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# Innovation Efficiency and Inventor Risk in Takeovers

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# Innovation Efficiency and Inventor Risk in Takeovers


## Abstract

Takeovers are risky board-level decisions, as many of them fail to deliver the synergies expected from combining the resources of both firms, with realizing R&D synergies being an important facet. This study is the first to examine how innovation efficiency (IE) changes after completed takeovers and what role the relative size of the target's inventor team plays. Drawing on the knowledge-based view, the acquired knowledge is held by inventors rather than residing in (formerly invented) patent portfolios, and its realization requires coordination. I argue that IE declines after takeovers because acquirers adjust their R&D budgets in anticipation of synergies that do not materialize immediately and because management attention shifts toward short-term financial results at the expense of long-term R&D. Since coordination costs increase with the number of people to be integrated, I expect a sharper decline when the target's inventor team is large relative to that of the acquirer. The analysis covers US takeovers completed between 2004 and 2020 and links United States Patent and Trademark Office patent and inventor data with financial and transaction data. As predicted, IE declines after takeovers, the decline increases with the relative size of the acquired inventor team, and it persists for five years. For boards, the relative size of the target's inventor team is thus an indicator, available at announcement, of an innovation risk that needs to be assessed before signing.



**Keywords:** M&A, Innovation Efficiency, Patents, Inventors, Risk Management, Post-Merger Integration

**JEL classification:** G32, G34, O32, O34, J24

**Data availability:** Data is publicly available from the sources identified in the paper.

# 1 Introduction

Takeovers are an important but risky strategic tool (Bauer and Matzler 2014) for accessing resources and expertise that cannot be developed internally, or only slowly, and for thereby achieving synergies (e.g., Cefis 2010; Bierly and Chakrabarti 1996; Valentini 2012; Bena and Li 2014). A significant portion of this synergy potential lies in joint research and development (R&D) (e.g., Hitt et al. 1990; Balakrishnan 1988; Shelton 1988), where the expertise sought is technical (Barney 1991; Coff 2002; Graebner 2004; Andrew et al. 2009). The corresponding value is partly held in patents and partly as tacit knowledge of experienced inventors (Bower 2001; Valentini 2012). Only in a takeover can the acquirer fully exploit this knowledge (Prabhu et al. 2005; Datta and Roumani 2015), provided that the inventors stay and cooperate (Ernst and Vitt 2000; Birkinshaw et al. 2000).

On the one hand, the expected benefits of a takeover are substantial (Lin and Lee 2010) as knowledge production exhibits significant economies of scale (Henderson and Cockburn 1996), complementary technological capital enables inventions that neither party could have produced on its own (Li et al. 2021), and the target company's financing constraints also regarding innovation can be alleviated (Granstrand and Sjölander 1990).

On the other hand, the expected synergies may fail to materialize or even turn into dis-synergies, as takeovers can reduce the innovative capacity that the transaction was intended to boost (Miller 1990; Puranam et al. 2009; Junni et al. 2015; van Oorschot et al. 2023; see Veugelers 2006 for a full overview). A case in point is Pfizer's takeover of Wyeth in 2009, which created the world's largest pharmaceutical company (Herper 2009; Karnitschnig 2009). The deal was mainly driven by the pursuit of cost savings of USD 4 billion per year (Karnitschnig 2009), and shortly after completion Pfizer reduced its global R&D space by 35% to "bolster productivity and reduce costs" (Lagorio 2009). Whether this would lead to increased efficiency depended on how well the remaining R&D business units could be coordinated so that R&D output held up, and at the time of the announcement, concerns were raised that the threat of

layoffs and bureaucracy could hinder R&D scientists in focusing on their work (Herper 2009).

One of these coordination issues is how many employees work in the target's R&D department and need to be integrated into the acquirer's company (e.g., Younge et al. 2015). When looking closely at R&D teams, it becomes evident that it is not the entire R&D department of a company that develops new technologies, but rather key inventors within the company who drive technological progress (e.g., Ernst and Vitt 2000; Grigoriou and Rothaermel 2014). Further, their productivity is skewed: The most productive one percent of inventors are five to 10 times as productive as the average (Narin and Breitzman 1995). Takeovers can jeopardize this knowledge, as key inventors may leave the company or reduce their patent output after takeovers (Ernst and Vitt 2000; Verginer et al. 2025), and integration of the target company into the acquirer's business is crucial to the success of a takeover (Cording et al. 2014). For the board that decides on such a takeover, this risk should be assessed before signing (e.g., Keller 2002; Patschureck et al. 2015; Poderiene and Darskuviene 2025). At this point, the size of the inventor teams on both sides can already be observed from patent data. Two questions therefore remain open. First, it is unclear how the acquirer's innovation efficiency (IE), i.e., how efficiently R&D expenditures translate into patents, changes after a takeover. Second, it is unclear whether this change depends on the size of the target's inventor team, which would allow boards to gauge the risk already at announcement.

To scrutinize this puzzle, I hypothesize that integration following a takeover impairs the R&D output of the inventors involved. After the takeover, the acquirer's executive management usually does not keep its R&D budget unchanged but adjusts it to the combined R&D organization, either by reducing it to eliminate duplicated R&D or by increasing it to exploit economies of scale and scope (Hitt et al. 1991; Cassiman et al. 2005). I argue that both directions impair IE. A reduction assumes that redundant R&D lines can be merged, which is difficult in practice (Miller 1990), whereas an increase enables more R&D projects (De Man and Duysters 2005), which are riskier and yield less output because more ideas are being tested (Fleming 2001). For this reason, I expect a decline in the acquirer's IE after the takeover is completed. Since the coordination effort grows disproportionately with the number of employees to be

integrated (e.g., Puranam et al. 2009), and the acquirer's absorptive capacity remains tied to its own R&D organization, I also expect this decline to increase with the relative size of target's inventor team. Furthermore, a large R&D team immediately expands the R&D base, while the associated patent output is delayed. Thus, I predict a reinforcing interaction effect.

To test my hypotheses, I analyze 204 completed US takeovers between 2004 and 2020. Following these takeovers, from five years before to five years after completion, i.e., years in total, the sample totals to 2,244 annual firm-level observations. I measure IE as the ratio of patent output—measured by the number of patents granted—to upstream R&D expenditures. Since R&D expenditures take time to translate into patents, I link expenditures from years $t_{-4}$ through $t_{-2}$ to patents granted between $t_{-2}$ and $t_0$ (Hall et al. 2001; Hirshleifer et al. 2013). I compare each acquirer's IE in the years before and after the takeover's completion. Further, I measure the relative size of the inventor teams as the ratio of those uniquely identified at the target company to those at the acquirer, counting all inventors named on a patent granted within the 10 years prior to the takeover so that inventors who patent only occasionally are also included (Narin and Breitzman 1995).

In line with the hypotheses, my results show that IE declines following the completion of a takeover. The empirical results reflect that the decline is more pronounced the larger the target's inventor team is relative to that of the acquirer. Event-time analysis further shows that there is no significant downward trend in the IE prior to the transaction. The decline begins upon completion and persists in the years after. Additional analyses using alternative moderators support the proposed mechanism.

I contribute to the literature in at least two ways. First, I combine research on takeovers and innovation with research on IE, two lines of research that have previously been pursued separately. The literature on takeovers and innovation measures either resource input *or* innovation output, but not on their efficiency ratio. Hitt et al. (1991) scale both R&D and patents separately by sales, which adjusts for firm size but not for the R&D input which is behind the patents, while Ahuja and Katila (2001) and Cloodt et al. (2006) only measure patent quantity, i.e., the number of patents, explicitly leaving the examination of

IE to future work. The literature on IE, in turn, calculates the ratio of these two variables but relates it to enduring firm characteristics, such as stock returns (e.g., Hirshleifer et al. 2013) or international diversification (e.g., Gao and Chou 2015), rather than to a specific event. By examining IE around takeovers, I show that the acquirer's R&D becomes less efficient after completion, without a prior downward trend, and remains so for at least five years, a change that remains hidden when input and output are considered separately. For boards, the decline is therefore not a temporary integration cost but a lasting risk to be considered when deciding on a takeover. Second, I assess the innovation resources to be integrated by the inventor teams rather than by patent portfolios. Research on technological acquisitions measures the acquired knowledge base by patent portfolios (Ahuja and Katila 2001; Cloodt et al. 2006), whereas the literature on key inventors examines the turnover and productivity of specific individuals (Ernst and Vitt 2000; Paruchuri et al. 2006; Hussinger 2012; Arroyabe et al. 2020; Verginer et al. 2025). I bridge the gap between these two levels by scrutinizing the size ratio of the inventor workforces to be merged as an organizational condition. My additional analyses further show that it is not access to external knowledge, but rather its coordination, that constitutes the binding constraint. Technological fit mitigates the decline. If both firms conduct R&D in the same technological fields, the decline is generally weaker, but it grows with the relative size of the target's inventor team.

The remainder of the paper is structured as follows. Section 2 covers background, related literature and develops the hypotheses. Section 3 describes the research design, while Section 4 presents the results. Section 5 concludes.

# 2 Background, related literature and hypotheses development

## *2.1 Background*

IE indicates how efficiently the R&D budget is utilized and how the R&D budget turns into R&D results. This ratio can be measured on a corporate level, for example, by the number of patents resulting from R&D expenses (Griliches 1990; Hall et al. 2001). In other words, its reciprocal indicates how

expensive each patent is. Thus, IE can change over one or more periods; a constant patent output accompanied by an increase in funding, or an output decline that exceeds a budget cut, represents a loss of efficiency. Consequently, there is the takeover risk that the R&D acquired does not translate into the R&D output that was expected (Patschureck et al. 2015).

Moreover, the success of high-risk R&D investments does not only depend on company characteristics per se, but rather on the individual researchers within the company. Top and middle management set the framework through budget allocation (Hitt et al. 1990), but the actual inventive activity lies with the inventors, who are highly heterogeneous in terms of their knowledge (Zucker et al. 1998). Thus, key inventors are central to the inventive process because of their superior technical knowledge (e.g., Grigoriou and Rothaermel 2014). They act as innovation leaders who initiate and guide new projects, so that their supervised projects have a higher probability of success (Kehoe and Tzabbar 2015). However, R&D results cannot be observed entirely on an individual basis, since a company's knowledge system frequently consists of collaborative networks of inventors (Nerkar and Paruchuri 2005; Eisenman and Paruchuri 2019). Through these networks, inventors share existing knowledge and jointly generate new knowledge, which is why the size of the R&D organization also affects individual productivity (Kim et al. 2009a, b).

In takeovers, the acquirer therefore buys not only patents but primarily the people who generate them. This makes the takeover a risky board-level decision, since this knowledge is embodied in inventors, who may leave the company or become less productive—and it is precisely these inventors who are central to realizing the intended synergies (Larsson and Finkelstein 1999; Chaturvedi and Weigelt 2024). These synergies only emerge when the acquirer incorporates the acquired knowledge into the own innovation process (Puranam and Srikanth 2007) and the inventors from both sides collaborate in shared networks. Integrating these networks is thus decisive. Technological complementarity between the key inventors of both companies enhances their creativity, mediated by their network position (Kong et al. 2026). Whether the potential for synergy is realized is therefore determined during post-merger

integration (Gates and Very 2003), making it a matter of board-level risk governance, since the board decides on the takeover and failures can be traced to its limited involvement in this phase (Poderiene and Darskuviene 2025).

### *2.2 Related literature*

Previous literature on the relationship between takeovers and innovation follows three main lines of research. The first line examines takeovers as a source of innovation gains. Takeovers serve to acquire technological expertise, R&D capabilities, and experienced personnel (Valentini 2012). Key channels of impact include economies of scale in knowledge production, the sharing of fixed costs, and greater specialization among researchers (Henderson and Cockburn 1996; Valentini 2012; Gao and Chou 2015), the pooling of complementary technological capital (Li et al. 2021), and the easing of the target company's financing constraints (Granstrand and Sjölander 1990). As such, takeovers can serve to renew the acquirer's business areas, as they enable companies to build on existing resources and acquire entirely different ones (Karim and Mitchell 2000), while external knowledge helps companies keep pace with new technological developments and remain flexible in dynamic environments (Grant 1996; Prabhu et al. 2005). Empirically, positive effects on patent output, internal R&D intensity, and the number of disruptive patents result from collaborative R&D involving inventors from both acquirer and target (Ahuja and Katila 2001; Cefis 2010; Li and Wang 2023). These gains are concentrated in technologically motivated deals, which improve innovation performance, whereas non-technological takeovers show no significant effect (Li et al. 2018; Zhang et al. 2024). Cefis and Marsili (2015) show that this effect depends on firm size. However, these studies measure either R&D input *or* innovation output, but do not relate the two to each other.

The second line of research does not investigate what a takeover can provide per se, but examines the costs of the takeover process itself and demonstrates how acquiring and integrating a target changes the way the acquirer manages and funds its R&D (e.g., De Man and Duysters 2005). This research shows

that takeovers can reduce R&D expenditures and patents relative to sales, as internal development is replaced by external takeovers and integration ties up management resources that are then lacking for pursuing new projects (Hitt et al. 1991; Somaya et al. 2008). Hitt et al. (1996) report that takeover-active companies tend to steer their business units through financial controls, that is, short-term quantifiable targets, rather than through strategic controls that assess the substance and long-term direction of a unit's work. Since R&D is thus more difficult to justify, internal innovation activities decline, and additional technology is acquired. Studies on technological acquisitions further show that the effect on the acquirer's *patent output* depends on the characteristics of the acquired patent portfolio, such as its size and relatedness to the acquirer's portfolio (Ahuja and Katila 2001; Cloodt et al. 2006). The same asymmetry appears at the firm level, as innovative performance of the acquirer deteriorates when a large company acquires a small one, while deals of comparable size perform better (Chakrabarti et al. 1994). Valentini (2012) shows that while patent output increases, the impact, originality, and breadth of the patents suffer under the pressure to deliver visible results in the short term. Whether synergies materialize is determined during the post-merger integration phase (Gates and Very 2003), and failures can be attributed to not devoting sufficient attention to this phase (Poderiene and Darskuviene 2025). Further, transactions that fail before they are finalized also have consequences, as companies cut back on their investments in innovation following a failed M&A attempt (Liu and Wang 2025).

A third, more recent line of research attributes these findings to knowledge holders. The success of technology-driven takeovers depends on whether R&D teams remain with the company and maintain their level of performance (Ernst and Vitt 2000), which is particularly critical given the distribution of inventors' productivity (Narin and Breitzman 1995). Key inventors often leave the company in significant numbers or reduce their patent output (Ernst and Vitt 2000; Verginer et al. 2025), with the sharpest declines in productivity occurring among those inventors who lose social status and network centrality (Paruchuri et al. 2006; Paruchuri and Eisenman 2012). This can be explained by the uncertainty that the transaction brings for the inventors themselves, as changes in R&D processes, reporting structures, and

career prospects reinforce their intention to leave the company (Bordia et al. 2004; Verginer et al. 2025). Further, implicit commitments such as long-term employment may be withdrawn, which weakens inventors' trust (Kuvandikov et al. 2020). However, the extent of the resulting loss depends on the acquirer's absorptive capacity and the targeted recruitment of new key inventors (Hussinger 2012; Arroyabe et al. 2020). How productive the remaining inventors are after the takeover depends on the technological fit (technological complementarity) between the two R&D organizations, as a close fit enhances individual creativity, facilitated by their centrality within the network and their role as a bridge between otherwise unconnected colleagues (Kong et al. 2026).

Overall, the three lines of research provide three points of reference. First, the literature focuses on input *or* output, not their relationship; however, success depends on how much output each unit of input yields, not on either component alone. Second, the efficiency literature examines enduring firm characteristics rather than a takeover (Hirshleifer et al. 2013; Gao and Chou 2015), which is a strategic decision of top management approved by the board (Poderiene and Darskuviene 2025) that entails considerable risk (Patschureck et al. 2015; Stein and Wiedemann 2016) and frequently fails to meet its objectives (Bauer and Matzler 2014). Third, the acquired knowledge base is measured by patent portfolios rather than by the inventors who will conduct future R&D (Ahuja and Katila 2001; Cloodt et al. 2006). This overlooks the risk that the acquired knowledge is embodied in the people—as in an "acqui-hire"—and that the deal fails to create value if these inventors leave (Ernst and Vitt 2000; Verginer et al. 2025). Addressing these three points, I seek to bridge this research gap by examining whether the board can assess the innovation risk that arises from the inventors to be integrated before deciding on a takeover.

### *2.3 Hypotheses development*

In the following, I argue that integration following a takeover impairs the R&D performance of the inventors involved, and that the acquirer's IE therefore declines after the transaction is completed (H1). On the one hand, factors such as economies of scale in knowledge production (van Oorschot et al. 2023),

greater specialization among researchers (Kim et al. 2009a, b), and the combination of complementary skills point toward an improvement in IE after takeovers (Cassiman et al. 2005). Furthermore, if redundant R&D projects can be discontinued or merged (Veugelers 2006), the productivity of the remaining R&D may even increase (Meyer 2001), provided that the previously separate teams successfully pool their expertise (Ahuja and Katila 2001). On the other hand, successfully leveraging these factors requires the effective integration of the target's R&D into the acquirer's R&D, which is subject to considerable risk (Stahl and Voigt 2008). Specifically, there are two key factors to consider that stand in the way of successful integration and outweigh the opportunities.

First, one of the key factors influencing R&D output is the R&D budget, which the acquirer will redefine once the transaction is completed (Griliches 1990; Hitt et al. 1991). Whether the acquirer cuts *or* increases the R&D budget, the short-term effect on IE is negative. *On the one hand*, acquirers often cut the R&D budget to achieve the targeted efficiency gains (e.g., Miller 1990; Hitt et al. 1991; Arroyabe et al. 2020). This cut is calibrated based on assumed synergies: it assumes that redundant lines of R&D can be merged and that the R&D departments of both sides will work together on the same risky projects in the future. However, this collaboration does not materialize automatically (Stahl and Voigt 2008). If it fails to materialize or is delayed, R&D output declines more sharply than funding, especially since a portion of the costs remains tied up in the short term and planned savings do not take effect immediately (e.g., Anderson et al. 2003; Kreilkamp et al. 2021). *On the other hand*, the ratio may also deteriorate even if the acquirer does not cut the budget but instead increases it to leverage the technological potential of the acquired R&D. In this case, additional funds are also directed toward riskier and longer-term projects (De Man and Duysters 2005; Gao and Chou 2015), whose results materialize only with considerable delay. Such projects may yield significant inventions, but the probability of such a breakthrough is low, as experimentation with new technological combinations leads to less useful inventions on average and increases the risk of failure (Fleming 2001; Kothari et al. 2002). Thus, the use of resources increases immediately, whereas the attributable patent output increases later, in smaller numbers and at a

considerably higher risk level. Regardless of the direction of the budget decision—if maintaining the same budget is not an option—the ratio of output to input deteriorates during the transition phase.

Second, board-level goals also need to be considered. Takeovers tie up a significant amount of management time and attention, which is then lacking for the oversight of ongoing R&D (Hitt et al. 1990, 1991). At the same time, the acquirer's management focus shifts toward financial metrics and away from strategic directions (Hitt et al. 1996), as the pressure on immediate results is particularly high after a takeover (Valentini 2012). This is reinforced by the fact that executive management is accountable to the board and shareholders for measurable results (Fama and Jensen 1983; Graham et al. 2005), whereas R&D is difficult to measure and pays off late (Holmstrom 1989). Thus, such a short-term orientation makes management more risk-averse toward long-term R&D (Hitt et al. 1990), so that projects with visible short-term results are favored. However, this does not correct the possibly unfavorable implementation of the budget decision.

Consequently, regardless of whether the acquirer raises or cuts the R&D budget, the same relative amount of R&D spending yields less R&D output. This reasoning leads to the following first hypothesis:

**H1**: IE *declines* after the takeover is completed.

Next, I argue that the effect of declining IE following the completed transaction is intensified by a larger inventor team at the target company (H2). Takeovers differ significantly in terms of the size of the R&D organization to be integrated (Gerpott 1995). Prior to the completion of a takeover, a large inventor team of the target initially appears to be a positive sign, as it indicates that the acquirer has selected a technologically strong company. However, after the takeover is completed, this advantage could be reversed for four reasons.

First, the complexity of coordination increases disproportionately with the size of the team to be integrated, since the number of interfaces and interdependencies grows with each additional team member. A large target team can hardly be managed autonomously because its activities must be integrated

with those of the acquirer. Thus, the degree of intervention increases, which weakens the inventors' motivation and disrupts their established routines, so that their productivity declines, or they even leave the company (Ernst and Vitt 2000; Puranam et al. 2009).

Second, the acquirer's capacity to absorb knowledge is limited and tied to its existing R&D organization (Hussinger 2012). A comparatively small acquirer team is unable to absorb, mentor, and integrate a large external team into existing projects to the same extent; as a result, with an increasingly unfavorable size ratio, a growing proportion of the acquired knowledge remains unused (Ahuja and Katila 2001; Cloodt et al. 2006). Thus, since a larger knowledge base also expands the R&D input side, the effect on IE may be even stronger than on output alone.

Third, the acquired knowledge is held by the target's inventors, and the larger the team to be integrated, the more key inventors are exposed to the integration. As outlined above, key inventors leave the company or reduce their performance after a takeover (Ernst and Vitt 2000; Verginer et al. 2025). Given the right-skewed distribution of productivity, the departure of even a small number of individuals is sufficient to noticeably reduce patent output (Narin and Breitzman 1995). Furthermore, the transfer of knowledge remaining within the firm requires voluntary cooperation, which is systematically disrupted by structural integration (Birkinshaw et al. 2000; Puranam et al. 2009).

Fourth, a large target team amplifies the cost effect already outlined in H1. Inventors incur personnel expenses that are directly incorporated into the R&D base and thus increase the patent input.

Thus, H2 reads:

**H2**: The post-takeover decline in IE is *more* pronounced the *larger* the target's inventor team is relative to the acquirer's inventor team.

# 3 Research Design

## *3.1 Sample*

Using the LSEG Deals Screener database, I examine domestic[1] US takeover transactions that were completed between January 1, 2004, and December 31, 2020. In line with previous takeover studies (e.g., Knauer et al. 2018; Bhattacharya and Li 2020; Masulis et al. 2023), I apply the following selection criteria: (1) both acquirer and target must be US companies listed on the American Stock Exchange (AMEX), Nasdaq Stock Market (NASDAQ), or New York Stock Exchange (NYSE). (2) The acquirer may hold no more than 50% of the target company's shares prior to the transaction and must own 100% after its completion (Li and Wang 2023). (3) The transaction value must be available and amount to at least USD 10 million. (4) Financial information must be available for both acquirer and target in Compustat Capital IQ. (5) There must be no overlap between two transactions within the 11-year window ranging from five years before to five years after the effective deal date, so that R&D expenses can be accurately allocated to a single transaction. (6) Financial institutions and government agencies are excluded based on SIC code ranges 60–67 and 90–99, respectively.

Having identified the eligible transactions, I link each takeover to the innovation data provided by Kogan et al. (2017) and match inventor information from the United States Patent and Trademark Office (USPTO) database.[2] Financial data are retrieved from the Capital IQ database. The resulting dataset is organized around the transaction. Each takeover forms one event, to which the acquirer's firm years from five years before to five years after the effective date are attached, yielding 11 annual observations per takeover. Patent, inventor, and financial data are assigned to this window, so that each observation

[1] The restriction on *domestic* transactions is based on two reasons. First, consistent patent and inventor data are available for US companies throughout the entire study period. Second, the study requires a comparable legal framework, since the mobility of inventors depends directly on labor and competition law (Younge et al. 2015), and cross-border transactions introduce additional institutional and cultural differences (Stahl and Voigt 2008; Li et al. 2018). Additionally, R&D in specific industries is heavily tied to national regulations. In the pharmaceutical industry, for example, the strength of patent protection varies considerably from one jurisdiction to another, and it has been shown that changes in national patent regulations cause companies to allocate their R&D investments differently (Grabowski 2002).

[2] The dataset from Kogan et al. (2017) is necessary here to assign the patents to the companies. USPTO data on the inventors have a unique code based on the inventor, allowing them to be assigned uniquely.

combines the IE of a given year with the R&D expenditures from previous years. Prior to the takeover, acquirer and target are separate entities, so their patents and R&D expenditures are accumulated. Starting from the effective date of the takeover, both are contained in the acquirer's reported figures. Although the transaction period ends in 2020, company and patent data are used through 2025. This allows the ratio of patents granted to R&D expenditures to be followed across the full post-takeover window of every transaction.

Table 1 provides an overview of the sample selection. The initial sample comprises 25,209 annual observations of takeover transactions between January 1, 2004, and December 31, 2020, that meet the previously defined selection criteria. Due to the lack of prior-year market values, 11,922 observations are excluded. In addition, 7,522 observations are excluded because their study periods overlap with those of other transactions. Finally, 3,521 observations are excluded because a complete history of patent development costs over 11 consecutive years is not available for them.[3] The final sample thus comprises 2,244 annual observations covering a total of 204 takeovers.

[Insert Table 1 here]

### *3.2 Variables*

#### *3.2.1 Dependent variable*

The dependent variable measures IE by comparing patent output to the time-lagged R&D

[3] This criterion excludes serial acquirers from the sample. Although it is necessary to assign R&D expenditures to a single transaction, this favors firms to be in the sample that rarely engage in takeovers and may raise concerns that the estimates reflect self-selection rather than the effects of the takeovers. I address this using Heckman's (1979) two-stage procedure. In the *first* stage, a probit model is used to estimate the probability that a firm will act as an acquirer within a specific year. The estimation sample comprises all Compustat firm-years between 2004 and 2020 that satisfy the exchange and industry criteria applied to the acquirers and for which lagged firm characteristics are available; industries without a single acquirer drop out through the industry fixed effects, leaving 20,270 firm-years. For identification, the model requires at least one variable that influences the selection but does not appear in the second-stage regression of IE. For this purpose, I use the industry's takeover activity as defined by Schlingemann et al. (2002), measured as the sum of the transaction values of a SIC-2 industry in the given year, scaled by its total assets. Thus, it increases the probability that a given firm will carry out a takeover ($p = 0.021$) but is not directly related to the number of patents that a firm generates per dollar of R&D. Acquirers do not differ from non-acquirers in terms of size ($p = 0.957$), but they do differ in terms of debt ratio, firm value, and R&D intensity. In the *second* stage, the inverse Mills ratio is included and remains insignificant ($p = 0.163$). The coefficients for H1 and H2 do not change in either sign or magnitude. The documented decline in IE is therefore not an artifact of sample selection.

expenditures required to develop it (Hirshleifer et al. 2013). More precisely, it is calculated considering the number of patents per unit of R&D expenditure incurred in the preceding years (*PAT_EFF*). Higher values thus indicate that a company generates more patents given a certain level of R&D investment. Conversely, this metric answers the question of how much R&D effort is required to develop a single patent.

The lag structure is necessary since R&D investments typically take time to translate into patent output (Hall et al. 2001). To account for it, different time-shifted measurement windows are used. In the main specification (1), in line with Hirshleifer et al. (2013), I compare the patents granted between $t_{-2}$ and $t_0$ to the R&D expenditures between $t_{-4}$ and $t_{-2}$.[4] In alternative specifications, I combine R&D expenditures between $t_{-5}$ and $t_{-2}$ with patent output between $t_{-3}$ and $t_0$ (2), and between $t_{-2}$ and $t_0$ (3), respectively.[5] In addition, following Chan et al. (2001), I construct an R&D indicator amortized over five years with an annual linear amortization rate of 20% that replaces the equally weighted window which captures the lag through the declining weights of past expenditures rather than through a shifted window (4). Here, R&D expenditures are assumed to lose one-fifth of their value each year, so that the stock in year *t* is the sum of the expenditures of five years, from the current year (weight 1) to the fourth preceding year (weight 0.2), with weights of 1, 0.8, 0.6, 0.4, and 0.2. Thus, the metric reflects that R&D conducted several years ago continues to contribute (albeit to a decreasing extent) to current patent output, and it smooths out the annual fluctuations in R&D expenditures. The various specifications account for the time lag between R&D investments and measurable patent output and enable assessing the robustness of the results across different innovation cycles. For simplicity, Figure 1 visualizes how the dependent variable is calculated in Models 1–4.

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[4] To verify the validity of the measurement windows used, I examine the time intervals between newly granted patents and the citations to existing patents disclosed therein. These backward citations must be specified as part of the patent grant process and allow for an approximate determination of the technological development period. The resulting duration of approximately two to three years is consistent with the existing literature (e.g., Hall et al. 2001; Gao and Chou 2015) and supports the use of time-lagged R&D expenditures.

[5] For robustness, I use not only the simple ratio of patent output to R&D input but also the logarithmic form of this ratio. The results remain the same for all models.

[Insert Figure 1 here]

*3.2.2 Independent variables*

The analysis is based on a panel of the acquirer's fiscal years. For each transaction, the acquirer's fiscal years range from five years prior to five years after the year of completion. Thus, the study contains 11 observations that can be unambiguously assigned to a single takeover due to the exclusion of overlapping transactions. Within this window, following Arroyabe et al. (2020), I use a post-takeover indicator (*POST_TAKEOVER*) as the key independent variable. The dummy variable takes the value zero in the five years prior to the transaction and the value one starting in the year of completion, including all five subsequent years (see also the x-axis in Figure 1 for a graphical illustration). Thus, it reflects the average change in IE following the completion of a takeover.

*3.2.3 Moderating variables*

The moderating variable captures the size of R&D workforce the acquirer has to take on, relative to the size of the current R&D workforce. In a takeover, one acquires not only the target's patent portfolio but also the people who created it, and these inventors must be integrated into an organization that already has its own projects, processes, and reporting structures (Verginer et al. 2025). A handful of inventors joining a large R&D organization poses a different challenge than an incoming group that matches or exceeds the current team in size, so what determines the integration effort is not the absolute number of inventors acquired, but their number relative to the acquirer's own workforce.

Measuring this relation requires a notion of what constitutes a firm's R&D workforce. For that, I consider the inventors involved in developing a patent. Every patent lists at least one inventor, and most are developed by several individuals, so innovation rarely rests on the work of a single person. A firm's inventor team is therefore defined as the set of its uniquely identified inventors, that is, all individuals

listed on at least one of its granted patents.[6]

I compute the moderating variable by dividing the number of unique inventors at the target by the corresponding number at the acquirer (*INVENT_RATIO*). I include all unique inventors who were listed on at least one patent held by the respective company that was granted within the 10 years prior to the effective takeover date.[7] The ten-year time frame captures the inventors who have contributed to a firm's patent output over an extended period and thereby smooths the year-to-year volatility of patenting. In this context, I assume that departing inventors are generally replaced by new employees, thereby largely maintaining the personnel capacity of the inventor team (e.g., Arroyabe et al. 2020). A value for *INVENT_RATIO* greater than one thus indicates that the target has a larger team of inventors than the acquirer, while a value less than one indicates a comparatively smaller team. For completeness, a value of one indicates that the team sizes are approximately equal. As the inventors are identified based on patents granted prior to the closing of the transaction, the variable is not influenced by subsequent changes resulting from the takeover.

This ratio reflects the relative importance of the innovation team to be integrated in terms of personnel. A large target team can provide the acquirer with extensive technological capabilities and additional knowledge, but at the same time increase the coordination requirements and the complexity of post-takeover integration. This is particularly relevant for R&D activities, as technological knowledge is often person-specific and tacit, and its transfer requires active collaboration among the employees involved (Ernst and Vitt 2000; Birkinshaw et al. 2000; Puranam et al. 2009).

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[6] Since the actual organizational team structures are not observable in patent data, each identified inventor is interpreted as a key or leading member of an underlying development team.

[7] The 10-year inventor window partially overlaps with the 11-year study period, as all relevant inventors up to the effective takeover date are included. However, no information from the post-takeover period is incorporated into the construction of the variable. Since the post-takeover indicator takes on a value of zero prior to the takeover, the interaction term captures the change following the completion of the transaction. Further, the window does not track personnel changes. Individuals who left the firm during this period are still counted, so the measure reflects the size of the R&D workforce behind a firm's patent stock rather than its headcount on the effective date. As an additional robustness test, the inventor window is shortened to five years; the results remain qualitatively unchanged.

### *3.2.4 Control variables*

To account for alternative explanations for the change in IE, I include 10 firm- and transaction-specific control variables in the analysis. First, I use *LEV* to control for the acquiring firm's leverage ratio, as a high level of debt can limit the financial flexibility for future R&D investments (He and Tian 2013; Jia et al. 2022). Second, *SIZE* captures the acquirer's firm size based on the logarithm of total assets since larger firms generally have more resources for innovation activities (Gao and Chou 2015). Third, by including *FOCP*, I account for the technological and operational proximity between the transaction partners. The dummy variable takes the value one if the acquirer and target belong to the same industry (same one-digit SIC-code), and zero otherwise (Matsusaka 1993; Berger and Ofek 1995). Fourth, the *DEAL_MARKET_RATIO* measures the relative significance of the transaction as the logarithmic ratio of the transaction value to the acquirer's market capitalization lagged by one year. Larger transactions may require more extensive integration processes and thus have a greater impact on the reallocation of R&D resources (Alexandridis et al. 2013). Fifth, *MTB* estimates the company's growth and investment opportunities while also accounting for how the capital market values the acquirer's intangible assets (Chan et al. 2001; Masulis et al. 2023). Since higher-valued companies tend to invest more in R&D (Miroshnychenko et al. 2020), failing to take this into account would distort the estimated effects on IE. Sixth, I use *STICKY* to assess cost stickiness to capture a company's limitation in the ability to adapt existing resources and cost structures to changing conditions in the short term (Anderson et al. 2003; Kreilkamp et al. 2021). Seventh, *CAPEX* captures investments in property, plant, and equipment, which can both strengthen the technological infrastructure and compete with R&D expenditures (Kothari et al. 2002). Eighth, *LIQUIDITY* accounts for the acquirer's financial flexibility (Hitt et al. 1991; Brown and Petersen 2011), while ninth, *SALES_GROWTH* assesses operational performance and the resulting opportunities for growth and innovation (Del Monte and Papagni 2003). Tenth, *CASH* represents the portion of the transaction paid in cash, as the chosen financing structure for the transaction can affect both remaining liquidity and the funds available for innovation activities following the takeover (Travlos

1987).

All continuous control variables with potential outliers are winsorized at the 1st and 99th percentiles. Additionally, I include year and industry-specific[8] fixed effects to control for unobserved time-dependent trends as well as time-invariant differences between firms in the same industry.

### *3.3 Empirical model*

The hypotheses are tested using linear regression models, which analyze changes in IE following the completion of a takeover. The observation unit is firm *i* in year *t*. To test the first hypothesis, I first estimate the following baseline model:

$$PAT_EFF_{i,t} = \beta_0 + \beta_1 \times POST_TAKEOVER_i + \beta_{2-12} \times CONTROLS_{i,t} \quad (1)$$

$PAT_EFF_{i,t}$ denotes the main dependent variable representing a company's patent output relative to its underlying R&D expenditures. $POST_TAKEOVER_i$ represents the key independent variable, whereas $CONTROLS_{i,t}$ denotes the control variables including industry and year fixed effects. Standard errors are clustered at the two-digit SIC industry level to account for heteroscedasticity and possible correlations among error terms within an industry (Petersen 2009).

Further, the interaction between the relative size of the inventor team $INVENT_RATIO_i$ and $POST_TAKEOVER_i$ is added to the base model to examine the moderating effect:

$$\begin{aligned} PAT_EFF_{i,t} = {} & \beta_0 + \beta_1 \times POST_TAKEOVER_i \\ & + \beta_2 \times POST_TAKEOVER_i \times INVENT_RATIO_i + \beta_{3-13} \times CONTROLS_{i,t} \end{aligned} \quad (2)$$

## 4 Results

### *4.1 Descriptive statistics and correlations*

Table 2 shows the distribution of takeover transactions by year (Panel A) and industry (Panel B).

[8] Here, I use industry fixed effects in the main analysis because industries differ systematically in terms of their technological capabilities, R&D intensity, propensity to file patents, and innovation cycles, all of which can influence the measured IE (Cohen and Levin 1989). In an additional robustness analysis, I replace the industry fixed effects with firm fixed effects, which account for all time-invariant firm-specific characteristics. The results remain qualitatively unchanged, indicating that they are not driven by unobserved, time-invariant differences between firms.

The total of 204 transactions is distributed relatively evenly over the period from 2004 to 2020, with 2007 seeing the most takeovers (21) and 2020 the fewest (5). Most of the transactions occur in the manufacturing sector (111 transactions), followed by the services sector (40 transactions) and the transportation, communications, and utilities sector (27 transactions). The remaining industries represent only a relatively small part of the sample.

[Insert Table 2 here]

Table 3 shows the descriptive statistics for the 2,244 observations. The dependent variable *PAT_EFF* has a mean of 0.17 and a standard deviation of 1.15. The right-skewed distribution, with numerous zero observations and a maximum value of 31.25, corresponds to the typical pattern of patent-based innovation measures: Patent output occurs irregularly and is concentrated in years following periods of high innovation activity. *PAT_EFF* thus captures both phases without immediately measurable patent output and significant differences in IE among companies. *INVENT_RATIO*, which measures the size of the target company's inventor team relative to the acquirer's inventor team, averages 0.55. The median of zero and the maximum value of 38.00 illustrate the pronounced heterogeneity of the acquired innovation resources. While many target companies have only small or no identifiable inventor teams in some transactions, they represent a technological resource that is particularly significant relative to the acquirer in other transactions. The control variables also exhibit considerable variation. In particular, the range of *SIZE* between USD 0.01 billion and USD 375.32 billion shows that the sample includes acquiring firms of very different sizes. The variation in *LEV* and *DEAL_MARKET_RATIO* further underscores the diversity of financing structures and transaction sizes.

[Insert Table 3 here]

Table 4 shows the correlation matrix of the variables used in the analysis, with the Pearson correlation coefficients shown in the lower left and the Spearman correlation coefficients in the upper right. In line with the expected temporal pattern, *PAT_EFF* correlates significantly negatively with *EVENT_TIME*, suggesting a decline in IE over time around the time of the takeover. For

*INVENT_RATIO*, however, a positive relationship with *PAT_EFF* is evident only in the rank-based Spearman correlation, while the Pearson coefficient is insignificant. The correlations between the dependent variable and the control variables are moderate throughout. The highest pairwise correlation among the explanatory variables is between *EVENT_TIME* and *FOCP.* Overall, the correlation matrix shows no sign of problematic multicollinearity. The variables therefore appear generally suitable for the subsequent multivariate analyses.

[Insert Table 4 here]

### *4.2 Tests of the hypotheses*

Table 5 shows the results of the regression analyses for the various specifications of IE conducted to test the first hypothesis H1. Model 1 represents the main specification and links R&D expenditures incurred between $t_{-4}$ and $t_{-2}$, while Models 2–4 serve as alternative specifications. Model 2 (3) links R&D expenditures between $t_{-5}$ and $t_{-2}$ ($t_{-5}$ and $t_{-2}$) to patents granted between $t_{-3}$ and $t_0$ ($t_{-2}$ and $t_0$). Model 4 uses an R&D base amortized over five years and links it to patents granted between $t_{-2}$ and $t_0$. Adjusted $R^2$ values are similar to those by Phillips and Zhdanov (2013) and range from 0.0336 to 0.0697.

In H1, I expect IE to decline following the takeover and thus expect the coefficient of *POST_TAKEOVER* to be significantly negative. Empirically, I find a significantly negative coefficient of -0.2282 ($p = 0.047$[9]) in Model 1. In the alternative specifications (Models 2–4), the coefficients remain negative and statistically significant (all $p < 0.10$), ranging from -0.2174 to -0.0513. Accordingly, IE is, on average, lower after the completion of a takeover than in the period prior to it. Economically, this implies that after the takeover, the combined firm generates approximately 0.2282 fewer patents per USD 1 million of R&D expenditure, which corresponds to a decline of about 34.24 % relative to the sample mean of *PAT_EFF* (0.17). Thus, H1 is supported.

[Insert Table 5 here]

[9] All p-values in this paper are two-tailed, unless stated otherwise.

Table 6 shows the results of the interaction analysis to test H2, as presented in Formula (2). The structure of the specifications for the dependent variable remains the same as in Table 5.

In H2, I argue that the effect of negative IE following a takeover is amplified when the target company's innovation team is larger, as measured relative to the acquirer's innovation team. Thus, the reinforcing interaction effect *INVENT_RATIO* × *POST_TAKEOVER* is expected to be significantly negative. Empirically, I find statistically significant negative coefficients of -0.0239 ($p = 0.02$) in Model 5, of -0.0251 ($p < 0.01$) in Model 6, of -0.0177 ($p < 0.01$) in Model 7, and of -0.0076 ($p < 0.01$) in Model 8. Economically, a one-standard-deviation increase in *INVENT_RATIO* (SD = 3.06) amplifies the post-takeover decline in IE by approximately 0.0731 patents per USD 1 million of R&D expenditure, corresponding to 43.00 % of the sample mean of IE. Hence, I infer support for H2.

[Insert Table 6 here]

### *4.3 Additional analyses*

#### *4.3.1 Composition of the IE measure*

The IE is measured as a ratio of two components: (1) patent grants and (2) time-lagged R&D expenses. To counter concerns that the documented decline in *PAT_EFF* is attributable solely to one of its components or to individual outliers, three robustness checks address this issue (untabulated), reporting $\beta_1$ (*POST_TAKEOVER*) and $\beta_2$ (*POST_TAKEOVER* × *INVENT_RATIO*) from Equation (2): First, the decline in IE persists even after winsorizing *PAT_EFF* at the 1st and 99th percentiles ($\beta_1$ = -0.1067, $p = 0.025$; $\beta_2$ = -0.0293, $p < 0.01$).[10] Second, the logarithmic specification yields the same result ($\beta_1$ = -0.0664, $p = 0.018$; $\beta_2$ = -0.0192, $p < 0.01$). Third, restricting the sample to the 1,268 fiscal years with strictly positive R&D expenditures confirms the decline ($\beta_1$ = -0.1694, $p = 0.053$).[11]

Furthermore, a separate analysis (untabulated) of the two components shows that both patent output

[10] The decline also persists when *PAT_EFF* is winsorized at the 5th and 95th ($\beta_1$ = -0.0275, $p = 0.043$; $\beta_2$ = -0.0141, $p < 0.01$) and the 10th and 90th percentiles ($\beta_1$ = -0.0160, $p = 0.040$; $\beta_2$ = -0.0072, $p < 0.01$).

[11] In this sample, $\beta_2$ is negative but not significant (-0.0210, p = 0.154), which is likely due to the lower statistical power, as the sample is reduced by almost half to 1,268 observations in 26 industry clusters.

($\beta_1$ = -0.2703, $p$ = 0.032) and R&D expenditures ($\beta_1$ = -0.3092, $p$ = 0.056) decline following the transaction.[12] The decline in IE thus reflects how R&D input and R&D output evolve in relation to one another and is consistent with the budget-cut scenario of H1, in which acquirers reduce R&D expenditures in the expectation of synergies, but patent output declines as well.

*4.3.2 Timing and persistence of the IE decline*

In the main analysis, the dummy variable *POST_TAKEOVER*, which measures the average level shift following the completion of the transaction, is used to determine the strength of the effect. In contrast, an event-time specification scrutinizes three sub-dimensions in a more granular way: (1) when the decline begins, (2) whether it is permanent, and (3) whether the companies were already following a downward trend beforehand. To investigate these questions, I replace the dummy variable with a complete set of annual event-date indicators relative to the Effective Deal Year (*EDY*), which reflects the year of the takeover. As such, I estimate the change in IE separately for each year over the window from *EDY-5* to *EDY+5*. To alleviate multicollinearity concerns, the year immediately preceding the transaction (*EDY-1*) serves as the omitted reference period (Wooldridge 2002; Borusyak et al. 2024). Normalizing relative to the period prior to treatment is the predominant convention in event-study designs (Sun and Abraham 2021; Baker et al. 2022) and is in line with recent applications in the accounting literature (Andres et al. 2026). All coefficients should thus be interpreted as deviations from the level immediately prior to the transaction.

Table 7 shows the results of the event-time analysis. In Models 9–11, none of the coefficients for the preceding periods (*EDY-5* through *EDY-2*) are statistically different from zero, so no leading trend can be identified (all $p > 0.17$). The decline begins upon completion of the transaction (Model 9: -0.1931, $p$ = 0.01; Model 10: -0.1665, $p$ = 0.011; Model 11: -0.1246, $p < 0.01$) and remains significantly negative

[12] Both components are measured in logarithmic form. Because of this transformation, the two coefficients cannot be interpreted as an additive decomposition of the coefficient for the ratio. Estimating patent counts with a Poisson pseudo-maximum-likelihood model likewise shows no significant change in patent output ($\beta_1$ = -0.1763, $p$ = 0.253).

in all five subsequent years. The effect documented in H1 is thus neither a continuation of an existing trend nor a temporary integration effect.

[Insert Table 7 here]

Figure 2 illustrates this pattern by showing the coefficients of Model 9 along with their 95 percent confidence intervals. Prior to the transaction, each confidence interval includes the value zero. In the year of the transaction, IE decreases sharply and remains at this lower level for the following five years, without returning to its pre-transaction level.

[Insert Figure 2 here]

Model 12 uses the R&D capital as the denominator of the IE measure, which is accumulated over five years and depreciated at a rate of 20% annually (Chan et al. 2001). In this specification, the coefficients for the preceding periods are significantly positive (0.0370 to 0.0932, all $p < 0.10$), while all coefficients from *EDY* onward remain insignificant. This is in line with the construction of the measure, as the R&D capital includes the expenditures of up to four preceding years and therefore smooths out the discontinuity at completion. Thus, Model 12 confirms that IE is lower from the year before the transaction onward than in the earlier pre-transaction years.

### *4.3.3 Technological fit as condition for successful inventor integration*

The decline in the IE documented above increases in the relative size of the team of inventors to be integrated. It is therefore of interest whether this decline arises from the acquirer's limited ability to absorb and reorganize the acquired R&D, or from the acquirer's access to external knowledge. The technological fit between acquirer and target captures the extent to which both parties conduct R&D in related technological areas and thus indicates whether the acquirer holds a knowledge base on which the acquired R&D can build. Further, it separates the two possibilities: (1) if access to external knowledge were the limiting factor, the decline would have to be largely independent of how closely the two knowledge bases are related, and (2) if integration is the limiting factor, the decline would have to diminish as the

knowledge bases converge. I therefore scrutinize the hypothesized mechanism using technological similarity as an alternative moderator in two steps. First, technological fit replaces the moderator *INVENT_RATIO*. Second, both moderators are included in the model simultaneously. Thus, the combined specification identifies the conditions under which integration becomes particularly difficult. In both steps, the moderator is specified at the transaction level, while the rest of the specification remains unchanged.

The first step requires a measure of technological fit (*PAT_SIM*). While *INVENT_RATIO* captures the size of the inventor teams to be integrated, *PAT_SIM* reflects the technological compatibility. Therefore, firstly patents are classified based on their CPC codes (Chin and Lee 2024). Each patent carries one or more such codes, so that a single patent can belong to several technological areas at once. A patent is counted in an area as soon as it holds at least one code there, and the individual codes within a patent are not weighted further (e.g., Bloom et al. 2013). For each firm, the counts across areas are then standardized by the total number of patent-area assignments, which yields a share vector describing how the firm's R&D is distributed across technological areas. Comparing acquirer and target therefore does not mean comparing individual patents but comparing these two distributions.[13] *PAT_SIM* is calculated as the cosine similarity between the two vectors for all patents granted in the five years prior to the takeover.[14] Hence, the measure takes values between zero and one, where one indicates an identical technological composition. Here, a broad aggregation is used, as the focus is not the overlap between individual technologies, but rather whether the acquirer possesses a related knowledge base that can be built upon. A more detailed classification would consider how both parties are working on the same specific technologies, thereby identifying redundancies rather than connections. For example, two companies conducting

[13] For illustration, consider an acquirer holding 10 patents, six of which carry at least one code in organic chemistry (C07) and four in electric communication (H04), and a target holding four patents, three in organic chemistry (C07) and one in electric communication (H04). The corresponding share vectors are (0.6, 0.4) and (0.75, 0.25), and their cosine similarity is 0.96 — closely related R&D, despite the fourfold difference in portfolio size. Had the target instead held all four patents in agriculture (A01), the vectors would be (0.6, 0.4, 0) and (0, 0, 1), and the cosine similarity would be zero.

[14] As a robustness check, the cosine similarity is additionally calculated over a ten-year period. The results remain unchanged.

R&D in the field of chemistry are treated as technologically closely related, even if their respective classes of connections differ—and it is precisely in this scenario that the acquirer can understand and expand upon the acquired knowledge rather than merely duplicating it. A classification at the level of individual technologies, in contrast, would classify such adjacent and complementary areas as dissimilar—that is, precisely those cases in which integration is most likely to succeed. Thus, I expect a moderating effect, since overlapping knowledge bases facilitate the understanding and exchange of external knowledge (Cohen and Levinthal 1990; Ahuja and Katila 2001) and an existing common foundation enables coordination without requiring disruptive structural integration (Kim and Kogut 1996; Puranam et al. 2009).

Table 8 shows the results of the interaction analysis using the technological similarity instead of the inventor ratio. The main effect of *POST_TAKEOVER* remains negative and significant in all specifications (Model 13: -0.2618, $p = 0.038$; Model 14: -0.2463, $p = 0.019$; Model 15: -0.1773, $p = 0.019$; Model 16: -0.0529, $p = 0.071$). The interaction term *POST_TAKEOVER* × *PAT_SIM*, on the other hand, is consistently positive and significant in Models 13–15 (0.3351, 0.2962, and 0.2152, all $p < 0.05$). The decline in IE is thus all the weaker, the greater the technological overlap between the patent portfolios of both parties. This finding supports the argument regarding H2: It is not access to external knowledge that is the limiting factor, but rather its integration. If the knowledge bases are compatible, coordination costs and absorption barriers decrease, and the negative impact of integration is reduced. For completeness, in Model 16, the interaction term is no longer significant (0.0370), which corresponds to the smoothing effect of R&D capital accumulated over five years, as already discussed in the event-time analysis. The negative main effect of *PAT_SIM* suggests that companies with significant technological overlap are already operating in densely populated technology fields prior to the transaction.

[Insert Table 8 here]

In the second step, both moderators enter the model simultaneously, so that *POST_TAKEOVER*, *INVENT_RATIO* and *PAT_SIM* are fully interacted. The coefficient on the three-way term indicates whether the moderating effect of the relative inventor team size varies with technological similarity.

Table 9 reports the results of the combined specification. The interaction *POST_TAKEOVER* × *PAT_SIM* remains positive and significant in Models 17–19 (0.4004, 0.3553, and 0.2584, all $p < 0.05$), so that the decline in IE again weakens as technological similarity increases. The three-way interaction is negative and significant in the same three specifications (-0.0815, -0.0703, and -0.0521, all $p < 0.10$)[15], while *POST_TAKEOVER* × *INVENT_RATIO* on its own is not statistically distinguishable from zero.[16] Thus, the moderating effect of the relative inventor team size does not operate uniformly across transactions but strengthens with technological similarity. When technological similarity is low, IE decreases regardless of the size of the team to be integrated; when similarity is high, there is no general decline, but the decline increases with the relative size of the target firm's inventor team. Technological proximity is thus the prerequisite under which the acquired R&D can be integrated at all, while the relative size of the inventor team determines whether the integration succeeds. This also puts the result for H2 into perspective: The moderating role of *INVENT_RATIO* documented above is concentrated in technologically close transactions, which is consistent with the interpretation that coordination costs and absorption limits only come into play once the acquired knowledge is usable. Access to external knowledge is therefore neither the constraint, nor is it the number of inventors per se—the constraint is the combination of both, i.e., a knowledge base on which the acquirer can build and a team small enough for its own R&D organization to absorb.

[Insert Table 9 here]

*4.3.4 Absence of the spatial inventor distance effect*

The mechanism behind the decline in IE is now examined from a different perspective, using the

[15] As in the preceding specification, both interaction terms lose significance in Model 20 (*POST_TAKEOVER* × *PAT_SIM*: 0.0497, $p = 0.208$; *POST_TAKEOVER* × *INVENT_RATIO*: -0.0139, $p = 0.259$), which again corresponds to the smoothing effect of R&D capital accumulated over five years.

[16] Since *PAT_SIM* is continuous, the model is additionally estimated with a dummy that splits the sample at the median of *PAT_SIM*, which eases interpretation without relying on the functional form of the continuous interaction. This specification yields the same pattern in sharper form (*POST_TAKEOVER* × *INVENT_RATIO* × *PAT_SIM_HIGH*: -0.0510, $p = 0.002$).

spatial distance between the inventor teams as a moderator, i.e., the different geographical locations. In this context, I investigate whether the decline initially originates within the acquirer's own R&D organization rather than in collaboration that fails between the two teams. The two explanations make opposite predictions about distance: (1) If the decline reflected collaboration that does not materialize, physical separation would have to deepen it, since distance raises the cost of joint work and weakens the informal contact on which it depends (Jaffe et al. 1993). (2) If instead the decline arises as the acquirer absorbs an external team into its existing organization, distance should be irrelevant, because the two teams rarely work on the same projects to begin with. The latter is what the argument developed above implies: inventors cannot simply be instructed to collaborate, and IE gains do not follow from placing two R&D organizations under one roof. Whether the acquired R&D becomes productive depends on how the integration is managed (Gerpott 1995). More precisely, IE is not about how easily inventors could meet in person, but rather about the successful connection of two R&D knowledge bases and the acquirer's ability to integrate the incoming team. Distance can only be a hindrance where actual collaboration is intended to take place. If the decline in IE were driven by collaboration that fails between the two teams, it would therefore have to increase with the spatial distance between them. If no such amplifying effect can be shown, this explanation finds no support, which is consistent with the proposed mechanism.

Spatial distance is captured by *GEO_DISTANCE* as the average geographical distance between the inventor teams of acquirer and target. The distance is measurable since the location of each named inventor is specified whenever a patent is granted.[17] Drawing on the disambiguated inventor and location data from the USPTO, each uniquely identified inventor is assigned the most recently observed location prior to the transaction. As with *INVENT_RATIO*, the observation period covers the 10 years prior to the transaction taking effect. Next, for each transaction, all pairwise Haversine distances[18] between the

[17] One limitation to note is that inventor locations are available only for a subset of the transactions, thereby reducing the sample to 593 observations.

[18] Using the Haversine formula, the shortest distance between two points on the surface of a sphere can be determined based on their latitudes and longitudes. In this calculation, I therefore use the longitudes and latitudes of the inventors.

inventors of the acquirer and target company are calculated, and their arithmetic mean in kilometers is used as a transaction-specific, time-invariant measure.

The results (untabulated) show no such amplifying effect. The interaction term *POST_TAKEOVER* × *GEO_DISTANCE* is not statistically different from zero in all four specifications (0.0197, 0.0174, 0.0123, and 0.0030; all $p > 0.27$). Further, the same applies to the main effect of *GEO_DISTANCE* (all $p > 0.26$). Hence, the results provide no indication that the decline in IE stems from collaboration impeded by geographical distance. Together with the finding on technological similarity, this suggests that the decline is related less to how far apart the inventor teams are than to how well their knowledge bases fit.

# 5 Conclusion

Previous research on takeovers and innovation shows that while transactions open access to technological knowledge, the acquirer's innovation output often declines afterwards. Numerous studies examine either the R&D funds invested *or* the resulting patent output, and a separate line of research focuses on the turnover and productivity of individual key inventors. However, the extent to which IE occurs and what factors influencing it, was unclear.

This study argues that the acquirer redefines its R&D budget once the transaction is completed and that this decision worsens the relation between R&D input and patent output in either direction. A budget cut is calibrated on synergies that do not materialize immediately, whereas an increase flows into longer-term projects whose output appears only with delay. At the same time, management attention shifts toward financial metrics and favors projects with visible short-term results, posing a significant risk to companies' strategic decision making. Thus, IE declines after completion, as supported by the empirical results. Further, this decline increases with the relative size of the inventor team to be integrated, since coordination costs and absorption limits grow with the number of people involved. Again, the empirical results confirm this argumentation. Event-time analysis further shows that the decline is not preceded by a pre-transaction trend; rather, it begins upon completion and persists over the following five years.

Alternative moderators support the hypothesized mechanism: a high degree of technological overlap in the patent portfolios mitigates the decline, while the geographical distance between the inventor teams shows no moderating effect. The decisive factor is therefore the substantive fit of the knowledge bases, not the geographical proximity of the teams.

The study has limitations which also offer starting points for future research. First, I consider only takeovers involving publicly traded US companies in which the acquirer holds all shares upon completion; smaller or privately held target companies, as well as other jurisdictions, may yield different results. Second, I measure innovation output using the number of granted patents, which focus on patentable and patented innovation but not every invention is filed and the propensity to patent varies across firms (Griliches 1990). Third, I identify inventor teams based on the individuals named on granted patents, which means that employees who have not been named on any patents are not considered. Future research could address several areas. For example, it could examine which integration measures mitigate the documented decline, such as compensation and retention programs for key inventors. Further, an international expansion of the study would, in addition to varying legal systems, be insightful to account for institutional differences in labor market regulation and intellectual property protection as constraints on integration.

# Appendix

**APPENDIX A.** VARIABLE DESCRIPTION.

| Variable | Description | Source |
|---|---|---|
| **Main analysis** | | |
| *PAT_EFF* | Measures IE by comparing innovation output—the number of patents granted between $t_{-2}$ and $t_0$—with innovation input—R&D expenditures incurred between $t_{-4}$ and $t_{-2}$. The variable is calculated as the ratio of patent output to R&D input. Higher values indicate that a company generates more patents with a given level of R&D input and converts its innovation resources more efficiently into measurable patent output. | Kogan et al. (2017); Compustat North America |
| *POST_TAKEOVER* | Dummy variable that takes the value zero for all years prior to the takeover and the value one starting with the effective year of takeover, including all subsequent years. | LSEG Deals Screener |
| *INVENT_RATIO* | Measures the ratio of the number of unique inventors at the target company to the number of unique inventors at the acquiring company. To qualify, inventors must have been involved in at least one patent granted within 10 years prior to the effective date of the takeover. | USPTO |
| *LEV* | Measures the acquirer's leverage ratio as the ratio of total debt to equity. | Compustat North America |
| *SIZE* | Measures the size of the acquiring company based on the natural logarithm of its total assets. | Compustat North America |
| *FOCP* | Dummy variable that takes the value one if the acquirer and target belong to the same industry according to their single-digit SIC classification, and zero otherwise. | LSEG Deals Screener |
| *DEAL_MARKET_RATIO* | Measures the relative magnitude of the transaction as the logarithm of the ratio of the transaction value to the acquirer's market capitalization. | Compustat North America; LSEG Deals Screener |
| *MTB* | Measures the acquirer's growth and investment opportunities using the ratio of market value of equity to book value of common stock. | Compustat North America |
| *STICKY* | Measures the proportion of total costs relative to revenue. Costs are calculated as the difference between revenue and earnings before extraordinary items. | Compustat North America |
| *CAPEX* | Measures the acquirer's investment intensity as the ratio of investments in property, plant, and equipment to revenue. | Compustat North America |
| *LIQUIDITY* | Measures the acquirer's liquidity as the ratio of cash and short-term investments to total assets. | Compustat North America |
| *SALES_GROWTH* | Measures the acquirer's annual revenue growth as the percentage change in revenue compared to the previous year. | Compustat North America |
| *CASH* | Measures the portion of the transaction consideration that is paid in cash. | LSEG Deals Screener |
| **Further variables** | | |
| *RD* | Measures the acquirer's R&D expenditures per year in USD million. | Compustat North America |
| *PAT* | Measures the number of patents granted to the acquirer per year. | Kogan et al. (2017) |
| *EDY* | Represents the time interval between an observation and the actual year of takeover (Effective Deal Year). Negative values indicate years prior to the takeover, zero indicates the actual year of takeover, and positive values indicate the years following it. | LSEG Deals Screener |

| | | |
|---|---|---|
| *PAT_SIM* | Measures the technological similarity of the patent portfolios of acquirer and target. Each patent is classified based on its CPC codes at the top level of the classification, the CPC section. For both parties, a count vector is generated for these sections from all patents granted five years prior to the transaction taking effect, and the cosine similarity between the two vectors is calculated. The variable takes values between zero and one, where one indicates an identical technological composition of both portfolios. | Kogan et al. (2017) |
| *GEO_DISTANCE* | Measures the geographical distance between the inventor teams of the acquirer and the target. Each uniquely identified inventor is counted once, based on the most recently observed position listed on a patent granted within the 10 years prior to the transaction taking effect. All pairwise Haversine distances between the inventors of both parties are calculated; the variable corresponds to their arithmetic mean in kilometers. Higher values indicate a greater geographical distance between the teams. | USPTO |

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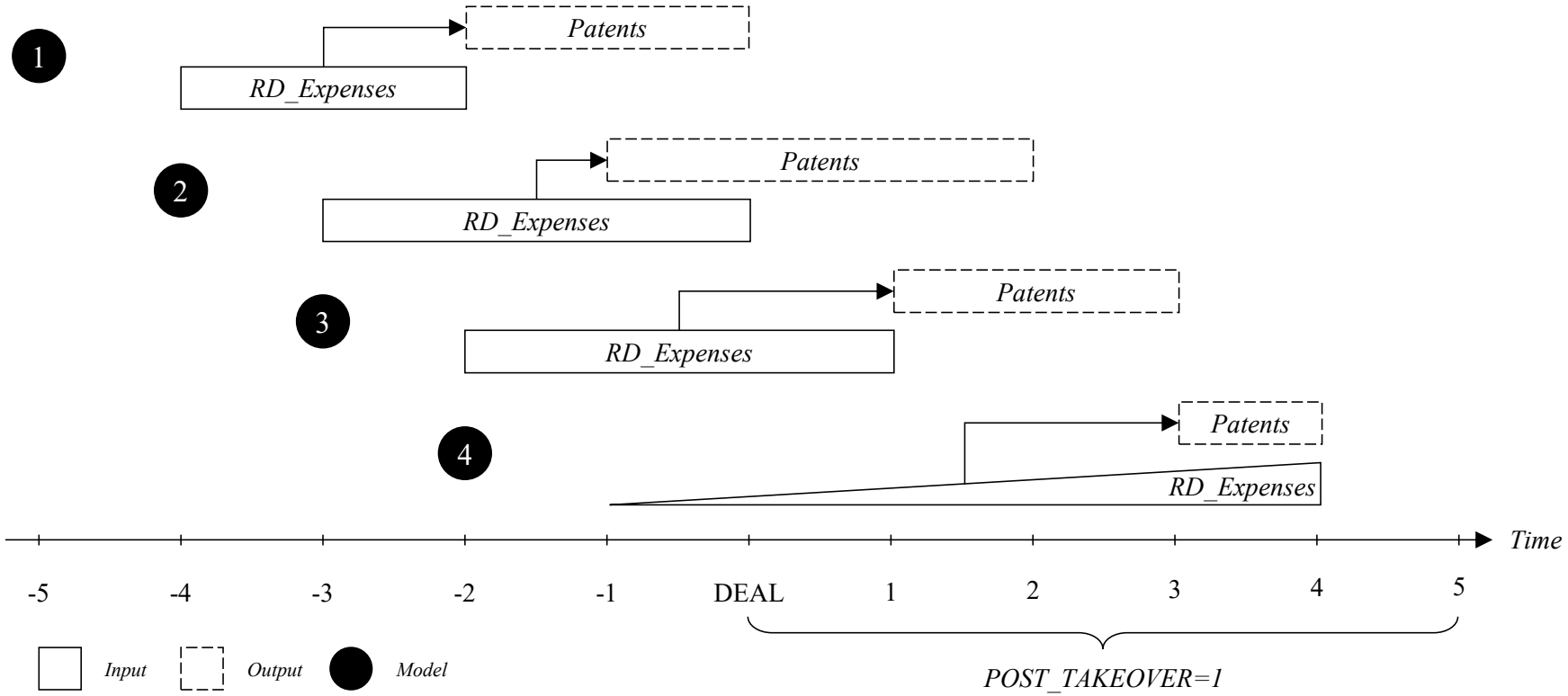
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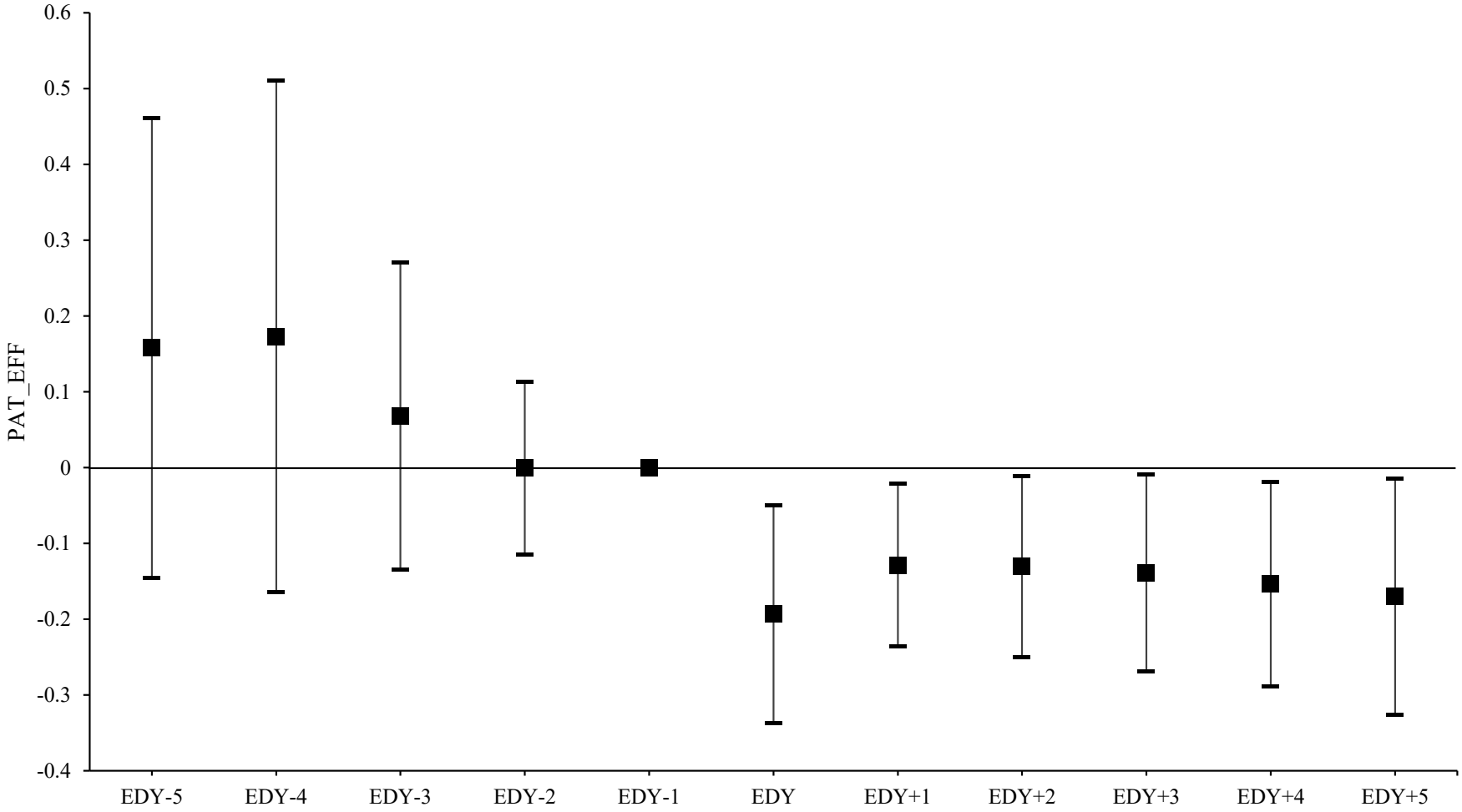
## Figures

**FIGURE 1.** PATENT EFFICIENCY COMPOSITION IN THE TAKEOVER.




The figure shows the temporal mapping of inputs and outputs across the four model specifications. The time axis is normalized to the completion of the transaction (*DEAL*), at which point *POST_TAKEOVER* takes on the value 1. Solid boxes represent the input (*RD_Expenses*), dashed boxes represent the output (*Patents*), and the circled number indicates the model number. Models 1–3 differ in the length of the aggregation window for R&D expenditures and in the delay with which the corresponding patent grants are attributed. Model 4 replaces the equally weighted window with a depreciated R&D stock, in which each year further in the past is assigned a weight that is 20 percent lower; the input therefore appears as a wedge rather than a rectangle.

**FIGURE 2.** PATENT EFFICIENCY IN EVENT TIME AROUND THE TAKEOVER.




The figure plots the event-time coefficients of *PAT_EFF* from Model 9 (Table 7) around the completion of the transaction. The time axis is normalized to the completion year (*DEAL*) and spans the five years before and after it. Squares indicate the estimated coefficients relative to the reference year (*DEAL − 1*), which is set to zero; whiskers indicate the corresponding 95 percent confidence intervals based on standard errors clustered at the industry level. The regression includes all control variables as well as industry and year fixed effects. Pre-takeover coefficients do not differ significantly from zero, whereas all coefficients from the year of completion onward are significantly negative.

# Tables

**TABLE 1.** SAMPLE SELECTION.

| Selection Sequence | Observations |
|---|---|
| Initial sample of takeover transactions between January 1, 2004, and December 31, 2020, that meet the defined selection criteria, including listing on major US stock exchanges, available financial data, and exclusion of financial and government institutions. | 25,209 |
| - Missing market value of the previous year | 11,922 |
| - Observations that overlap with other takeovers within the [-5; +5] year window around the year of the takeover | 7,522 |
| - Transactions for which a complete transaction history (covering 11 consecutive years) of patent development costs is not available [a)] | 3,521 |
| **Total Sample of yearly observations [b)]** | **2,244** |
| Unique Takeovers | 204 |

Notes: [a)] To counteract the possibility of self-selection, Heckman's (1979) two-stage test was conducted. The results do not suggest a self-selection effect (see also Footnote 3 for further details). [b)] The sample selection reflects the observations regarding the execution of the deals analyzed in main analysis.

**TABLE 2.** TAKEOVERS PER YEAR AND INDUSTRY.

**Panel A.** Distribution by year.

| Year | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | ∑ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Number of deals | 9 | 11 | 13 | 21 | 11 | 10 | 16 | 9 | 12 | 14 | 6 | 17 | 17 | 7 | 15 | 11 | 5 | 204 |

**Panel B.** Distribution by Industry.

| Division | Standard Industrial Classification | Number of deals |
|---|---|---|
| A | Agriculture, Forestry and Fishing | 1 |
| B | Mining | 7 |
| C | Construction | 3 |
| D | Manufacturing | 111 |
| E | Transportation, Communications, Electric, Gas, And Sanitary Services | 27 |
| F | Wholesale Trade | 6 |
| G | Retail Trade | 9 |
| I | Services | 40 |
| ∑ | | 204 |

**TABLE 3.** SUMMARY DESCRIPTIVE STATISTICS.

| Variable | n | Mean | SD | Min | Q25 | Q50 | Q75 | Max |
|---|---|---|---|---|---|---|---|---|
| **Main analysis** | | | | | | | | |
| *PAT_EFF* | 2,244 | 0.17 | 1.15 | 0.00 | 0.00 | 0.00 | 0.00 | 31.25 |
| *INVENT_RATIO* | 2,244 | 0.55 | 3.06 | 0.00 | 0.00 | 0.00 | 0.02 | 38.00 |
| *LEV* | 2,244 | 0.49 | 23.32 | -776.59 | 0.04 | 0.46 | 0.92 | 381.99 |
| *SIZE* | 2,244 | 9.10 | 25.05 | 0.01 | 0.75 | 2.20 | 6.68 | 375.32 |
| *FOCP* | 2,244 | 0.37 | 0.48 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *DEAL_MARKET_RATIO* | 2,244 | 0.63 | 1.73 | 0.00 | 0.10 | 0.28 | 0.61 | 41.77 |
| *MTB* | 2,244 | 2.89 | 17.30 | -447.56 | 1.46 | 2.17 | 3.65 | 137.22 |
| *STICKY* | 2,244 | 1.03 | 1.32 | -1.77 | 0.91 | 0.95 | 0.99 | 56.64 |
| *CAPEX* | 2,244 | 0.09 | 0.29 | 0.00 | 0.02 | 0.04 | 0.07 | 6.97 |
| *LIQUIDITY* | 2,244 | 0.14 | 0.15 | 0.00 | 0.03 | 0.08 | 0.19 | 0.91 |
| *SALES_GROWTH* | 2,244 | 0.15 | 0.63 | -0.70 | 0.00 | 0.08 | 0.19 | 20.93 |
| *CASH* | 2,244 | 57.22 | 42.33 | 0.00 | 0.00 | 63.93 | 100.00 | 100.00 |
| **Additional analysis** | | | | | | | | |
| *PAT_SIM* | 2,244 | 0.09 | 0.23 | 0.00 | 0.00 | 0.00 | 0.00 | 0.97 |
| *GEO_DISTANCE* | 593 | 31.15 | 21.58 | 5.60 | 17.83 | 25.62 | 41.36 | 102.86 |
| **Further analysis** | | | | | | | | |
| *RD* | 2,244 | 97.23 | 452.88 | 0.00 | 0.00 | 7.06 | 63.58 | 11,581.00 |
| *PAT* | 2,244 | 0.01 | 0.10 | 0.00 | 0.00 | 0.00 | 0.00 | 2.21 |

This table shows the arithmetic mean (Mean), standard deviation (SD), minimum (Min), first quartile (Q25), median (Q50), third quartile (Q75), and maximum (Max) for all observations (n) over the entire period. *STICKY* is calculated as (Revenue − Net Income)/Revenue and may be negative if net income exceeds revenue, for example, due to non-operating income. *LEV* is the ratio of total debt to common equity. It can be negative if reported equity is negative due to accumulated losses; negative values do not, therefore, imply negative debt. All monetary values are reported in USD (e.g., *SIZE* in billions, *RD* in millions), and *GEO_DISTANCE* is reported in hundreds of kilometers. All values are presented in raw form and are neither centered around the mean, winsorized nor logarithmized. All variables are defined in Appendix A.

**TABLE 4.** CORRELATION MATRIX.

| | *a)* | *b)* | *c)* | *d)* | *e)* | *f)* | *g)* | *h)* | *i)* | *j)* | *k)* | *l)* | *m)* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *a) PAT_EFF* | | -0.08*** | 0.26*** | -0.08*** | -0.07*** | 0.14*** | -0.10*** | 0.19*** | -0.08*** | 0.01 | 0.23*** | 0.04* | 0.00*** |
| *b) EVENT_TIME* | -0.09*** | | 0.00 | 0.12*** | 0.23*** | -0.61*** | -0.21*** | -0.07*** | 0.02 | -0.03 | -0.09*** | -0.12*** | 0.00*** |
| *c) INVENT_RATIO* | 0.02 | 0.00 | | 0.03 | -0.07*** | 0.12*** | 0.05** | 0.07*** | 0.00 | -0.06*** | 0.22*** | 0.03 | 0.00*** |
| *d) LEV* [a b] | -0.02 | 0.07*** | 0.00 | | 0.14*** | -0.10*** | 0.17*** | 0.28*** | 0.12*** | -0.01 | -0.28*** | -0.02 | 0.00*** |
| *e) SIZE* | 0.04** | 0.22*** | -0.10*** | 0.14*** | | -0.08*** | -0.19*** | 0.06*** | -0.19*** | 0.23*** | -0.33*** | -0.03 | 0.00*** |
| *f) FOCP* | 0.09*** | -0.61*** | 0.03 | -0.05** | -0.06*** | | 0.17*** | 0.02 | -0.05** | 0.06*** | 0.04** | 0.07*** | 0.00*** |
| *g) DEAL_MARKET_RATIO* [a] | -0.06*** | -0.18*** | 0.09*** | 0.12*** | -0.25*** | 0.15*** | | -0.34*** | 0.38*** | -0.06*** | -0.14*** | -0.08*** | 0.00*** |
| *h) MTB* [a b] | -0.01 | -0.01 | -0.02 | 0.63*** | 0.02 | 0.04* | 0.00*** | | -0.28*** | 0.03 | 0.14*** | 0.18*** | |
| *i) STICKY* [a b] | -0.02 | -0.05** | 0.01 | 0.06*** | -0.15*** | -0.04* | 0.19*** | 0.00*** | | -0.12*** | 0.00 | -0.16*** | 0.00*** |
| *j) CAPEX* [a b] | 0.02 | -0.03 | -0.04** | 0.12*** | 0.11*** | -0.01 | 0.09*** | -0.03 | 0.30*** | | -0.12*** | 0.03 | 0.00*** |
| *k) LIQUIDITY* [a b] | 0.00 | -0.12*** | 0.05** | -0.14*** | -0.36*** | 0.05** | -0.09*** | 0.05** | 0.18*** | -0.07*** | | 0.09*** | 0.01 |
| *l) SALES_GROWTH* [a b] | 0.00 | -0.12*** | 0.01 | 0.02 | -0.07*** | 0.05** | 0.04* | 0.04** | 0.22*** | 0.13*** | 0.09*** | | -0.07*** |
| *m) CASH* | 0.00 | 0.00 | 0.08*** | 0.05** | 0.09*** | 0.07*** | -0.28*** | 0.09*** | -0.13*** | -0.08*** | 0.01 | -0.07*** | |

Notes: The table shows the Pearson (lower left diagonal) and Spearman (upper right diagonal) correlation coefficients for the sample (N=2,244). The superscript symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. [a]) Variable is mean-centered. [b]) Variable is winsorized at the 1st and 99th percentile. All variables are defined in Appendix A.

**TABLE 5.** MAIN ANALYSIS REGRESSION RESULTS.

| | *PAT_EFF* | | | |
|---|---|---|---|---|
| Period allocation: R&D | [-4; -2] | [-5; -2] | [-5; -2] | [-5; -2] |
| Period allocation: Patents | [-2; 0] | [-3; 0] | [-2; 0] | [-2; 0] |
| Amortized R&D | No | No | No | Yes |
| Model | 1 | 2 | 3 | 4 |
| *POST_TAKEOVER* | -0.2282** | -0.2174** | -0.1569** | -0.0513* |
| | (0.1112) | (0.0935) | (0.0675) | (0.0254) |
| *INVENT_RATIO* | 0.0089 | 0.0085 | 0.0067 | 0.0040*** |
| | (0.0063) | (0.0060) | (0.0043) | (0.0013) |
| *LEV* [a b] | 0.0146 | 0.0097 | 0.0078 | 0.0042 |
| | (0.0183) | (0.0160) | (0.0113) | (0.0033) |
| *SIZE* | 0.0356 | 0.0342 | 0.0251 | 0.0049 |
| | (0.0238) | (0.0222) | (0.0155) | (0.0045) |
| *FOCP* | 0.1131 | 0.0761 | 0.0486 | 0.0172 |
| | (0.1069) | (0.0984) | (0.0700) | (0.0232) |
| *DEAL_MARKET_RATIO* [a] | -0.0592 | -0.0470 | -0.0341 | -0.0115 |
| | (0.0572) | (0.0476) | (0.0336) | (0.0104) |
| *MTB* [a b] | -0.0049 | -0.0032 | -0.0021 | -0.0013 |
| | (0.0057) | (0.0051) | (0.0036) | (0.0010) |
| *STICKY* [a b] | 0.0211 | 0.0127 | 0.0127 | 0.0033 |
| | (0.0551) | (0.0472) | (0.0357) | (0.0090) |
| *CAPEX* [a b] | 0.1663 | 0.1415 | 0.1263 | 0.0385 |
| | (0.3527) | (0.3246) | (0.2293) | (0.0559) |
| *LIQUIDITY* [a b] | 0.0534 | 0.0195 | 0.0144 | -0.0109 |
| | (0.2128) | (0.1954) | (0.1395) | (0.0338) |
| *SALES_GROWTH* [a b] | -0.0082 | 0.0051 | 0.0043 | -0.0073 |
| | (0.0557) | (0.0421) | (0.0350) | (0.0100) |
| *CASH* | -0.0009 | -0.0009 | -0.0007 | 0.0000 |
| | (0.0013) | (0.0012) | (0.0008) | (0.0002) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,244 | 2,244 | 2,244 | 2,244 |
| Unique Takeover | 204 | 204 | 204 | 204 |
| $R^2$ | 0.0664 | 0.0789 | 0.0663 | 0.1012 |
| Adjusted $R^2$ | 0.0337 | 0.0466 | 0.0336 | 0.0697 |
| F Value | 3.40 | 3.68 | 3.78 | 2.73 |
| *Difference* | -0.2176*** | -0.2028*** | -0.1440*** | -0.0556*** |

Notes: This table shows the results of hypothesis tests based on a panel regression analysis estimated using linear regression with multiple fixed effects. The estimated coefficients are shown, with robust standard errors (in parentheses) grouped at the industry level. For robustness, firm-level fixed effects are used; the results remain statistically unchanged. *Difference* reports the difference in the mean of *PAT_EFF* after and before the completion of the takeover (post minus pre), without control variables or fixed effects; its significance is based on a two-sample t-test. The superscript symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. [a]) Variable is mean-centered. [b]) Variable is winsorized at the 1st and 99th percentile. All variables are defined in Appendix A.

**TABLE 6.** MAIN ANALYSIS CONSIDERING PATENT INVENTORS.

| | *PAT_EFF* | | | |
|---|---|---|---|---|
| Period allocation: R&D | [-4; -2] | [-5; -2] | [-5; -2] | [-5; -2] |
| Period allocation: Patents | [-2; 0] | [-3; 0] | [-2; 0] | [-2; 0] |
| Amortized R&D | No | No | No | Yes |
| Model | 5 | 6 | 7 | 8 |
| *POST_TAKEOVER* | -0.2175* | -0.2062** | -0.1489** | -0.0479* |
| | (0.1133) | (0.0952) | (0.0688) | (0.0259) |
| *POST_TAKEOVER × INVENT_RATIO* | -0.0239** | -0.0251*** | -0.0177*** | -0.0076*** |
| | (0.0099) | (0.0085) | (0.0064) | (0.0026) |
| *INVENT_RATIO* | 0.0222** | 0.0224** | 0.0165** | 0.0082*** |
| | (0.0087) | (0.0083) | (0.0062) | (0.0024) |
| *LEV* [a b] | 0.0137 | 0.0088 | 0.0072 | 0.0039 |
| | (0.0184) | (0.0160) | (0.0113) | (0.0033) |
| *SIZE* | 0.0353 | 0.0339 | 0.0249 | 0.0049 |
| | (0.0239) | (0.0222) | (0.0155) | (0.0045) |
| *FOCP* | 0.1099 | 0.0727 | 0.0462 | 0.0162 |
| | (0.1075) | (0.0990) | (0.0704) | (0.0233) |
| *DEAL_MARKET_RATIO* [a] | -0.0595 | -0.0473 | -0.0343 | -0.0116 |
| | (0.0571) | (0.0475) | (0.0336) | (0.0104) |
| *MTB* [a b] | -0.0047 | -0.0029 | -0.0020 | -0.0012 |
| | (0.0057) | (0.0052) | (0.0036) | (0.0010) |
| *STICKY* [a b] | 0.0223 | 0.0139 | 0.0136 | 0.0036 |
| | (0.0551) | (0.0473) | (0.0358) | (0.0089) |
| *CAPEX* [a b] | 0.1647 | 0.1398 | 0.1252 | 0.0380 |
| | (0.3530) | (0.3249) | (0.2294) | (0.0561) |
| *LIQUIDITY* [a b] | 0.0377 | 0.0031 | 0.0028 | -0.0159 |
| | (0.2135) | (0.1958) | (0.1397) | (0.0343) |
| *SALES_GROWTH* [a b] | -0.0094 | 0.0038 | 0.0033 | -0.0077 |
| | (0.0561) | (0.0427) | (0.0356) | (0.0099) |
| *CASH* | -0.0009 | -0.0009 | -0.0007 | 0.0000 |
| | (0.0013) | (0.0012) | (0.0008) | (0.0002) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,244 | 2,244 | 2,244 | 2,244 |
| Unique Takeover | 204 | 204 | 204 | 204 |
| $R^2$ | 0.0674 | 0.0803 | 0.0677 | 0.1031 |
| Adjusted $R^2$ | 0.0343 | 0.0476 | 0.0346 | 0.0712 |
| F Value | 4.43 | 4.69 | 3.99 | 2.92 |

Notes: This table shows the results of hypothesis tests based on a panel regression analysis. The estimated coefficients are shown, with robust standard errors (in parentheses) grouped at the industry level. For robustness, firm-level fixed effects are used; the results remain statistically unchanged. In contrast to the analysis before (Table 5), the interaction term between *POST_TAKEOVER* and the inventor ratio between the acquirer and the target (*INVENT_RATIO*) is added to the original variables below. The superscript symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. [a]) Variable is mean-centered. [b]) Variable is winsorized at the 1st and 99th percentile. All variables are defined in Appendix A.

**TABLE 7.** REGRESSION RESULTS USING SINGLE-TIME VARIABLES.

| | *PAT_EFF* | | | |
|---|---|---|---|---|
| Period allocation: R&D | [-4; -2] | [-5; -2] | [-5; -2] | [-5; -2] |
| Period allocation: Patents | [-2; 0] | [-3; 0] | [-2; 0] | [-2; 0] |
| Amortized R&D | No | No | No | Yes |
| Model | 9 | 10 | 11 | 12 |
| ***EVENT TIME*** | | | | |
| *EDY-5* | 0.1580 | 0.0379 | 0.0497 | 0.0932* |
| | (0.1498) | (0.0458) | (0.0366) | (0.0485) |
| *EDY-4* | 0.1731 | 0.1451 | 0.1392 | 0.0767** |
| | (0.1666) | (0.1265) | (0.1003) | (0.0367) |
| *EDY-3* | 0.0683 | 0.0915 | 0.0547 | 0.0370** |
| | (0.0999) | (0.0896) | (0.0652) | (0.0175) |
| *EDY-2* | -0.0005 | 0.0258 | 0.0174 | 0.0597* |
| | (0.0563) | (0.0419) | (0.0386) | (0.0322) |
| *EDY* | -0.1931** | -0.1665** | -0.1246*** | -0.0036 |
| | (0.0711) | (0.0625) | (0.0438) | (0.0066) |
| *EDY+1* | -0.1288** | -0.1524** | -0.0943*** | -0.0045 |
| | (0.0531) | (0.0574) | (0.0332) | (0.0197) |
| *EDY+2* | -0.1305** | -0.1515** | -0.0930** | -0.0064 |
| | (0.0591) | (0.0651) | (0.0396) | (0.0212) |
| *EDY+3* | -0.1384** | -0.1589** | -0.1020** | -0.0048 |
| | (0.0643) | (0.0683) | (0.0439) | (0.0193) |
| *EDY+4* | -0.1535** | -0.1629** | -0.1063** | -0.0095 |
| | (0.0665) | (0.0738) | (0.0449) | (0.0210) |
| *EDY+5* | -0.1703** | -0.1882** | -0.1214** | 0.0085 |
| | (0.0769) | (0.0838) | (0.0523) | (0.0226) |
| *INVENT_RATIO* | 0.0095 | 0.0088 | 0.0070 | 0.0043*** |
| | (0.0070) | (0.0063) | (0.0045) | (0.0014) |
| *LEV* [a b] | 0.0138 | 0.0097 | 0.0076 | 0.0039 |
| | (0.0180) | (0.0162) | (0.0114) | (0.0033) |
| *SIZE* | 0.0346 | 0.0339 | 0.0246 | 0.0050 |
| | (0.0238) | (0.0222) | (0.0156) | (0.0046) |
| *FOCP* | 0.1319 | 0.0794 | 0.0573 | 0.0180 |
| | (0.1264) | (0.1199) | (0.0841) | (0.0281) |
| *DEAL_MARKET_RATIO* [a] | -0.0617 | -0.0480 | -0.0352 | -0.0122 |
| | (0.0594) | (0.0489) | (0.0346) | (0.0107) |
| *MTB* [a b] | -0.0049 | -0.0031 | -0.0021 | -0.0013 |
| | (0.0056) | (0.0052) | (0.0036) | (0.0011) |
| *STICKY* [a b] | 0.0194 | 0.0116 | 0.0119 | 0.0027 |
| | (0.0544) | (0.0475) | (0.0360) | (0.0087) |
| *CAPEX* [a b] | 0.1577 | 0.1464 | 0.1280 | 0.0343 |
| | (0.3493) | (0.3293) | (0.2325) | (0.0552) |
| *LIQUIDITY* [a b] | 0.0400 | 0.0201 | 0.0115 | -0.0144 |
| | (0.2151) | (0.1944) | (0.1387) | (0.0328) |
| *SALES_GROWTH* [a b] | -0.0089 | -0.0003 | 0.0007 | -0.0089 |
| | (0.0597) | (0.0463) | (0.0380) | (0.0110) |
| *CASH* | -0.0010 | -0.0009 | -0.0007 | 0.0000 |
| | (0.0013) | (0.0012) | (0.0008) | (0.0002) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |

| | | | | |
|---|---|---|---|---|
| Observations | 2,244 | 2,244 | 2,244 | 2,244 |
| Unique Takeover | 204 | 204 | 204 | 204 |
| $R^2$ | 0.0683 | 0.0801 | 0.0683 | 0.1076 |
| Adjusted $R^2$ | 0.0316 | 0.0439 | 0.0317 | 0.0725 |
| F Value | 6.56 | 4.81 | 8.90 | 10.17 |

Notes: This table shows results of additional analyses based on a panel regression analysis. The estimated coefficients are shown, with robust standard errors (in parentheses) grouped at the industry level. For robustness, firm-level fixed effects are used; the results remain statistically unchanged. In contrast to the main analysis (Models 1–8), this analysis uses an event-time analysis based on individual years instead of the *POST_TAKEOVER* dummy variable. *EDY* represents the effective deal year of the transaction. To mitigate multicollinearity, *EDY-1* is excluded. The superscript symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. [a]) Variable is mean-centered. [b]) Variable is winsorized at the 1st and 99th percentile. All variables are defined in Appendix A.

**TABLE 8.** REGRESSION RESULTS USING TECHNOLOGICAL SIMILARITY.

| | *PAT_EFF* | | | |
|---|---|---|---|---|
| Period allocation: R&D | [-4; -2] | [-5; -2] | [-5; -2] | [-5; -2] |
| Period allocation: Patents | [-2; 0] | [-3; 0] | [-2; 0] | [-2; 0] |
| Amortized R&D | No | No | No | Yes |
| Model | 13 | 14 | 15 | 16 |
| *POST_TAKEOVER* | -0.2618** | -0.2463** | -0.1773** | -0.0529* |
| | (0.1215) | (0.1004) | (0.0721) | (0.0285) |
| *POST_TAKEOVER* × | 0.3351** | 0.2962** | 0.2152** | 0.0370 |
| *PAT_SIM* | (0.1591) | (0.1298) | (0.0918) | (0.0365) |
| *PAT_SIM* | -0.3046* | -0.2752* | -0.2036** | -0.0252 |
| | (0.1516) | (0.1376) | (0.0952) | (0.0304) |
| *LEV* [a b] | 0.0138 | 0.0089 | 0.0072 | 0.0042 |
| | (0.0195) | (0.0171) | (0.0121) | (0.0035) |
| *SIZE* | 0.0393 | 0.0377* | 0.0277* | 0.0049 |
| | (0.0236) | (0.0215) | (0.0149) | (0.0046) |
| *FOCP* | 0.1378 | 0.0986 | 0.0654 | 0.0208 |
| | (0.1141) | (0.1046) | (0.0743) | (0.0245) |
| *DEAL_MARKET_RATIO* [a] | -0.0554 | -0.0434 | -0.0313 | -0.0109 |
| | (0.0570) | (0.0473) | (0.0334) | (0.0102) |
| *MTB* [a b] | -0.0047 | -0.0030 | -0.0019 | -0.0014 |
| | (0.0062) | (0.0056) | (0.0039) | (0.0011) |
| *STICKY* [a b] | 0.0350 | 0.0251 | 0.0218 | 0.0041 |
| | (0.0537) | (0.0447) | (0.0332) | (0.0096) |
| *CAPEX* [a b] | 0.1704 | 0.1450 | 0.1288 | 0.0381 |
| | (0.3540) | (0.3255) | (0.2298) | (0.0561) |
| *LIQUIDITY* [a b] | 0.1263 | 0.0872 | 0.0659 | 0.0004 |
| | (0.2294) | (0.2119) | (0.1509) | (0.0346) |
| *SALES_GROWTH* [a b] | 0.0040 | 0.0162 | 0.0125 | -0.0058 |
| | (0.0492) | (0.0362) | (0.0302) | (0.0091) |
| *CASH* | -0.0008 | -0.0008 | -0.0006 | 0.0001 |
| | (0.0013) | (0.0012) | (0.0008) | (0.0002) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,244 | 2,244 | 2,244 | 2,244 |
| Unique Takeover | 204 | 204 | 204 | 204 |
| $R^2$ | 0.0691 | 0.0816 | 0.0691 | 0.1004 |
| Adjusted $R^2$ | 0.0360 | 0.0490 | 0.0361 | 0.0685 |
| F Value | 5.03 | 4.22 | 4.62 | 9.64 |

Notes: This table shows the results of hypothesis tests based on a panel regression analysis. The estimated coefficients are shown, with robust standard errors (in parentheses) grouped at the industry level. For robustness, firm-level fixed effects are used; the results remain statistically unchanged. In contrast to the main analysis, the interaction term between *POST_TAKEOVER* and the patent similarity between the acquirer and the target (*PAT_SIM*) is used. The superscript symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. [a]) Variable is mean-centered. [b]) Variable is winsorized at the 1st and 99th percentile. All variables are defined in Appendix A.

**TABLE 9.** REGRESSION RESULTS USING INVENTOR RATIO AND TECHNOLOGICAL SIMILARITY.

| | *PAT_EFF* | | | |
|---|---|---|---|---|
| Period allocation: R&D | [-4; -2] | [-5; -2] | [-5; -2] | [-5; -2] |
| Period allocation: Patents | [-2; 0] | [-3; 0] | [-2; 0] | [-2; 0] |
| Amortized R&D | No | No | No | Yes |
| Model | 17 | 18 | 19 | 20 |
| *POST_TAKEOVER* | -0.2646** | -0.2478** | -0.1790** | -0.0543* |
| | (0.1286) | (0.1068) | (0.0767) | (0.0298) |
| *POST_TAKEOVER × INVENT_RATIO* | -0.0109 | -0.0139 | -0.0094 | -0.0053 |
| | (0.0129) | (0.0116) | (0.0083) | (0.0034) |
| *POST_TAKEOVER × PAT_SIM* | 0.4004** | 0.3553** | 0.2584** | 0.0497 |
| | (0.1699) | (0.1391) | (0.0979) | (0.0388) |
| *INVENT_RATIO × PAT_SIM* | 0.0519 | 0.0449 | 0.0326 | 0.0131 |
| | (0.0507) | (0.0488) | (0.0365) | (0.0114) |
| *POST_TAKEOVER × INVENT_RATIO × PAT_SIM* | -0.0815* | -0.0703* | -0.0521* | -0.0139 |
| | (0.0448) | (0.0409) | (0.0299) | (0.0122) |
| *INVENT_RATIO* | 0.0145 | 0.0158 | 0.0118 | 0.0061** |
| | (0.0110) | (0.0114) | (0.0082) | (0.0027) |
| *PAT_SIM* | -0.3485* | -0.3149* | -0.2325** | -0.0376 |
| | (0.1719) | (0.1574) | (0.1093) | (0.0332) |
| *LEV* [a b] | 0.0127 | 0.0079 | 0.0064 | 0.0039 |
| | (0.0194) | (0.0170) | (0.0121) | (0.0034) |
| *SIZE* | 0.0397 | 0.0380* | 0.0280* | 0.0052 |
| | (0.0244) | (0.0221) | (0.0154) | (0.0047) |
| *FOCP* | 0.1284 | 0.0896 | 0.0587 | 0.0175 |
| | (0.1120) | (0.1033) | (0.0734) | (0.0243) |
| *DEAL_MARKET_RATIO* [a] | -0.0567 | -0.0447 | -0.0323 | -0.0114 |
| | (0.0573) | (0.0475) | (0.0336) | (0.0103) |
| *MTB* [a b] | -0.0044 | -0.0026 | -0.0017 | -0.0013 |
| | (0.0061) | (0.0055) | (0.0039) | (0.0011) |
| *STICKY* [a b] | 0.0342 | 0.0248 | 0.0217 | 0.0041 |
| | (0.0537) | (0.0453) | (0.0340) | (0.0094) |
| *CAPEX* [a b] | 0.1715 | 0.1459 | 0.1296 | 0.0388 |
| | (0.3570) | (0.3282) | (0.2319) | (0.0567) |
| *LIQUIDITY* [a b] | 0.0919 | 0.0531 | 0.0406 | -0.0132 |
| | (0.2364) | (0.2184) | (0.1555) | (0.0371) |
| *SALES_GROWTH* [a b] | 0.0001 | 0.0125 | 0.0097 | -0.0068 |
| | (0.0503) | (0.0373) | (0.0312) | (0.0092) |
| *CASH* | -0.0009 | -0.0008 | -0.0006 | 0.0001 |
| | (0.0013) | (0.0012) | (0.0008) | (0.0002) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,244 | 2,244 | 2,244 | 2,244 |
| Unique Takeover | 204 | 204 | 204 | 204 |
| $R^2$ | 0.0709 | 0.0840 | 0.0715 | 0.1039 |
| Adjusted $R^2$ | 0.0361 | 0.0497 | 0.0368 | 0.0704 |
| F Value | 11.82 | 19.91 | 17.80 | 16.04 |

Notes: This table shows the results of hypothesis tests based on a panel regression analysis. The estimated coefficients are shown, with robust standard errors (in parentheses) grouped at the industry level. For robustness, firm-level fixed effects are used; the results remain statistically unchanged. In contrast to the main analysis, the technological similarity of the two patent portfolios (*PAT_SIM*) is added and fully interacted with *POST_TAKEOVER* and the inventor ratio between the acquirer and the target (*INVENT_RATIO*), so that the three-way interaction term indicates whether the moderating effect of the inventor ratio varies with technological fit. The superscript symbols *, **, and *** indicate statistical significance at the 10%, 5%, and

1% levels (two-tailed), respectively. [a]) Variable is mean-centered. [b]) Variable is winsorized at the 1st and 99th percentile. All variables are defined in Appendix A.