
# of observations	38,465	38,465	38,465	38,465	38,465	38,465	38,465	38,465

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Private x post x with CVC	0.346***	0.462***	0.333***	0.345***	0.326***	0.448***	0.319***	0.312***
(γ^{cvc})	(0.093)	(0.147)	(0.085)	(0.093)	(0.089)	(0.139)	(0.082)	(0.086)
Private x post x without CVC	0.089**	0.123*	0.072*	0.082**	0.078**	0.108*	0.068*	0.066**
(γ^{novc})	(0.037)	(0.066)	(0.040)	(0.034)	(0.032)	(0.060)	(0.037)	(0.028)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.833	0.720	0.870	0.821	0.854	0.736	0.880	0.839
# of observations	43,660	43,660	43,660	43,660	43,660	43,660	43,660	43,660
Private x post x with AE	0.138***	0.186***	0.106***	0.127***	0.122***	0.168***	0.103***	0.105***
(γ^{wae})	(0.038)	(0.066)	(0.040)	(0.036)	(0.034)	(0.060)	(0.038)	(0.030)
Private x post x without AE	-0.043	-0.054	0.040	-0.040	-0.044	-0.046	0.021	-0.031
(γ^{woae})	(0.091)	(0.175)	(0.101)	(0.079)	(0.076)	(0.155)	(0.092)	(0.062)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.832	0.719	0.869	0.820	0.853	0.735	0.879	0.838
# of observations	43,660	43,660	43,660	43,660	43,660	43,660	43,660	43,660

Table 10. Announcement abnormal returns

This table reports OLS estimates with the acquirer 5-day cumulative abnormal return around the deal announcement date for private and public target acquisitions as the dependent variable. The regressions include acquisitions of private and public targets which are 1:1 matched based on year, industry, size, and book to market ratio. *Private target* is a dummy variable set to 1 when the target is a private firm and 0 for public targets. $\Delta Innovation$ measures the increase from the pre- to post-acquisition period for the patent count (Column 2), forward cites (Column 3), and patent value (Columns 4). We form quartiles by $\Delta Innovation$ and the lowest quartile, Q_1, is the reference category. All regressions include year and Fama-French 30 industry fixed effects. Standard errors clustered at the firm level are reported in parentheses. All variables are defined in Appendix D and winsorized at the 1^{th} and 99^{th} percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)
	Baseline	Patent count	Forward cites	Patent value
Private target	0.014***	0.002	0.007	0.007
	(0.003)	(0.005)	(0.005)	(0.005)
ΔInnovation Q_2		-0.008	-0.015***	-0.000
		(0.006)	(0.005)	(0.006)
ΔInnovation Q_3		-0.009	-0.013**	-0.013**
		(0.006)	(0.006)	(0.006)
ΔInnovation Q_4		-0.007	-0.011**	-0.013**
		(0.006)	(0.005)	(0.006)
Private target x ΔInnovation Q_2		0.018**	0.004	0.004
		(0.008)	(0.008)	(0.008)
Private target x ΔInnovation Q_3		0.010	0.009	0.008
		(0.008)	(0.008)	(0.008)
Private target x ΔInnovation Q_4		0.023***	0.016**	0.017**
		(0.008)	(0.008)	(0.008)
Cash only	0.015***	0.014***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
Hostile deal	-0.011	-0.012	-0.013	-0.009
	(0.019)	(0.019)	(0.019)	(0.019)
Horizontal deal	-0.007**	-0.007**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
R&D expenditure	-0.001	-0.001	-0.001**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Size	0.020**	0.021**	0.021**	0.021**
	(0.010)	(0.010)	(0.010)	(0.010)
Leverage	-0.018**	-0.018**	-0.018**	-0.017*
	(0.009)	(0.009)	(0.009)	(0.009)
Industry concentration	-0.025***	-0.024***	-0.025***	-0.025***
	(0.009)	(0.009)	(0.009)	(0.009)
Constant	0.015	0.026	0.039*	0.032
	(0.020)	(0.021)	(0.021)	(0.022)
FF 30 industry fixed effects	yes	yes	yes	yes
Calendar year fixed effects	yes	yes	yes	yes
R^2	0.034	0.037	0.038	0.037
# of observations	4,082	4,082	4,082	4,082

Figure 1: Parallel trends

This figure shows year and FF 30 industry adjusted differences in means between private versus public target acquirers (and their 90% confidence intervals) for annual growth rates for patent count, forward cites, and patent value during the pre-acquisition years from -5 to -1.

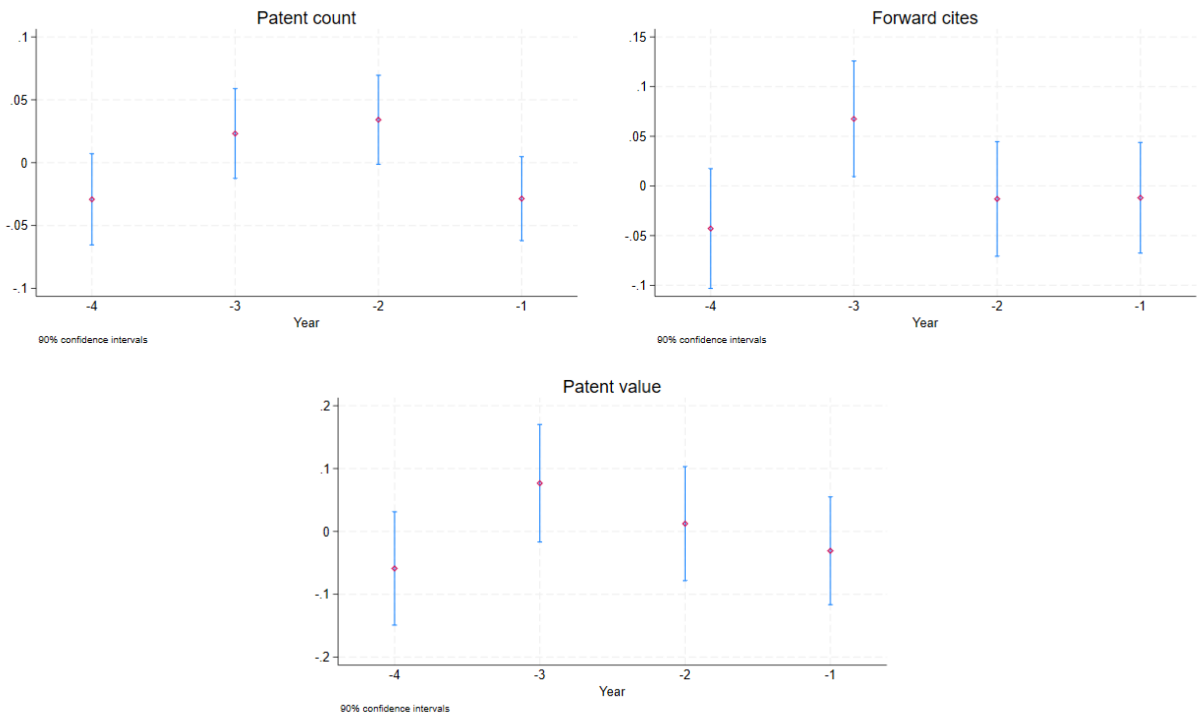


Figure 2: Yearly patenting outcomes

This figure plots yearly beta coefficients (and their 90% confidence intervals) corresponding to the baseline regressions in Table 4; the interaction term *Private* x *Post* is replaced by post-event year dummies, $Post_j$, which are set to 1 for private target acquisitions j years after the acquisition announcement year $t = 0$, and 0 otherwise. The x axis shows event time in years.

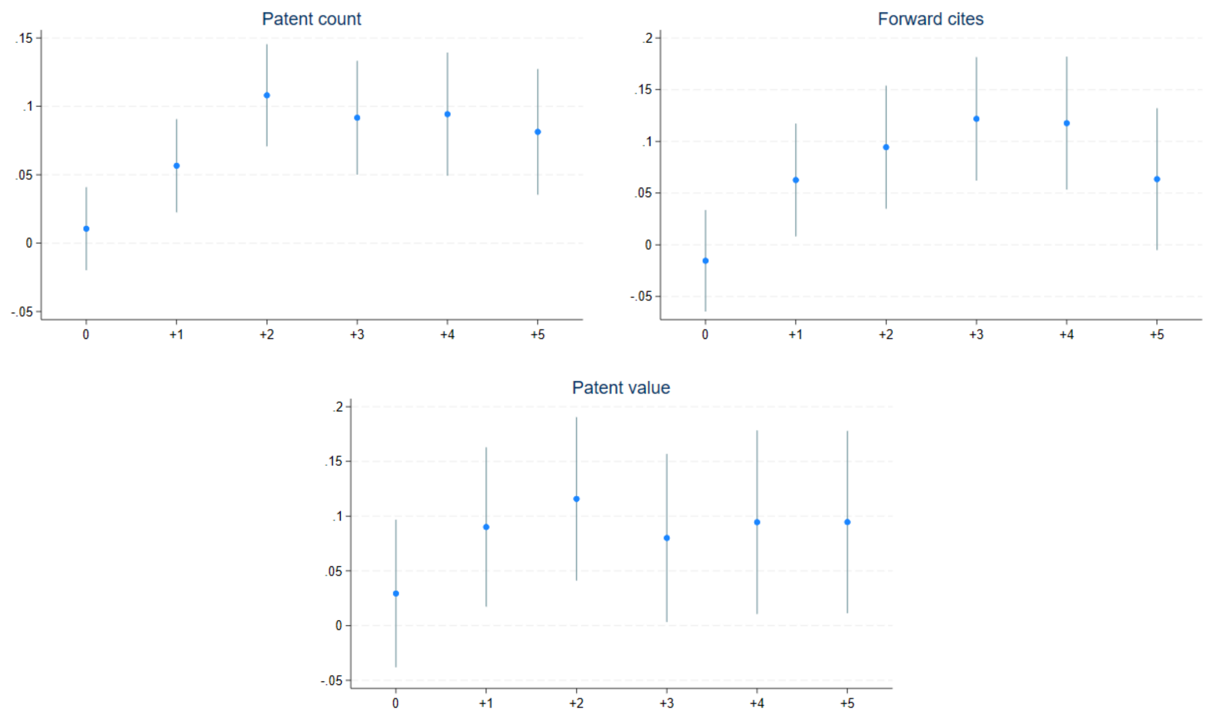
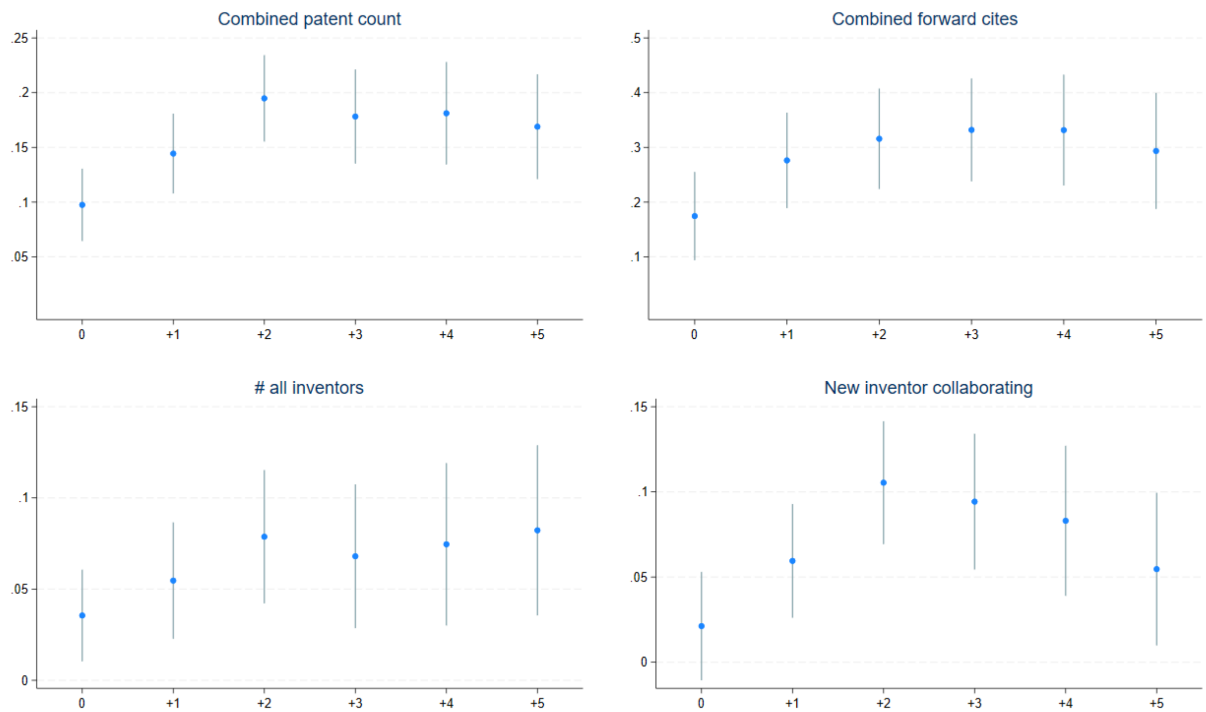


Figure 3: Yearly synergistic outcomes
This figure plots yearly beta coefficients (and their 90% confidence intervals) corresponding to the synergy regressions in Table 6; the interaction term *Private* x *Post* is replaced by post-event year dummies, $Post_j$, which are set to 1 for private target acquisitions j years after the acquisition announcement year $t = 0$, and 0 otherwise. The x axis shows event time in years.



Appendix A Examples of private and public target acquisitions

This section provides a short description for two acquisitions by HP Inc from our data set. The first one is of a private Persist Technologies Inc undertaken in 2003 and illustrates high growth prospects in the particular market of e-mail archiving. The second acquisition is of public target Pregrine Systems Inc completed in 2005. Pregrine experienced financial difficulties since 2002. HP saw the potential of becoming a market leader in the segment and of operational synergies through cross-selling to different groups of customers.

HP Inc acquired Persist Technologies Inc

Following is a quote from a HP's news announcement on 11 November 2003: "HP today signed a definitive agreement to acquire Persist Technologies, Inc., a leading provider of software designed for long-term storage and access of reference information. The acquisition is expected to improve HP's ability to deliver complete information lifecycle management (ILM) solutions. ILM is HP's strategy to actively manage information from its creation through deletion and according to its changing business relevance over time. With Persist's active archiving software, HP expects to deliver enhanced archiving solutions to assist customers in complying with emerging and stringent data retention regulations and extract business value from large amounts of reference information."

eWeek commented on 10 November 2003: "Persist spun-off from compliance and electronic discovery firm Zantaz Inc. in 2002. Its customers include the U.S. Army and E-Trade Group Inc., officials previously said. 'They are very clever. They are going after someone with the technology but that does not burden them with a lot of history, and with a low purchase price,' industry analyst Sara Radicati said, of The Radicati Group Inc., also based in Palo Alto. Regarding the e-mail archiving market: 'We think its a very high-growth area. Its a very big deal,' Radicati said."

HP Inc acquired Peregrine Systems Inc

A quote from a HP's new announcement on 19 December 2005: "HP today announced the completion of its acquisition of Peregrine Systems, Inc., a leading IT asset and service management software company. Effective immediately, Peregrine will become part of the HP OpenView business unit, which is led by Todd DeLaughter, vice president and general manager. The acquisition, initially announced in September 2005, will add key asset and service management components to the HP OpenView portfolio, a distributed management software suite for business operations and IT. With these components, HP can offer chief information officers more insight into and control over their technology environments in an efficient and cost-effective manner."

The IDC News Service commented on 19 September 2005: "Peregrine has had a troubled financial past. The company filed for Chapter 11 bankruptcy in September 2002 after accounting irregularities surfaced leading to an investigation by the U.S. SEC. The irregularities eventually totaled $250 million. In order to cut costs during 2002, Peregrine halved its staff, closed offices and sold off its Remedy service management business to BMC Software. Peregrine emerged from Chapter 11 in August 2003 and has been playing catch-up with restating its SEC financial filings ever since. ... DeLaughter noted that HP has been monitoring Peregrine's financial status closely for some time.

... There is some overlap between HP's and Peregrine's service management software offerings, according to DeLaughter. HP has a road map to put in place once the deal is approved to merge Peregrine's ServiceCenter with ServiceDesk products and any related software in development at Peregrine over the coming 12 months to 18 months, he said. Since HP has relied on 'an assortment of partners' in the asset management space to date, there's no product overlap with Peregrine's AssetManager, DeLaughter said. AssetManager will form the basis for HP's asset management strategy going forward, he added. ... DeLaughter sees only a 20 percent to 25 percent overlap between the companies' customers on the service management side and none on the asset management side. 'There's a tremendous opportunity to do cross-selling,' he said.

... By integrating Peregrine's products into its HP OpenView systems management suite, HP hopes to position itself as one of the market leaders in asset management software."

Appendix B Identifying patents of private targets

Following Kelly et al. (2021) and Kogan et al. (2017), we match patents to private targets by matching private target names from SDC to patent assignee names from KPST database. The KPST database provides information on patent numbers and corresponding assignee names from 1836 to 2015. We perform a probabilistic record linkage procedure (Wasi and Flaaen, 2015) based on an approximate string comparison function which allows the values with the most "similar" strings identified as matches. This procedure involves three steps: 1) pre-processing; 2) probabilistic linking; and 3) clerical review of machine matched pairs (Wasi and Flaaen, 2015).

The first step, pre-processing, ensures that both target and patent assignee names have the same format and that chosen fields are meaningful for matching. Standardizing common character strings usually achieves higher quality matching.

The second step involves linking records from the target data set to the patent assignee data set. We choose a standardized name to input into the probabilistic matching algorithm [Jana: isn't this part of the first step?. For each name record from the target data set, the algorithm selects candidates from the patent assignee data set. Then, for each pair of target name and patent assignee, the program uses a string comparison function to calculate a field-similarity score. This is accomplished for each input field individually, and then a (composite) pair-similarity score is constructed as the sum of all field-similarity scores, adjusted by specified weights (Wasi and Flaaen, 2015). The candidate with the highest pair-similarity score is chosen as a match.

Although the pair-similarity score is highly correlated with correct matches, it is an imperfect metric. A manual check of the machine-generated matched pairs is necessary, especially for pairs with low similarity scores. Perfect name matches will result in the highest pair-similarity score of 100%. The lower the score, the less likely that patent assignee name is a suitable match for the target name. To ensure that we obtain correct pair matches, we focus on pair-similarity scores of above 95%. It is very unlikely that below 95% score results in a suitable match. For the score above 95% and below 100%, we manually check target names to ensure that corresponding target firms have a record for filing a patent.

Appendix C Inventor data set

To track inventors' career paths and establish inventor-employer linkages over time, we rely on the PatentsView database which provides a unique identifier for each assignee (firm) and inventor. Each patent lists its corresponding assignees and inventors, which allows to link inventors to firms. We use the KPSS database to match inventors to CRSP firms. To identify an inventor's employer(s) throughout their patenting career, we follow Li and Wang (2023).

First, using PatentsView we identify inventor-year observations when an inventor *applies* for at least one patent in that year. For each inventor-year observation, we then compile assignees linked to the inventor's patents for that year. If all patents for one inventor-year observation have a single assignee, that assignee is clearly identified as the inventor's employer for that year. At the end of this step, we can categorize inventor-year observations into two groups: inventor-years with a single assignee and inventor-years with multiple assignees.

The second step assigns single assignees for the group of inventor-years with multiple assignees. We proceed with three options. First, we use information from the single assignee group. In particular, we take each inventor-year observation with multiple assignees and check whether the inventor is associated with the same assignee for the prior year in the set of single assignees. If we still cannot find a single assignee, we pick the assignee with the most inventor's patents during that year. For inventor-year observations where we are not able to decide based on patent frequency, we choose one of the assignees randomly. This process yields inventor-assignee-year (I-A-Y) observations for years in which an inventor applied for at least one patent.

In the third step, we expand the I-A-Y sample by filling in gaps when an inventor is not connected to an assignee because of lack of filed patents in those years. If we have two obervations I-A-Y_t and I-A-Y_u in the sample and there are no other observations of inventor I between years Y_t and Y_u, we assume that inventor I worked for assignee A during the period from Y_t to Y_u. If we have two observations I-A_i-Y_t and I-A_j-Y_u in the sample and there are no other observations for inventor I between years Y_t and Y_u, we assume that inventor I worked for assignee A_i during the period from Y_t to the midpoint year (Y_m), and for assignee A_j during the period from the midpoint year ($Y_m + 1$) to Y_u. This approach gains

I-A-Y data for each inventor's active career, encompassing the year of their first patent application to the year of their last patent application recorded in the PatentsView database.

The fourth step uses the patent-PERMCO linkage from the KPSS database to match I-A-Y observations with US public firms. We first merge patent-PERMCO pairs from KPSS with patent-assignee pairs from PatentsView based on patent numbers, retaining only patent-PERMCO pairs with a single assignee. Subsequently, we match the resulting assignee-PERMCO pairs with the inventor-assignee-year sample using patent numbers. We end up with a set of inventor-PERMCO-year observations.

The inventor-PERMCO-year sample derived from the above step can be categorized into two groups: those inventor-year pairs linked with a unique public firm and those inventor-year pairs linked with multiple public firms. In cases of inventor-PERMCO-year observations within unique public firm, the public firm is identified as the inventor's employer for that year. In instances within the set of multiple public firms, we utilize data on the commencement and cessation dates of firm names as provided by CRSP to exclude firms if the timeframe of the matched firm name does not include the specific year of interest. For inventor-year pairs still associated with multiple firm names, we conduct a manual inspection and select the most plausible match.

Appendix D Variable definitions

The table uses the following abbreviations: KPSS for Kogan, Papanikolaou, Seru, and Stoffman patent data library (https://iu.app.box.com/v/patents). KPST for Kelly, Papanikolaou, Seru, and Taddy patent data library (https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Replication-Kit/tree/master/input_data). NBER for National Bureau of Economic Research patent data (https://www.nber.org/patents/). DLM for Demerjian, Lev, and McVay managerial ability data (https://peterdemerjian.weebly.com/managerialability.html).

Variable	Definition	Source
Patenting variables		
Patent count	The number of new patents that the focal firm files in year t scaled by the total number of new patents filed by all firms in the same year. Regressions use a logarithmic transformation following Chen and Roth (2023) described in Section 4.1. In particular, we normalize the minimum nonzero value to 1 by dividing all observations by the minimum nonzero value and then take their log. All zero observations are set to $-x$ with x alternating between 1 and 0.	KPSS
Forward cites	The number of future citations that each patent receives scaled by the total citation count of all patents in the same technological class and year, summed across all patents filed by the focal firm in year t. Regressions use a logarithmic transformation following Chen and Roth (2023) described in Section 4.1. In particular, we normalize the minimum nonzero value to 1 by dividing all observations by the minimum nonzero value and then take their log. All zero observations are set to $-x$ with x alternating between 1 and 0.	KPSS
Patent value	The cumulative dollar value of all patents filed by the focal firm in year t scaled by the firm's market capitalization. Based on stock market reactions to patent grants (Kogan et al., 2017). Regressions use a logarithmic transformation following Chen and Roth (2023) described in Section 4.1. In particular, we normalize the minimum nonzero value to 1 by dividing all observations by the minimum nonzero value and then take their log. All zero observations are set to $-x$ with x alternating between 1 and 0.	KPSS
Inventor variables		
# all inventors	The number of inventors that a firm has in year t. Regressions use a logarithmic transformation following Chen and Roth (2023) described in Section 4.1. In particular, we normalize the minimum nonzero value to 1 by dividing all observations by the minimum nonzero value and then take their log. All zero observations are set to $-x$ with x alternating between 1 and 0.	PatentsView, KPSS

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Variable	Definition	Source
New inventors collaborating	The number of inventors who file their first patent and appear on focus firm's patents together with incumbent acquirer's inventors as filed in year t. Regressions use a logarithmic transformation following Chen and Roth (2023) described in Section 4.1. In particular, we normalize the minimum nonzero value to 1 by dividing all observations by the minimum nonzero value and then take their log. All zero observations are set to $-x$ with x alternating between 1 and 0.	PatentsView, KPSS
Deal variables		
Private (public)	A dummy variable set to 1 for acquirers of private (public) targets for all event years from -5 to $+5$ and to 0 otherwise.	SDC
Post	A dummy variable set to 1 for all observations with event years between 0 and +5 and to 0 otherwise.	SDC
TargetWP (TargetWoP)	A dummy variable set to 1 for all acquisitions of targets with (without) existing patents.	SDC, KPST
Breakthrough (traditional) sector	A dummy variable set to 1 for sector-year observations above (below) the sample median value for the fraction of breakthrough patents and 0 otherwise.	KPST
High (low) managerial ability; MA	A dummy variable set to 1 for acquirers in the top quartile of managerial ability, which measures the efficiency with which managers convert resource inputs into outputs relative to their industry peers (Demerjian et al., 2012).	Compustat, DLM
With (without) CVC	A dummy variable for acquirers that own (do not own) a corporate venture capital division.	Compustat, Prequin
Acquisition experience; AE	A dummy variable set to 1 if the acquirer has previous experience acquiring private targets at the time of the acquisition announcement and 0 otherwise.	SDC
Control variables		
Size	The acquirer's total sales. In regressions used as a natural logarithm.	Compustat
R&D expenditure	The acquirer's R&D expenditure. In regressions used as a natural logarithm.	Compustat
Capital expenditure	The acquirer's property, plant, and equipment scaled by total assets.	Compustat
Leverage	The acquirer's long-term debt scaled by total assets.	Compustat
Net income	The acquirer's net income scaled by total assets.	Compustat
Industry concentration	The Herndahl-Hirschman index computed as a sum of the squared market shares based on net sales within the acquirer's 3-digit SIC industry.	Compustat
Extra variables in the abnormal return regressions		
Private target	A dummy variable set to 1 when the target is a private firm and 0 for public targets.	SDC
CAR(-2,2)	The 5-day cumulative return around the deal announcement date for the acquirer adjusted by the value-weighted market index return.	SDC, CRSP
ΔInnovation	The natural logarithm of the ratio of the average patent count (or forward cites or patent value) over the post-deal period to the average patent count over the pre-deal period, in regressions split into quartiles.	KPSS, NBER
Cash only	A dummy variable set to 1 for cash only deals and 0 otherwise.	SDC
Horizontal deal	A dummy variable set to 1 for acquirer and target coming from the same FF 30 industry and 0 otherwise.	SDC
Hostile deal	A dummy variable indicating that the deal attitude is classified as hostile.	SDC

Appendix E Small-scale analysis of private target acquisitions

We perform a small-scale in-depth analysis of a random sample of 21 acquisitions of private targets that do not own any existing granted patents. Because of the lack of patents in the target before the acquisition, we cannot compare innovators between targets and their acquirers. However, we are able to assess the innovative nature of the target, the main reasons for the acquisition, and patenting of the target's founders or top managers after the acquisition.

We make the following three observations from the anecdotal evidence. First, we confirm that 18 out of the 21 private targets are acquired because of their innovative activities. The 3 remaining targets have an interesting product or an interesting customer base. As an example of target's innovative activity, in 2011 Walmart (variety stores industry) acquired OneRiot (direct mail advertising services), a mobile and social ad targeting startup. OneRiot first ventured into the advertising world in 2009 with RiotWise, an ad format which places content in an emphasized position in their real time feed. OneRiot also launched RiotWise Trending Ads. This data mining attracted Walmart to OneRiot and its technology. The Walmart's acquisition announcement stated: "OneRiot has developed some pretty nifty technology that analyzes social media signals from popular networks like Twitter and Facebook to deliver ads that are relevant to consumers' interests. As our teams debated the finer points of Big Data, Fast Data, and machine learning technologies, it became clear to us that we could find no better colleagues than the guys at OneRiot."

Our second observation is that the target's employees often join the acquirer company, as is clearly communicated in the OneRiot case above. Also, the acquirers often state that they are interested in collaborating with the target firm team on new ideas. Here comes the example of acquisition of InnerLogix Inc. by Schlumberger, Ltd. in 2007, both operating in data quality management for the exploration and production industry. Dag Heggelund, president of InnerLogix, said: "Our relationship with Schlumberger will accelerate and expand our technology development for the delivery of best quality data across all business processes for the global exploration and production market."

The third observation is that the target founder or CEO in some instances features as an innovator on patents filed by the acquirer after the acquisition. For example, Dag Heggelund, president of InnerLogix, files a patent with Slumberger as the assignee after the acquisition. Therefore, all of the above anecdotal evidence are in line with the notion that acquired private targets may not need existing patents and still increase patenting post acquisition.

Internet appendix (not for publication) to

"M&As and innovation: Evidence from acquiring private firms"

This appendix presents supplementary results not included in the main text.

List of Internet Appendix Tables

Table I.1. Matching statistics for 1:5 matched sample
This table reports post-matching means for acquirers of public target and their corresponding matched acquirers of private targets when matching up to 5 private target deals for each public deals. The corresponding pre-matching means are reported in Table 1. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. Patenting variables are in their log transformation. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 0$ and $x = 1$. ***, ** and * indicate significance at the one-, five- and ten-percent levels, respectively.

	(1)	(2)	(3)
	After matching		
	Private	Public	Mean difference
# of observations	10,452	2,143	
Total assets	21.66	21.92	-0.25***
Book to market ratio	0.386	0.411	-0.025
Propensity score	0.195	0.208	-0.014***
Size (log of sales)	21.263	21.433	-0.170***
R&D expenditure	12.933	13.260	-0.326
Leverage	0.151	0.150	0.001
Net income	0.037	0.018	0.018 ***
Industry concentration	0.211	0.198	0.013 ***
x=1			
Patent count	2.118	2.207	-0.089
Forward cites	5.372	5.505	-0.133
Patent value	4.153	4.229	-0.076
# all inventors	4.20	4.28	-0.08
New inv. collaborating	1.83	1.88	-0.04
x=0			
Patent count	2.363	2.441	-0.078
Forward cites	5.699	5.827	-0.128
Patent value	4.407	4.482	-0.075
# all inventors	4.20	4.28	-0.08
New inv. collaborating	2.15	2.19	-0.04

Table I.2. Robustness tests

This table shows estimation results for Regression (1) with patent count, forward cites, and patent value as dependent variables, which are in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–3 and 4–6, respectively, The data set covers years -5 to $+5$ around the acquisition announcement year ($t = 0$). Panel A includes private and public target acquirers 1:5 matched based on year, industry, size, and book to market ratio. Panel B splits the main DiD effect by the median transaction value. Panel C adds fixed effects for Cooperative Patent Classification (CPC) on the first (letter) level. Panel D includes additional interaction terms of Post with all control variables (size, R&D expenditure, leverage, net income and industry concentration). Panel E includes regressions with a shorter event window, i.e., years -3 to $+3$ around the acquisition announcement year 0. All specifications include calendar year and matched pair fixed effects, and the following control variables: acquirer size, R&D expenditure, leverage, net income, and industry concentration. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1^{st} and 99^{th} percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	$x = 1$			$x = 0$		
	Patent count	Forward cites	Patent value	Patent count	Forward cites	Patent value
Panel A: Public target acquisition matched up to 5 private target acquisitions						
Private x post (β)	0.060***	0.036	0.107***	0.047**	0.032	0.095***
	(0.023)	(0.030)	(0.041)	(0.020)	(0.026)	(0.036)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.75	0.67	0.56	0.77	0.68	0.58
# of observations	127,523	127,523	127,523	127,552	127,552	127,552
Panel B: Target size						
Private x post x small (γ^s)	0.024	-0.020	0.003	0.018	-0.021	0.001
	(0.065)	(0.079)	(0.109)	(0.054)	(0.069)	(0.094)
Private x post x large (γ^l)	0.359***	0.292***	0.308**	0.334***	0.261***	0.282***
	(0.089)	(0.109)	(0.122)	(0.079)	(0.098)	(0.107)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.85	0.80	0.66	0.87	0.81	0.68
# of observations	28,421	28,421	28,421	28,421	28,421	28,421
Panel C: Additional CPC fixed effects						
Private x post (β)	0.061***	0.047**	0.065*	0.054***	0.044**	0.059**
	(0.018)	(0.023)	(0.034)	(0.015)	(0.020)	(0.029)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
CPC fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	43,660	43,660	43,660	43,660	43,660	43,660
# of observations	0.892	0.856	0.733	0.902	0.862	0.749
Panel D: Interaction terms with the post dummy						
Private x post (β)	0.081***	0.074**	0.087**	0.071***	0.068**	0.078**
	(0.023)	(0.030)	(0.040)	(0.019)	(0.027)	(0.035)
Private	0.029	0.032	0.019	0.026	0.024	0.016
	(0.032)	(0.044)	(0.047)	(0.028)	(0.039)	(0.042)
Post	-0.692***	-0.966***	-0.508	-0.443**	-0.663**	-0.322
	(0.255)	(0.312)	(0.389)	(0.213)	(0.269)	(0.333)
Size	0.148***	0.164***	0.124***	0.140***	0.154***	0.109***
	(0.024)	(0.030)	(0.034)	(0.021)	(0.026)	(0.030)
Size x post	0.038***	0.048***	0.030	0.025***	0.034***	0.020
	(0.012)	(0.014)	(0.018)	(0.010)	(0.012)	(0.016)

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	(1)	(2)	(3)	(4)	(5)	(6)
	$x = 1$			$x = 0$		
	Patent count	Forward cites	Patent value	Patent count	Forward cites	Patent value
R&D expenditure	0.102***	0.123***	0.139***	0.086***	0.106***	0.123***
	(0.008)	(0.010)	(0.010)	(0.007)	(0.009)	(0.009)
R&D expend. x post	-0.008***	-0.013***	-0.027***	-0.005**	-0.010***	-0.024***
	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)
Leverage	-0.518***	-0.568***	-0.825***	-0.425***	-0.470***	-0.724***
	(0.138)	(0.175)	(0.223)	(0.118)	(0.154)	(0.194)
Leverage x post	-0.256*	-0.218	0.390	-0.299***	-0.260*	0.349*
	(0.135)	(0.163)	(0.242)	(0.111)	(0.140)	(0.209)
Net income	-0.227***	-0.183***	-0.231**	-0.199***	-0.171***	-0.214**
	(0.077)	(0.070)	(0.116)	(0.064)	(0.059)	(0.103)
Net income x post	0.342***	0.323***	0.404***	0.282***	0.279***	0.357***
	(0.092)	(0.094)	(0.153)	(0.076)	(0.081)	(0.133)
Ind. concentration	0.447*	0.742**	0.092	0.426**	0.737**	0.084
	(0.243)	(0.341)	(0.333)	(0.212)	(0.306)	(0.292)
Ind. conc. x post	-0.421***	-0.134	-0.148	-0.374***	-0.101	-0.117
	(0.110)	(0.163)	(0.165)	(0.096)	(0.146)	(0.146)
Constant	-2.064***	-2.341***	-0.033	-1.440***	-1.635***	0.726
	(0.530)	(0.642)	(0.738)	(0.458)	(0.565)	(0.647)
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.838	0.776	0.657	0.857	0.787	0.676
# of observations	43,660	43,660	43,660	43,660	43,660	43,660
			Panel E: Shorter event window			
Private x post (β)	0.070***	0.063**	0.085**	0.062***	0.060**	0.078**
	(0.020)	(0.029)	(0.040)	(0.017)	(0.026)	(0.034)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	28,757	28,757	28,757	28,757	28,757	28,757
# of observations	0.850	0.785	0.672	0.869	0.795	0.691

Table I.3. Reasons for withdrawing acquisitions
This table lists withdrawal reasons from news articles for 30 randomly picked deals.

Ann. date	Target name	Acquirer name	Reason for withdrawing
07/02/2000	Amazescape.com Inc	Premier Concepts Inc	Target firm committed a material and substantial breach of the Merger Agreement. Target's progress to date on its business plan has been modest at best and are led to conclude that target is not currently even prosecuting its business plan in a meaningful way. Certain ongoing problems, such as AmazeScape's failure to satisfy its obligations to major suppliers.
06/06/2000	Impac Medical Systems Inc	Varian Medical Systems Inc	Department's Antitrust Division announced its intent to block the transaction, saying it would reduce competition significantly in the sale of radiation oncology management systems software and medical devices known as linear accelerators sold in the United States.
08/02/2001	Adexa Inc	Freemarkets Inc	Both companies attributed the failed merger to the slowing economy, sour market conditions and delays in winning regulatory approval from the Securities and Exchange Commission. Instead, FreeMarkets and Adexa have both agreed to enter a nonexclusive partnership that calls for selling each other's software and services to joint clients.
28/03/2001	MAYAN Networks Corp	Ariel Corp	MAYAN Networks notice to Ariel cited the failure of the Merger to close on or before August 31, 2001 as the primary reason for the unilateral termination of the merger agreement. Nasdaq cited their opinion that the combination of Ariel and MAYAN Networks would not meet the initial listing standards for the Nasdaq National Market, and that Ariel failed to meet the continued listing standards for the Nasdaq National Market.
22/08/2001	Eos Biotechnology	Pharmacopeia Inc	The merger has faced public opposition from at least one of Pharmacopeia's stockholders, OrbiMed Advisors LLC, which owns about 10 percent of Pharmacopeia's stock.
24/10/2001	Graphco Technologies Inc	PerfectData Corp	N/A
30/04/2002	Cogentrix Energy Inc	Aquila Inc	Both companies agreed that the current uncertainty of the electric power market made proceeding with the transaction impractical and not in either company's best interest.
14/11/2001	Pegasus Pharmacy Inc	Restaurant Teams International Inc	As a result of various irreconcilable circumstances between the Company and management of the two subsidiaries, the Company signed a Settlement and Separation Agreement (the "Separation Agreement") in which ownership of MedEx and Pegasus was returned to the original owners and the Company received a perpetual, paid-up license to utilize, improve, resell, and distribute the technology within a protected territory in the United States consisting of 158 CMSA's in the United States and all international rights.
14/11/2001	MedEx Systems Inc	Restaurant Teams International Inc	As a result of various irreconcilable circumstances between the Company and management of the two subsidiaries, the Company signed a Settlement and Separation Agreement (the "Separation Agreement") in which ownership of MedEx and Pegasus was returned to the original owners and the Company received a perpetual, paid-up license to utilize, improve, resell, and distribute the technology within a protected territory in the United States consisting of 158 CMSA's in the United States and all international rights.
08/02/2002	Aspect SemiQuip International	Patriot Scientific Corp	An acquisition would not meet the business objectives of either company. With present market conditions and the present strategic direction of PTSC, it was decided the acquisition would not have been productive.
19/02/2002	Incubation Park Business Development Inc	TeleServices Internet Group Inc	The company announced that it had signed a letter of intent to acquire Incubation Park Business Development Inc. ("Incubation Park"), subject to certain terms and conditions (the "Letter of Intent"). The Company has had no success to date in raising the capital needed to fulfill the various terms of the Letter of Intent. On April 3, 2002, Incubation Park notified the Company that they had received an offer of financing from another party. Since the Company has not been able to raise the necessary capital to fulfill the terms of the Letter of Intent, nor is there any prospect it will be able to do so, by mutual agreement between the Company and Incubation Park the Letter of Intent has been cancelled.
27/02/2002	Southwick Management Inc	VPN Communications Corp	All parties decided it was in the best interest of the shareholders of both entities for the companies to pursue separate paths
15/03/2002	BaySpec Inc	Finisar Corp	Current market conditions and the outlook for capex spending within the telecommunications industry, make it difficult to complete the BaySpec acquisition as planned," said Jerry Rawls, Finisar's President and CEO.

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Ann. date	Target name	Acquirer name	Reason for withdrawal
18/03/2002	Screenphone.net Inc	Telco-Technology Inc	During the quarter ended March 31, 2002, the Company obtained loans from certain private parties in the aggregate amount of $85,000. The loans bear interest at 6.75% and mature in 6 months. During the same quarter, the Company loaned $35,000 to ScreenPhone in connection with the transaction contemplated by the Letter of Intent as a result of the decision to not proceed with the proposed business combination.
21/03/2002	Reliant Pharmaceuticals Inc	Alkermes Inc	The companies agreed to terminate the merger agreement due to general market conditions.
16/05/2002	Franklin Bank of California	Wal-Mart Stores Inc	A coalition of consumer groups, unions, independent banks, credit unions, and realtors managed a legislative feat in California last month when they pushed through an 11th hour bill to block Wal-Mart's attempt to acquire a small bank. Wal-Mart filed an application with state regulators in April to buy Franklin Bank of California, an industrial bank with $2.5 million in assets and three employees in Orange County. The new law prohibits non-financial firms from buying state-chartered banks.
11/07/2002	IDS Software Systems Inc	HPL Technologies Inc	HPL Technologies, Inc. today reported that the audit committee of the Company has initiated an investigation into financial and accounting irregularities involving revenue reported during prior periods. HPL also announced that, in light of the recent developments, it is unlikely that the Company will be able to complete the pending acquisition of IDS Software Systems.
29/08/2002	Bob Baker Auto Group	Asbury Automotive Group Inc	Asbury Automotive Group, one of the largest automotive retailers and service companies in the U.S., today announced that it expects to restructure its previously announced acquisition of the Bob Baker Auto Group. Following Asbury's recently announced agreement to acquire the Bob Baker Auto Group, Asbury requested franchise purchase approval from each relevant manufacturer. Ford Motor Company recently informed Asbury that it does not intend to approve Asbury's pending acquisition of the Bob Baker Ford franchise, contending that Asbury has not complied with its contractual agreement with Ford Motor Company.
12/11/2002	DxCG Inc	I-trax Inc	DxCG terminated the merger agreement because the Company failed to satisfy certain conditions to closing, including third party financing for the cash portion of the purchase price.
07/05/2003	Donobi Inc	Reality Wireless Networks Inc	Reality Wireless Networks, Inc., has failed, inter alia, to satisfy the conditions precedent to the obligations set forth in the proposed definitive agreement and has not cured these breaches. Therefore, Donobi, Inc., has decided to terminate the agreement for Reality Networks, Inc.'s, failure to satisfy the conditions.
26/06/2003	Kiboga Systems Inc	DataLogic International Inc	The Company had attempted to expand via merger and acquisition but was not able to achieve the desired results. The Company had incurred sizable expenses, as paid in capital, for the M&A effort without adding any significant net gain to the bottom line in fiscal 2003. The majority of the expenses were in consulting and legal fees for market research, due diligence and legal representation.
06/02/2004	SunWest Communications Inc	USURF America Inc	Reogranization between USURF and SunWest.
16/03/2004	Argent LLC	MaxxZone.com Inc	As a result of due diligence concerns, MaxxZone has terminated its Letter of Intent to acquire Argent, LLC, enabling MaxxZone to enter into this Letter of Intent with the Target. Established more than 20 years ago, the Target is an international forwarding and logistic company based in Hong Kong and specializing in Sea and Air Freight.
19/04/2004	Apex Sight LLC	VoIP Inc	After extensive time delays and due diligence, Apex Sight LLC is withdrawing from the proposed merger. Henry Cooper, CEO, Apex Sight LLC stated, "After spending considerable time and expense, it was determined that the long term value for the shareholders of Apex Sight LLC would not recognize the potential returns on their investment by completing the merger.
18/05/2004	BioHorizons Implant Systems Inc	Encore Medical Corp	The two parties agreed to end the merger when the deadline passed late last week. Davis Henley, vice president of business development for Encore Medical says the deal was quashed, in part, because the Securities and Exchange Commission did not complete its evaluation of the deal by the beginning of September. Additionally, between the time Encore Medical entered into the agreement with BioHorizons, the Austin company acquired St. Paul, Minn.-based medical device company Empi Inc for $360 million, an acquisition that Henley calls an order of magnitude bigger than the BioHorizons deal. Both we and BioHorizons had some concerns about how that acquisition would impact our transaction with BioHorizons," Henley says. "The BioHorizons acquisition became less significant and less important for us."

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Ann. date	Target name	Acquirer name	Reason for withdrawal
10/01/2005	Aptus Corp	InsynQ Inc	In April 2005, this deal was rescinded by mutual agreement, and the 40 million shares of common stock were returned to us and we returned the 1,500 "MyBooks" licenses to Aptus Corp. This was done in anticipation of an asset purchase agreement to be executed on April 30, 2005, in which we purchased all the intellectual property rights and applications codes from Aptus Corp, which included the source code of MyBooks.
19/01/2005	Brazos Resources Inc	Opus Communities Inc	Further due diligence on the acquisition showed the cost for the property was higher than expected.
31/01/2005	Omni Oil	Gas Inc	Empiric Energy Inc & Empiric Energy Inc., Dallas, (Pink Sheets: EPRC) has terminated its letter of intent with Dallas-based independent Omni Oil & Gas Inc. Though an acquisition may still occur in the future, the companies have agreed it would not be beneficial for either company at this time.
18/05/2005	South Seas Data Inc	Nayna Networks Inc	Acquisitions may disrupt or otherwise have a negative impact on our business. We plan to use this as a strategy to grow our business. If we buy a company, then we could have difficulty in integrating that company's personnel and operations. In addition, the key personnel of the acquired company may decide not to work for us. An acquisition could also distract our key management and employees and increase our operating and other expenses. Furthermore, we may have to incur debt or issue equity securities to pay for any such future acquisitions, the issuance of which could be dilutive to our existing stockholders. Our common stock price is highly volatile and the current market for our common stock is limited.
06/07/2005	Hands On	GoAmerica Inc	The mergers will occur only if stated conditions are met, including the approval of the merger agreement and the mergers by the stockholders of VRS and SLS and the approval of the issuance of the GoAmerica shares to be issued in the mergers by the GoAmerica stockholders, and the absence of any material adverse effect in the businesses of GoAmerica or Hands On. Many of these conditions are outside the control of Hands On and GoAmerica. In addition, both parties also have the right to terminate the merger agreement in certain circumstances. Accordingly, there may be uncertainty regarding the completion of the mergers. This uncertainty may cause customers and suppliers to delay or defer decisions concerning Hands On or GoAmerica, which could negatively affect their respective businesses. Customers and suppliers who dealt with either GoAmerica or Hands On in the past may choose not to continue to do business with the combined company. Any delay or deferral of those decisions or changes in existing relationships could have a material adverse effect on the respective businesses of Hands On and GoAmerica, regardless of whether the mergers are ultimately completed.

Table I.4. Matching with the withdrawn deals
Panel A shows coefficient estimates and standard errors (in parentheses) for logit models predicting the probability of withdrawn private (public) target acquisition with FF 30 industry fixed effects and data over 1995-2015. *Private withdrawn* (*Public withdrawn*) equals 1 for firms withdrawing from acquiring a private (public) target in the given year and 0 for firms with successful private (public) target acquisitions. All explanatory variables are lagged. In Panel B, Columns 1 to 3 (Columns 4 to 6) show means for acquirers of successful versus withdrawn private target deals before (after) matching. Panel C shows the same statistics for acquirers of public targets. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. Patenting variables are in their log transformation. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 0$ and $x = 1$. ***, ** and * indicate significance at the one-, five- and ten-percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Probit regressions			
Dependent variable	Constant	Total assets	BM	FF30 FE	χ^2	# obs.
Private withdrawn	3.932***	-0.433***	0.050	yes	133.9	11,322
	(0.951)	(0.042)	(0.031)			
Public withdrawn	4.049***	-0.274***	-0.033	yes	107.48	2,412
	(0.747)	(0.033)	(0.038)			
			Panel B: Private withdrawn matching statistics			
	Before matching			After matching		
	Withdrawn private	Successful private	Mean diff.	Withdrawn private	Successful private	Mean diff.
# of observations	101	11,221		94	94	
Total assets	18.20	20.75	-2.55***	18.17	18.34	-0.17
Book to market ratio	0.474	0.391	0.083	0.480	0.524	-0.043
Propensity score	0.033	0.009	0.024***	0.024	0.026	-0.003
Size (log of sales)	17.61	20.41	-2.79***	17.55	17.83	-0.28
R&D expenditure	9.49	12.13	-2.65	9.89	10.31	-0.41
Leverage	0.145	0.146	-0.001	0.143	0.102	0.040
Net income	-0.585	-0.009	-0.577***	-0.621	-0.204	-0.417
Industry concentration	0.242	0.236	0.006	0.238	0.266	-0.029
x=1						
Patent count	-0.112	1.471	-1.583***	-0.045	0.087	-0.133
Forward cites	1.206	3.989	-2.782***	1.198	1.518	-0.320
Patent value	1.323	3.788	-2.464***	0.596	0.862	-0.266
# all inventors	1.855	3.554	-1.700***	1.855	1.845	0.010
New inv. collaborating	-0.309	1.229	-1.539***	-0.309	0.139	-0.449
x=0						
Patent count	0.532	1.796	-1.264***	0.572	0.672	-0.101
Forward cites	1.919	4.430	-2.511***	1.889	2.157	-0.267
Patent value	1.973	4.120	-2.146***	1.220	1.447	-0.227
# all inventors	1.855	3.554	-1.700***	1.855	1.845	0.010
New inv. collaborating	0.362	1.644	-1.281***	0.362	0.518	-0.156

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Panel C: Public withdrawn matching statistics

	Before matching			After matching		
	Withdrawn public	Successful public	Mean diff.	Withdrawn public	Successful public	Mean diff.
# of observations	247	2,165		237	237	
Total assets	20.77	21.93	-1.16***	21.13	20.71	0.41
Book to market ratio	0.420	0.407	0.013	0.354	0.417	-0.062
Propensity score	0.148	0.097	0.051***	0.129	0.116	0.013 **
Size (log of sales)	20.25	21.45	-1.20***	20.18	20.72	-0.54**
R&D expenditure	10.38	13.19	-2.81***	10.60	11.53	-0.93
Leverage	0.167	0.150	0.017	0.165	0.178	-0.013
Net income	-0.045	0.019	-0.064***	-0.047	0.005	-0.052
Industry concentration	0.224	0.199	0.025**	0.229	0.184	0.044***
x=1						
Patent count	0.860	2.196	-1.337***	0.876	1.444	-0.569***
Forward cites	2.576	5.423	-2.847***	2.602	4.175	-1.574***
Patent value	1.559	3.158	-1.600***	1.286	1.981	-0.695***
# all inventors	3.051	4.272	-1.221***	3.056	3.516	-0.459**
New inv. collaborating	0.700	1.871	-1.172***	0.686	1.113	-0.427*
x=0						
Patent count	1.329	2.432	-1.103***	1.336	1.782	-0.446***
Forward cites	3.155	5.746	-2.591***	3.175	4.585	-1.409***
Patent value	2.042	3.413	-1.370***	1.760	2.327	-0.567***
# all inventors	3.051	4.272	-1.221***	3.056	3.516	-0.459**
New inv. collaborating	1.214	2.186	-0.972***	1.194	1.504	-0.309 *

Table I.5. Patenting effects when comparing to non-acquirers
This table shows estimation results for Regression (1) with patent count, forward cites, and patent value as dependent variables, which are in logarithmic transformations. For each variable, we divide all observations by the minimum nonzero value and then take their logarithm. Zero initial values are set to $-x$. We opt for $x = 1$ and $x = 0$ in Columns 1–3 and 4–6, respectively. The sample covers completed acquisitions of private (public) targets and their matched non-acquiring counterparts in Panel A (Panel B). Both panels cover years −5 to +5 around the acquisition announcement year ($t = 0$). *Private* (*Public*) is a dummy variable indicating an acquisition of a private (pubic) target and is set to 0 for matched firms without acquisitions. *Post* is a dummy variable set to 1 for all event years between 0 and +5 and 0 otherwise. All regressions include calendar year and matched pair fixed effects and the following control variables: acquirer size, R&D expenditure, leverage, net income and industry concentration. Standard errors are clustered at matched pair level and reported in parentheses. All variables are defined in Appendix D and winsorized at the 1st and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	$x = 1$			$x = 0$		
	Patent count	Forward cites	Patent value	Patent count	Forward cites	Patent value
	Panel A: Private target acquisitions					
Private x post (β^{pr})	0.080***	0.080***	0.137***	0.062***	0.062***	0.119***
	(0.017)	(0.021)	(0.046)	(0.014)	(0.018)	(0.042)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.64	0.57	0.43	0.66	0.56	0.43
# of observations	208,561	208,561	208,561	208,564	208,564	208,564
	Panel B: Public target acquisitions					
Public x post (β^{pu})	0.016	0.082	0.129	-0.008	0.059	0.111
	(0.047)	(0.057)	(0.138)	(0.040)	(0.050)	(0.128)
Controls	yes	yes	yes	yes	yes	yes
Pair fixed effects	yes	yes	yes	yes	yes	yes
Calendar time fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.70	0.64	0.49	0.71	0.64	0.50
# of observations	34,172	34,172	34,172	34,172	34,172	34,172

Table I.6. Summary statistics for the abnormal return regressions
This table reports mean, standard deviation, 25th percentile, median, and 75th percentile for a cross-section of acquirers with private versus public targets used for the abnormal return regressions in Table 10. Acquisitions of public targets are 1:1 matched to private target acquisitions based on year, industry, size, and book to market ratio. The firm and deal characteristics are lagged by one year relatively to the M&A announcement. All variables are defined in Appendix D and winsorized at the 1th and 99th percentiles.

	(1)	(2)	(3)	(4)	(5)	(6)
	# obs.	Mean	St. deviation	25^{th} perc.	Median	75^{th} perc.
CAR(-2,2)	4,082	-0.007	0.086	-0.034	-0.004	0.027
Private target	4,082	0.502	0.500	0.000	1.000	1.000
ΔPatent count	4,082	-0.069	0.760	-0.349	-0.033	0.186
ΔForward cites	4,082	-0.140	0.764	-0.400	-0.013	0.131
ΔPatent value	4,082	-0.059	0.196	-0.098	-0.007	0.009
Cash only	4,082	0.300	0.458	0.000	0.000	1.000
Hostile deal	4,082	0.005	0.072	0.000	0.000	0.000
Horizontal deal	4,082	0.590	0.492	0.000	1.000	1.000
R&D expenditure	4,082	13.238	8.368	0.000	17.410	19.555
Size	4,082	21.444	2.340	20.084	21.675	23.302
Leverage	4,082	0.148	0.152	0.020	0.123	0.216
Net income	4,082	0.028	0.172	0.019	0.051	0.090
Industry concentration	4,082	0.202	0.176	0.082	0.151	0.254

Table I.7. Announcement abnormal returns for 1:5 matched sample

This table reports OLS estimates with the acquirer 5-day cumulative abnormal return around the deal announcement date for private and public target acquisitions as the dependent variable. The regressions include acquisitions of private versus public targets which are 1:5 matched based on year, industry, size, and book to market ratio. *Private target* is a dummy variable set to 1 when the target is a private firm and 0 for public targets. Δ*Innovation* measures the increase from the pre- to post-acquisition period for the patent count (Column 2), forward cites (Column 3), and patent value (Columns 4). We form quartiles by Δ*Innovation* and the lowest quartile, Q_1, is the reference category. All regressions include year and Fama-French 30 industry fixed effects. Standard errors clustered at the firm level are reported in parentheses. All variables are defined in Appendix D and winsorized at the 1th and 99th percentiles. ***, ** and * indicate significance at the one-, five- and ten-percent levels.

	(1)	(2)	(3)	(4)
	Baseline	Patent count	Forward cites	Patent value
Private target	0.012***	0.002	-0.000	0.006
	(0.002)	(0.004)	(0.004)	(0.004)
ΔInnovation Q_2		-0.006	-0.018***	-0.002
		(0.006)	(0.006)	(0.006)
ΔInnovation Q_3		-0.009	-0.016***	-0.013**
		(0.006)	(0.006)	(0.006)
ΔInnovation Q_4		-0.006	-0.014**	-0.014**
		(0.006)	(0.006)	(0.006)
Private target x ΔInnovation Q_2		0.015**	0.018***	0.003
		(0.006)	(0.006)	(0.006)
Private target x ΔInnovation Q_3		0.011*	0.015**	0.008
		(0.006)	(0.006)	(0.006)
Private target x ΔInnovation Q_4		0.017***	0.018***	0.016***
		(0.006)	(0.006)	(0.006)
Cash only	0.005**	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Hostile deal	-0.006	-0.007	-0.008	-0.004
	(0.020)	(0.020)	(0.020)	(0.020)
Horizontal deal	-0.003*	-0.003*	-0.003*	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
R&D expenditure	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.012**	0.013**	0.012**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
Leverage	-0.005	-0.005	-0.005	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)
Industry concentration	-0.005	-0.004	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.037***	0.042***	0.055***	0.053***
	(0.012)	(0.014)	(0.013)	(0.014)
FF 30 industry fixed effects	yes	yes	yes	yes
Calendar year fixed effects	yes	yes	yes	yes
R^2	0.016	0.018	0.017	0.017
# of observations	12,028	12,028	12,028	12,028