What Affects Post-Merger Innovation Outcomes? An Empirical Study of R&D Intensity in High Technology Transactions Among U.S. Firms

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Abstract

High levels of global M&A activity have characterized the past decade, making the policy debate over the impact of mergers on innovation even more pertinent. Innovation is a significant driver of economic growth and therefore a negative effect of mergers on innovation outcomes may have detrimental consequences. Nevertheless, the existing literature demonstrates mixed results leaving it unclear whether the overall effect is positive or negative. This paper contributes to existing literature on the relationship between mergers and innovation and examines the effects of M&A on the subsequent innovative activity of acquiring firms that operate in high technology (high-tech) industries. I construct a sample of U.S.-based public-to-public deals from 2010-2019 involving high-tech acquiring firms. Using multivariable regression with robust considerations, I analyze factors that may explain post-merger R&D intensity defined as the merged entity's R&D expenditure divided by its total assets one year after deal completion. I consider firm characteristics of the target and acquirer, including size, industry, and age, and industry competition. I find potential positive impact of relative target size on post-merger R&D intensity and significant interaction effects between relative target size and firm age, relative target size and industry relatedness, and target industry competition and industry relatedness. My results suggests that beyond the occurrence of a merger, specific deal characteristics may affect post-merger innovation outcomes.

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Keywords: M&A; Innovation; R&D; High-tech industries

I. Introduction

Mergers and acquisitions (M&A) involve the consolidation of companies or assets via financial transactions. More specifically, a merger occurs when two companies combine to form a single new entity and an acquisition refers to one company purchasing another and incorporating it into the larger business. Despite these differences, unless otherwise noted, the terms *merger* and *acquisition* will both denote deals between two firms combining in some manner. Given the rise in M&A over the past decade and related antitrust concerns, the relationship between mergers and innovation has become of increasing importance. Innovation is vital for economic growth and understanding how mergers may affect innovative activity is an important consideration for authorities aiming to establish a socially optimal antitrust policy (Entezarkheir & Moshiri, 2017). Therefore, the fundamental question becomes the following: What affects post-merger innovation outcomes?

While the literature has established that a relationship between mergers and innovation exists, the exact impact of M&A on innovation is ambiguous. Given that mergers typically result in market consolidation, reduced competition, and higher prices, M&A activity may stifle innovation. On the other hand, however, mergers often lead to risk reduction and support economies of scale and R&D activities, which may incentivize innovative activity (Entezarkheir & Moshiri, 2017). Several papers find evidence of a positive impact that may support the latter of these two proposed relationships. For instance, Kulick & Card (2023) argue for a highly robust link between M&A activity and innovation in recent years. They use two different innovation proxies, patent applications and R&D expenditure, and in both cases, find that mergers are associated with increased innovative activity. Entezarkheir & Moshiri (2017) also find support for a positive effect and specify that it may increase in the long run. Despite these findings, some empirical studies point to a negative impact. Haucap et al. (2019) offer evidence for the reduction of post-merger innovation output both for the merged entity and rival firms and Cloodt et al. (2006) argue for a delayed negative effect.

In this paper, I aim to enhance the current understanding of the relationship between mergers and innovation through examining the post-deal innovative activity of high technology (high-tech) acquiring firms, namely companies with a primary line of business in a high-tech industry. More specifically, I investigate factors that may explain post-merger R&D intensity defined as the merged entity's R&D expenditure divided by its total assets one year after deal completion. I consider firm characteristics of the target and acquiring firm, namely size, industry, and age, and industry competition.

In recent years, the high-tech space has received considerable attention given its association with cutting-edge technology. The term *high tech* is somewhat versatile and can been used to describe companies, industries, occupations, and products. A high-tech firm is defined as one engaged in the highest form of technology to date. More specifically, this firm develops new products and/or processes that are either the latest and/or the most advanced on the market. The term is often used in contrast to low technology, which refers to relatively simple and unsophisticated development. From this definition follows the importance of innovation for companies looking to succeed in the high-tech space.

Beyond serving as a hub for innovation, the high-tech sector is an important driver for economic activity. High-tech industries are those containing a substantial amount of representation of high-tech firms and include electronics, pharmaceutical and medicine manufacturing, and communications equipment (Hecker, 2005). According to the most recent publication by the U.S. Bureau of Labor Statistics, in 2016, high-tech industries accounted for almost 10% of total employment and more than 18% of output in the United States (U.S. Bureau of Labor Statistics, 2018). Furthermore, a significant amount of merger activity takes place in the space. Between 2000 and 2018, high tech represented the industry category with the greatest amount of M&A activity by deal count in the United States. It accounted for almost 20% of total transactions announced during this time period. When measuring merger activity in terms of deal value, high tech falls slightly behind healthcare and energy and power, generating about 2.8 billion dollars in total (IMAA Institute, 2021). Following this period, dealmaking in the high-tech space stood out for its resilience during the COVID-19 pandemic and its aftermath (West Monroe, 2020).

High-tech industries are primarily knowledge-driven and the great deal of M&A activity and innovation occurring in high tech make it both a suitable and interesting context for investigating post-merger innovation. Moreover, alternative settings containing non-technological firms may be less appropriate for exploring innovation. Ahuja & Katila (2001) do not find support for an appreciable impact of transactions lacking a technological element on innovation. Cloodt et al. (2006) confirm this result and find strong evidence that non-technological mergers have little impact on the innovative activity of the acquiring firm. Considering both the nature of high tech and these findings, I focus my study on deals involving high-tech acquiring firms. Despite being concentrated in a particular space, however, the selection still allows for analysis of factors related to industry group, since several distinct high-tech industries exist and are present in my sample.

Beyond adding to an area of limited empirical research, my work contributes to the current academic literature in several ways. Among papers concerned with establishing how the merger market affects innovation, only some specify firm and industry factors that may affect post-merger innovation outcomes. Furthermore, few consider features of both the target and acquiring firm and instead focus on either target characteristics or acquirer attributes. My dataset is also distinct from others used in the space. I construct a sample of deals from the 2010-2019 time period that involve U.S.-based firms operating in high-tech industries. Most studies on mergers and innovation focused on high-tech industries have time horizons that conclude before 2010 and therefore exclude the most recent decade ending in 2019. M&A deal volume has significantly increased in the past ten years, especially among high-tech firms, and therefore analysis of this decade may lead to more powerful insights (IMAA Institute, 2021). While some prior studies have either analyzed samples that include deals announced during the 2010s or transactions restricted to high tech, my research is unique in pairing these selections.

The following section contains a brief literature review, in which I discuss existing research and further highlight how my work fills an important gap. Section III will outline the theories underlying my work and establish the framework for analyzing my hypotheses and Section IV will describe the data. Section V outlines the empirical specification and findings. In the final section, I discuss limitations, directions for future work, and policy implications.

II. Literature Review

I identify three bodies of relevant research. The first set of papers explore how the M&A market affects innovative activity but distinguish between technological and non-technological deals and are therefore most related to my work. I include a second set of papers that also provide insight into firms' post-M&A innovation but lack an industry focus. The final set of literature investigates the reverse relationship and discusses how innovation may affect M&A activity. This area arguably presents more empirical challenges and has therefore received considerably less attention in the literature. Nevertheless, I include a few notable papers on the topic. The discussion of mergers and innovation would be incomplete without outlining the bidirectional nature of the relationship.

Effects of Mergers on Innovation Considering Technological Deals:

In examining how M&A affects subsequent innovation, Ahuja and Katila (2001) differentiate between technological acquisitions and non-technological ones. They define a technological deal as one in which the target firm's assets contain a technology element. Using an international sample of transactions among companies from the global chemicals industry, they conclude that the size of the target firm's knowledge base measured in terms of successful patent applications matters. More specifically, the absolute size of the acquired knowledge base increases innovation while the size of the acquired knowledge base relative to that of the acquirer decreases performance. Ahuja and Katila (2001) also explore whether the relatedness of the target and acquiring firm affects innovation. Relatedness is calculated by dividing the number of patents common between the knowledge bases of the target and acquiring firm by the absolute size of the target's knowledge base. They find empirical support for a curvilinear relationship between relatedness and post-merger innovation output.

Cloodt et al. (2006) replicate the work of Ahuja and Katila (2001) but extend the set of deals to include a wider range of industries. Analyzing a sample of transactions occurring in four high-tech sectors, namely aerospace and defense, computers and office machinery, pharmaceuticals, and electronics and communications, they draw conclusions consistent with some of the results found by Ahuja and Katila (2001). For instance, they find support for the curvilinear relationship between relatedness and innovation established in the original study.

They do, however, call into question a conclusion by Ahuja and Katila (2001) and in doing so, provide new insight into post-acquisition performance. Essentially, Cloodt et al. (2006) find that acquiring a target firm with a large absolute knowledge base increases innovation output for the first few years post-deal, but after this, find evidence of a negative effect. Together, the research of Ahuja and Katila (2001) and Cloodt et al. (2006) are foundational to much of my work as I seek to illuminate some of their findings.

Haucap et al. (2019) investigate how M&A affects the innovative outcomes for both the combined entity and rival firms. Their work is novel for two reasons. First, they consider how deals influence firms outside the transaction and second, they employ a sample of horizontal mergers involving European pharmaceutical companies. Haucap et al. (2019) highlight the pharmaceutical space as one of high research intensity and therefore an appropriate setting to analyze innovation outcomes. To measure innovative activity, they use both patent applications and R&D expenditure. Contrary to several papers discussed so far, Haucap et al. (2019) find an overall negative impact of mergers on subsequent innovation. This result holds for both the merged company and competitors. Haucap et al. (2019) establish an important point in identifying significant effects on rival firms. That is, the number of parties affected by the impact of mergers on innovation may be greater than initially assumed.

Liu and Zou (2008) assess different sources of international technology spillovers on innovation, including greenfield foreign direct investment and cross-border M&As. In analyzing a sample of deals between Chinese domestic target firms and foreign acquiring firms, Liu and Zou (2008) address an important gap in the literature, since the majority of papers on the effects of M&A on innovation contain samples of U.S. or European firms. They also limit their study to transactions occurring in high-tech industries. Liu and Zou (2008) find that cross-border M&A

activity has a positive effect on the Chinese target firm's innovation performance, conditional on the acquirer and target operating in different industries. Among intra-industry transactions, they find a neutral effect. Innovative performance is measured as the ratio of the firm's new product sales to total sales. This may suggest that some forms of cross-border M&A activity enhance domestic innovation (Liu and Zou, 2008).

Impact of M&A on Innovation:

Sevilir & Tian (2012) seek to understand what drives innovation and examine the relation between mergers and subsequent innovation output. Their choice of innovation proxy is notable as they consider both quantity and quality of patents obtained by a firm, using the number of patents granted and number of non-self citations received by each. They find an overall positive relationship and to establish causality, they compare projected innovation output of failed acquirers to that of successful acquirers. In this case, a failed acquirer is one part of an announced yet withdrawn deal and a successful acquirer is one part of an announced and completed transaction. Sevilir & Tian (2012) further differentiate their work by analyzing deal performance, which is less common in M&A literature given the lack of robust performance metrics. Nevertheless, they find that purchasing innovative target firms is positively correlated with the acquirer's abnormal returns at announcement and long-term post-deal stock return.

Kulick & Card (2023) use a sample of transactions spanning 2008 to 2020 and thereby contribute to knowledge of more recent connection between M&A and innovation. They find strong evidence that positively links M&A activity to innovation output, using both patent applications and R&D expenditure as measures of innovative activity. Through applying the

Granger causality test, Kulick & Card (2023) are able to elevate their conclusions to causal claims.

Table I. Recent Papers on the Impact of Mergers on Innovative Activity

Authors	Region	Time Horizon	Industry Focus	Innovation Proxy
Ahuja & Katila (2001)	Europe, U.S., and Japan	1980-1991	Global chemicals	Successful patent applications
Cloodt et al. (2006)	North America, Europe, and Asia	1985-1994	High-tech	Number of patents granted
Liu & Zou (2008)	China	1997-2004	High-tech	Ratio of new product sales to total sales
Sevilir & Tian (2012)	U.S.	1990-2006	No restriction	Number of patents filed & number of citations received by new patents
Entezarkheir & Moshiri (2017)	U.S.	1980-2003	Manufacturing	Citation-weighted patent stock
Haucap et al. (2019)	Europe	1991-2007	Pharmaceuticals	Number of patent applications & R&D expenditure
Beneish et al. (2021)	U.S.	2001-2015	No restriction	Use purchase price to measure unpatented innovation
Wu et al. (2022)	China	2011-2018	No restriction	Number of patent applications, ratio of R&D expenditure to operating income, & ratio of number of technicians to total employees
Kulick & Card (2023)	U.S.	2008-2020	No restriction	Patent applications & R&D expenditure

Table I outlines recent work examining the role of mergers in innovation outcomes. I note two important takeaways. First, despite a few studies focusing on high-tech industries and a few containing more recent time horizons, no paper has combined these elements. I address this gap in selecting a sample of transactions among high-tech acquiring firms spanning a time horizon from 2010 to 2019. Second, the diversity of innovation proxies is noteworthy and demonstrates the lack of a single commonly accepted method for measuring a firm's innovative activity.

The Role of Innovation in Merger Propensity:

The relationship between mergers and innovation appears to be two-sided. That is, beyond the impact of M&A on innovation, innovative activity may affect the propensity to merge. The pursuit of synergy is arguably one of the most common motives for merging. In this context, synergy is the possible financial gain realized through consolidation and occurs when the value of the new company exceeds the sum of the values of the former two separate entities. A primary source of synergies is cost-based, involving decreased expenses that result from the combined company experiencing increased efficiencies. For instance, firms may enjoy savings from the elimination of redundant departments and improved supply chain relationships as a combined entity. Whereas the M&A literature has paid significant attention to such cost synergies, Bena and Li (2014) point to another category of synergies that plays a significant role in driving transactions. Using a sample of around 1,760 U.S.-based mergers occurring during the time horizon spanning 1984 to 2006, they find evidence that the joining of two firms' innovation competencies serves as deal motivation.

Entezarkheir & Moshiri (2018) also explore innovation-related benefits as a cause and highlight how mergers can internalize positive knowledge spillovers that result from a firm's innovative activities. Innovative firms may wish to combine research and development resources, reduce industry competition, and learn from one another. Another appeal is that, compared to direct investments, M&A is often a more efficient means to increasing capital (Entezarkheir & Moshiri, 2018). Entezarkheir & Moshiri (2018) provide empirical evidence for innovation-driven transactions using a panel dataset of 800 distinct transactions spanning the 1980-2003 time period that contains deals involving public manufacturing companies. They find a significant positive relationship between innovative activities of the acquiring firm and the firm's decision to merge. To measure innovation, they use a citation-weighted stock representing both the quantity and quality of a firm's patents and run robustness tests using different innovation metrics such as a firm's R&D intensity. They also find that the magnitude of the positive correlation between innovative activities and merger decisions is dependent on industry.

Denes et al. (2018) take the analysis a step further and investigate the impact of innovation on merger waves, which are simply periods of time during which an abnormal number of merger bids materialize (AMSA, 2019). They focus on determining whether a specific kind of technological shock, namely the concurrent expiration of patents in a given industry, results in merger waves. To explore the link between merger waves and innovation cycles, they use data on patent activity and identify *patent expiration waves*, defined as phases characterized by strong clustering in patent expirations (Denes et al., 2018). They ultimately find support that patent expiration waves trigger industry merger waves and identify an amplified effect in patent-intensive industries such as electronic equipment.

Similar to literature discussing the impact of mergers on innovation, research on the reverse aspect of the relationship includes fewer papers focused of foreign firms. Nonetheless, Lehto & Lehtoranta (2006) restrict their analysis to deals involving Finland-based firms when considering whether possessing innovation increases the probability that a company will merge. They recognize the fact that in some industries, it may be common for the acquirer to transfer technology to the target firm while in others, the opposite is true. To address this detail, they separate companies that operate in processing industries from those that operate in non-processing industries. Consistent with findings from studies of U.S.-exclusive samples, Lehto & Lehtoranta (2006) find evidence supporting the role of innovation in merger activity. Their main finding is that in processing industries, innovative firms purchase inefficient firms and in non-processing industries, less innovative firms acquire innovative ones.

I discuss a final paper that deviates from the analysis of propensity to merge but provides insight into innovation measurement. Beneish et al. (2021) evaluate the role of innovation in merger value creation, but rather than using a patent-based innovation proxy typical among research on innovative activity, they attempt to capture the role of unpatented innovation. They stress the importance of considering unpatented technology when measuring a firm's innovation output and emphasize flaws associated with merely focusing on patent-based metrics. Since information on unpatented innovation is not publicly accessible, Beneish et al. (2021) employ a unique approach in using the fair value of innovation acquired via the transaction to identify unpatented activity and separating the purchase price assigned to technology and R&D into a patented component and an unpatented component. They find support for the impact of innovation on merger value creation suggesting the importance of accounting for unpatented activity when measuring a firm's innovative activity.

III. Theoretical Framework

Mergers are a common source of external innovation for firms and are often considered a less expensive alternative to direct investments (Entezarkheir & Moshiri, 2018; Wu et al., 2022). As a result, managers may prioritize external growth via acquisitions over in-house innovative activity consistent with high R&D intensity. The choice between pursuing internal development versus external development is known as the "make or buy" decision and is recurrent among literature on firm innovation strategy (Blonigen & Taylor, 2000; Liu & Zou, 2008). Furthermore, this theory may apply to firms operating in the high-tech space (Blonigen & Taylor, 2000).

Blonigen & Taylor (2000) find a negative relationship between R&D intensity and M&A activity across companies in high-tech industries, suggesting that high-tech firms adopt the "make or buy" approach. I consider this finding as I hypothesize how different elements of a merger affect post-deal R&D intensity. My propositions are conditional on my sample representing firms using M&A to benefit from a target firm's innovative capabilities.

Target firm size may affect knowledge transfer in deals. It is expected that larger target companies have the capacity to undergo a greater amount of knowledge transfer given a higher number of employees involved in the process (Bresman et al., 2010). The potential for a larger target to contribute more to an acquirer's existing innovative activity, however, may depend on the acquirer's capability of absorbing and assimilating the target firm's knowledge base. A larger target firm relative to that of the acquirer may present challenges for knowledge absorption and therefore restrict the ability for a target firm to effectively serve as an external innovation source, thus increasing the need for subsequent in-house R&D spending.

Hypothesis 1. Mergers involving a larger target relative to the size of the acquirer result in greater post-deal R&D intensity.

Beyond size, a second important factor is industry competition. Competitive industries are characterized by a high number of market players. Therefore, a firm looking to acquire a company that operates in a competitive industry has many options when selecting its target. To outline the significance of the size of the target pool available, I draw on literature exploring entry-timing of acquirers within industry merger waves. Evidence of an early-mover advantage exists in which acquirers that undergo deals earlier in a wave have access to a greater number of possible targets, allowing them to choose the company with the highest potential (Carow et al., 2004). Based on this principle, I expect that an acquirer faced with many target options will ultimately find and select a more suitable firm. This should enhance the integration of the target's innovative activities with those of the acquirer, and thereby make subsequent in-house R&D spending less essential.

A selection process with many options likely requires more due diligence. Consequently, one stipulation is that the acquiring firm invests the necessary resources to perform sufficient due diligence in selecting its target. Nonetheless, this assumption seems reasonable given the competitive nature of the high-tech space, which leaves little room for failed investments and adds pressure to find a suitable target. Hence,

Hypothesis 2. Transactions involving a target from a competitive industry lead to less post-deal R&D intensity.

Operating in the same industry may imply greater technological similarity and enhanced integration (Liu & Zou, 2008). Each should help the acquirer better utilize the target's innovative capabilities and leave less need for subsequent in-house R&D spending. Similarity between the acquirer and target should therefore have a negative impact on post-deal R&D intensity.

It should be noted, however, that from an innovation standpoint, there are limits to gains from similarity. A target that contains too much overlap with its acquirer may have less to offer in terms of innovative potential (Ahuja & Katila, 2001). Nevertheless, I expect the former effect is stronger. Integration challenges are more well-established barrier to deal success compared to excess relatedness between firms. Thus,

Hypothesis 3. Transactions involving an acquirer and target from the same industry result in less post-deal R&D intensity.

The final factor I consider is firm age, or the number of years since a company was founded. Younger firms tend to be more innovative and therefore may be a more valuable source of external innovation (Stiebale & Reize, 2011). This may decrease the need for additional R&D expenditure after the acquisition. In considering the acquirer, it may be more worthwhile to regard age as an indicator of experience. An older acquirer with greater experience may be more skilled in integration and absorption of the target firm's innovation resources. In accordance, my final set of hypotheses are:

Hypothesis 4a. Deals with younger target firms trigger decreased post-deal R&D intensity.

Hypothesis 4b. Deals with older acquiring firms lead to less post-deal R&D intensity.

IV. Data

Deal Screening:

The SDC Platinum M&A database (SDC) is updated daily and contains information on both public and private transactions. Over 116,100 domestic deals with announcement dates ranging from 1979 to the present and 147,000 international deals dating back to 1988 are included. Beyond standard mergers and acquisitions, around 10 additional types of transactions, such as leveraged buyouts and spinoffs, are represented. There are more than 1,400 data elements listed per transaction including target and acquirer profile details, such as industry and location, and deal terms, such as termination fees and acquisition techniques (HBS Baker Library, n.d.).

Several alternative M&A databases exist, including ones developed by Capital IQ, Pitchbook, FactSet, and Dealogic. Despite these options, SDC offers the most historical data, sophisticated screening capabilities, and contains a relatively higher number of transactions and data elements per deal. For this reason, SDC appears as a source in much of the existing empirical M&A research. Nevertheless, issues related to data quality and missing data are worth noting. Relative to a hand-collected database, SDC may be more susceptible to errors on certain deal types, like those involving smaller, high book-to-market buyers with weak announcement period market reactions (Barnes et al., 2014). Furthermore, there is a substantial amount of missing data for common deal variables like transaction value and enterprise value. One workaround is to supplement SDC data with that from alternative datasets and/or company filings. In some instances, certain variables may contain fewer missing observations in alternative databases.

I use SDC to source data on U.S. deals only, that is, transactions involving both acquirers and targets with a primary business located in the United States at the time of the deal. As referenced previously, I filter for deals announced between January 2010 and December 2019 inclusive and while this selection largely relates to my work's intended contribution, it is also consistent with two other considerations. M&A activity is highly cyclical and correlated with the business cycle. In choosing my sample, I aim to study relatively recent transactions but minimize influence from periods of economic uncertainty, namely the 2007-2008 financial crisis and the COVID-19 pandemic. The period from 2010 to 2019 offers the continuous time period that is best aligned with this goal. Moreover, I notice that more recent deals suffer significantly less from missing data problems, further supporting my selection. I recognize, however, that the choice is not without drawbacks. The impact of mergers on innovation may be of importance during uncertain economic times given both may play a part in stimulating economic recovery, and by selecting ten years of positive GDP growth, I am unable to contribute to current understanding in this area. Nonetheless, the lack of activity in both M&A and innovation during recessionary times make empirical studies in this regard particularly challenging.

Primarily for the purpose of data availability, I include public-to-public transactions only and exclude any withdrawn or pending deals. I also eliminate company repurchases in which a firm buys back its own shares. I ensure that the acquirer does not already hold the majority of target shares pre-merger but ultimately gains sufficient control post-merger by retaining transactions only if the acquirer owns less than 50% of the target firm before deal completion and at least 90% after deal completion. Similar to the literature, I screen for deals with a transaction value of $10 million or more, attempting to exclude activity with relatively less economic significance. Finally, I filter for deals involving high-tech acquiring firms and among the resulting transactions, I ensure that no acquirer comes from the financial sector. Financial acquirers typically differ greatly from strategic ones in terms of deal motivation. Excluding financial firms is also common practice in M&A literature given these companies often have higher amounts of leverage that may be considered abnormal and signal distress for firms in non-financial industries.

When forming my sample, I also consider the deal attitude and form, but ultimately do not apply further constraints. In the process of filtering for prior criteria, I eliminate hostile deals and those with post-announcement reception changes (i.e., friendly to hostile or hostile to friendly) and types of transactions beyond the standard merger.

After filtering, I obtain a sample of 110 deals. I download most information regarding my variables of interest from SDC. Among the available SDC data, however, there are instances in which I am unable to locate a variable of interest or encounter significant missing values for a variable I find. In these cases, I attempt to supplement existing data with information from alternative sources. Nevertheless, I ultimately remove any transactions that present data constraints and/or present challenges for the calculation of my dependent variable. I discuss all of these decisions in greater detail when outlining my variables of interest.

Overview of Dependent Variable:

To measure a deal's post-merger innovation outcome, I calculate the merged firm's R&D intensity defined as its R&D expenditure divided by its total assets. Rather than use R&D expenditure directly, I follow existing papers and adjust for firm size, which is measured differently among the literature. Both Hall (1987) and Blonigen & Taylor (2000) use R&D intensity to measure innovation and similarly normalize by assets. Haucap et al. (2019), however, define the metric as the ratio of R&D expenditure to total sales and Wu et al. (2022) divide R&D expenses by operating income. Nonetheless, I standardize using assets since both sales and income may be less stable for high-tech firms. I use fiscal year data from one year after the transaction is effective and completed. The computation for transaction *i's* R&D intensity is reiterated as

$$Post\ R\&D\ Intensity_{it} = \frac{R\&D\ Expenditure_{m(t+1)}}{Total\ Assets_{m(t+1)}}$$

where *m* represents the merged entity and *t* is the year effective.

I consider other time frames but find that shorter ones are less meaningful since they may not allow sufficient time for integration to take place and longer ones increase the chance of events beyond the sample deal occurring that could explain innovation output. One such event is further M&A activity which also presents limitations in accessing financial data for the merged company. I discuss this more below. Furthermore, the literature indicates that one year may be sufficient for integration. Dinneen et al. (2021) suggest 12-month waiting period before evaluating a deal's success to give the combined company adequate time to undergo integration. I acknowledge, however, that the integration process differs across deals and therefore, depending on the merging companies involved, one year may not be enough time for knowledge transfer to take place. Moreover, I assess innovation using fiscal year data because it is publicly available, but this presents another limitation related to timing. Fiscal year-ends vary depending on the company, and therefore, my dependent variable inputs do not necessarily reflect the innovation outcome exactly one year after deal completion. There seems to exist a tradeoff between selecting a shorter versus longer time frame and this problem is not uncommon among research examining post-merger results. In fact, a similar dilemma arises when determining how long is needed before the abnormal returns of a merger can be assessed (Dinneen et al., 2021).

I further discuss the strengths and weaknesses of my selected innovation proxy. Given innovative activity may assume many forms, no universal group of innovation metrics has emerged and as a result, more than one way of gauging innovation exists. I select an R&D-based measure because R&D expenditure data offers a reliable metric for comparison across ventures and industries. It is also publicly accessible via company filings and easily interpreted. Notwithstanding these advantages, the common concern regarding R&D expenditure is that not all R&D activity necessarily results in intended innovation output. A firm may spend on a project that is ultimately unsuccessful, which would mean that R&D expenditure reflects unproductive investment (Entezarkheir & Moshiri, 2018).

Despite these flaws, the most common alternatives are patent-based, and while these may be more suitable than R&D metrics in some areas, they also come with drawbacks. For instance, patent counts do not necessarily capture the value of a firm's patents or knowledge base (Entezarkheir & Moshiri, 2018). In response to this criticism, a more sophisticated patent count that considers the number of citations associated with a patent has emerged, but even this may fall short. Beneish et al. (2021) establish the importance of considering unpatented technology, which is unaccounted for in the citation-weighted patent measure.

Refinitiv's M&A database provides the best access to my dependent variable inputs. Therefore, I merge my SDC dataset with data on total assets and R&D expenditure for the fiscal year after deal completion downloaded from Refinitiv. Among the 110 deals, 49 are subject to missing values for at least one of the two variables needed to calculate my innovation proxy. Using company filings, I fill in all absent data for 26 of the 49 affected observations. The remaining 23 transactions are omitted because they either fail to publicly list out R&D expenses or represent a special case that renders my innovation proxy less meaningful. This special case arises when additional M&A activity occurs within one year after completion of the sample deal. These subsequent transactions do not allow for the collection of financial data on the combined entity from the sample deal, which is an input to my dependent variable. This highlights the previously mentioned timing-related flaw with my innovation proxy. For instance, in May 2016, Brocade Communication Systems acquired Rukus, but shortly afterward, in November 2017, Broadcom acquired Brocade (Saran & Iburg, 2016). I am therefore unable to gather 2017 data on Brocade after acquiring Rukus but before being acquired by Broadcom. In eliminating such cases from my dataset, I recognize this may bias my sample as firms involved in frequent M&A likely share characteristics that affect innovative activity. Similarly, I introduce bias when omitting transactions involving firms that lack public R&D figures.

Removal is far more prevalent than other approaches to handling missing data in the relevant literature. Nevertheless, the added bias associated with listwise deletion merits a consideration of alternative approaches. Therefore, I consider replacing missing values with imputed averages, or medians in the case of skewed data, but ultimately conclude that this is not an appropriate substitute. Assigning the same level of post-merger innovation to affected observations would likely result in an underestimate of standard errors, a problem that seems no better than the added bias from discarding.

Overview of Independent Variables:

My explanatory variables are selected according to my four hypotheses. They include the size of the target firm relative to that of the acquirer, a measure of competitiveness of the target firm's industry, an indicator for industry similarity between the target and acquirer, and indicators related to the age of the target and acquirer at the time of the transaction.

I define relative target size as the ratio of total target assets to total acquirer assets for the fiscal year prior to deal announcement. Data on target size comes from SDC and I find acquirer size via Refinitiv. Since the distribution of relative target size shows significant right skew, I use a logarithmic transformation to produce a measure that is more approximately normal. I examine relative rather than absolute size because it may be more indicative of integration potential between the two deal partners. Considering target size in isolation ignores the fact that the acquiring firm must properly utilize the resources of the target for them to matter. The acquirer's absorption ability may be reflected in whether it is roughly equal or different in size from the target. Literature on M&A performance has established that relative size matters for deal success, defined as deal completion or higher abnormal returns. For this reason, considering relative size is not uncommon among M&A-focused papers.

I use S&P Global's Capital IQ to locate data for my target industry competition metric because it allows me to view the number of companies listed in an industry as of a custom time rather than the present date. It also provides an industry mapping file that facilitates the conversion of SIC codes to industry categories specific to Capital IQ. Based on the file, I match the target firm's SIC code listed in the SDC data to its equivalent Capital IQ industry code. I am able to generate a list of the constituents in that particular industry as of the deal's year effective.

A more precise indicator of market competition is the Herfindahl–Hirschman index, a commonly accepted metric used by the U.S. Department of Justice in assessing antitrust cases. For any given industry, the index is computed by squaring each market participant's percentage market share and then finding the sum of the squares. I face data constraints in trying to generate the HHI for the firms in my sample given the lack of accessible market share data. I attempt to perform market share calculations for each company in a particular SIC industry by dividing its total revenue before deal announcement by the total industry revenue. This becomes less feasible given many industries represented in my sample have significant missing values for revenue. Therefore, I settle for the number of market players per industry.

I assume that industries with more market players face greater competition and those with fewer companies face less competition. One limitation is that this fails to account for the nature of the product being sold in each industry. For instance, two industries may both have a high number of constituents, but if the first offers greater opportunity for product differentiation, it is likely less competitive. Nevertheless, the number of companies per industry may reflect the potential for product differentiation as those with less opportunity have higher barriers to entry. The more serious limitation is that the number of participants does not capture firm size.

I consider including a similar variable measuring industry competition for the acquirer as a control but decide against this. A substantial number of my deals involve target firms and acquirers from the same industry so adding separate metrics for the target firm and the acquirer results in multicollinearity.

I use information from the initial SDC deal data to code a binary variable that reflects firm relatedness in terms of industry. The measure indicates whether a transaction involves a target and an acquirer that operate in the same macro industry.[1] I use macro industries generated by SDC rather than SIC industries to allow for a broader definition of firm similarity.

Finally, to calculate firm age at the time of the merger, I first locate the year each included target and acquirer was founded. While SDC offers information on a company's founding, I encounter constraints in accessing its year founded variable. Therefore, I use Pitchbook to lookup year founded and address any missing cases by searching the company profile included on given firm's website. To compute a firm's age, I subtract its year founded from the year effective that corresponds to the deal in which it is involved.

When plotting my dependent variable against acquirer age, I find clustering at the tail ends of the graph rather than a linear relationship. The link between my response variable and the target age is similarly not linear. Therefore, I dichotomize age into "young" and "old" categories and determine the age thresholds a priori to limit bias. In converting a continuous numerical metric to a categorical one, I lose information, but the use of categories suffices given I am more concerned with general trends. Fewer papers in this space consider the year of a company's founding and among the broader set of research that analyzes firm age, there is a lack of consensus on what is considered young versus old. This makes it challenging to select an appropriate threshold. Nevertheless, I consider target firms separately from acquiring firms and

[1] SDC may categorize a firm's primary business as high-tech but also assign it to a macro industry other than "High Technology." Therefore, there is some diversity in acquirer macro industry among my sample, which means a value of 1 for the same industry indicator does not necessarily imply both firms belong to "High Technology."

base my selections on contextual information and the literature most relevant to my work, respectively. I define a young target as one below the age of 20 and a young acquirer as one below the age of 40. For easier interpretation, I code the variables based on my hypotheses, setting the young target indicator to one when firm age is less than 20 and the old acquirer indicator to one when firm age is greater than or equal to 40. While a startup is often considered less than 5 or 10 years of age, I attempt to include firms founded during or after the late 1990s dot-com bubble in the young category. Both Huergo & Jaumandreu (2004) and Cucculelli (2017) study innovation in relation to firm age and use 40 years to define a mature firm. This is also well above the current average lifespan for a U.S.-based company, which according to most estimates, is just under 20 years (Garelli, 2016).

Overview of Controls:

I include four control variables in my model. These comprise numerical variables representing deal size and target firm profitability and indicator variables for year effective and source of funds. All are obtained from SDC, although I draw from additional sources to fill in missing value for source of funds. To measure deal size, I take the natural logarithm of the transaction value. The distribution of transaction value exhibits significant right skew, so I use a logarithmic transformation to generate a metric that is more approximately normal. A substantial number of target firms in my sample are technology companies. There is a natural tendency to prioritize growth over profitability in the technology industry, which makes gauging profitability for firms in my sample particularly challenging. No metric is without drawbacks, but EBITDA margin is a common choice given EBITDA eliminates business-specific factors and allows for comparison among companies from different industries. Therefore, I measure target profitability using the firm's EBITDA margin, which shows significant left skew. The presence of negative observations does not allow for a basic logarithmic transformation, so I attempt to add a constant to EBITDA margin and take the natural logarithm of the result. This did not substantially alter the distribution, so I revert to the original values. There are three target companies in my sample that were not generating revenue prior to deal announcement. To these, I assign the median EBITDA margin of the revenue-generating targets and impute the median rather than the mean given the skewed data. To account for time effects, I add a variable that indicates the number of years since 2008 the deal was effective and completed. I select 2008 as the benchmark given its significance as the year of the last financial crisis. For 45 of my observations, SDC provides details on deal funding which I use to code my payment method variable. I handle the remaining cases by gathering information from tender offer statements via SEC Edgar. The variable is a binary measure that assumes a value of 1 if the deal was primarily financed with cash and 0 if the deal was primarily financed with equity or a combination of the two.

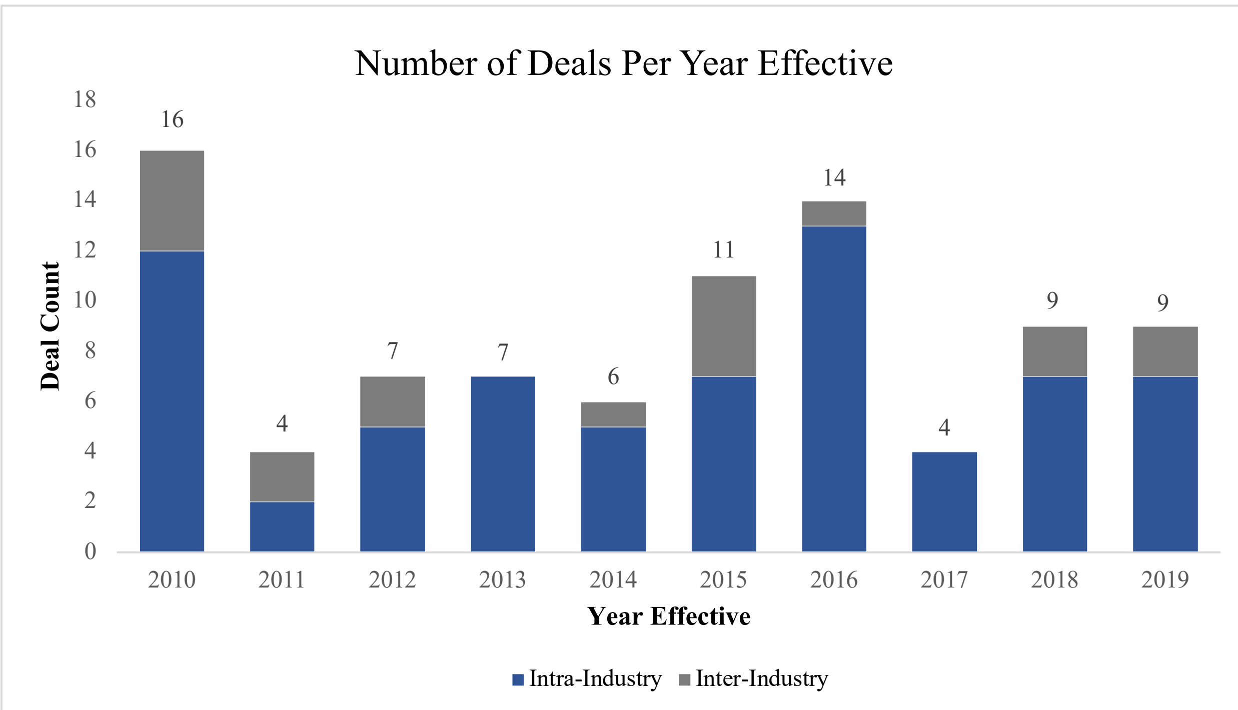
Table II. Variable Definitions

Variable	Description & Calculation	Data Source	Additional Handling
Dependent Variable			
Post-Merger R&D Intensity	Ratio of combined company R&D expenditure to its total assets as of fiscal year following year effective	SDC Platinum, Refinitiv, SEC Edgar (10K Reports)	Computation
Independent Variables			
Log Relative Target Size	Natural logarithm of the ratio of target firm total assets to acquiring firm total assets as of fiscal year prior to announcement	SDC Platinum, Refinitiv, SEC Edgar (10K Reports)	Computation
Target Industry Competition	Number of market players listed in target firm's SIC industry as of year effective	S&P Global's Capital IQ	N/A
Same Industry	Binary measure of whether the target firm and the acquiring firm operate in the same SDC-defined macro industry (1)	SDC Platinum	Coding
Young Target	Binary measure indicating whether the target firm is less than 20 years old (1) where firm age is the difference between the time of deal completion and the time of the target firm's founding	Pitchbook, Company Websites	Computation, coding
Old Acquirer	Binary measure indicating whether the acquiring firm's age is greater than or equal to 50 years (1) where firm age is the difference between the time of deal completion and the time of the target firm's founding	Pitchbook, Company Websites	Computation, coding
Controls			
Log Transaction Value	Natural logarithm of the transaction value	SDC Platinum	Computation
Target Profitability	Target firm EBITDA margin: Ratio of target firm EBITDA to target firm total sales as of one fiscal year prior to deal announcement	SDC Platinum	Computation
Years Since 2008	Difference between the year the deal was effective and completed and the year of the financial crisis	SDC Platinum	Computation
Paid in Cash	Binary measure indicating whether the transaction payment method is cash only (1)	SDC Platinum, SEC Edgar (Tender Offer Statements)	Coding

Sample Description:

My final sample includes 87 deals. The average transaction value is $2,814 million, while the median is $1,016 million. The majority of deals are paid for with cash only, although about 20 percent are financed with purely equity or a combination of the two.

Figure I. Deal Count Over Time Horizon

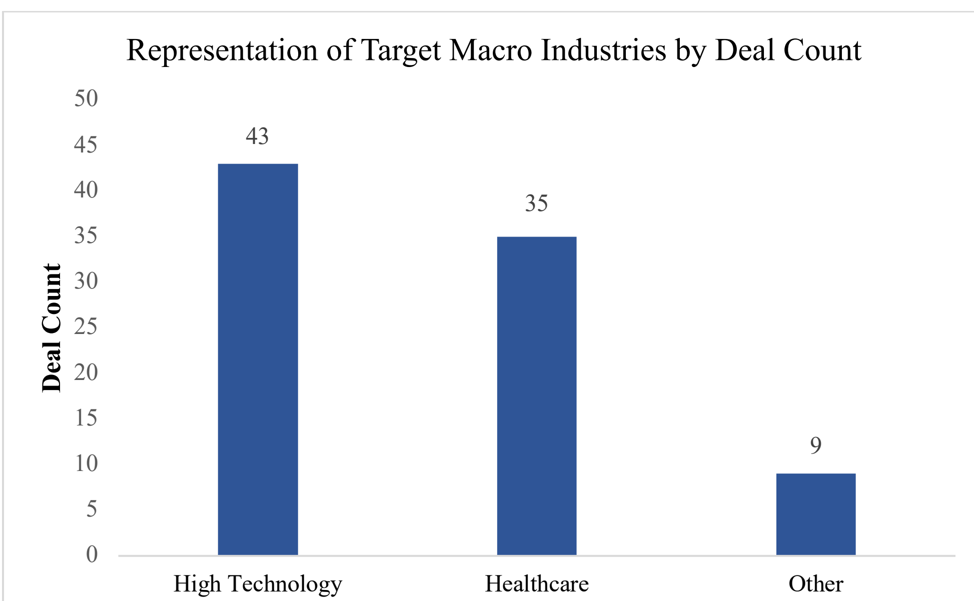


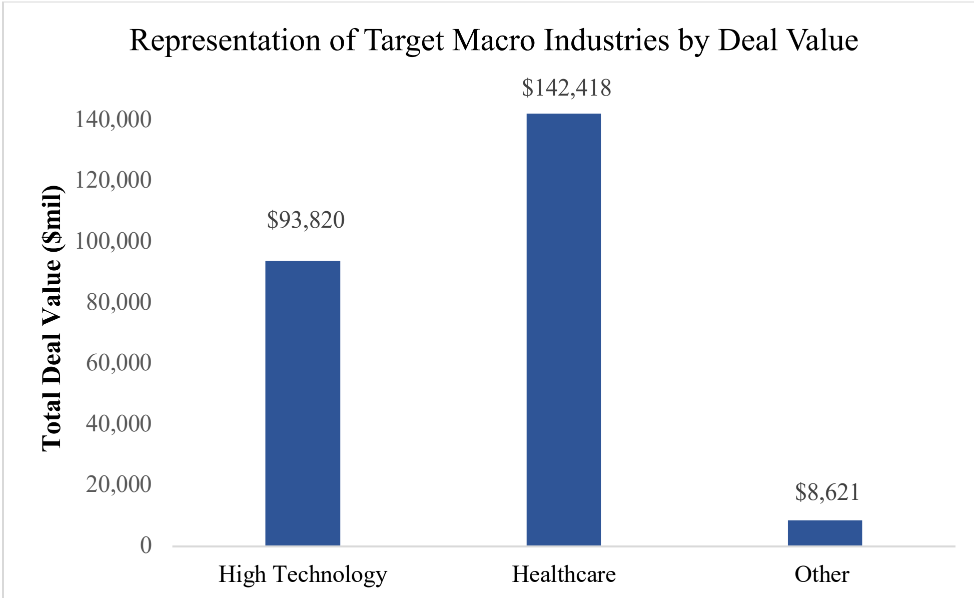
As shown in the above figure, for each year effective represented in my time horizon, there are at least four deals, although the most occur in 2010.

In a substantial number of deals, the target and acquirer demonstrate relatedness. About 79 percent of observations, or 69 deals exactly, involve a target and acquiring firm that operate in the same SDC-defined macro industry and about 25 percent, or 22 deals exactly, involve firms that operate in the same state. The macro industries with the greatest representation among the inter-industry deals are “High Technology” and “Healthcare.” Almost all the inter-state deals are also inter-industry with only two transactions having a target and acquirer that operate in the same state but different industries. Furthermore, most inter-industry mergers occur in California which makes sense given my industry focus.

In my dataset, there are 87 distinct target firms and 71 distinct acquirers represented. The average firm age for target companies is 20 years whereas the average firm age for acquirers is 54 years, but a wide range exists. The youngest target is Facet Biotech Corporation at two years old and the oldest is Beckman Coulter Inc. at 76 years old. The gap for acquirers is wider with the youngest acquirer being Fortive Corporation which has an age of one year and the oldest being Pfizer Inc. which has an age of 171 years. I identify 11 acquiring firms that are involved in more than one transaction in my sample. Among these repeat acquirers, the average number of sample deals per acquirer is 2.8 while the median number of sample deals per acquirer is two. The repeat acquirers are, on average, older and belong to more competitive industries in terms of the number of participants.

Figures II & III. Target Firm Industry Representation

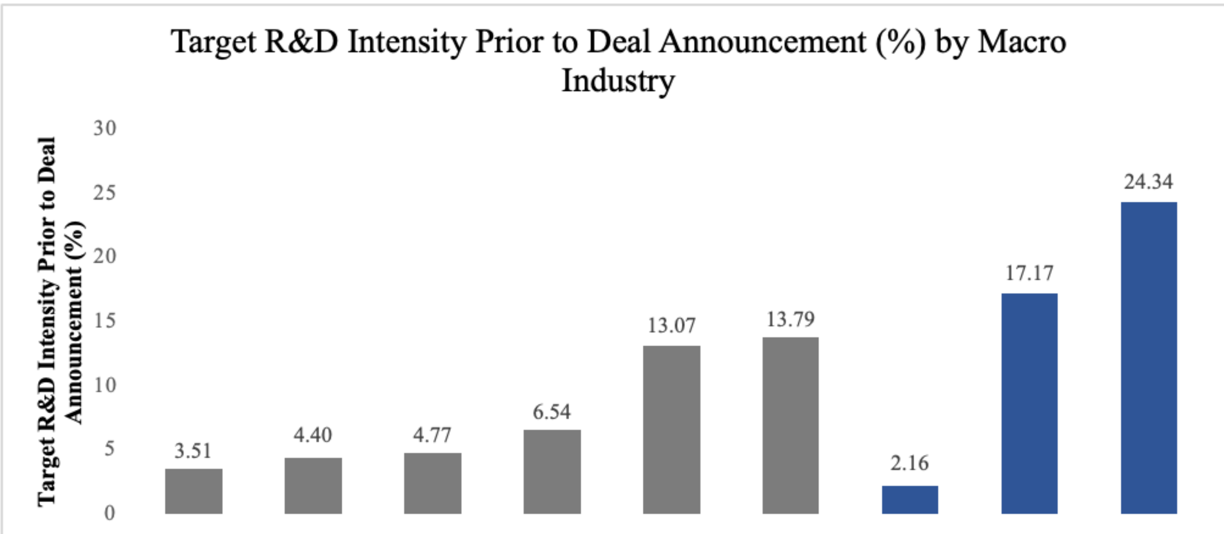




The figures above demonstrate the breakdown of target macro industries represented in my dataset. The first measures representation by number of deals in an industry and the second uses total transaction value of the deals in an industry. Some of the macro industries included in the "Other" category are Industrials and Consumer Products and Services. I also consider a more specific industry categorization designated by SIC code. There are 22 distinct SIC codes represented among target firms, with the most common being Prepackaged Software, Pharmaceutical Preparations, and Semiconductors and Related Equipment with 19, 18, and 12 transactions respectively. Other frequent industries are Biological Products (8), Computer Integrated Systems Design (3), and Computer Storage Devices (3).

While all acquiring firms operate in high-tech industries, interestingly, more SIC codes are represented among acquirers than targets. Out of the 25 total, the most common acquirer SIC industries mirror those of the target firms. They are Pharmaceutical Preparations, Prepackaged Software, and Semiconductors and Related Equipment with 26, 19, and 9 transactions respectively. Other common acquirer industries include Surgical and Medical Instruments and Apparatus (7), Biological Products (3), and Industrial Instruments for Measurement, Display, and Control of Process Variables (3). There is some diversity in both the target and acquirer location with the inclusion of 18 U.S. states plus the District of Columbia for each.

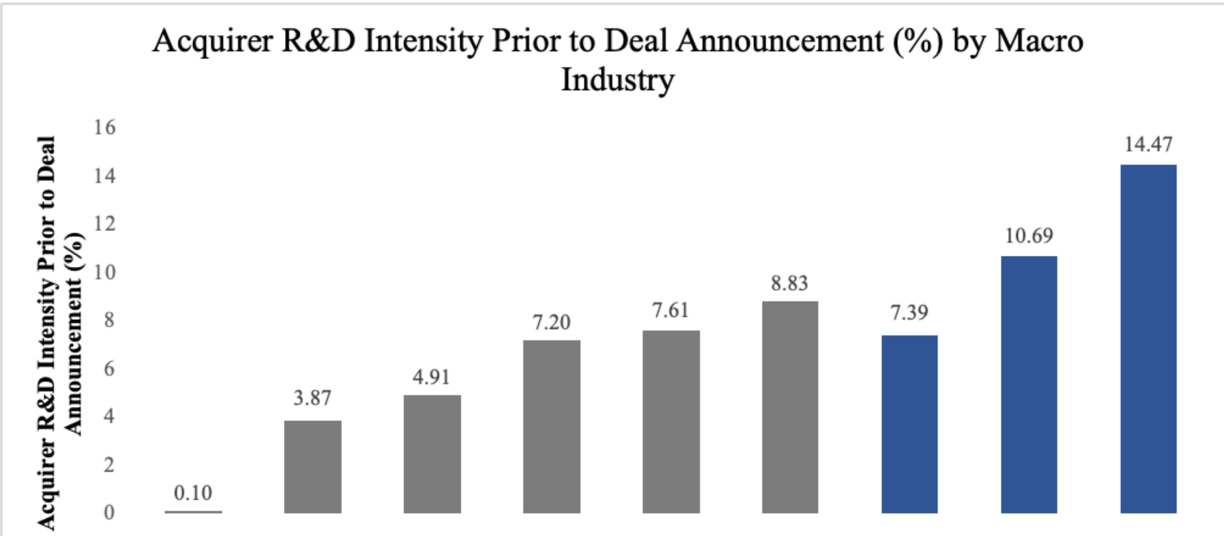
Figure IV & Table III. Pre-Merger Target R&D Intensity



Note: See following figure for horizontal axis labels.

Macro Industry	Target R&D Intensity Prior to Deal Announcement (%)
Inter-industry (Gray)	
Consumer Products and Services	3.51
Media and Entertainment	4.40
Industrials	4.77
Telecommunications	6.54
Healthcare	13.07
High Technology	13.79
Inter-industry Average	7.68
Intra-industry (Blue)	
Industrials	2.16
High Technology	17.17
Healthcare	24.34
Intra-industry Average	14.56
Overall Average	9.97

Figure V & Table IV. Pre-Merger Acquirer R&D Intensity



Note: See following figure for horizontal axis labels.

Macro Industry	Acquirer R&D Intensity Prior to Deal Announcement (%)
Inter-industry (Gray)	
Media and Entertainment	0.10
Healthcare	3.87
Industrials	4.91
Telecommunications	7.20
Consumer Products and Services	7.61
High Technology	8.83
Inter-industry Average	5.42
Intra-industry (Blue)	
Industrials	7.39
Healthcare	10.69
High Technology	14.47
Intra-industry Average	10.85
Overall Average	7.23

The figures above display the R&D intensity of targets and acquirers for the fiscal year preceding the year of deal completion. It is notable that the average pre-merger R&D intensity for target firms is higher than that for acquiring firms. This result also holds when comparing inter-industry and intra-industry deals and when considering most macro industry categories. For instance, target firms in the "High Technology" macro industry have a mean pre-merger R&D intensity above that of acquirers assigned to "High Technology" in both the inter-industry and intra-industry categories. Furthermore, pre-merger R&D intensity appears to be highest in the "High Technology" and "Healthcare" macro industries. Together, these observations may suggest that target firms acquired in high-tech deals offer innovative potential. In fact, in 60 out of the 87 sample deals, pre-merger R&D intensity for the target is higher than that for the acquirer.

Table V. Descriptive Statistics

Variable	Mean	Median	Standard Deviation	Minimum	Maximum	Skewness
Dependent Variable						
Post R&D Intensity	0.0788	0.0627	0.0655	0.0005	0.4188	2.59
Independent Variables						
Relative Target Size	0.3165	0.0365	1.2723	0.0001	11.5569	8.26
Log Relative Target Size	-3.23	-3.31	2.16	-9.41	2.45	-0.16
Target Industry Competition	545.67	635.00	367.25	3.00	1,201.00	-0.17
Same Industry	0.79	1.00	0.41	0.00	1.00	-1.47
Target Age	20.36	17.00	13.00	2.00	76.00	1.97
Young Target	0.60	1.00	0.49	0.00	1.00	-0.41
Acquirer Age	54.20	33.00	47.83	1.00	171.00	1.19
Old Acquirer	0.40	0.00	0.49	0.00	1.00	0.41
Controls						
Transaction Value ($mil)	2,814.46	1,016.11	4,187.92	14.08	20,773.97	2.31
Log Transaction Value ($mil)	6.84	6.92	1.69	2.64	9.94	-0.33
Target Profitability	-4.81	0.02	28.01	-251.82	2.66	-8.25
Years Since 2008	6.40	7.00	3.02	2.00	11.00	-0.09
Paid in Cash	0.80	1.00	0.40	0.00	1.00	-1.56

Univariate Analysis:

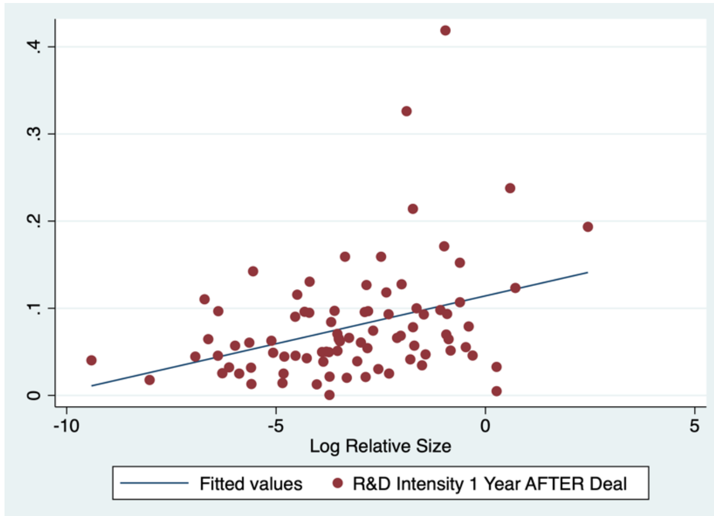
To further explore the data, I generate visuals to depict the relationship between my response variable, post-merger R&D intensity, and each of my predictor variables. I use scatter plots when analyzing continuous numerical variables and bar charts when analyzing binary ones. I briefly discuss any initial patterns and how they relate to my hypotheses outlined in section III.

Table VI. Predicted Effects of Independent Variables

Independent Variable	Predicted Effect	Relevant Hypothesis
Log Relative Target Size	(+) Greater relative size leads to higher post-merger R&D intensity	H_1: Mergers involving a larger target relative to the size of the acquirer result in greater post-deal R&D intensity.
Target Industry Competition	(-) Greater relative size leads to lower post-merger R&D intensity	H_2: Transactions involving a target from a competitive industry lead to less post-deal R&D intensity.
Same Industry	(-) Greater relative size leads to lower post-merger R&D intensity	H_3: Transactions involving an acquirer and target from the same industry result in less post-deal R&D intensity.
Young Target	(-) Greater relative size leads to lower post-merger R&D intensity	H_{4a}: Deals with younger target firms trigger decreased post-deal R&D intensity.
Old Acquirer	(-) Greater relative size leads to lower post-merger R&D intensity	H_{4b}: Deals with older acquiring firms lead to less post-deal R&D intensity.

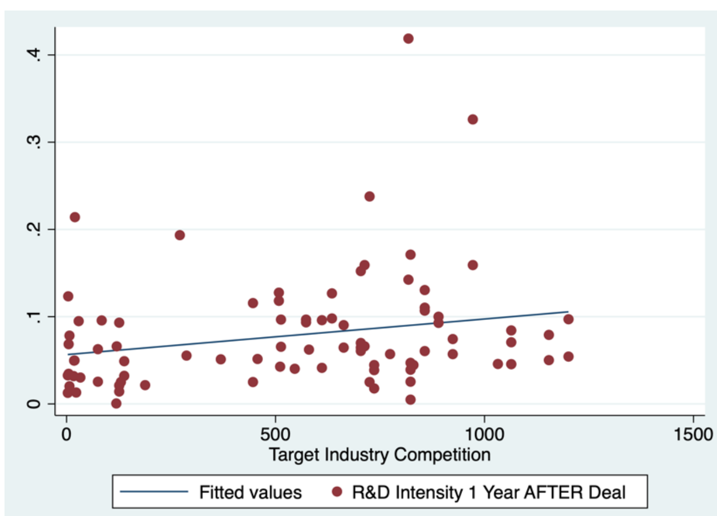
The table above simply restates the predicted effect and relevant hypothesis associated with each of my independent variables. I use this information to guide my analysis.

Figure VI. Post R&D Intensity vs. Log Relative Target Size



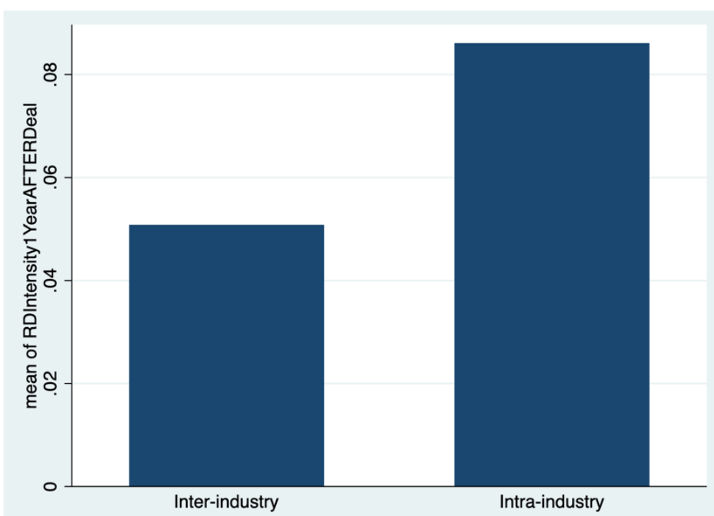
There appears to be a weak-moderate positive linear relationship between post-merger R&D intensity and target size relative to that of the acquiring firm. This aligns with my first hypothesis that the larger the relative size of the target firm, the greater the subsequent R&D intensity.

Figure VII. Post R&D Intensity vs. Target Industry Competition



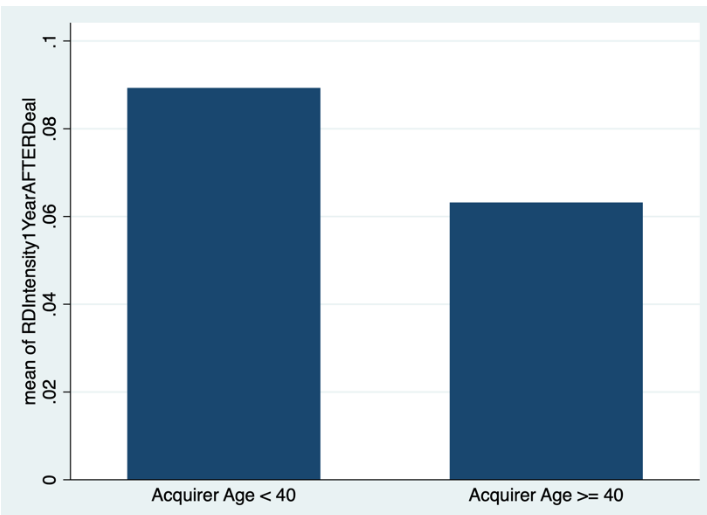
Post-merger R&D intensity and target industry competition exhibit a weak positive correlation. This is inconsistent with my hypothesized effect, which motivates me to consider whether the impact of target industry competition is dependent on another factor in my multivariable regression analysis. Nevertheless, rationales beyond that outlined in my second hypothesis are worth acknowledging and may explain a positive impact. In keeping with the entry-timing perspective, my second hypothesis proposes that an acquirer faced with more target options may ultimately be able to find a more suitable target, which would promote enhanced knowledge transfer. This may not be the case, however, as greater optionality could hinder the quality of an acquirer's decision. It is not hard to imagine how too many choices could lead to a more difficult evaluation process and therefore a worse target decision. A more general reason for a positive effect is that increased target competition may imply increased competition for the merged entity, adding pressure to pursue both external and internal sources of innovation to stay ahead.

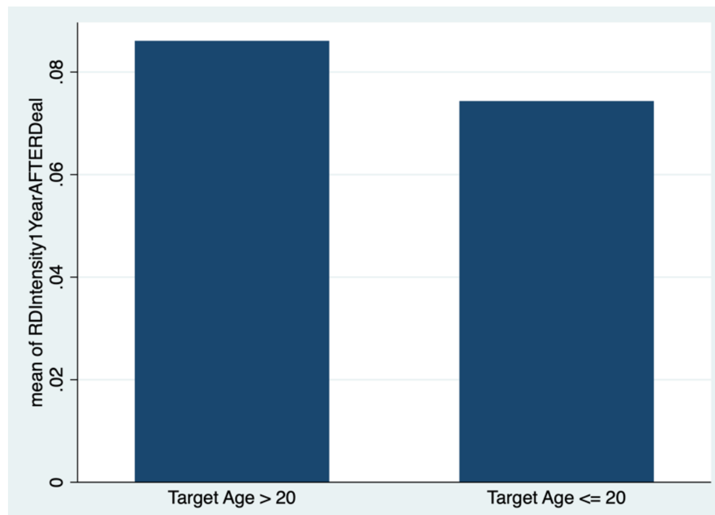
Figure VIII. Post R&D Intensity by Similarity



Average post-deal R&D intensity is higher for mergers involving similar firms in terms of industry. This also contradicts my hypothesis, and similarly motivates me to consider whether the impact of target and acquirer relatedness is dependent on other factors in my multivariate analysis. Like the case of target industry competition, however, explanations different from that described in my third hypothesis exist. Firm similarity could indicate that the target and acquirer have less diverse knowledge to exchange and absorb from each other, limiting the ability of the merger to serve as a sufficient source of external innovation (Ahuja & Katila, 2001).

Figures IX & X. Post R&D Intensity by Firm Age Category





As expected, both deals involving old acquiring firms and those with young target firms exhibit a lower mean post-merger R&D intensity, although the difference is slight in both cases.

V. Empirical Specification & Results

Multivariable Regression:

To investigate the impact of my predictors on post-merger R&D intensity, I employ multivariable OLS regression. I specify the complete linear regression model as the following:

$$
\begin{aligned}
\text{Post\_R\&D\_Intensity}_i = \; & \\
& \beta_0 + \beta_1 \text{Log\_Relative\_Target\_Size}_i \\
& + \beta_2 \text{Target\_Industry\_Competition}_i + \beta_3 \text{Same\_Industry}_i \\
& + \beta_4 \text{YoungTarget}_i + \beta_5 \text{Old\_Acquirer}_i \\
& + \beta_6 \text{Log\_Transaction\_Value}_i + \beta_7 \text{Target\_Profitability}_i \\
& + \beta_8 \text{Years\_Since\_2008}_i + \beta_9 \text{Paid\_In\_Cash}_i \\
& + \beta_{10} \text{Log\_Relative\_Target\_Size}_i * \text{Young\_Target}_i \\
& + \beta_{11} \text{Log\_Relative\_Target\_Size}_i * \text{Old\_Acquirer}_i \\
& + \beta_{12} \text{Log\_Relative\_Target\_Size}_i * \text{Same\_Industry}_i \\
& + \beta_{13} \text{Target\_Industry\_Competition}_i * \text{Same\_Industry}_i \\
& + \beta_{14} \text{Same\_Industry}_i * \text{Log\_Relative\_Target\_Size}_i + \varepsilon_i
\end{aligned}
$$

As mentioned in my univariate analysis, I suspect that some of my predictor effects may depend on others. For instance, the impact of relative target size may depend on firm age. Based on my first and fourth hypotheses, I anticipate that the presence of a young target and/or an old acquirer would dampen the predicted positive effect of relative size on post-deal R&D intensity. That is, a more innovative target and an older, more experienced acquirer would each lessen the knowledge absorption challenges associated with a relatively larger-sized target firm. I add interaction terms between relative size and each of my age indicators accordingly.

Furthermore, whether the target and acquirer operate in the same industry may affect the impact of relative target size and that of target industry competition on the response variable. As described in section III, industry overlap may imply technological relatedness between the target and acquirer. This may facilitate knowledge absorption and reduce the magnitude of the expected positive impact of relative target size. It's questionable, however, how industry similarity may interact with target industry competition. Drawing from my second and third hypotheses, it could be concluded that the anticipated negative impact of target industry competition would amplify in an intra-industry setting. However, an alternative rationale exists that might explain a different effect. An intra-industry deal implies that industry competition is equal for the target and the acquirer. Therefore, when considering this interaction, I may assess the impact of acquirer industry competition on post-merger R&D intensity. This effect could be positive given an acquirer may find benefit in pursuing both external and internal sources of innovation to outperform in a competitive space. These considerations motivate the addition of two more interaction terms, one between industry relatedness and relative target size, and the other between industry relatedness and target industry competition.

Beyond my economic reasoning, more objective findings also support the inclusion of these interactions. Between each interaction term's pair of predictors, there is moderate correlation. Moreover, the model including interactions compared to that without demonstrates better fit in terms of a higher R-squared value formally supported by results from an F-test for overall significance. The model containing interactions has an R-squared of 0.386 and an F-statistic of 3.70 with a corresponding p-value of 0.0002 while the model excluding interactions has an R-squared of 0.281 and an F-statistic of 4.02 with a corresponding p-value of 0.0003. Given both exhibit significant F-statistics, I can conclude each model has an R-squared value different from zero. Although seemingly low, both R-squared values fall in line with those typical of this research domain, and therefore indicate explanatory power. Nevertheless, the model with interactions demonstrates better fit given it has a considerably higher R-squared value.

Table VII. OLS Regression Output

Variable	Post R&D Intensity
Log Relative Target Size	0.01559***
	(0.00465)
Target Industry Competition	-0.00003
	(0.00002)
Same Industry	0.06018*
	(0.03358)
Young Target	-0.06477*
	(0.03515)
Old Acquirer	-0.04076**
	(0.02006)
Log Relative Target Size * Young Target	-0.01727**
	(0.00838)
Log Relative Target Size * Old Acquirer	-0.01346***
	(0.00452)
Same Industry * Log Relative Target Size	0.01837**
	(0.00893)
Same Industry * Target Industry Competition	0.00007*
	(0.00003)
Log Transaction Value ($mil)	-0.00278
	(0.00361)
Target Profitability	-0.00008
	(0.00011)
Years Since 2008	0.00487**
	(0.00242)
Paid in Cash	0.01713
	(0.02412)
Constant	0.08101**
	(0.04020)
Observations	87
R-squared	0.3862

Robust standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1

The table above outlines my regression results. I note that because I transformed the variables for relative target size and value of transaction into natural logarithm form, for interpretive purposes, I divide their regression coefficients by 100 along with the coefficients of the three interaction terms including relative target size. The reduced coefficients describe how a one percent increase in the given predictor impacts post-merger R&D intensity. My hypotheses specify predictions for main effects in isolation, which may become less feasible to interpret after adding interaction terms. Interactions imply that the effect of an independent variable on the response variable will depend on the values of another predictor. In some cases, even the sign of the main effect may depend on the other factor, but otherwise the sign may be identified. I check to see if this is the case for my predictors.

I generate an interaction plot for each interaction term to determine if any main effects are meaningful. Since all included interactions are between a continuous and binary independent variable, the graphs assume a similar form. The y-axis represents the fitted values of the dependent variable, and the x-axis represents values for the continuous predictor. Two lines are displayed that each correspond to a possible value of the binary predictor. Based on the plots, none of the main effects appear to be meaningful given that each graph contains intersecting lines. The presence of intersection implies that when considering an interaction, the mean post-merger R&D intensity is not consistently higher or lower for one binary category compared to the other. This also makes the sign of the main effects for the binary indicators present in my interactions inconclusive. Despite this result, I comment on trends that may point to the sign of the main effects for my continuous interacted variables.

All interaction plots involving relative target size indicate that it is positively correlated with post-merger R&D intensity regardless of the value of the factor with which it interacts. This may suggest a positive main effect of relative target size on my response variable, which would support my first hypothesis that greater relative size leads to higher post-deal R&D intensity.

This builds on the findings of Ahuja & Katila (2001) and Cloodt et al. (2006) who also examine the impact of relative target size on innovation outcomes. They find that an increase in this measure decreases post-merger innovation performance. This does not necessarily contradict my result, however, since I operationalize both relative target size and innovation differently, enough so to affect the interpretations. Rather than total assets, Ahuja & Katila (2001) and Cloodt et al. (2006) use patent count to represent size and instead of R&D intensity, they use the number of successful patents as their innovation proxy. Given a larger target relative to acquirer size, the process of knowledge transfer may be more difficult. It is possible this leads to a reduced number of successful patents and an increase in R&D intensity, potentially because at least in the beginning, the target is a less sufficient source of external innovation.

I am unable to conclude as much regarding my remaining hypotheses. I analyze the plot for the interaction between target industry competition and industry similarity and find positive association between competition and my response variable for the intra-industry category and a similar level of negative association for the inter-industry category. Therefore, the overall sign of the main effect for target industry competition in the presence of interactions is ambiguous. As noted above, the directions of the main effects for the binary indicators are also unclear, leaving my third and fourth hypotheses unsupported. Beyond main effects, however, it is notable that under one or more significance levels, all included interaction terms may be considered statistically significant. Therefore, I proceed to highlight insights gained from the interactions themselves.

I find support for the impact of relative target size being dependent on firm age. The interactions between relative target size and each of the firm age indicators are both negative. This indicates that an increase in relative target size would decrease the value of the effect of both age indicators on the response variable. That is, the association of target age with R&D intensity and the association of acquirer age with R&D intensity would decrease. The reverse also holds. If either age indicator were to increase from zero to one, the significance effect of relative target size would drop. This implies that the joint impact of relative target size and firm age is less than their totaled individual effects.

The two remaining interaction terms have positive coefficients and therefore demonstrate the opposing relationship. The impact of relative target size is dependent on whether a deal is intra-industry and an increase in the former would increase the value of the effect of the latter. The same is concluded for target industry competition and industry relatedness. This is supported by a widening difference in post-merger R&D intensity between inter-industry deals and intra-industry deals as target industry competition increases. In both cases, the collective effect of the interacted variables is greater than their summed separate effects. These positive interactions suggest that industry relatedness matters more in terms of innovation output in settings involving a large target relative to acquirer size and those with high target industry competition.

Further Considerations:

I check whether my model exhibits heteroskedasticity by performing a Breusch-Pagan test and White test. The former indicates the presence of heteroskedasticity while the latter does not. I follow up by plotting the residuals against fitted values which does not assume the classic cone shape, but nevertheless supports the presence of heteroskedasticity. To adjust for the underestimated variance, I run both regressions using STATA's "vce(robust)" option to allow for robust standard errors.

Despite including several variables common among the literature, my set of controls is in no way comprehensive. Moreover, data availability constrains the addition of certain desired control variables. For instance, I would ideally control for whether a merger is horizontal or vertical, but there is no easily accessible public data on this. Rather, I would need to examine qualitative information on deal rationale for each transaction and code the merger type case-by-case. Furthermore, there are several details on a firms' internal functioning that are kept private and reasonably so given the potential mimicry by rivals. As an example, it may be worthy to control for the number of employees assigned to supporting the post-merger integration process. This factor may affect the trajectory of integration and therefore the ability for knowledge transfer, thereby influencing subsequent innovation outcomes. These data limitations contribute to the lack of an all-inclusive list of controls. This ultimately brings about the possibility of omitted-variable bias.

As previously discussed in the literature review, the relationship between mergers and innovation may be bi-directional. Given the potential for innovation to affect the propensity to merge, it is likely that innovation also impacts features of deals, such as the size, similarity, and experience of target and acquiring firms. This makes it likely that my model is subject to unobserved endogeneity, which would imply biased and inconsistent estimates. As a result, I consider running a two-stage least-squares regression, but given the lack of an appropriate instrumental variable, ultimately decide against this. I am unable to identify a measure that would relate to aspects of the merger but lack correlation with post-merger R&D intensity. Nevertheless, a few existing papers examine the impact of mergers on innovation output and do an instrumental variable, but I argue that in many cases, the selected instrument is inappropriate for the context of my study. I explain further by evaluating the most common instrument.

Entezarkheir & Moshiri (2017) study the impact of merger activity on innovation measured by patent count and to control for unobserved heterogeneity, they use the acquirer's prior merger activity as an instrumental variable. They look for previous activity anywhere from two to beyond five years before the year of deal completion. Effective use of this instrument relies on the assumption that an acquirer's previous M&A activity is unrelated to its current patent-based innovation output, but I suspect this may not hold in the high-tech setting. Given the nature of the space, innovation synergies may be a more frequent motivation for M&A among high-tech firms. In this case, if deals take longer in terms of knowledge absorption, then a prior transaction may still impact the present innovation outcome. Therefore, this instrument may violate the exclusion restriction as there is likely to be at least some relationship between prior merger activity and current innovation.

Haucap et al. (2019) acknowledge the lack of reliable instruments and employ a propensity score matching method to account for endogeneity, which is a prevalent approach used in the existing literature. Using nearest neighbor matching, Haucap et al. (2019) form a control group of non-merging firms with similar pre-deal attributes and innovative activity levels to those in their treatment group containing merging firms. This allows them to estimate the counterfactual case of innovation in the absence of M&A. Despite this potential workaround to the instrumental variable limitations, I do not pursue this approach. Since matching methods typically result in sample attrition, my sample size may be considered too small to gain meaningful insight using propensity score matching.

VI. Conclusion

In this study, I contribute to research on the relationship between mergers and innovation, an area of limited empirical work. Using a sample of 87 recent public-to-public transactions among U.S.-based firms in the high-tech setting, I investigate specific features of mergers that may impact R&D-based innovation outcomes. I find support for a potential positive impact of relative target size on post-merger R&D intensity and significant interaction effects between relative target size and firm age, relative target size and industry relatedness, and target industry competition and industry relatedness. My results suggests that beyond the occurrence of a merger, specific deal characteristics may affect post-merger innovation outcomes. Despite the lack of more specific insight, few papers in this area have looked at target and acquirer features, and therefore my results may serve as a springboard for subsequent research.

My study has several limitations that motivate promising directions for future work. First, I restrict my analysis to a single geography and industry type which limits my sample size and generalization of my findings. Data permitting, it would be worthwhile to consider cross-border M&A. Accelerated globalization has led companies to look to new geographies for growth opportunities, such as acquiring foreign entities to promote brand awareness and reach new markets and customers. However, beyond typical motivations, existing papers have found support for cross-border M&A activity playing an important role in corporate innovation strategy (Liu and Zou, 2008). Therefore, it would be valuable to extend my work to the cross-border context. Furthermore, although the high-tech space suits the topic of post-merger innovation outcomes, widening the industry scope would allow for greater analysis of industry-specific effects. Besides industry competition, my research was limited to firm characteristics. The inclusion of more diverse industries would allow for more insight into both industry competition and other industry features. Another possible extension involves the inclusion of one or more innovation proxies besides R&D intensity. This would be more challenging in terms of data collection but given the seemingly unbounded nature of innovation, the use of one metric is limiting. Including a patent-based metric may be meaningful given it may be more indicative of innovation output rather than input and that high-tech patenting has been experiencing rapid growth lately. Finally, future work should consider how to better address the possible presence of endogeneity. I admit my failure to address the fact that a firm's innovative activity may influence not only the propensity to merge, but also features of the deal, such as the size and the age of the firms involved, is not an insignificant matter. Future studies that expand the sample scope may have better success utilizing a matching method to control for unobserved endogeneity. Additionally, further thought may be given to possible instruments appropriate for the high-tech setting.

Obtaining a better understanding of how merger activity influences innovation outcomes may result in higher quality decision-making on antitrust matters. More specifically, knowing how deal factors, such as target and acquirer characteristics, shift innovative activity may indicate the types of transactions that best promote innovation. There is a long-standing debate over the economic impact of deregulation. Proponents argue it stimulates economic activity and leads to greater welfare while others claim the opposite citing limited competition that results in lower standards and higher prices. The effect of mergers on innovation may be central to this discussion. Deregulation often facilitates M&A activity and therefore understanding the impact on innovation may help antitrust authorities determine whether restricting or extending deregulation is socially optimal.

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