Three Essays in Empirical Corporate Finance

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Hamed Davari
Mannheim, Germany

Dean: Joachim Lutz
Referent: Prof. Ernst Maug, Ph.D.
Correferent: Prof. Dr. Erik Theissen

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Introduction

Firms engage in transactions to reorganize their activities and adapt to their dynamic environment. This dissertation focuses on spin-offs, carve-outs, mergers and acquisitions as major corporate transactions. In the first chapter, I ask how reorganization of a firm through two common divestiture methods, namely, spin-offs and carve-outs affect the incentives of its pool of knowledge workers. This is an important question, because on the one hand, innovation ensures sustainability of firms and also is crucial for the economic growth. On the other hand, inventors, in contrast to other employees, play a very essential role in innovation. Based on the theoretical literature in organizational economy, I build two main hypotheses regarding departure and productivity of the inventors who experience a spin-off or a carve-out. I conjecture that these inventors would enjoy the less hierarchical organizational structure of the spun-off or the carves-out firm, which provides them with more authority in choosing their own innovative activities. Hence, I expect these inventors to depart less and produce more innovative outputs. I employ a difference-in-differences methodology on a matched sample and provide support for these hypotheses. However, I document a very interesting behaviour from the inventors in response to a divestiture: even though they exhibit a lower innovation output in terms of number of filed patents (quantity) after the divestiture, they show a large and significant increase in patent citation, a measure for quality of innovation output.

The second chapter investigates the relationship between firms' inventor recruiting and technology acquisition decisions. I explore how firms' hiring of inventors with similar or new technological expertise affects their target selection in mergers and acquisitions. The findings reveal that firms hiring inventors with similar technological expertise tend to acquire technologically similar targets, while those hiring inventors with new technological expertise are more likely to acquire technologically distant targets. Furthermore, this study also sheds light on the channels through which these two decisions may be related. I provide strong support for the channel, in which firms assess the complementarity of new technologies with their existing technology portfolio by initially hiring inventors with the desired expertise and subsequently choosing targets similar to the inventors with the highest complementarity.

The third chapter focuses on the role of rivals in the merger review process and their lobbying activities on antitrust agencies' decisions. I examine the association between rivals' lobbying efforts and the likelihood of a merger being challenged, focusing on the lobbying activities and connections of rivals to politicians in judiciary committees of the House and Senate. The results support the hypothesis that lobbying activities of rivals who react positively to the merger announcement are negatively associated with the merger being challenged, while lobbying activities of rivals who react negatively to the merger announcement are positively associated with the merger being challenged. I further establish a causal link between rivals' lobbying activities and merger review outcomes by exploiting the unexpected departure of influential politicians from the judiciary committees of the House and Senate.

Chapter I

Inventor's Incentive and Authority

Abstract

New ideas that lead to innovation usually emerge in a bottom-up process[a], in which inventors propose their ideas to the superior and seek resources, fitting a principal-agent setting with an uninformed principal. In this setting, organizational economics theory predicts that authority is delegated to the agent to motivate them in taking initiative and to establish truthful communication. I ask how the transfer of authority to inventors through spin-offs and carve-outs affects their mobility and productivity. Employing a difference-in-differences methodology on a matched sample of inventor-employers in the US from 1980 to 2015, I find strong evidence showing the positive effect of authority on inventors' mobility and productivity. Inventors experiencing a spin-off or a carve-out are 0.8% less likely to depart from their employer and show a significant 11-fold increase in the quality of their patents, measured by patent citation.

[a] *"Innovation comes from distributed decision-making. Top-down teams are effective at optimizing existing processes and enforcing the completion of work, but only decentralized, bottom-up teams can consistently generate new ideas."* - Jeff Bezos

1.1 Introduction

The process of innovation revolves around matching resources with human capital that generates innovative ideas. Within an organization, inventors typically propose their ideas to their superiors and request resources. However, the superiors often know less about these novel ideas, creating an information asymmetry that makes them hesitant to approve the project and also presents the inventor with the opportunity to misrepresent the quality of the project. As a result, the superior may sub-optimally choose to allocate resources to more routine projects with more clear prospects. Additionally, innovation is a multi-stage process that makes defining the duration, terms, and tasks of innovative projects difficult, if not impossible, to specify in a contract.

The theoretical literature in organizational economics has vastly examined the question of transfer of authority[1] from a principal to an agent, which fits well to the superior-inventor framework described above. For instance, Aghion and Tirole (1997)'s model feature an agent assessing potential projects and a principal approving or rejecting (i.e., authority) the agent's proposals. The model predicts that delegating authority to the agent can improve their incentives to acquire information on the potential projects and facilitate their participation in the contractual relationship. This is because, in cases where the supervisor rejects the agent's ideas, it leads to a decrease in the agent's ex-ante effort in taking the initiative. Further, Baker et al. (1999) discuss the possibility of transferring authority through divestiture when delegation is efficient but infeasible. They describe the conditions under which informal authority can be delegated as a promise by the superior to ratify any project the subordinate proposes. In some cases, the principal may be tempted to renege on their promise, and therefore, authority can only be transferred formally, for example, through a spin-off. Moreover, Dessein (2002) models a setting in which the agent can strategically misrepresent information to extract private benefits. His model predicts that delegation dominates if the principal's uncertainty about the environment is sufficiently large, compatible

[1] Throughout the paper, I use **Authority** and **Autonomy** interchangeably. This is following Aghion and Tirole (1997) definition of authority, which is an individual characteristic describing one's control over use of assets. The individual-level authority could be confused with authority at organization level, which describes the level of authoritativeness in an organization. Where ever necessary I add autonomy in parentheses to avoid this confusion, yet follow the standard literature in organizational economics.

with innovative environments.

Thus, transferring authority effectively incentivizes inventors to take the initiative in exploring novel ideas and to communicate truthfully. As Coase (1937) succinctly stated, "Managerial authority replaces the price mechanism when contracting over resources is too costly". Jensen and Meckling (2009) refers to this phenomenon as the "collocation of knowledge and decision authority." This transfer of authority aids in overcoming information asymmetry and enhances the allocation of resources for innovative projects.

In this paper, I concentrate on inventors and examine how authority influences their incentives by exploring two significant choices: mobility and productivity. According to Aghion and Tirole (1997), I define authority as the decision-making power regarding the use of resources, which, in the context of innovation, may encompass: discretion over a predetermined budget[2], forming a team by employing other inventors, and even allocating a portion of one's regular working hours[3].

Following prediction of Baker et al. (1999) regarding divestitures as a means to transfer authority, I focus on the effect of two prevalent divestitures, namely "spin-off"s and "carve-out"s, on the productivity and mobility of the inventors in the divested subsidiary. By constructing an inventor-employer sample in the US from 1980 to 2015, I utilize spin-offs and carve-outs as quasi-shocks to authority and investigate inventors' mobility and productivity responses. In spin-offs and carve-outs, the subsidiary separates from its parent company and becomes an independent public corporation without significant changes to its management team. Moreover, spin-offs and carve-outs are undertaken to grant subsidiary managers greater autonomy, among other reasons. These corporate transactions effectively remove at least one management layer from the hierarchy, thereby granting more authority to inventors within the subsidiary. For brevity, I refer to these transactions as spin-off. Section 1.2 elaborates on why the distinction between spin-offs and carve-outs is inconsequential for my analysis.

[2]Innovative firms designate specific resources for particular R&D fields, a practice known as **strategic bucketing** (Hutchison-Krupat and Kavadias (2014)), which grants project managers discretionary power in resource allocation.

[3]Google founders Larry Page and Sergey Brin wrote in their IPO letter: *"We encourage our employees, in addition to their regular projects, to spend 20% of their time working on what they think will most benefit Google. This empowers them to be more creative and innovative. Many of our significant advances have happened in this manner."*

Building on the works of Aghion and Tirole (1997), Baker et al. (1999), Stein (1989), and Dessein (2002), I derive two hypotheses regarding inventors' mobility and productivity. First, inventors experiencing a spin-off (henceforth referred to as *spinoff-inventors*) are less likely to leave their employer. Second, *spinoff-inventors* who remain with their employer are more motivated to innovate, resulting in a higher number and more radical patents.

Developing a research design to evaluate these hypotheses presents several challenges, primarily due to the endogenous nature of changes in organizational structure and the self-selection of firms undergoing a spin-off. Nonetheless, the decision to reorganize a firm occurs at the firm level, making it improbable for inventors at the spin-off firm to ex-ante self-select into the company and be systematically different in unobservable factors correlated with their choice of employer and innovation effort.

Another potential issue is that spin-offs not only alter the hierarchical structure of firms but also involve the transition of a private company to a public one. This process, by itself, can impact an inventor's incentives and innovative output (e.g., Bernstein (2015)). To isolate the effects of the positive change in authority resulting from a spin-off, I employ a difference-in-differences methodology, focusing on inventors whose employers undergo a spin-off and carefully matching them with inventors in firms that have recently conducted an initial public offering (IPO), referred to as *IPO-inventors*.

To further validate the results obtained from the *spin-off vs. IPO* comparison, I conduct two additional difference-in-differences analyses, comparing the departure and productivity of *spinoff-inventors* and *IPO-inventors* to inventors in a set of "pure control" firms. These *control-inventors* work in companies that have not experienced any corporate events. The findings from these supplementary analyses lend further support to the results of the *spin-off vs. IPO* comparison.

I find compelling evidence supporting the first hypothesis: *spinoff-inventors* exhibit a lower probability of departure (average treatment effect on the treated (ATT) = 0.8%) compared to their matched IPO peers. The presence of parallel trends (also known as common trends) indicates a causal effect of authority on inventor's departure response. Additionally, using the same empirical design, I examine the effect of the transfer of authority on inventors' productivity in two dimensions: quantity (*patent* *count*) and quality (*patent citation*). The results also lend support to the second hypothesis, with an intriguing nuance. Although *spinoff-inventors* file fewer patents following the spin-off, their patents are of notably higher quality. The difference-in-differences results reveal an ATT demonstrating an eleven-fold increase in *patent citations* compared to IPO peers, and a sixfold increase compared to pure control peers.

The trade-off between quality and quantity can be rationalized in two ways. First, after a spin-off, inventors are granted increased authority, which incentivizes them to undertake more ambitious projects that carry a higher probability of failure but potentially offer a more significant scientific contribution. Consequently, inventors with more authority file patents less frequently; however, when successful, their patents boast a higher scientific quality. Second, the parent firm may choose to spin off its subsidiary to separate more scientifically obscure tasks that are difficult to measure and monitor from those that are not. According to Holmstrom and Milgrom (1991)[4], organizing tasks based on measurability characteristics prevents inventors from substituting quality for quantity and enables the parent firm to provide tailored incentives for each task. These two explanations could be complementary.

To the best of my knowledge, this paper is the first to provide large-scale empirical evidence on the positive effect of authority on inventors' incentives. As a result, I contribute to three strands of literature. First, I contribute to the literature on organizational economics and corporate finance by demonstrating how changes in corporate structure through a spin-off impact employee-inventors and their innovative output. While Caliendo et al. (2020) and Caliendo and Rossi-Hansberg (2012) explore the effects of restructuring by adding management layers on productivity, they do not specifically focus on the context of innovation.

Second, I contribute to the innovation literature by revealing an intriguing interplay between innovation quality and quantity as a result of increased authority. This finding emphasizes the importance of authority in shaping inventors' behavior and their choice between pursuing high-quality, ambitious projects or focusing on the quantity of their output. This aspect of my paper expands upon the existing innovation literature by providing a new perspective on how organizational structure can impact the quality

[4] Holmstrom (1989) and later Hellmann and Perotti (2011) also discuss the same issue.

and quantity trade-off in innovation.

Third, my findings propose a new explanation for why firms choose to divest a subsidiary through a spin-off, thereby contributing to the corporate finance literature. Eckbo and Thorburn (2012) surveys the restructuring motives behind spin-offs and carve-outs, but none of the reasons discussed involve separating hard-to-measure activities from the rest of the activities in the parent company through carve-outs or spin-offs. My paper, on the other hand, highlights the potential benefits of spinning off subsidiaries to focus on specific, hard-to-measure tasks, which can ultimately improve the overall performance of both the parent and subsidiary companies. In doing so, my paper adds a new dimension to the understanding of corporate restructuring and its implications for innovation and employee incentives.

The structure of the paper is as follows. In Section 1.2, I review the literature and develop my hypotheses. In Section 1.3, I discuss the construction of the sample and present summary statistics. In Section 1.4, I explain the research design and discuss the results. Section 1.5 concludes.

1.2 Literature Review and Hypotheses development

Corporate innovation often originates from the ideas of inventors at the lower levels of the organization. After generating an idea, the inventor must convince their immediate supervisor to provide the necessary resources, which may be as simple as allowing the inventor to allocate time to the new project. However, if the required resources exceed a certain threshold, the supervisor may need to seek approval from their superior, and this persuasion game repeats as one moves up the organizational hierarchy. Innovative projects are typically multi-stage, idiosyncratic, and not easily comparable to other projects Holmstrom (1989). As a result, the superior cannot readily evaluate the quality of the idea, as they may lack the knowledge, the ability to consult with third-party experts, or learn about the project's quality at a later stage. This information asymmetry between the inventor and the supervisor creates difficulties in evaluating innovative projects, leading to two distinct agency costs: the first occurring at the information extraction stage, where the inventor takes the initiative and assesses potential projects and their quality, and the second occurring at a later stage, where the inventor communicates this information to the superior. In this paper, I use four models from the literature to examine how transferring authority to the agent(s) can solve these two agency issues.

Aghion and Tirole (1997) focus on the first agency issue. In their model, the principal proposes a contract that allocates formal authority to the principal or the agent over project selection. Both parties privately gather information on potential projects and pool their proposals, and the party with authority allocates capital to a subset of the available projects. The principal may delegate authority to the agent if learning about the projects is too costly or the principal's overruling might hurt the agent[5]. Their model predicts that delegation increases the agent's incentive to acquire information and also facilitates the agent's participation in the contractual relationship. Without delegation, if the supervisor and the inventor disagree on project selection, the supervisor may reject the inventor's ideas, leading to a decrease in the agent's

[5]The cost associated with learning in Aghion and Tirole (1997) mostly arises from the supervisor's workload and span of control. However, in the context of innovation, other factors such as a lack or scarcity of necessary skills to evaluate the project can make learning even more costly. According to a survey by Graham et al. (2015), CEOs delegate capital allocation decisions when they are overloaded, distracted by recent acquisitions, or need input from divisional managers.

ex-ante effort in taking the initiative.

Baker et al. (1999) discuss the possibility of divestiture to transfer authority when delegation is efficient but infeasible. In a setting similar to Aghion and Tirole (1997), the subordinate proposes a project to the supervisor. The authors model the relationship between the subordinate and the supervisor as a repeated game, with the subordinate proposing a new idea each time. Their model describes the conditions under which informal authority is delegated as a promise by the superior to ratify any project the subordinate proposes. In situations where the superior's payoff is high, they may be tempted to renege on their promise. In these situations, the authority can only be transferred *formally*, for example, through a spin-off.

Furthermore, Stein (2002) addresses the effect of organizational design on the capital allocation of banks in small-business lending. Their model is useful in the context of innovation because the information exchange between a small-business loan officer and their superior is analogous to that between an inventor and their supervisor, as both projects involve "soft" information that is unverifiable and cannot be documented or passed along to a superior in an unambiguous manner. The author contrast two organizational forms: (1) decentralization, in which small, single-manager firms choose among few projects, and (2) hierarchy, in which large firms with multiple management layers evaluate many projects. According to his model, a decentralized organization provides stronger incentives for the loan officer to conduct more research, while a large hierarchy may discourage them from doing so because their proposed loan might get rejected by their superiors. Both Aghion and Tirole (1997) and Stein (2002) endogenize authority (the decision/control over resources) in their models and predict that authority may optimally transfer from the principal to the agent (delegation), leading to stronger incentives for the agent. The delegation, in effect, creates flatter, decentralized organizational structures[6].

Dessein (2002) studies the second agency issue. Noisy communication can occur at

[6]Interestingly, Rajan and Zingales (2001) reach somewhat similar conclusions in their model about the organization of the firm, but from a different starting point. Their setting includes an entrepreneur-CEO who chooses to organize their firm either as a small, flat hierarchy or a large, steep one to prevent their subordinates from stealing their idea and setting up a competitor, a process called spin-out. Although the model predictions are somewhat similar to those of Stein (2002) and Aghion and Tirole (1997), they assume that the key information is in the entrepreneur-CEO's hands, thus at the top of the hierarchy. This contrasts with the setting in Aghion and Tirole (1997), where the subordinate(s) generate and possess the key information.

a later stage in the innovation process, where the inventor knows about the project quality, but would strategically misrepresent the information to extract private benefits. The authors model the trade-off between loss of control in delegation and loss of information in communication, predicting that delegation dominates if the principal's uncertainty about the environment is sufficiently large, which is fitting for innovative environments[7]. Moreover, Acemoglu et al. (2007) focuses on the same trade-off but from a different perspective, explaining which types of firms may optimally move toward a decentralized structure. They predict and also find empirical evidence that firms closer to the technological frontier, firms in more heterogeneous environments, and younger firms are more likely to choose decentralization[8].

Following prediction of Baker et al. (1999) regarding divestitures as a means to transfer authority, I focus on the effect of two prevalent divestitures, namely "spin-off"s and "carve-out"s, on the productivity and mobility of the inventors in the divested subsidiary. "Spin-offs" and "carve-outs" are two types of corporate transactions that transfer control to lower levels of the organization by creating an independent entity from a subsidiary. These transactions are suitable for studying the impact of autonomy on the productivity and mobility of inventors, because they involve removing at least one layer of hierarchy and, as a result, granting autonomy to the former manager of the subsidiary, who becomes the CEO. Spin-offs and carve-outs encompass three key elements: (1) the separation of a subsidiary from its parent organization, (2) the issuance of new shares and their public offering, and (3) the establishment of a new company with its own board and executive leadership. Moreover, spin-offs and carve-outs are pursued for similar reasons, including enabling the subsidiary to secure its own financing for growth[9], enhancing investor comprehension of the subsidiary, granting

[7] Dessein (2002) is motivated by the decentralization wave in US corporations in the 1990s, such as AT&T, General Electric, Eastman Kodak, Fiat, Motorola, United Technologies, Xerox, and Ford.

[8] In general, studies show that firms are becoming flatter through a delayering process in response to competition under liberalization and globalization. Rajan and Wulf (2006) find that the number of levels between division heads and CEOs decreased, and more managers are directly reporting to the CEO. This change is also reflected in managers' compensation packages through higher pay and greater long-term incentives. Guadalupe and Wulf (2010) and Bloom et al. (2010) find causal evidence of the flattening effect of competition on organizational structure in US firms.

[9] Most studies on equity carve-outs are rooted in information asymmetry among various parties and the idea that the carve-out subsidiary possesses significant growth opportunities that remain unrealized and obscured within the parent company's conglomerate structure. Nanda (1991) builds upon the framework developed by Myers and Majluf (1984). In his model, firms opt for an equity carve-out to rectify market misvaluation by divesting an overvalued subsidiary, implying that the

subsidiary managers increased autonomy, revising incentive contracts[10], and refocusing corporate attention (Miles and Rosenfeld (1983), Schipper and Smith (1983), and Schipper and Smith (1986)). Furthermore, both carve-outs and spin-offs exhibit similarities in the parent company's control over the subsidiary's top management[11].

Although carve-outs and spin-offs share the aforementioned characteristics, carve-outs diverge in that the newly issued shares are offered to new shareholders (akin to an IPO), resulting in cash proceeds and the formation of a minority interest group. Conversely, spin-offs distribute the new shares to existing shareholders on a pro-rata basis, precluding the creation of a minority interest group and the generation of cash proceeds. Moreover, equity carve-outs appear to be a temporary state, often culminating in a spin-off, re-acquisition by the parent, or liquidation within 5 to 6 years after the carve-out. Approximately 60% of carve-out firms in Schipper and Smith (1986)'s sample later experienced re-acquisition by their parents, complete divestiture, spin-offs, or liquidation[12]. In addition, although a primary motive for conducting a carve-out is to grant subsidiary managers greater autonomy (i.e., transfer of authority), the

consolidated firm is undervalued. Powers (2003) provides empirical support for Nanda (1991)'s predictions. As an alternative explanation, Allen and McConnell (1998) propose a model of managerial discretion in which the CEO is reluctant to relinquish control over the firm's divisions unless capital constrained.

[10]Regarding the decision to carve out a 27 percent minority interest, Charles Erhart, vice-chairman of Grace, stated that the environment at Grace stifled El Torito's management's entrepreneurial style. "These are people-sensitive businesses. They [El Torito management] are independent cats who need a piece of the action to motivate them." (Business Week, December 19, 1984).

[11]Schipper and Smith (1986) demonstrate that in 76% of their sample, at least one member of the parent board or parent top management serves on the board of directors of the carve-out company. Furthermore, 30% of the sample carve-outs share the same chairman, CEO, or president with the parent company. The majority of directors and top management of spin-off firms also serve as board members and top managers of the parent company. In spin-offs, Wruck and Wruck (2002) report that approximately 70% of spin-offs have only former managers of the parent company in top management positions. Seward and Walsh (1996) find that 61% of spin-off firm CEOs were previously divisional managers of the spun-off subsidiary, 21% were former CEOs of the divesting parent company, and only 15% were "outsiders." In addition, both spin-off and carve-out managers are compensated through incentive plans, including stocks and options. Schipper and Smith (1986) report that 94% of carve-out companies adopt incentive compensation plans, generally stock option and income-based plans. Spin-off CEOs and executives also receive a portion of their compensation in the form of options (Seward and Walsh (1996)).

[12]Perotti and Rossetto (2007) develop a model to explain why most carved-out subsidiaries undergo a follow-on transaction. Carve-outs can be viewed as a costly "learning option" that allows the parent company to gather information from the financial market at the expense of decreased efficiency at the organizational level. The listing of a subsidiary while retaining control provides the parent company with a "put option to sell" and a "call option to reacquire" the subsidiary. Desai et al. (2011) build upon Perotti and Rossetto (2007)'s work and examine the factors affecting the acquisition likelihood and acquisition premium of the carve-out company. According to the authors, carve-out acquisitions are more likely when the parent company aims to unlock the value of its subsidiary and when the parent and subsidiary share a product-market relationship.

parent company does not fully relinquish control and typically retains approximately 75% of voting rights in the subsidiary[13]. However, given the substantial impact both transactions have on a firm's authority and control, I use them both as a quasi-shock to autonomy and employ the term spin-off to encompass both types of transactions. Later in the analysis, I address the differences between spin-offs and carve-outs and their impact on the results.

Nevertheless, spin-offs (in the broader sense) involve two simultaneous changes: first, the change from private to public status, and second, the change in authority. For instance, Bernstein (2015), Ferreira et al. (2014), and Aggarwal and Hsu (2014) demonstrate that going public affects innovation. Hence, to isolate the effect of authority on innovation, it is crucial to distinguish the effect of going public. Bernstein (2015) uses an instrumental variable approach to show that IPOs result in a 40% reduction in innovation quality, measured by citations, while keeping quantity constant. The study also reveals that IPOs are followed by a large exodus of key inventors and a shift in the innovation strategy of the IPO company, where firms are more likely to acquire new technologies instead of developing them internally. Ferreira et al. (2014) develops a model to relate managers' incentive to innovate and the choice of equity financing through IPOs or private equity markets. Private firms are more willing to invest in exploratory projects, as insiders can profitably liquidate their stakes upon receiving bad news. However, in public firms, the cash flow of projects is observable to outsiders, rendering insider's exit unprofitable, making insiders less tolerant of failure. This mechanism leads to short-termism in public firms, with insiders preferring exploitative projects with a high probability of early success. Aggarwal and Hsu (2014) compares the innovation output of young firms after their choice of exit mode, finding that innovation quality is highest under private ownership and lowest under public ownership. They discuss two main mechanisms driving the results: information confi-

[13] In Schipper and Smith (1986)'s sample, the parent company retains, on average, approximately 75% of the voting rights, while Allen and McConnell (1998) reports 69%. At least three reasons may compel a parent company to maintain a majority or super-majority voting interest in a carved-out subsidiary. First, effective control facilitates the preservation of existing operational and financial synergies. The parent company typically creates and holds Class B shares with multiple voting rights. Second, 80 percent voting control is required for tax consolidation purposes. Tax consolidation benefits arise if the operating losses or tax credits that would otherwise go unused by either the parent or subsidiary can be used to offset the taxable income of the more profitable firm, thereby reducing the consolidated entity's taxes. Third, majority ownership simplifies re-acquisition or other restructurings that necessitate a shareholder vote.

dentiality and inventor incentives. They find that more analyst coverage is associated with a significant drop in patent citations and no effect on patent count. Focusing on the labor market implications of IPO, Babina et al. (2020) shows that going public leads to the departure of high-wage employees to start-ups but does not significantly affect the earnings of stayers. In conclusion, these studies indicate that going public is followed by structural changes in the workforce, compensation plans, and scope, all of which affect inventor productivity and mobility.

Overall, I build my hypotheses on Aghion1997, Baker et al. (1999), Stein (2002), Dessein (2002) and posit that transfer of authority to the inventor (control over the resources) positively affects inventor's incentives in initiating innovative projects and thus their productivity. In addition, transfer of authority facilitates their participation in the firm. Therefore, in accord with prediction of Baker et al. (1999), I use spin-offs as a quasi-shock to inventors who work at the spun-off subsidiary and study their departure rate and productivity. Spin-offs involve the separation of a subsidiary from its parent and therefore, entail removing at least one layer of hierarchy. Hence, I proxy for the inventor's authority by the hierarchical distance between the subsidiary in which they work and the headquarter of the parent company. That is following the logic that authority is allocated the most at the top of the organization and the least at the bottom. In addition, spin-offs also change the location of the headquarter and thus affect the distance between the inventors and their superiors. Accordingly, I use the geographical distance between the inventor and the headquarter as a measure of ease of exchanging information and exploit this heterogeneity across spin-off firms to investigate the effect of proximity to the headquarter on inventor mobility and productivity responses. Glaeser et al. (2022) also find that geographical proximity to the HQ increases the productivity and creativity of the inventors. Hence, I posit the two following hypotheses:

Departure hypothesis: Authority (autonomy) positively affects contractual participation of inventors, hence, the inventors experiencing a spin-off (*spinoff-inventors*) are less likely to depart from their employer.

Productivity hypothesis: The inventors who stay in the subsidiary after the spin-off (henceforth, *stayer-inventors*) file more, more radical patents in a spun-off firm. The effect is stronger for hierarchically and geographically far inventors.

1.3 Data

In this section, I explain the construction of the sample. Next, I provide summary statistics, and finally, I discuss the data limitations.

1.3.1 Sample construction

To investigate the effect of authority on inventors' incentives, I construct a sample of inventors in firms who are gone through an IPO, a spin-off[14] and firms who were not involved in any corporate transaction (i.e., "control firms"), in the 1980-2015 period. I start with the dynamic patent reassignment dataset provided by Arora et al. (2021), which match patents to Compustat firms in 1980-2015 and track their ownership due to changes in ownership structure and company names. They have a bottom-up approach in the sense that they first assign patents to the subsidiary who filed the patent and then to its ultimate parent, a Compustat firm[15]. They then track ownership of the patent following any corporate transactions which ensues change in ownership of the patents, including merger and acquisitions, divestitures, and spin-offs. Thus, using Arora et al. (2021) I am able to identify the patenting subsidiaries who undergo a spin-off along with their patent filings. In addition, I identify the firms who did not participate in any corporate transactions, i.e., control firms.

Next, I construct a sample of IPO firms in the same period following Bernstein (2015). I use the SDC Platinum database and filter new and completed issues in the US. Next, I exclude IPO filings of financial firms (SIC between 6000 and 6999), unit offers, closed-end funds (including REITs), American depositary receipts (ADRs), limited partnerships, and special acquisition vehicles. I identify 7,207 completed IPOs. To obtain a clean event period and avoid having confounding effects due to multiple transactions, I filter spin-offs and IPOs that do not experience any follow-up transaction in or less than 4 years after the focal transaction.

Furthermore, I construct a inventor-employer sample for each of the three samples (*spin-off*, *IPO*, and *control* sample), using PATSTAT database. I identify the inventors who filed any patent in the period of four to one year before the spin-off and IPO

[14] Throughout the paper, I use the term spin-off as a corporate transaction that involves the IPO of a subsidiary. In a finer definition, this includes carve-outs as well.

[15] Arora et al. (2021) use SDC, ORBIS, 10K filings, and extensive manual checks to establish corporate structure.

transactions period, i.e., $[-4, -1]$. The identified inventors are the individuals who are actively filing patents and are affected by the transaction. For the set of control firms, however, since there is no transaction, I identify all their inventors regardless of the timing of the filing. This yields 405,783 inventors and 662,416 patents. Since this data is computationally difficult to manage, I randomly select 10% of the observations only within the control firms.

Having identified the inventors experiencing a spin-off, an IPO, and also the inventors in *control firms*, I construct a yearly panel starting from the year in which a given inventor files their first patent until their last filing year. Additionally, I drop patents that are filed more than 10 years beyond the deal year. Furthermore, to track inventors, I only keep inventors who have at least one patent before and at least one patent after the transaction. This filter does not apply to inventors in the control firms. Since inventors rarely file patents consecutively each year, I cannot exactly pinpoint the year in which an inventor changes employers. Hence, I assume that the inventor moves at the midpoint of two consecutive filing years, a common assumption in the literature Melero et al. (2020). An inventor is considered to have left the subsidiary if the subsidiary to which they assign the patent is different from the focal subsidiary-employer for at least two consecutive years. This is because inventors may temporarily collaborate with organizations such as universities and laboratories, and therefore, filing a patent with another institute does not necessarily mean changing employers. Accordingly, I define a variable called *departure* as an indicator equal to 1 if an inventor moves to a new employer and stays for at least two years, and 0 otherwise.

Moreover, using patent-based metrics, I am also able to observe the quantity and quality of inventors' productivity. I assign patent productivity measures, i.e., *patent count* and *patent citation* equally across the inventors who jointly file a patent. I fill the missing values in the year(s) with no filed patents with zero. Thereafter, I add firm-level characteristics from Compustat. Also, the financial information of IPO firms before their IPO is extracted from their prospectuses.

Finding information about the organizational structure of corporations in the US is challenging. However, some firms voluntarily publish the list of their subsidiaries and their hierarchical levels in their 10-K filings on EDGAR, starting from 1993. Since my sample starts from 1980, I am not able to find the hierarchical level data for nearly half of the sample. Nevertheless, I take subsidiary and hierarchy data from Corpwatch, which uses automated parsers to extract the subsidiary relationship information from Exhibit 21 of companies' 10-K filings with the SEC. To find the hierarchical level of the spin-off subsidiary, I connect the subsidiary with its parent's CIK code and then use fuzzy name matching along with location data and the reporting date to find the closest match. Using this approach, I am able to find a match for 39 out of 132 spin-offs in my sample. Consequently, I define a dummy variable, *Hierarchy far* equal to 1 if the hierarchical level (i.e., the number of owners until the ultimate parent) of the spun-off subsidiary is above the median and zero otherwise. Similarly, I construct another dummy variable, *Geographically far*, which is equal to one for above median geographical distance of the inventor to the headquarter of the employer.

1.3.2 Summary Statistics

The summary statistics of inventor-year, subsidiary-year, and firm-year are reported in Tables 1.1-1.3, respectively. Table 1 presents the characteristics of the inventors, with the unit of observation being inventor-year. On average, inventors are between 43 to 44 years old and predominantly male across the spin-off, IPO, and control firms, with IPO inventors being relatively younger and slightly more diverse in gender. An inventor is classified as a *generalist* if their patent portfolio has a number of unique technology classes above the median, and *independent* if their team size is below the median for all inventors over the entire sample period. The proportion of *generalist* inventors is higher in spin-off firms (34%) than in IPO firms (23%), but lower than in control firms (38%). However, the proportion of *independent* inventors is similar across the three firm groups. Regarding event-related statistics, an average inventor in control firms has a lower probability of leaving the firm in any given year (*departure* = 0.5%), followed by inventors in IPO firms (0.6%), and both are lower than the unconditional annual departure probability of inventors in spin-off firms (0.8%). Furthermore, the geographical location of inventors ranges from 293 meters to 17,000 to 19,000 kilometers from their employer's headquarters, indicating a wide distribution of inventors across all firms and within each firm group.

I present the subsidiary-year summary statistics in Table 1.2. As explained earlier,

Table 1.1: Inventor-year summary statistics.

Inventor-year summary statistics. Panel 1-3 show the statistics of inventors in spin-offs, IPOs, randomly selected control firms. Departure is an indicator equal to 1 if the inventor leaves the employer. Inventor generalist is an indicator equal to one if the inventor's patent portfolio has above median number of unique technology classes. Inventor independent is another dummy equal to one if the inventor has below median team-size. Inventor_HQ_distance is the geographical distance between the inventor location and location of HQ in kilometers.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
Spin-off	132							
Inventors	8,908							
Departure	109,681	0.008	0.090	0	0	0	0	1
Male_flag	109,681	0.892	0.310	0	1	1	1	1
Generalist	109,681	0.341	0.474	0	0	0	1	1
Independent	109,681	0.838	0.368	0	1	1	1	1
Patent Count	109,681	0.718	1.904	0	0	0.250	0.800	130
Patent Citation	109,681	10.989	47.004	0	0	0	14	5,244
Age	109,681	43.893	8.192	29	38	44	50	60
HQ_distance	103,805	1,678.067	2,719.343	0.293	24.538	348.726	2,231.214	18,852.120
IPO	1,106							
Inventors	10,313							
Departure	122,249	0.006	0.075	0	0	0	0	1
Male_flag	122,249	0.869	0.338	0	1	1	1	1
Generalist	122,249	0.227	0.419	0	0	0	0	1
Independent	122,249	0.812	0.391	0	1	1	1	1
Patent Count	122,249	0.641	1.602	0	0	0.200	0.686	86.667
Patent Citation	122,249	10.922	65.346	0	0	0	1	4,152
Age	122,249	42.998	8.470	29	37	42	49	60
HQ_distance	113,050	1,762.558	2,849.718	0.293	16.852	82.278	2,765.453	17,568.920
Control	1,939							
Inventors	91,939							
Departure	1,500,073	0.005	0.068	0	0	0	0	1
Male_flag	1,500,073	0.891	0.311	0	1	1	1	1
Generalist	1,500,072	0.380	0.485	0	0	0	1	1
Independent	1,500,073	0.829	0.377	0	1	1	1	1
Patent Count	1,500,073	0.512	1.525	0	0	0	0.500	436.350
Patent Citation	1,500,073	5.512	42.719	0	0	0	0.500	15,510.650
Age	1,500,073	44.396	10.052	26	37	45	52	62
HQ_distance	1,405,864	2,386.538	3,265.565	0.093	105.420	913.642	3,230.629	18,801.650

I am only able to retrieve the hierarchical level of subsidiaries for 39 out of 132 subsidiaries, comprising only 769 of 2,515 subsidiary-year observations. The subsidiary hierarchy level, defined as the number of owners until the ultimate parent, ranges from 1 to 71 for this sub-sample, with a mean around 10. On average, a spin-off subsidiary has around 54 inventors (ranging from 1 to 1,987), while an IPO firm has only around 10 inventors (ranging from 1 to 3,318), which is much smaller. The average control firm, however, has around 24 inventors (ranging from 1 to 10,979), lying somewhere in between the other two groups. Regarding *patent count* and *citation*, the average spin-off firm has 30 and 1,377 *patent count* and *citation*, respectively, which is the highest across the three groups. The average control firm has 11 and 535 *patent count* and *citation*, respectively, and the average IPO firm has 5 and 368 *patent count* and *citation*, respectively. However, the set of control firms has a wider range of *patent count* and *citation* than the other two groups. For instance, patent *patent count* range from 0 to 8,670 for the control firms, while they range from 0 to 1,563 for the spin-off firms and 0 to 2,611 for the IPO firms.

Table 1.2: Subsidiary-year summary statistics.

Subsidiary-year summary statistics. Hierarchy shows the number of owners between the subsidiary and the HQ. Inventor count is derived from the patenting activity of the subsidiary and is equal to the sum of number of inventors who assigned the patent right to the given subsidiary according to Arora et al. (2021). Patent count and patent citation is also obtained from Arora et al. (2021).

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
Spin-off								
Hierarchy	769	10.425	13.943	1	2	9	11	71
Inventor count	2,515	54.134	157.186	1	3	8	39	1,987
Patent count	2,515	30.560	99.782	0	0	3	19	1,563
Citation count	2,515	1,377.592	4,526.435	0	0	14	627	62,313
IPO								
Inventor count	20,075	10.240	44.433	1	2	4	9	3,318
Patent count	20,075	4.731	34.172	0	0	0	3	2,611
Citation count	20,075	367.925	1,786.671	0	0	0	82	56,530
Control								
Inventor count	59,122	24.039	165.127	1	2	4	9	10,979
Patent count	59,122	11.003	105.378	0	0	0	1	8,670
Citation count	59,122	535.810	6,547.432	0	0	0	0	490,243

Table 1.3 presents firm-year statistics. On average, firms that spin off a subsidiary are the largest, while IPO firms are the smallest in terms of revenues ($8,500m vs.

$167m), with control firms falling in the middle ($3,000m). This is also reflected in the number of inventors filing patents in a given year and the average number of subsidiaries within each group. The ultimate parent of a spin-off firm has an average of 3 subsidiaries (ranging from 1 to 18), more than double the number of the average subsidiary in IPO firms, which is 1.3 and ranging from 1 to 10. The control firms have an average of 1.7 subsidiaries. Furthermore, the number of active inventors on average across the three groups is 126, 24, and 48 in spin-off, IPO, and control firms, respectively. Parent-level innovation output is also the highest in the spin-off group (64 *count* and 2,900 *citations* on average), followed by the control group (16 *count* and 650 *citations* on average), and smallest in the IPO group (8 *count* and 600 *citations* on average).

1.3.3 Data limitations

There are three shortcomings with the data. First, I cannot directly measure authority given to the lower layers of organizations and consequently use spin-off and carve-outs as quasi-shocks to authority, which in turn introduces self-selection concerns. Ideally, authority can be measured in surveys as in Bloom et al. (2012) and Bresnahan et al. (2002)[16]. Alternatively, hierarchy is measured using occupational codes in administrative databases (e.g., Caliendo et al. (2015), Caliendo et al. (2020) and Antoni et al. (2019)). However, neither of these methods are feasible in this project. Second, I am attributing inventors to their employers and track their mobility based on their patenting. Following the literature (e.g., Bernstein (2015)), I only keep the inventors who actively patent after and before the corporate transaction and drop those who stop patenting. Hence, while acknowledging the possibility of this case being an exit, it is not regarded as such due to the potential scenario of the inventor remaining within the company but discontinuing patent filings. Despite this, it has a negligible impact on the estimations, as the proportion of inventors who depart and terminate patent activities between the treatment and control clusters does not exhibit significant dissimilarities.

[16] Bloom et al. (2012) ask plant managers about their decisions over investment (a maximum capital investment that could be made without explicit sign-off from the HQ), hiring, marketing, and product introduction and construct an empirical summary of decentralization combining these four measures. Moreover, Bresnahan et al. (2002) survey employees on their right to decide on the pace of the work or the method with which they can do the job.

Table 1.3: Firm-year summary statistics.

Firm-year summary statistics. Panels 1-3 show the firm year summary statistics for spin-off, IPO, control firms respectively.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
Spin-off								
Subsidiary No.	2,397	3.138	3.046	1	1	2	4	18
Inventor No.	2,394	126.612	236.704	1	8	31	138	1,360.920
Patent count	2,397	64.123	140.218	0	0	7	64	890.240
Patent citation	2,397	2,875.814	6,948.367	0	0	128	2,051	43,650.320
Sales	2,397	8,467.628	23,925.640	0.141	172.349	1,238.694	6,380	171,061.400
R&D intensity	2,375	0.086	0.128	0.0002	0.016	0.039	0.101	0.779
ROA	2,397	-0.027	0.302	-2.290	-0.015	0.045	0.082	0.306
Tangibility	2,397	0.266	0.182	0.009	0.127	0.234	0.366	0.771
Leverage	2,396	0.199	0.199	0	0.028	0.145	0.310	0.850
Capx_asset	2,397	0.056	0.044	0.001	0.024	0.046	0.075	0.216
Q	2,396	2.352	2.089	0.817	1.202	1.602	2.520	13.405
Size	2,397	7.002	2.378	1.093	5.350	7.187	8.712	12.184
Cash_liquidity	2,397	0.345	0.202	0.059	0.197	0.290	0.461	0.895
IPO								
Subsidiary No.	18,533	1.340	1.245	1	1	1	1	10
Inventor No.	18,533	23.580	86.788	1	3	5	10	708.680
Patent count	18,533	8.869	35.160	0	0	0	3	285.680
Patent citation	18,533	602.635	2,286.384	0	0	0	147	17,322.360
Sales	18,525	167.112	499.445	0	3.471	22.238	90.253	3,584.923
R&D intensity	18,468	0.313	0.411	0.001	0.081	0.186	0.374	2.633
ROA	18,525	-0.372	0.743	-4.687	-0.522	-0.138	0.050	0.387
Tangibility	18,525	0.172	0.148	0.003	0.062	0.127	0.237	0.694
Leverage	18,494	0.075	0.143	0	0	0.010	0.072	0.701
Capx_asset	18,525	0.068	0.076	0.0003	0.021	0.044	0.087	0.414
Q	18,494	3.727	3.536	0.664	1.763	2.711	4.215	24.232
Size	18,525	3.829	1.670	0.498	2.669	3.639	4.861	8.544
Cash_liquidity	18,525	0.578	0.238	0.076	0.390	0.590	0.779	0.974
Control								
Subsidiary No.	33,473	1.741	1.997	1	1	1	1	14
Inventor No.	33,473	47.697	150.172	1	2	5	19	1,050
Patent count	33,473	16.729	64.982	0	0	0	3	479.560
Patent citation	33,473	650.013	2,741.624	0	0	0	49	21,198.320
Sales	33,470	3,052.260	8,046.056	0	29.574	413.389	2,355.733	58,282.940
R&D intensity	33,308	0.123	0.286	0	0.016	0.043	0.094	2.092
ROA	33,470	-0.206	0.906	-6.586	-0.043	0.050	0.089	0.286
Tangibility	33,470	0.271	0.170	0	0.138	0.253	0.380	0.744
Leverage	33,470	0.205	0.213	0	0.020	0.149	0.309	0.913
Capx_asset	33,470	0.062	0.052	0	0.026	0.050	0.085	0.285
Q	33,470	3.066	5.328	0.676	1.160	1.571	2.585	39.630
Size	33,470	5.587	2.672	0.200	3.520	5.844	7.746	11.260
Cash_liquidity	33,470	0.358	0.199	0.039	0.226	0.309	0.431	0.967

Third, this paper lacks data on the development of the inventor's compensation over the course of the study. Since both inventor mobility and productivity are functions of the level and composition of compensation, ignoring these factors might lead to biased estimates through omitted variable bias. However, since the literature (e.g., Schipper and Smith (1986), Seward and Walsh (1996), Feldman (2016)) shows that both IPOs and spin-off lead to higher amount of compensation and adoption of stock- and option-based incentive plans for the managers, I assume that the changes in the inventor's wages and incentive schemes are somewhat similar among spin-off and IPOs.

1.4 Analysis and Results

In this section, I review the hypotheses, introduce the research design, and present and discuss the results. I pose and test the two following hypotheses: first, inventors experiencing a spin-off (*spinoff-inventors*) are less likely to leave the spun-off firm, compared to *IPO-inventors* and *control-inventors*. This effect is more pronounced the more distant (in the hierarchy and geographical distance) the subsidiary is to the HQ. The second hypothesis posits that *stayer-inventors* file more, more radical patents in a spun-off firm. I expect the effect to be stronger for the hierarchically and geographically far inventors, because they arguably experience a greater change of autonomy due to the spin-off.

To investigate the effect of authority on inventors' departure and productivity, I need to control for the other factors (discussed in Section 2) which could potentially affect the outcome variables, i.e., inventor's *departure*, *patent count*, and *patent citation*. In particular, spin-offs along with the change in authority involve some confounding factors. For instance, going public affects inventors mobility (e.g., Bernstein (2015)), it increases information disclosures of the IPO firm and thus affects innovation output (e.g., Aggarwal and Hsu (2014)), it changes the managers' compensation packages by employing stock and options (e.g. Seward and Walsh (1996)), and lastly, it puts the firm under pressure for delivering short-term results (e.g., Stein (1989) and Ferreira et al. (2014)). Hence, to isolate the effect of the change in authority in spin-offs, I employ a dynamic difference-in-differences model in the $[-4, 4]$ years around the spin-offs and study the mobility and productivity of *spinoff-inventors* in comparison to the *IPO-inventors*. Specification 1.1 shows the difference-in-differences model.

$$Y_{isft} = \alpha + \sum_{k=-4, k\neq -1}^{4} \beta_k \times treat_{isfk} + X_{it}^{i}\Gamma + X_{st}^{s}\Lambda + X_{ft}^{f}\Omega + \gamma_i + \lambda_s + \omega_f + \theta_t + \epsilon_{it} \quad (1.1)$$

Y_{isft} denotes the outcome variables (inventor *departure* and productivity, *patent count* and *patent citation*) of inventor i in the subsidiary s of firm f at time t. The coefficients of interest are β_k, which capture the dynamic effect of the treatment versus the control. X^i, X^s, and X^f, include the inventor, subsidiary, and firm-level controls, respectively. Finally, $\gamma_i, \lambda_s, \omega_f$ and θ_t are inventor, subsidiary, firm, and time fixed effects. I use the probability linear model (OLS) for departure and a count model (Poisson model) for inventor productivity regressions. Throughout the paper, the estimation is based on Sun and Abraham (2021) estimators who correct for the bias in event studies stemmed from heterogeneity in treatment effects[17].

Nevertheless, I am aware that firms self-select into spin-offs and IPOs, thus there is a legitimate concern about the comparability of inventors in a spin-off firm and an IPO firm. Even though the decision to go IPO or spin off a subsidiary is made at the firm level and not the inventor level, spin-off and IPO firms might have different recruitment strategies and provide different amounts or types of resources to the inventors, which in turn would affect their departure and innovation output.

I adopt different strategies to control for these concerns. First, I use inventor, subsidiary, and firm fixed effects to capture the unobservable, time-invariant heterogeneity across these entities. These fixed effects at least partly address the concerns about the differences in governance, shareholder base, and employee incentive mechanisms between spin-offs and IPOs. Furthermore, to ensure the comparability of the inventors, I employ propensity score matching using the nearest neighbor on the inventor level along with subsidiary level characteristics[18]. At the inventor level, I match on age and gender and at the subsidiary level, I match on subsidiary size (measured by the average number of inventors in the subsidiary over the three years before going public) and the subsidiary's innovation output before the treatment. I cannot use the usual measures of size (i.e., assets or sales), because these information is not available at the subsidiary level. However, using subsidiaries' number of inventors as a measure of subsidiary size is advantageous in this context, because it captures the labor input into innovation production. Matching on one significant innovation input, i.e., labor, along with the innovation output (the other matching variable), addresses the concern that spin-offs and IPO firms may have different innovation strategies or different capabilities in producing innovation. In addition, I match the subsidiary's primary technology class (28 number of 2-digit technology classes). In sum, I compare inventors who have

[17]I bin the variables outside of the $[-4, 4]$ window and use robust standard errors clustered at the deal level.

[18]Matching on a variable is a superior controlling technique than specifying the same variable in an OLS model because it allows controlling for the undesirable variation in a non-linear fashion.

the same age and gender, work in the same industry and in approximately similar-size firms and with comparable innovation output. I use the same matching estimator proposed by Abadie and Imbens (2006) and used in Çolak and Whited (2007) who also use matching and correct for the bias in the average treatment effect resulting from firm self-selection into the divestiture method.

To further investigate the self-selection effects and as a sanity check, I separately run the same regressions, comparing both *spinoff-inventors* and *IPO-inventors* to *control-inventors*, who do not experience any corporate event. This triangular comparison (*spin-offs* versus *IPOs*, *spin-offs* versus *controls*, and *IPOs* versus *controls*) provides a benchmark with which one can examine the coefficient estimates relative to one another. If the results turn out to be compatible, they provide further support for the main difference-in-difference results, i.e., *spinoff-inventors* versus *IPO-inventors*. In addition, it is closer to the conventional difference-in-differences method in which the control group does not receive any treatment.

For each of the two hypotheses, I run the triangular difference-in-differences described above on the matched sample. I use propensity score matching with replacement on inventor *age*, *gender*, subsidiary size (*number of inventors*), subsidiary innovation output (pre-treatment *patent count*), and subsidiary technology class.

Table 1.4 shows the matching results for all the inventors, i.e., the *spinoff-inventors*, *IPO-inventors*, and *control-inventors*. This matched sample includes all the inventors who depart and stay with their employer and corresponds to the *departure* hypothesis. The columns show sample mean in the treated, and control groups respectively. In addition, columns 3-7 show standardized mean differences (Std. Mean Diff.), variance ratios (Var. Ratio), and mean and maximum of the empirical cumulative density function (eCDF). Values of standardized mean differences and eCDF statistics close to zero and values of variance ratios close to one indicate a good balance. In the first panel, I report the matching results of *spinoff-inventors* vs. *IPO-inventors*. Matching improves the similarity of subsidiary size and innovation output at a loss in the similarity of inventor age across treated and non-treated groups. This is not surprising, because matching on firm size and innovation forces the matching algorithm to look for inventor pairs only in those IPO firms that are active longer than the average IPO firm, i.e., those who have older inventors. Consequently, matched inventors at the IPO are significantly older. Yet, there is a sizable gap between the spin-off and IPO inventors on the size and innovation output of their firm. This aspect of the data presents a challenge to the comparison between spin-offs and IPOs. However, this issue is partly mitigated the matching outcomes from the spin-off versus control and IPO versus control comparisons, which exhibit better balance in matching. Panel 2 and 3 of Table 1.4 report the matching statistics for *spin-off vs. controls* and *IPOs vs. controls*, respectively. Matching significantly improves the balanceness of the treated and non-treated groups. Even though there is still a difference between the size and innovation output of the spin-off and control groups, matching inventors in IPO and control group results in a nearly perfect match.

Turning to the *productivity* hypotheses, I match the *stayer-inventors* in spin-off and IPO firms. I use the same matching criterion described above and match the *stayer-inventors* pairs between the spin-off and IPO firms, between the spin-off and control firms, and lastly between the IPO and control firms. The matching results are reported in Table 5. Similar to the matching results in Table 1.4, the size and innovation output of the IPO firms are significantly smaller than the ones of the spin-off firm, which does not improve even after matching. However, matching with the inventor in control firms significantly improves the results as shown in panels 2 and 3 of Table 1.5.

Table 1.6 shows the regression results for inventor *departure* according to specification (1). The outcome variable is a dummy indicating the departure of the inventor in $[-4, 4]$ clean window around the treatment. The first two columns show the *spin-offs vs. IPOs*, the middle two columns show the results for *spin-offs vs. controls*, and the last two columns correspond to the *IPO vs. control* comparison. Moreover, the results in every second column are based on the matched sample for each of the three comparison groups. Columns 1 and 2 both show that the inventors are less likely to leave their employer after a spin-off compared to an IPO. The coefficients are consistently negative after the treatment, without any discernible pre-trend. The average treatment effect is -0.8%, which means that the inventors in spin-off firms are on average 0.8% less likely to leave their employers than inventors in IPO firms, four years after the event. Furthermore, the departure of inventors in spin-off and pure control

Table 1.4: Matching Summary on the Departures

This table shows the matching summary on the departure decision. Matching is done using nearest neighbour matching with replacement. Inventor year level data (panel) is matched based on inventor's age, gender, subsidiary's size and innovation output before the treatment, 28 industries according to 2-digit CPC system. In Spin-off versus IPO matched sample, 9,723 out of 122,249 non-treated units are matched to 108,597 out of 109,681 units. In the spin-off vs. controls, 21,229 out of 1,500,073 non-treated units are matched to 109,496 out of 109,681 treated units. In IPOs vs. controls, 51,485 out of 1,500,073 non-treated units are matched to 122,091 of 122,249 treated units.

	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
Spin-offs vs. IPOs						
-Full sample						
distance	0.812	0.168	2.146	3.285	0.452	0.769
Age	43.893	42.998	0.109	0.935	0.029	0.059
Male_flag	0.892	0.869	0.076		0.024	0.024
Subsidiary size	524.023	22.709	1.031	197.726	0.334	0.715
Subsidiary innovation output	341.777	12.390	0.954	271.816	0.377	0.704
-Matched Sample						
distance	0.812	0.481	1.104	0.713	0.251	0.598
Age	43.824	55.080	-1.374	1.247	0.352	0.611
Male_flag	0.892	0.893	-0.002		0.001	0.001
Subsidiary size	525.188	45.012	0.988	77.509	0.176	0.599
Subsidiary innovation output	343.215	26.753	0.917	116.577	0.189	0.692
Spin-offs vs. Controls						
-Full sample						
distance	0.258	0.054	0.703	16.379	0.328	0.430
Age	43.893	44.396	-0.061	0.664	0.048	0.081
Male_flag	0.892	0.891	0.003		0.001	0.001
Subsidiary size	524.023	1,209.276	-1.409	0.063	0.099	0.255
Subsidiary innovation output	341.777	742.416	-1.161	0.074	0.089	0.217
-Matched Sample						
distance	0.257	0.271	-0.049	0.840	0.001	0.182
Age	43.878	48.741	-0.594	0.570	0.135	0.259
Male_flag	0.892	0.865	0.087		0.027	0.027
Size	522.827	239.151	0.583	1.831	0.116	0.396
Subsidiary innovation output	340.778	133.711	0.600	2.490	0.110	0.439
IPOs vs. Controls						
-Full sample						
distance	0.313	0.056	1.878	1.462	0.529	0.732
Age	42.998	44.396	-0.165	0.710	0.055	0.105
Male_flag	0.869	0.891	-0.067		0.023	0.023
Subsidiary size	22.709	1,209.276	-34.313	0.0003	0.287	0.691
Subsidiary innovation output	12.390	742.416	-34.873	0.0003	0.253	0.663
-Matched Sample						
distance	0.313	0.313	-0.001	1.009	0.001	0.008
Age	42.991	43.695	-0.083	0.755	0.034	0.064
Male_flag	0.869	0.860	0.024		0.008	0.008
Subsidiary size	22.708	20.855	0.054	1.377	0.004	0.117
Subsidiary innovation output	12.391	9.121	0.156	1.726	0.008	0.205

Table 1.5: Matching Summary on the Productivity

Matching productivity summary. Matching is done using nearest neighbour matching with replacement. Stayer-inventor year level data (panel) is matched based on inventor's age, gender, subsidiary's size and innovation output before the treatment, 28 industries according to 2-digit CPC system. In spin-off vs. IPO matched sample, has 5,749 of 80,258 non-treated are matched to 76,234 of 76,940 treated units. In spin-off vs. controls, 14,942 of 1,048,997 non-treated units are matched to 76,798 of 76,940 treated units. In IPOs vs. controls, 34677 of 1,048,997 non-treated units are matched to 79,815 of 80,258 treated units.

	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
Spin-offs vs. IPOs						
-Full sample						
distance	0.848	0.146	2.513	2.907	0.474	0.816
Age	43.981	43.068	0.112	0.917	0.030	0.062
Male_flag	0.890	0.862	0.089		0.028	0.028
Subsidiary size	586.118	24.685	1.148	177.247	0.331	0.768
Subsidiary innovation output	383.749	13.515	1.055	250.029	0.377	0.753
-Matched sample						
distance	0.848	0.462	1.382	0.611	0.293	0.662
Age	43.931	55.151	-1.375	1.361	0.351	0.613
Male_flag	0.890	0.910	-0.064		0.020	0.020
Subsidiary size	587.060	42.738	1.113	84.224	0.187	0.672
Subsidiary innovation output	384.998	25.495	1.025	130.860	0.184	0.733
Spin-offs vs. Controls						
-Full sample						
distance	0.291	0.052	0.742	20.621	0.344	0.471
Age	43.981	44.413	-0.053	0.675	0.046	0.078
Male_flag	0.890	0.885	0.017		0.005	0.005
Subsidiary size	586.118	1,293.473	-1.447	0.060	0.104	0.273
Subsidiary innovation output	383.749	792.219	-1.164	0.072	0.095	0.232
-Matched sample						
distance	0.290	0.305	-0.046	0.860	0.001	0.217
Age	43.965	48.862	-0.600	0.554	0.137	0.280
Male_flag	0.890	0.874	0.053		0.016	0.016
Subsidiary size	585.076	270.720	0.643	1.763	0.129	0.394
Subsidiary innovation output	382.849	159.661	0.636	2.154	0.120	0.435
IPOs vs. Controls						
-Full sample						
distance	0.332	0.051	1.808	1.931	0.548	0.758
Age	43.068	44.413	-0.158	0.736	0.052	0.101
Male_flag	0.862	0.885	-0.065		0.023	0.023
Subsidiary size	24.685	1,293.473	-34.549	0.0003	0.305	0.703
Subsidiary innovation output	13.515	792.219	-35.098	0.0003	0.268	0.679
-Matched sample						
distance	0.331	0.331	-0.002	1.009	0.001	0.010
Age	43.035	43.587	-0.065	0.788	0.029	0.057
Male_flag	0.863	0.841	0.063		0.022	0.022
Subsidiary size	24.617	23.041	0.043	1.358	0.005	0.113
Subsidiary innovation output	13.480	10.461	0.136	1.665	0.008	0.190

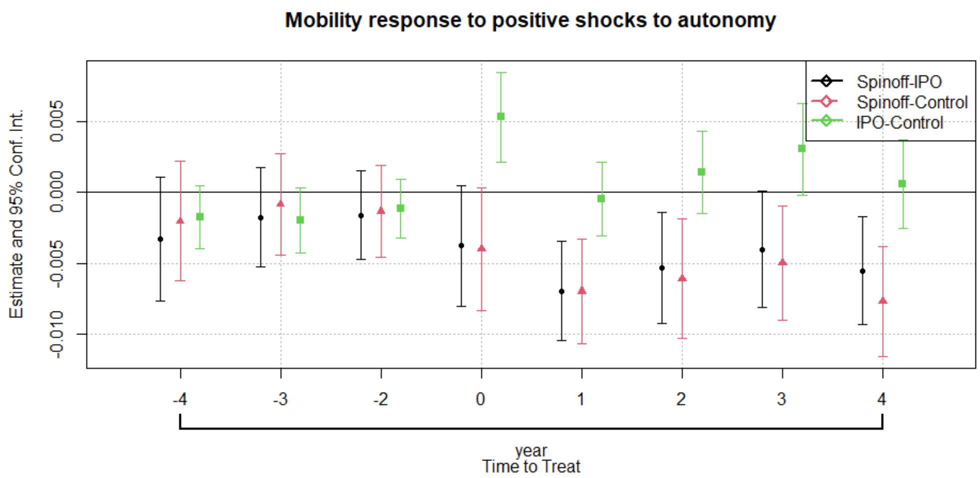


Figure 1.1: Coefficients of the event study, capturing inventor departure around spin-offs and IPOs.

Coefficients of the event study according to specification 1, capturing inventor departure in the $[-4, 4]$ window around spin-offs and IPOs.

firms is very similar, which provides supporting evidence for the results in the first two columns. Finally, the last two columns show that inventors are more likely to leave the IPO firm compared to the controls, consistent with findings in Bernstein (2015). The coefficients of the event study are depicted in Figure 1.1.

Moreover, in order to address the concern about the differences in spin-off and carve-outs, as discussed in Section 1.2, I run the same regression above on the matched *spin-off vs. IPO* sample and split the full sample into spin-offs and carve-outs. The results are reported in Table 1.11 in the appendix. Spin-offs exhibit a larger and more statistically significant coefficient (1%, t-stat = 4.8) compared to the carve-outs (0.7%, t-stat = -1.98), consistent with the greater degree of autonomy granted to the subsidiary manager through a spin-off. Nevertheless, the results across the two sub-samples are quantitatively similar and therefore, justifies pooling the inventors experiencing spin-offs and carve-outs together.

In addition, to examine whether there is heterogeneity in the effect on mobility based on the characteristics of the subsidiary, I split the matched sample of *spin-off vs. IPO* based on the hierarchical and geographical distance of the subsidiary to the headquarter (HQ). Following my first hypothesis, *spinoff-inventors* are even less likely to leave the subsidiary, if they are farther from the headquarter in the hierarchy and geographical distance. This hypothesis follows from the inverse relationship between

Table 1.6: The Event Study Results of the departure Rates around *Spin-offs*, *IPOs*, and for the *control firms*.

This table shows the result of an event study of the probability of inventor departure in linear probability model according to $Y_{isft} = \alpha + \sum_{k=-4,k\neq-1}^{4} \beta_k \times treat_{isfk} + X^i_{it}\Gamma + X^s_{st}\Lambda + X^f_{ft}\Omega + \gamma_i + \lambda_s + \omega_f + \theta_t + \epsilon_{it}$. X^i, X^s, X^f are respectively inventor, subsidiary, firm level controls. γ, λ, ω are inventor, subsidiary, firm level fixed effects. The results are summarised to brevity. Complete results are reported in Table 1.13. Column 1 and 2 correspond to spin-off vs. IPO, columns 3 and 4 to spin-off vs. control, and columns 5 and 6 correspond to IPO vs. control comparison. estimation is based on bias-corrected estimator by Sun and Abraham (2021). Standard errors are robust and clustered at the transaction level.

Dependent Variable:	Departure					
	Spin-off vs. IPO		*Spin-off vs. Control*		*IPO vs. Control*	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
year = -4	0.0006	-0.003	-0.0002	-0.002	-0.002**	-0.002
	(0.38)	(-1.5)	(-0.14)	(-0.95)	(-2.0)	(-1.5)
year = -3	0.0002	-0.002	8.8×10^{-5}	-0.0008	-0.002	-0.002*
	(0.15)	(-0.98)	(0.07)	(-0.47)	(-1.5)	(-1.7)
year = -2	-0.001	-0.002	-0.001	-0.001	-0.0009	-0.001
	(-0.92)	(-1.0)	(-0.81)	(-0.80)	(-0.96)	(-1.1)
year = 0	-0.002	-0.004*	-0.002*	-0.004*	0.006***	0.005***
	(-1.4)	(-1.7)	(-1.8)	(-1.8)	(3.4)	(3.3)
year = 1	-0.006***	-0.007***	-0.006***	-0.007***	0.0006	-0.0005
	(-3.6)	(-3.9)	(-3.9)	(-3.7)	(0.51)	(-0.36)
year = 2	-0.006***	-0.005***	-0.007***	-0.006***	0.002*	0.001
	(-4.0)	(-2.7)	(-5.2)	(-2.8)	(1.7)	(0.93)
year = 3	-0.006***	-0.004*	-0.006***	-0.005**	0.003**	0.003*
	(-3.4)	(-1.9)	(-4.2)	(-2.4)	(2.2)	(1.9)
year = 4	-0.009***	-0.005***	-0.010***	-0.008***	0.0008	0.0006
	(-5.6)	(-2.9)	(-6.5)	(-3.9)	(0.65)	(0.35)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes
Subsidiary FE	Yes	Yes	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Public Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Matched Sample		Yes		Yes		Yes
Fit statistics						
Observations	231,780	118,714	1,609,342	134,416	1,621,816	176,233
R^2	0.09528	0.09545	0.07731	0.14765	0.07805	0.19261
Within R^2	0.00573	0.00881	0.00125	0.00853	0.00066	0.00379

Clustered (deal_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

hierarchy and authority. Spinning off a subsidiary which is at the bottom of the corporate hierarchical structure provides more authority to its inventors relative to the subsidiary which is already at a higher level. In other words, spinning off a hierarchically far subsidiary gives a greater dose of treatment, i.e., authority, to its inventors. As for geographical distance, inventors working at a geographically distant subsidiary can hardly transmit their innovative ideas to the managers in the HQ, who need to ultimately approve their proposals. Hence, in effect, a spin-off relocates the HQ and makes the decision-makers more accessible, and facilitates transmitting innovative ideas.

Therefore, I run the same regression and split the sample based on the hierarchical and geographical distance to the HQ. Since I am not able to obtain data on the hierarchical level of all the subsidiaries before the spin-off, I do the analysis only on a part of the matched sample. This reduces the number of observations from around 120K to 60K inventor year observations in the matched sample. The results are reported in Table 1.7. The first column shows the average treatment effect of the spin-off on the probability of departure in the matched sample. Columns 2 and 3 show the results for the split in close (below median) and far (above median) hierarchical distance, respectively. Moreover, columns 4 and 5 show the split based on the geographical distance, with the former containing the inventors who are close (below median) to the HQ and the latter containing inventors far from the HQ (above median). The findings substantiate the first hypothesis and show that the inventors in the far spin-offs, both in the hierarchy and in geographical distance, are even less likely to leave the spin-off firm (-0.6%, t-stat = 2.1 and -1%, t-stat = 4.2), while the inventors who are close to the HQ show no significant difference in the likelihood of departure between a spin-off and IPO firms. In sum, the findings reported in Tables 1.6 and 1.7 provide evidence for the first hypothesis, that is, inventors are less likely to leave the spin-off firm than an IPO. Moreover, this effect is more pronounced for spin-offs that are far from the HQ, both in hierarchical and geographical distance.

In addition, to check whether there is heterogeneity across inventors in their mobility response to authority, I split the matched sample on the two following characteristics. Inventors are defined to be *independent* (or team-dependent) and *specialist* (or generalist) based on their patenting behavior over the sample period. An inventor is

Table 1.7: *ATT* of *Spin-offs* on Departure Probability of Inventors, Split by Hierarchical and Geographical Distance.

This table shows the average departure probability of spin-off inventors compared to the matched sample of IPO inventors (ATT). The matched sample is split by hierarchical and geographical distance. The outcome variable is the probability of inventor departure in a linear probability model. The results are summarised for brevity. The estimation is adjusted for heterogeneity of treatment effects by the estimator from Sun and Abraham (2021). Standard errors are robust and clustered at the transaction level.

Dependent Variable:		Departure			
Hierarchy Far	Full sample	0	1		
Geography Far				0	1
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
ATT	-0.008***	-0.005	-0.006**	-0.004	-0.010***
	(-3.7)	(-0.18)	(-2.1)	(-0.02)	(-4.2)
Fixed-effects					
Inventor	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Subsidiary	Yes	Yes	Yes	Yes	Yes
Parent Firm	Yes	Yes	Yes	Yes	Yes
Public Firm	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	118,714	36,977	22,708	62,254	60,769
R^2	0.10137	0.10290	0.13083	0.13155	0.11600
Within R^2	0.01529	0.01264	0.03294	0.02583	0.02174

Clustered (deal_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

independent (team-dependent) if he has below (above) median team size. Similarly, an inventor is defined to be a *specialist* (generalist) if the number of distinct technology classes in his filed patents is below (above) the median. Table 1.8 shows the mobility response to authority split by these two inventors' characteristics. The first column shows the average treatment effect for the full sample and is repeated here for reference. The split for *specialist* versus *generalist* is reported in columns 2 and 3. While the *generalist* in spin-offs exhibits no significant difference compared to ones in the IPOs, the *specialists* in spin-offs are more likely to stay with the spun-off firm (non-specialists: 0.01%, t-stat = -0.01 and *specialists*: 0.8%, t-stat = -3.4). This result is consistent with the predictions in Hart and Moore (2005), as the firm becomes less hierarchical through a spin-off, the *specialists* will have more authority and thus are more likely to stay. Moreover, *independent* (vs. team-dependent) splits are reported in columns 4 and 5. The average treatment effect for both are significant and negative (team-dependent: -1%, t-stat= -2.1, *independent*: 0.7%, t-stat= -2.8), but the coefficient for the *independent* inventors is smaller. This evidence is in line with the intuition that *independent* inventors can move more easily than team-dependent inventors, whose innovation production stifles if they move without their team members.

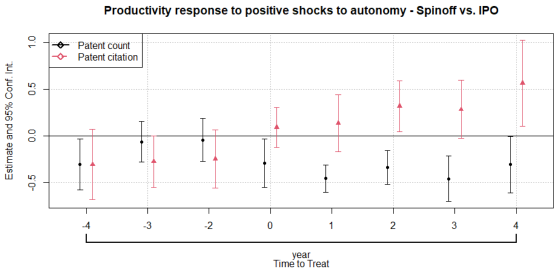
Next, I turn to the inventor's *productivity* response to authority. Table 9 shows the regression results of a Poisson model (according to specification 1) with the *stayer-inventor*'s output in patent *count* (innovation quantity) and in the patent *citation* (innovation quality) as outcome variables and on the matched sample. Similar to the departure response, I report the results for *spin-off vs. control* firms in columns 3 (*count*) and 4 (*citation*) and the results for *IPO vs. control* firms in columns 5 (*count*) and 6 (*citation*). The first row of the table shows the *ATT*. The Spin-off vs. IPO comparison shows that while the patent quantity does not show a significant effect (0.14, t-stat = 0.5), the patent quality increases significantly (2.5, t-stat = 6.1) after the spin-off compared to an IPO. The results of the spin-off vs. control and IPO vs. controls provides further supporting evidence. As can be seen in columns 3 and 4, inventors in spin-off firms show a significant decline in patent quantity (-0.29, t-stat=-2.5) and a significant increase in patent quality (-0.29, t-stat = 6.3) compared to the ones in the control firms. This means that the innovation quality of an average spin-off-

Table 1.8: *ATT* of *Spin-offs* on Departure Probability of Inventors, Split by Inventor Types.

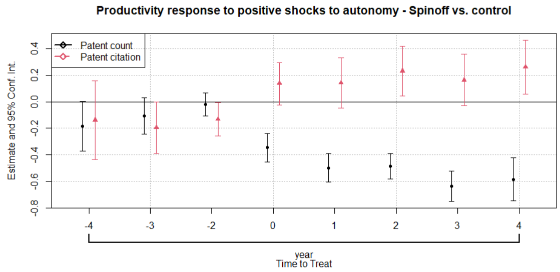
This table shows the average departure probability of spin-off inventors compared to the matched sample of IPO inventors (ATT). The matched sample is split based on inventors' patent portfolio characteristics. An inventor is specialist if his patent portfolio has below median (across inventors over the sample period) number of distinct technology classes. An inventor is independent is he has below median team size, across inventors over the sample period. The results are summarised for brevity. The estimation is adjusted for heterogeneity of treatment effects by the estimator from Sun and Abraham (2021). Standard errors are robust and clustered at the transaction level.

Dependent Variable:			Departure		
inventor_specialist	Full sample	0	1		
inventor_independent				0	1
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
ATT	-0.008***	-0.0001	-0.008***	-0.01**	-0.007***
	(-3.7)	(-0.01)	(-3.4)	(-2.1)	(-2.8)
Fixed-effects					
Inventor	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Subsidiary	Yes	Yes	Yes	Yes	Yes
Parent Firm	Yes	Yes	Yes	Yes	Yes
Public Firm	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	118,287	39,310	78,977	18,994	99,293
R^2	0.10180	0.10338	0.11316	0.13712	0.10697
Within R^2	0.01526	0.02781	0.01979	0.06009	0.01870

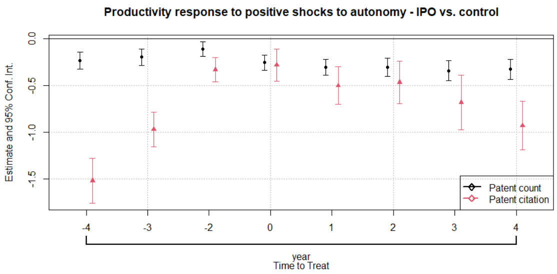
Clustered (deal_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*



(a) Spin-off vs. IPO



(b) Spin-off vs. Control



(c) IPO vs. Controls

Figure 1.2: Coefficients of the event study, capturing inventor productivity around *spin-offs*, *IPOs*, and *Control firms*.

inventor increased nearly 11 fold (= $exp(2.5) - 1$) compared to an IPO-inventor, and increased by nearly 6 fold (= $exp(1.9) - 1$) compared to a control-inventor. In addition, comparing IPO firms and control firms in columns 5 and 6 shows that IPO inventors experience a significant drop in both quality (-.029, t-stat = -6.3) and quantity (-0.48, t-stat = -3.8) of their patents. Furthermore, Table 9 reports the event study coefficients in a $[-4, 4]$ window, which demonstrates that the matched inventors' productivity in spin-off and IPO firms almost behave the same before the event, hence, the parallel trends assumption.

These results reveal an interesting nuance about the trade-off between quality and quantity of innovation in spin-off firms. Having more authority directs more effort to innovative projects which are more likely to get rejected otherwise, that is, projects whose information is "soft". As such, the inventor with more authority undertakes projects which are more exploratory and more original and thus have a higher probability of failure, but if they become successful they get more citations. These findings are also consistent with predictions in Holmstrom and Milgrom (1991), who consider a multi-task principal-agent model in which tasks differ in the measurability of their

Table 1.9: Event Study Results of Inventor's Productivity around *Spin-offs*, *IPOs*, and for the *Control Firms*

This table shows the result of an event study of productivity of inventors in a Poisson model according to $Y_{isft} = \alpha + \sum_{k=-4,k\neq-1}^{4} \beta_k \times treat_{isfk} + X_{it}^{i}\Gamma + X_{st}^{s}\Lambda + X_{ft}^{f}\Omega + \gamma_i + \lambda_s + \omega_f + \theta_t + \epsilon_{it}$. X^i, X^s, X^f are respectively inventor, subsidiary, firm level controls. γ, λ, ω are inventor, subsidiary, firm level fixed effects. Columns 1 and 2 correspond to spin-off vs. IPO, columns 3 and 4 to spin-off vs. control, and columns 5 and 6 correspond to IPO vs. control comparison. The results are summarised for brevity. The estimation is adjusted for heterogeneity of treatment effects by the estimator from Sun and Abraham (2021). Standard errors are robust and clustered at the transaction level.

Dependent Variables:	Patent Count	Patent Citation	Patent Count	Patent Citation	Patent Count	Patent Citation
	Spin-off vs. IPO		*Spin-off vs. Control*		*IPO vs. Control*	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
ATT	0.14	2.5***	-0.29**	1.9***	-0.29***	-0.48***
	(0.50)	(6.1)	(-2.5)	(11.1)	(-6.3)	(-3.8)
year = -4	-0.30**	-0.30	-0.18*	-0.14	-0.23***	-1.5***
	(-2.2)	(-1.6)	(-1.9)	(-0.91)	(-4.9)	(-12.3)
year = -3	-0.06	-0.27*	-0.11	-0.20**	-0.20***	-0.97***
	(-0.54)	(-1.9)	(-1.5)	(-2.0)	(-4.5)	(-10.3)
year = -2	-0.04	-0.24	-0.02	-0.13**	-0.11***	-0.33***
	(-0.35)	(-1.5)	(-0.45)	(-2.0)	(-2.7)	(-5.0)
year = 0	-0.29**	0.09	-0.35***	0.14*	-0.26***	-0.28***
	(-2.2)	(0.85)	(-6.3)	(1.7)	(-6.4)	(-3.2)
year = 1	-0.45***	0.14	-0.50***	0.14	-0.30***	-0.50***
	(-6.1)	(0.90)	(-9.1)	(1.5)	(-6.9)	(-4.8)
year = 2	-0.33***	0.32**	-0.49***	0.23**	-0.30***	-0.47***
	(-3.6)	(2.3)	(-9.8)	(2.4)	(-6.1)	(-4.0)
year = 3	-0.46***	0.29*	-0.64***	0.16*	-0.34***	-0.68***
	(-3.7)	(1.8)	(-10.9)	(1.7)	(-6.3)	(-4.6)
year = 4	-0.30**	0.57**	-0.58***	0.26**	-0.33***	-0.93***
	(-2.0)	(2.4)	(-7.1)	(2.5)	(-6.0)	(-7.0)
Fixed-effects						
Inventor	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Subsidiary	Yes	Yes	Yes	Yes	Yes	Yes
Parent Firm	Yes	Yes	Yes	Yes	Yes	Yes
Public Firm	Yes	Yes	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	82,026	78,581	88,523	82,106	110,581	85,144
Squared Correlation	0.37355	0.31095	0.40627	0.35997	0.40158	0.51855
Pseudo R^2	0.25426	0.48296	0.28144	0.48841	0.25210	0.66617
BIC	258,659.2	1,598,328.8	323,344.8	1,613,654.8	415,049.0	1,821,959.3

Clustered (deal_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

outcomes. Holmstrom and Milgrom (1991) discuss the quality (hard to measure) and quantity (measurable) trade-off and solve for the job design that would incentivize both quality and quantity. Their model implies that tasks need to be grouped based on their measurability, i.e., a group of inventors specialize in activities that are hard to monitor and others in activities that are easily monitored. Therefore, separating the tasks based on their measurability characteristics, e.g., through a spin-off, enables the parent company to provide strong incentives for tasks that are hard to measure without being concerned that the agent will substitute efforts to the easy-to-measure tasks.

In addition, I split the matched sample of the *stayer-inventors* of the *spin-off vs. IPO* based on hierarchy and geographical distance and study their productivity response. Table 1.10 shows the results. Columns 1 and 2 show the full sample results as the reference. Columns 3-6 correspond to the hierarchical distance, with columns 3 (5) and 4 (6) being the patent *count* and *citation* of the hierarchically close (far) inventors, respectively. Similarly, columns 7-10 show the average treatment effect for the geographical distance. Under my second hypothesis, the hierarchically far inventors show a larger increase (1.1, t-stat= 2.8) in the quality of their innovation output than the inventors who are close in the hierarchy (0.8, t-stat= 0.002). Likewise for the geographical distance, inventors who are far from the parent's headquarters experience a larger increase in innovation quality than those who are close to the headquarter, i.e., 3 (t-stat= 8.1) compared to 1.6 (t-stat=3.3). The coefficients corresponding to patent quality are insignificant across different samples but change direction from hierarchically far sub-sample (0.21, t-stat= 0.94) to hierarchically close sub-sample (-0.85, t-stat=-0.11).

Table 1.10: *ATT* of *Spin-offs* vs. *IPOs* on Inventor's Productivity, Split by Hierarchy and Geographical distance.

This table shows the average productivity response of spin-off inventors compared to the matched sample of IPO inventors (ATT), in patent count and patent citation. The matched sample is split by hierarchical and geographical distance. The outcome variables are patent count (odd columns) and patent citation (even columns) of inventor in a Poisson model. The results are summarised for brevity. The estimation is adjusted for heterogeneity of treatment effects by the estimator from Sun and Abraham (2021). Standard errors are robust and clustered at the transaction level.

Dependent Variables:	Patent Count	Patent Citation	Patent Count	Patent Citation	Patent Count	Patent Citation	Patent Count	Patent Citation	Patent Count	Patent Citation
Hierarchy Far	Full sample	Full sample	0	0	1	1				
Geography Far							0	0	1	1
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
ATT	0.14	2.6***	-0.85	0.80	0.21	1.1***	0.12	1.6***	0.11	3.0***
	(0.50)	(6.4)	(-0.11)	(0.002)	(0.94)	(2.8)	(0.35)	(3.3)	(0.48)	(8.1)
Fixed-effects										
Inventor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subsidiary	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Public Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	82,026	78,581	26,660	25,245	14,252	12,669	46,125	42,744	37,010	35,320
Squared Correlation	0.36558	0.35011	0.40641	0.34398	0.34650	0.39721	0.37929	0.38847	0.37674	0.39914
Pseudo R^2	0.26653	0.49259	0.26228	0.53568	0.38001	0.67963	0.26252	0.59815	0.30596	0.56859
BIC	259,996.8	1,610,823.7	89,288.2	546,788.3	61,752.4	338,070.1	154,495.8	740,149.2	135,570.7	720,709.1

Clustered (deal_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

1.5 Conclusion

This study set out to investigate the effect of authority on inventors' departure and productivity following a spin-off event. I put forth two main hypotheses and test them using a dynamic difference-in-differences model, coupled with propensity score matching to control for confounding factors and firm self-selection. The first hypothesis posits that inventors experiencing a spin-off event would be less likely to leave the spun-off firm compared to *IPO-inventors* and *control-inventors*, particularly if the spun-off subsidiary is far from the headquarters in terms of hierarchy and geographical distance. The second hypothesis postulates that *stayer-inventors* would file more radical patents in a spun-off firm, with a more pronounced effect for those who are hierarchically and geographically distant from the headquarters.

The results of this study provides robust evidence in support of the first hypothesis. Inventors in spun-off firms are indeed less likely to leave their employers compared to those in IPO firms, with an even more pronounced effect for inventors far from the headquarters both hierarchically and geographically. The findings on the second hypothesis are more nuanced, revealing an interesting trade-off between the quality and quantity of innovation in spun-off firms. While there is no significant effect on the patent quantity for inventors in spun-off firms compared to IPO firms, there is a significant increase in patent quality. Moreover, inventors who were hierarchically and geographically far from the headquarters experienced a larger increase in innovation quality than their counterparts who were close to the headquarters.

These results highlight the importance of authority in shaping inventors' behavior and innovation outcomes following a spin-off event. By granting inventors greater autonomy, spun-off firms appear to foster a more conducive environment for exploratory and original research that may yield significant breakthroughs, despite the inherent risks associated with such endeavors. This observation is consistent with the theoretical predictions of Holmstrom and Milgrom (1991), who propose that separating tasks based on their measurability allows firms to provide strong incentives for hard-to-measure tasks without the risk of effort substitution.

Furthermore, the study's findings underscore the value of examining the interaction between authority and other factors, such as hierarchical and geographical distance, in understanding the dynamics of inventors' departure and productivity. By focusing on these dimensions, the study contributes to a more comprehensive understanding of the impact of spin-offs on inventors and innovation outcomes.

Several limitations and avenues for future research should be acknowledged. First, the analysis is conducted using a subset of the data due to the unavailability of hierarchical information for all subsidiaries prior to the spin-off event. Expanding the dataset to include a more comprehensive sample of inventors and subsidiaries may yield further insights into the relationship between authority and inventors' behavior. Second, this study uses an indirect measure of authority, while constructing a direct measure through surveys or occupational codes can contribute to validity of the results. Third, the study does not investigate the new employer of the leaving inventors, which could potentially illuminate their choices regarding authority in the new employer.

In conclusion, this study sheds light on the significant role of authority in influencing inventors' departure and productivity following a spin-off event. By granting inventors more autonomy and aligning incentives with hard-to-measure tasks, spun-off firms can foster an environment conducive to radical innovation and breakthroughs. These findings have important implications for managerial decision-making, as well as for the broader understanding of the factors shaping innovation outcomes in firms.

1.6 Appendix

1.6.1 Robustness checks and Extended Tables

Table 1.11: *ATT of Spin-offs vs. IPOs on the Departure Probability.*

This table shows the average departure probability of spin-off and carve-out inventors compared to the matched sample of IPO inventors (ATT). The outcome variable is the probability of inventor departure in a linear probability model. The results are summarised for brevity. The estimation is adjusted for heterogeneity of treatment effects by the estimator from Sun and Abraham (2021). Standard errors are robust and clustered at the transaction level.

Dependent Variable:		Departure	
	Full sample	Spin-off	Carve-out
Model:	(1)	(2)	(3)
Variables			
ATT	-0.008***	-0.010***	-0.007**
	(-3.7)	(-4.8)	(-1.98)
Fixed-effects			
Inventor	Yes	Yes	Yes
year	Yes	Yes	Yes
Subsidiary	Yes	Yes	Yes
Parent Firm	Yes	Yes	Yes
Public Firm	Yes	Yes	Yes
Fit statistics			
Observations	118,714	71,228	47,486
R^2	0.10137	0.10290	0.13083
Within R^2	0.01529	0.01264	0.03294

Clustered (deal_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 1.12: The Event Study Results of the Departure Rates Around *Spin-offs*, *IPOs*, and for the *control firms*-Extended.

Mobility response. This table shows the result of an event study of the probability of inventor departure in linear probability model according to $Y_{isft} = \alpha + \sum_{k=-4,k\neq-1}^{4} \beta_k \times treat_{isfk} + X_{it}^{i}\Gamma + X_{st}^{s}\Lambda + X_{ft}^{f}\Omega + \gamma_i + \lambda_s + \omega_f + \theta_t + \epsilon_{it}$. X^i, X^s, X^f are respectively inventor, subsidiary, firm level controls. γ, λ, ω are inventor, subsidiary, firm level fixed effects. The results are summarised to brevity. Complete results are reported in Table 13. Column 1 and 2 correspond to spin-off vs. IPO, columns 3 and 4 to spin-off vs. control, and columns 5 and 6 correspond to IPO vs. control comparison. estimation is based on bias-corrected estimator by Sun2021. Standard errors are robust and clustered at the transaction level.

Dependent Variable:	Departure					
	Spin-off vs. IPO		*Spin-off vs. Control*		*IPO vs. Control*	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
year = -4	0.0006	-0.003	-0.0002	-0.002	-0.002**	-0.002
	(0.38)	(-1.5)	(-0.14)	(-0.95)	(-2.0)	(-1.5)
year = -3	0.0002	-0.002	8.8×10^{-5}	-0.0008	-0.002	-0.002*
	(0.15)	(-0.98)	(0.07)	(-0.47)	(-1.5)	(-1.7)
year = -2	-0.001	-0.002	-0.001	-0.001	-0.0009	-0.001
	(-0.92)	(-1.0)	(-0.81)	(-0.80)	(-0.96)	(-1.1)
year = 0	-0.002	-0.004*	-0.002*	-0.004*	0.006***	0.005***
	(-1.4)	(-1.7)	(-1.8)	(-1.8)	(3.4)	(3.3)
year = 1	-0.006***	-0.007***	-0.006***	-0.007***	0.0006	-0.0005
	(-3.6)	(-3.9)	(-3.9)	(-3.7)	(0.51)	(-0.36)
year = 2	-0.006***	-0.005***	-0.007***	-0.006***	0.002*	0.001
	(-4.0)	(-2.7)	(-5.2)	(-2.8)	(1.7)	(0.93)
year = 3	-0.006***	-0.004*	-0.006***	-0.005**	0.003**	0.003*
	(-3.4)	(-1.9)	(-4.2)	(-2.4)	(2.2)	(1.9)
year = 4	-0.009***	-0.005***	-0.010***	-0.008***	0.0008	0.0006
	(-5.6)	(-2.9)	(-6.5)	(-3.9)	(0.65)	(0.35)
R&D intensity	0.0004	-0.010	0.0003	-0.004	0.0003*	0.0003
	(1.1)	(-1.1)	(1.5)	(-0.44)	(1.8)	(1.4)
Size	0.002***	0.003*	0.001***	0.004**	0.001***	0.001***
	(4.2)	(2.0)	(3.0)	(2.5)	(2.9)	(2.7)
Tangibility	0.003	-0.0002	0.0004	-0.001	0.0008	0.002
	(0.76)	(-0.02)	(0.13)	(-0.15)	(0.31)	(0.36)
Leverage	-0.001	-0.008*	-0.002**	-0.004	-0.002**	0.002
	(-0.33)	(-1.7)	(-2.3)	(-0.97)	(-2.2)	(0.59)
Q	2.6×10^{-5}	0.0004	2.4×10^{-7}	0.0004	-3×10^{-6}	-6.7×10^{-6}
	(0.23)	(0.98)	(0.15)	(1.2)	(-0.89)	(-0.86)
ROA	0.0002	-0.002	4.8×10^{-7}	0.0004	-6.3×10^{-6}	-1.4×10^{-5}
	(0.41)	(-0.50)	(0.14)	(0.15)	(-0.88)	(-0.82)
Cash liquidity	0.003	-0.002	0.001	-0.0006	0.002	0.004
	(0.74)	(-0.31)	(0.53)	(-0.07)	(0.87)	(1.1)
Subsidiaries No.	-6.3×10^{-5}	-0.0004*	6.1×10^{-5}	-9.2×10^{-5}	6.8×10^{-5}	0.0002
	(-0.43)	(-1.8)	(0.55)	(-0.46)	(0.61)	(0.93)
Inventors No.	6.1×10^{-7}	4×10^{-6}**	-2.4×10^{-7}	2.7×10^{-6}	-2.5×10^{-7}	-2.2×10^{-6}
	(0.46)	(2.2)	(-1.1)	(1.4)	(-1.2)	(-1.1)
Fixed-effects						
Inventor	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Subsidiary	Yes	Yes	Yes	Yes	Yes	Yes
Parent Firm	Yes	Yes	Yes	Yes	Yes	Yes
Matched Sample		Yes		Yes		Yes
Fit statistics						
Observations	231,780	118,714	1,609,342	134,416	1,621,816	176,233
R^2	0.09528	0.09545	0.07731	0.14765	0.07805	0.19261
Within R^2	0.00573	0.00881	0.00125	0.00853	0.00066	0.00379

Clustered (deal_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Chapter II

Learning-by-hiring and M&A activity

Abstract

In this paper, I investigate the interplay between firms' inventor recruiting and technology acquisition decisions. Using a comprehensive sample of mergers and acquisitions (M&As) and inventor mobility data, I first establish a connection between hiring inventors and engaging in M&A activities. The findings reveal that firms recruiting inventors with **similar** technological expertise tend to acquire technologically **similar** targets, while those hiring inventors with **new** technological expertise are more likely to acquire technologically **distant** targets. I further explore the channels through which these two decisions may be related. I provide strong support for the channel, in which firms assess the complementarity of new technologies with their existing portfolio by initially hiring inventors with the desired expertise and subsequently choosing targets similar to the inventors with the highest complementarity.

2.1 Introduction

Firms explore new technologies through various avenues, one of which is hiring talented individuals with experience in the desired technological domains. The **learning-by-hiring** phenomenon, as documented in the literature (e.g., Arrow (1962), Lacetera et al. (2004), and Song et al. (2003a)), demonstrates that firms can gain valuable insights and develop new capabilities by bringing in experts from outside their organization[1]. Another strategy for firms to strengthen their technology portfolio or extend their existing technologies is through mergers and acquisitions (M&A). This approach, referred to as **Techover**, enables firms to acquire new technologies by incorporating other companies with desired capabilities (e.g., Hart and Moore (1990), Holmstrom and Roberts (1998), Levine (2017)). The literature suggests that these external sources of innovation are not substitutes but rather complementary (e.g., Cassiman and Veugelers (2006); Rothaermel and Hess (2007)). This paper seeks to investigate the interplay between firms' inventor hiring and technology acquisition decision and explore the channels through which these two decisions could be related.

The interplay between these two decisions can be ascribed to the following factors. First, since hiring is generally less costly than acquiring, it could serve as a precedent stage for exploring potential new technologies. In this stage, the focal firm tests whether the new technologies and inventors would fit well within the organization and its competitive environment. This process allows firms to assess the compatibility of the new technology with their existing portfolio and make informed decisions regarding

[1]In April 2018, Apple hired John Giannandrea, previously Google's head of AI and Search, to lead Apple's machine learning and artificial intelligence strategy. Giannandrea was responsible for the development of the Google AI platform, which includes Google Translate, Google Photos, and Google Speech. Giannandrea was tasked with creating an AI strategy that will help Apple catch up to industry rivals like Google and Facebook, both of which have invested heavily in AI research in recent years. After hiring John Giannandrea in April 2018, Apple went on to make dozens of smaller and bigger acquisitions in the following years in order to acquire talent and intellectual property in the AI field. These included acquisitions of companies like Drive.ai, Xnor.ai, Silk Labs, and Voysis. Apple also made several hires from tech giants like Google, Amazon, and Microsoft, as well as from universities, in order to further bolster its AI capabilities. In addition, the company has been investing heavily in research and development in the AI field, with the number of AI professionals in the company doubling and the number of PhD holders in the field tripling in the last three years. John Giannandrea played a role in these acquisitions. He was responsible for setting the company's overall AI strategy and overseeing its execution. He also worked closely with the teams responsible for the acquisitions to ensure the best possible outcomes in terms of the company's AI capabilities. Giannandrea also worked to foster collaboration between the different teams and divisions within Apple, as well as with external partners, in order to ensure that Apple's AI initiatives remain on the cutting edge.

future acquisitions (Song et al. (2003b); Rosenkopf and Almeida (2003)). Hiring as a precursor to acquisition enables firms to mitigate risks associated with integrating new technologies and ensures a smoother transition in the event of an acquisition.

Second, by hiring inventors with expertise in new technologies, the focal firm develops "absorptive capacity", positioning itself better for acquiring a technologically distant target. Absorptive capacity refers to a firm's ability to recognize the value of new external information, assimilate it, and apply it to commercial ends (Cohen and Levinthal (1990)). This capacity also aids post-acquisition integration and facilitates collaboration between inventors in the focal firm and the target, ultimately enhancing the realization of synergies and improving the overall success of the acquisition (Lane et al. (2006);Zahra and George (2002)). Hiring talent with new technological expertise thus serves as a strategic move for firms, enabling them to enhance their absorptive capacity and better integrate acquired technologies.

Lastly, the moving inventor could act as an expert, assisting the focal firm in target selection decisions for an otherwise unknown technology, thereby bridging the information gap between the focal firm and the target. Inventors' specialized knowledge in a specific technology domain can be invaluable for the hiring firm, allowing them to make more informed decisions regarding potential targets (Agrawal et al. (2006); Singh and Agrawal (2011a)). By leveraging the expertise of the hired inventor, the firm can better identify suitable targets and anticipate potential challenges or opportunities, ultimately increasing the likelihood of a successful acquisition (Kapoor and Lim (2007); Somaya et al. (2008)).

To examine the relationship between hiring and M&A decisions, I construct a sample of potential mergers following Bena and Li (2014) in 1980-2020. Using patent data, I observe the inventor recruitment behavior of potential acquirers. I classify the moving inventors to *NT-inventors* (New Technology inventors) and *ET-inventors* (Existing Technology inventors). *NT-inventors* are those inventors who introduce a completely new technology to the acquirer and *ET-inventors* are those possessing technology expertise similar to the hiring firm. Furthermore, I categorize firms based on their inventor hiring behaviors, distinguishing between those with technology exploratory motives and those seeking to reinforce their existing technologies. A firm primarily hiring *NT-inventors* (*ET-inventors*) is classified as an *NT-employer* (*ET-employer*). I hypothesize that *NT-employers* are more likely to acquire technologically distant targets, whereas *ET-employers* tend to pursue technologically similar targets. Additionally, I posit that both *NT-employers* and *ET-employers* are more inclined to partner with targets resembling their newly hired inventors.

The findings strongly support these hypotheses. First, I establish that hiring inventors and engaging in M&A activities are interdependent decisions, as firms hiring inventors are more likely to participate in M&A. Second, I demonstrate that firms recruiting *ET-inventors* tend to acquire technologically similar targets, indicating a motive to strengthen their existing technology portfolio. Moreover, this paper shows that firms hiring *NT-inventors* are more likely to acquire technologically distant targets, suggesting a motive to explore new technologies through M&A. As complementary evidence, the paper shows that acquired targets are indeed technologically similar to the pool of inventors recently hired by the acquirer, which holds true for both *ET-* and *NT-employers.*

Two possible channels can justify these findings. The first channel, referred to as the ***experiment*** channel, suggests that firms initially enter into an explorative experiment by hiring *NT-inventors* to extract information about technologies that would fit their current technology portfolio. This new information effectively shortlists a larger set of potentially promising technologies through the hired inventors, which turn out to be successful and thus worthy of pursuing further through an acquisition. The *experiment* channel predicts that the hiring firm selects targets that are technologically similar to the fitting inventors and does not select targets similar to the non-fitting inventors.

The second channel, called the ***expert*** channel, posits that the firm hires the *NT-inventor* to benefit from her expertise in a technology planned for acquisition in the near future. The hired *NT-inventor* can assist the firm in both pre- and post-acquisition stages. Before the acquisition, the *NT-inventor* can help the firm screen the fittest target, while after the acquisition, she can increase the firm's "absorptive capacity", facilitating post-merger integration and better realization of synergies. The *expert* channel predicts that the higher the expertise of the hired inventor, the better she can help the firm, and therefore, the likelier it is that the firm acquires a target(s) technologically similar to the inventor. In contrast to the *experiment* channel, the *expert* channel does not necessarily predict that targets similar to non-expert inventors are less likely to be chosen per se. Instead, the *expert* channel suggests that the firm is more likely to base its target selection decision on the opinions of the most expert inventors, thus choosing targets that are technologically similar to the inventors with the most expertise.

The findings provide stronger support for the *experiment* channel, by showing that acquirers indeed choose targets which are technologically similar to the fitting inventors and do not choose targets similar the non-fitting inventors. Nevertheless, the results for the expert channel are not as conclusive, with some results suggesting the possibility of substitutability between hiring and acquisition. Overall, the findings indicate that acquisition strategy and inventor hiring strategy of acquirers are dependent and that technological similarity plays an important role in M&A activity.

The contributions of this paper are threefold. First, the study establishes a connection between inventor hiring and technology acquisition within a firm, a link that has not been explored in previous literature to the best of my knowledge. Second, the paper uncovers empirical evidence supporting a distinctive technology scouting mechanism employed by firms, which involves learning-by-hiring *NT-inventors* to assess the compatibility and complementarity of new technologies with the firm's existing technologies prior to making larger investments through M&A activities. Lastly, the research constructs the most comprehensive sample of M&As and inventor mobility to date, utilizing a novel measure of technological similarity, the *Mahalanobis* measure, which is markedly superior in capturing the complementarity of technologies.

The study most closely related to my paper might be Bena and Li (2014), which examines the connection between innovation metrics and M&As, demonstrating that increased technological overlap between two firms positively impacts transaction occurrence. This leads to the conclusion that the synergies derived from merging innovation capabilities are significant drivers of acquisitions. Hoberg et al. (2010) and Rhodes-Kropf and Robinson (2008) also underscore the importance of complementary assets in merger formation. Huang and Xie (2023) construct a search and matching model, predicting that companies with greater bilateral knowledge spillovers are more likely to finalize a merger agreement, and their findings align with the model's predictions. Phillips and Zhdanov (2013) present a model and empirical tests indicating that smaller firms may strategically choose to innovate more and subsequently sell to larger firms in response to an active acquisition market. The role of hiring in promoting organizational change has been investigated in only a handful of studies. Song et al. (2003b) suggest that an influx of new employees can enable knowledge transfer and spur innovation. Parrotta and Pozzoli (2012) explore inter-firm labor mobility and discover that hiring knowledge carriers positively influences a firm's value-added. Tzabbar (2017) reveal that recruiting scientists from distant fields is positively correlated with a firm's technological repositioning. Wagner and Goossen (2018) demonstrate that relocating scientists facilitates the creation of technology-oriented alliances between their employers.

The structure the paper is as follows. In Section 2.2, I review the relevant literature and develop my hypotheses. In Section 2.3, I explain the sample construction and provide the summary statistics. In Section 2.4, I explain the methodology, motivate the regressions, and interpret the results. I conclude in Section 2.5.

2.2 Literature Review and Hypotheses development

Learning-by-hiring[2] is a concept that describes how firms explore new technological directions through hiring employees who possess specialized knowledge and skills. This concept was first introduced by Gilfillan (1935) and later by Arrow (1962) maintaining that mobility of knowledge-workers spurs knowledge spillovers across firms and thus, levels the knowledge difference between them. Inventors play a key role in the process of generating ideas and knowledge in organizations and thus are key contributors to successful technological advancements. Exploratory search, which involves experimentation to identify new solutions and inventions, is a risky but necessary research orientation for firms to achieve sustainable competitive advantage and launch new products. However, many firms lack the necessary human capital and expertise to undertake exploration-oriented strategies, and the uncertain outcomes of such strategies may lead to failure.

The literature of learning-by-hiring has studied the recruitment of knowledge workers for searching beyond the firm's existing technological boundaries. The recruited scientists perform gate-keeping and boundary-spanning roles that enable the firm to collect, assimilate, filter, and apply external knowledge. Scientists with distant knowledge, i.e., beyond the firm's technological boundaries, have been shown to engage in exploratory research activity, contributing to improving the firm's exploration abilities and competences. Additionally, scientists with a heterogeneous knowledge background

[2] There are multiple pieces of evidence on the firms recruitment of inventors, scientists, engineers, and other professionals from other firms who are far from their existing technology. For example, Amazon hired Babak Parviz, a former Google executive, to lead its health-care division, Amazon Care. Parviz played a key role in Amazon's health care initiatives, responsible for working with companies to create partnerships and develop innovative health care solutions and services. He was also instrumental in deciding which markets to expand Amazon Care offerings in. Amazon subsequently acquired many firms in the field of health care. For example, Amazon acquired the online pharmacy company PillPack for $753 million in 2018 and launched Amazon Pharmacy in 2020 as a prescription and medication delivery service. Babak Parviz played a key role in these acquisitions, as his experience as a former Google executive and his knowledge of Echo technology were invaluable in furthering Amazon's health-care ambitions.

Moreover, In 2010, Tesla hired Peter Rawlinson, an experienced engineer who had worked on the development of electric vehicles for other companies. Rawlinson was brought on to lead the development of the Tesla Model S, which went on to become one of the most successful electric vehicles on the market. In 2012, Amazon hired Charlie Kindel, a former Microsoft employee who had led the development of the Windows Home Server. Kindel was brought on to lead the development of Amazon's Echo and Alexa products, which have become some of the most successful smart home devices on the market. In 2020, Uber hired Raquel Urtasun, a renowned expert in self-driving technology and a professor at the University of Toronto. Urtasun was brought on to lead Uber's self-driving division and help the company in the development of its autonomous vehicle technology.

are able to reorient their R&D focus to pursue innovations associated with exploratory research activities.

Song et al. (2003a) suggests that human mobility can serve as a mechanism for the acquisition of externally developed knowledge, and examines the conditions under which the mobility of R&D engineers is most likely to facilitate inter-firm knowledge transfer. The authors apply evolutionary economics to study the mobility of engineers in the global semiconductor industry and track engineer mobility and patent citation data to trace inter-firm knowledge flows. They argue that learning-by-hiring is useful for innovation beyond the firm's current technological and geographic boundaries. The findings suggest that the most useful conditions for learning-by-hiring are when the hiring firm has a lower technological capability level than the knowledge source and when the hiring and source firms are geographically distant. Moreover, Parrotta and Pozzoli (2012) investigates as well the phenomenon of inter-firm labor mobility as a potential channel for knowledge transfer. The authors use data from the Danish employer-employee register covering the period 1995-2005 to study how knowledge carriers, i.e., technicians and highly educated workers recruited from a donor firm, contribute to knowledge diffusion and enhanced productivity in the hiring (recipient) firm. The research question is how newly recruited workers from other firms affect productivity in the hiring firm. Using structural estimation, the authors find that the impact of the recruitment of knowledge carriers on a firm's value added is an increase of 1% to 2%.

Lacetera et al. (2004) explores the question of whether firms can build new capabilities by hiring new people, specifically in the context of the pharmaceutical industry's movement towards science-driven drug discovery. The study uses data on the movement and publication of "star" scientists to examine the correlation between the adoption of science-based drug discovery within the firm and the hiring of star scientists. The findings suggest that the hiring of highly talented scientists appears to have a significant impact on the behavior of scientists already working within the firm, consistent with the idea that hiring may change organizational capabilities through the interaction of new talent with existing policies, routines, and people. Singh and Agrawal (2011b) addresses the question how the hiring firms use prior ideas of moving inventors. More especially, how firms better utilize a new recruit's stock of prior ideas and how this process evolves over time. They hypothesize that firms who recruit inventors experience higher levels of knowledge flows and this results in positive effect of recruiting inventors on innovation output. They find empirical evidence for the effect, and this positive effect is stronger for firms that are more similar to the firms from which the inventors were recruited, but at a decreasing rate over time.

Palomeras and Melero (2010) examine the relationship between the type of knowledge embodied by inventors and their probability of moving to another firm. The authors analyze data on inventors working at IBM and use patent data to track their movement and characterize the kind of know-how they hold. They find that the quality of an inventor's work positively influences the probability of leaving their employer, while the complementarity of their knowledge with that of other inventors and their expertise in the firm's core areas where the firm is dominant are negatively associated with the probability of moving.

More closely related to exploarative motives of learning-by-hiring, Tzabbar (2017) investigate the effect of recruiting technologically distant scientists on the technological repositioning of biotechnology companies. The study analyzes 2,643 hiring events between 1973 and 1999 and finds that recruiting scientists from distant fields positively correlated with technological repositioning, especially at moderate levels of technological breadth. However, firms that depend on one or a few "star" scientists are less likely to experience repositioning. Interestingly, the author explains that the acquisition of knowledge does not necessarily lead to successful exploitation, and firms need appropriate internal mechanisms, structures, and cultures to exploit their resources and capabilities. To integrate and employ technologically distant knowledge, members of a firm must be able and motivated to share knowledge, and existing structures and processes determine which strategies are feasible. The study thus provides insights into the challenges of developing "combinative capabilities"[3] by hiring scientific personnel

[3] Kogut and Zander (1992) Combinative capabilities pertain to an organization's capacity to merge and assimilate existing expertise, assets, and skills in order to generate new insights and foster innovation. This capacity entails the aptitude to recognize, obtain, incorporate, and employ knowledge and resources from a variety of sources for the creation of novel products, procedures, or business models. Numerous factors influence a company's combinative capabilities, such as its in-house knowledge reservoir, resource diversity, robustness of external partner relationships, efficiency of communication and collaboration methods, and its organizational framework and culture.

and the conditions under which recruitment results in significant transformation of a firm's technological capabilities.

Overall, the the literature of learning-by-hiring provides evidence to support the idea that recruiting inventors from other firms can enhance a firm's access to external ideas and promote innovation and knowledge flow.

Rothaermel and Hess (2007) aims to explore the role of individual-, firm-, network-level skills in determining firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments, i.e., "Dynamic capabilities". The study proposes multilevel theoretical model instead of an uni-level approach that accounts for heterogeneity in and across three distinct levels of analysis when explaining and predicting innovation. The authors develop hypotheses pertaining to each of the three levels of analysis to challenge the assumption of homogeneity across levels of analysis. They also advance two competing interaction hypotheses concerning the potential complementary or substitutive nature of these three innovation determinants. The authors find that all the individual, firm, and network-level factors all contributing to a firm's ability to innovate. In addition, the authors find evidence of complementarity between individual-firm and individual-network effects, while firm-network effects are substitutive. The study highlights the importance of considering multiple levels of analysis and their interplay when examining firm innovation and the potential for dynamic capabilities.

Techovers Mergers and Acquisitions (M&A) have become an increasingly popular means of acquiring technology in the business world[4]. The difficulty in managing in-

[4]**Google and Motorola** Google's acquisition of Motorola Mobility in 2012 was to gain access to Motorola's extensive portfolio of patents related to mobile phone technology. By acquiring Motorola, Google was able to secure the rights to use these patents in its own mobile phone business, as well as to license them to other companies. Additionally, Google hired a number of experienced engineers and inventors from Motorola who had developed cutting-edge technology in areas such as mobile phones, set-top boxes and video compression. With the help of these experts, Google was able to accelerate the development of its own mobile phone software, Android, and expand its mobile phone hardware business. By acquiring a company with a strong portfolio of patents and hiring experienced engineers and inventors, Google was able to improve its own mobile phone business and gain a competitive advantage in the market. **Intel and Altera**, another example of a firm using the strategy of M&A to access a certain technology can be found in the case of Intel's acquisition of Altera in 2015. Altera was a leading company in the field of field-programmable gate arrays (FPGAs), which are a type of semiconductor device that can be configured to perform various digital functions. Intel was interested in acquiring Altera because it wanted to expand its product offerings in the field of data center and internet of things (IoT) technology, which rely heavily on FPGAs. By acquiring Altera, Intel was able to gain access to Altera's extensive portfolio of FPGA technology, as well as its experienced team of engineers and inventors who had developed this technology. With the help of these experts, Intel was

vestments specific to a particular business relationship through arm's-length contracting arises because the return to the investments made by one party can be captured by the other party via its bargaining power. The Hart and Moore (1990) incomplete contracts theory of the firm argues that firms engaging in relationship-specific investments should be under common ownership. An important prediction of this theory is that when two firms consider entering into a business relationship that requires substantial specialized investments, they are likely to merge to avoid the contracting challenges arising from potential hold-up problems. Furthermore, Holmstrom and Roberts (1998) propose that M&A transactions are frequently utilized as a means to acquire innovation. The purchase of innovation is typically not a viable alternative to M&As due to the need for disclosing sensitive information in order to establish the innovation's value. Because, a potential buyer is disincentivized to pay once this information is divulged. Hart and Holmstrom (2010) analysis further demonstrates that in cases where two firms' production functions exhibit externalities, such as when coordination of technologies is necessary, a merger enables coordination that would otherwise be unattainable.

Faria (2008) presents an equilibrium model in which mergers allow acquirers to obtain knowledge about a new technology, and thus, the model tries to explain merger waves as a subsequent phase of a technological shock. Mergers are a way for a firm to acquire the organization capital of another firm. After the technological shock, some firms adopt the new technology, while others prefer to wait and get the new technology through acquisition of the early adopters. Mergers occur clustered in time—i.e., "wave"—and they are an equilibrium outcome in which acquirers "marry" targets to gain access to their organization capital. In Zhao (2009), the author examines whether technological innovation plays a role in a firm's propensity to engage in acquisition activities, whether more or less innovative bidders are more likely to complete deals, and whether a completed or failed acquisition affects subsequent innovation success and how. Suggesting that innovation-motivated acquisitions may be a general phenomenon in the economy, the author also finds that firms that lag behind in internal innovation investments are more likely to complete an acquisition deal, consistent with predictions

able to accelerate the development of its own FPGA products and expand its business in the data center and IoT markets.

in Faria (2008).

Levine (2017) proposes a model of mergers where M&A deals are used to reallocate growth opportunities. In the model, acquirers lack internal growth options and seek out projects from targets in the M&A market. The firm's investment opportunities are modeled as "seeds," each of which gives the firm the option to install a unit of revenue-generating physical capital. In a merger, the acquirer captures the seeds of the target firm, expanding its investment opportunity set. Firms differ in their ability to implement a given project, making the costs of production firm-specific and time-varying. In equilibrium, firms with high production costs are more likely to sell their seeds by becoming targets. Firms with low costs of production, but lacking sufficient internal options for growth, acquire these targets to expand their investment opportunity set. The model explains many features of the merger data, including the high productivity, investment, and valuation of target firms. The profitability of a firm is highly predictive of acquisition, and merger transactions lead to a substantial drop in profitability despite creating value for the acquirer. He further finds evidence that acquirers buy firms with high-quality investment opportunities in response to a lack of internal growth options. Specifically, target firms have productivity, sales growth, and investment rates that are higher than the average firm, suggesting that they have quality projects. Conversely, these targets have low profitability, revealing that their costs are higher than other firms. On the other hand, acquirers have both high productivity and low costs. Yet, surprisingly, acquirers engage in only meager capital investment, indicating that acquirers have a comparative advantage in their cost of production but have limited ability to grow organically. The study sheds light on the importance of intangible assets in the M&A market and provides a novel explanation for the motives behind mergers and acquisitions. Higgins and Rodriguez (2006) study 160 pharmaceutical acquisitions between 1994 and 2001 and find that companies that are facing reduced internal productivity tend to resort to acquisitions to replenish their research pipelines. The findings of Higgins and Rodriguez (2006) are in line with Levine (2017)'s model.

In a broader study with a larger sample, Bena and Li (2014) investigate the role of synergies obtained from combining corporate innovation activities as an important driver of mergers and acquisitions (M&As). The authors examine the relation between characteristics of corporate innovation activities and whether a firm becomes an acquirer or a target firm. They then study whether technological overlap between firm pairs affects transaction incidence. Finally, they estimate the effect of a merger on future innovation output when there is pre-merger technological overlap between merging firms. Using patent and M&A data from 1984 to 2006, the authors show that both acquirers and target firms are active in technological innovation, but with different characteristics. They find that the presence of technological overlap between two firms' innovation activities, as captured by the proximity of patent portfolios, shared knowledge bases, and mutual citations of patent portfolios, has a significant effect on the probability of a merger pair formation. Finally, they use a quasi-experiment to estimate the treatment effect of a merger on post-merger innovation output and show that the presence of premerger technological overlap between merging firms leads to a significant improvement in the combined firms' post-merger innovation output. The authors highlight the ex ante selection effects of corporate innovation activities and the ex post treatment effect of a merger on firms' innovation output.

More recently, Huang and Xie (2023) employ a search and matching model to analyze the behavior of firms in the M&A market. The authors explore the impact of firm heterogeneity, management skills, and industry-specific knowledge capital on the decision-making process of firms in the M&A market. The authors focus on the role of technology centrality and bilateral knowledge spillovers in the M&A market's individual firms' behavior. Their model has three predictions. First, acquirers with higher technology centrality and management skills will exert higher search intensities. Second, targets with higher technology centrality and lower management skill will exert higher search intensities. Finally, acquirer-target firm pairs with larger bilateral knowledge spillovers will generate a larger surplus and are more likely to consummate a merger deal. The authors find empirical evidence for the theoretical predictions of their model.

It is worth noting that there are innovation-related motives for M&As, which are not directly related to acquiring technology. For example, Chen et al. (2021) show that acquiring human capital is a key motive for M&As in presence of frictions in the labor market, such as inevitable disclosure doctrines[5]. The other closely related but different case is the case of "killer acquisitions" in Cunningham et al. (2021), where incumbent firms acquire innovative targets and terminate their development of potential competitors. The study argues that incumbents may acquire innovative targets to preempt competition in the future[6].

The link between mobility of knowledge workers and corporate transactions is not limited to M&As and can be extended to join ventures (JV) and alliances. For example, Wagner and Goossen (2018) studies the relationship between the mobility of inventors between competing firms and the formation of technology-oriented alliances. The authors argue that inventor mobility shapes firms' strategic actions and other innovation-related organizational outcomes. The authors suggest that mobile inventors play an important role in the decision-making process leading to the formation of technology-oriented alliances by reducing information asymmetry and facilitating the alignment of decision frames applied by both organizations. The authors present a nuanced view on how inventor mobility and alliance formation are interlinked and suggest that the positive link between mobility and alliance formation is stronger when mobile employees possess more firm-specific knowledge and when the firms are less familiar with each other's capabilities. The authors test their theoretical predictions using data on inventor mobility and alliance formation among 42 large pharmaceutical firms between 1990 and 2004.

[5]Chen et al. (2021) exploit the staggered adoption of the Inevitable Disclosure Doctrine (IDD) by U.S. state courts, which prevents a firm's workers who have knowledge of their firm's trade secrets from working for another firm. Using a panel of 123,212 U.S. public firms from 1980 to 2013, the authors show that firms headquartered in states that recognize the IDD experience an increase in the likelihood of being acquired by approximately 0.8 percentage points relative to firms headquartered in states that do not recognize such a doctrine.

[6]Cunningham et al. (2021) finds that projects acquired by incumbents with overlapping products are 23.4% less likely to have continued development activity compared to drugs acquired by non-overlapping incumbents. The development patterns for overlapping acquired drugs are similar to those for non-overlapping acquired drugs and non-acquired drugs in the years before acquisition. The study concludes that the findings are robust to controlling for economic forces, and future competition reduces the incentive for killer acquisitions. The paper highlights that killer acquisitions continue to exist even when the entrepreneur's new project is qualitatively superior to the incumbents' existing projects, when incumbents benefit from development synergies relative to entrepreneurs, and when there are multiple potential acquirers.

2.2.1 Hypotheses development

The learning-by-hiring literature suggests that firms can acquire new knowledge and skills through hiring employees with relevant expertise and experience. In particular, studies have shown that firms with high levels of knowledge-intensive activities tend to rely more on hiring new employees as a way of acquiring knowledge and skills than on internal research and development (R&D) activities (Song et al. (2003a), Lacetera et al. (2004), Palomeras and Melero (2010), Parrotta and Pozzoli (2012), Singh and Agrawal (2011b), and Tzabbar (2017))

On the other hand, M&A activities are often used by firms to acquire new technologies and strengthen their technology portfolio (e.g., Levine (2017), Bena and Li (2014)). The literature also suggests that these external sources of innovation are not substitutes but rather complements to internal R&D activities ,e.g., Cassiman and Veugelers (2006). In particular, firms can acquire new technologies through M&A activities that they may not have been able to develop internally or through hiring.

The two decisions of hiring and M&A activities are likely to be dependent on each other for several reasons. First, hiring can be a less costly way for firms to explore for potential new technologies before committing to an acquisition. This allows the focal firm to test whether the new technology inventor would fit well with the organization and its competitive environment before making a more significant investment. Second, hiring inventors with expertise in new technologies can help the focal firm develop absorptive capacity, which is the ability to recognize, assimilate, and apply external knowledge (Cohen and Levinthal (1990)). This absorptive capacity can better position the firm for acquiring a technologically distant target and help with post-acquisition integration and collaboration between inventors in the focal firm and the target. Third, the inventor's mobility can act as an expert helping the focal firm in the target selection decision on an otherwise unknown technology, thereby bridging the information gap between the focal firm and the target (e.g., Wagner and Goossen (2018)). This information asymmetry between the focal firm and the target can be significant, especially when dealing with complex and specialized technologies. By hiring inventors with expertise in these areas, the focal firm can gain insights that might not be otherwise available.

Overall, the literature suggests that the decision to hire inventors and engage in M&A activities to acquire new technologies is likely to be interdependent. Hiring can provide a low-cost way to explore new technologies before committing to a more significant investment, while M&A activities can be an effective way to acquire new technologies that might not be available through hiring or internal R&D activities. In addition, the absorptive capacity developed through hiring can help with post-acquisition integration and collaboration. Finally, the mobility of inventors can act as an expert helping the focal firm in the target selection decision, thereby bridging the information gap between the focal firm and the target. Therefore, a firm's hiring decision can affect the technological direction of a firm's innovation activities, as the pool of inventors available to the firm influences its ability to innovate and acquire new technologies. In addition, learning from *NT-inventors* is more likely than learning from *ET-inventors*. This is because *NT-inventors* often bring new perspectives and ideas to a firm's innovation activities, while *ET-inventors* may be more constrained by the firm's existing knowledge and practices.

H1-1 *NT-employers* (employers whose recent hires are mostly *NT-inventors*) are more likely to become acquirer of a technologically distant targets, and conversely, *ET-employers* (employers whose recent hires are mostly *ET-inventors*) are more likely to acquire technologically similar targets.

H1-2 Both *NT-employers* and *ET-employers* are more likely to pair with targets who are similar to the pool of newly hired inventors.

In addition, in order to test possible mechanisms explaining the effect of learning-by-hiring on M&A, I pose the following two channels; the **experiment** and the **expert** channel. The experiment channel holds that the firms that hire *NT-inventors* engage in an explorative experiment to extract information about potentially promising technologies that would fit their current technology portfolio. This information helps the firm shortlist a set of larger technologies that are worthy of pursuing further through acquisition. This experiment channel predicts that the firm will select targets that are technologically similar to the fitting inventors, and will not select targets that are similar to the non-fitting inventors. On the other hand, the expert channel assumes that firms hire *NT-inventors* to benefit from their expertise in a technology that is planned to be acquired in the near future. The *NT-inventor* can aid the firm in both pre- and post-acquisition stages. The expert channel predicts that the higher the expertise of the hired inventor, the better they will be able to help the firm. Therefore, the firm is more likely to acquire targets that are technologically similar to the inventor with the most expertise. This hypothesis implies that the firm is more likely to base its target selection decision on the opinions of the most expert inventors, thereby choosing targets that are similar to them. Unlike the experiment channel, the expert channel does not necessarily predict that targets similar to the non-expert inventors are less likely to be chosen. Therefore, the following hypothesis follows.

H2 According to the **experiment** channel, the employer-acquirer is more (less) likely to pair with a target who is technologically similar to the fitting (non-fitting) *NT-inventor*.

H3 According to the **expert** channel, the employer-acquirer is more likely to pair with a target who is technologically similar to the expert *NT-inventor*.

2.3 Data

In this section I explain the sample construction and provide summary statistics.

Merger data I start from the SDC Platinum database to retrieve the data about the completed mergers and acquistions with more than 1 million USD value in 1980-2020, among public companies, whose target is located in the US . I exclude bankruptcy acquisitions, divestitures, exchange offers, privatizations, leveraged buyouts, management buyouts, management buy-ins, liquidations, recapitalization, and repurchases. Moreover, I exclude the deals that either target's or the acquirer's primary SIC is in financial industry. In addition, I only consider deals in which the acquirer ownes less than 50% of the shares before the deal and seeks to acquir more than 50% of the shares after the deal. As a result, I end up having 16,531 mergers and acquisitions retrieved from the SDC. Next, I look for the financial information of the firms using *Compustat*, which reduces the number of transactions to 9,560. Furthermore, I am able to find the financial information for 4,617 acquirers and 6,287 targets[7].

In order identify the set of potential merger parties (acquirer and targets), I use propensity score matching on industry, size, and book-to-market ratio following Bena and Li (2014), with some modifications. More precisely, for each **actual** merger party, I identify firms in the *Compustat* universe active at the year prior to the merger and in the same industry (*SIC* 4-digit code) whose size and book-to-market ratio lie within one standard deviation of the actual merger party. I call the set of identified firms the **potential** merger parties, that is, any number of firms that qualify the matching criteria. This is slightly different approach than Bena and Li (2014), who find only 5 firms for each actual merger party. I maintain that is approach is better able to capture the industry structure of the respective merger party and thus provides a better reflection of the world. Since I need to investigate acquirer and target pairing and acquirer's target selection, fixing the number of potential targets would ignore the real set of potential targets from which the acquirer can choose. Nevertheless, I limit the maximum number of matched targets to 12 to economize on the available computational resources. As a result, the number of matched acquirers and targets varies from 1 to

[7] A unique acquirer in my sample engages in 3 transactions, on average. The most active acquirer is *Cisco Systems Inc* with 117 transactions.

12 and mean of 3.5 and a median of 2 per each merger party. Lastly, for each actual merger, the matching exercise leads to a cross section of potential mergers between any two pairs of acquirers and targets. Therefore, for the 9,560 actual mergers, I construct a sample of additional mergers 122,565 with potential merger parties (any pair between the matched acquirer and targets), with 31,568 unique merger-acquirers and 34,336 unique merger-target observations. **Table 2.1** and **Table 2.2** shows the acquirer-level and target-level firm characteristics, respectively. The first row of these tables, *acquirer-treated* and *target-treated* is dummy equal to one, indicating whether the firm i actually part of a merger and equal to zero for the potential merger party. Thus, out of 144,838 acquirer-target pairs or potential mergers, 18.8% are actual acquirers and 16.9% are actual targets.

Table 2.1: Acquirer-level Characteristics Summary Statistics

The table shows the summary statistic for the acquirer-level characteristics. The *Compustat* measures are winsorized at 1%.*Actual* is a dummy equal to one, indicating whether the firm i actually part of a merger and equal to zero for the potential merger parties. *Citwpat* is the acquirer's citation-weighted patents and *Patindex* is the acquirer's patent index. The definition of the rest of the variables can be found in the variable definition section of the Appendix.

	n	mean	sd	min	Q0.25	median	Q0.75	max
Actual	144, 838	0.188	0.391	0	0	0	0	1
Citwpat	144, 838	2.221	2.931	0	0	0	4.654	13.425
Patindex	144, 838	7.413	49.227	0	0	0	1	1, 613.746
Sales (USD million)	144, 540	1, 090.277	4, 133.883	0	19.541	88.031	418.846	39, 906.410
Market Value	70, 692	1, 691.819	7, 167.468	3.574	42.197	145.433	587.445	66, 623.020
R&D_intensity	144, 838	0.071	0.121	0	0	0.012	0.094	0.588
ROA	144, 571	-0.072	0.285	-1.388	-0.096	0.026	0.069	0.281
Tangibility	143, 320	0.293	0.262	0	0.080	0.199	0.460	0.909
Leverage	144, 370	0.188	0.211	0	0.004	0.111	0.316	0.923
Capx_asset	142, 370	0.072	0.081	0	0.019	0.044	0.091	0.395
Q	144, 838	2.072	1.764	0.577	1.117	1.443	2.240	11.217
B/M	144, 838	0.586	0.418	-0.724	0.294	0.518	0.790	3.824
Size	144, 838	5.001	2.036	0.999	3.525	4.765	6.282	11.537
Cash_liquidity	143, 471	0.392	0.253	0.015	0.181	0.349	0.572	0.963
Sales growth (%)	128, 193	32.225	106.314	-79.410	-2.717	10.360	30.575	729.799
Stock return (%)	130, 300	22.442	88.551	-84.246	-28.061	3.129	41.408	461.926

Innovation measures Next, I obtain the information of patents, inventors, and the patent applicant firms from *PATSTAT*, supplement it with Kogan et al. (2017), who provide technology classification (*CPC*[8]) for each patent. Moreover, I use the

[8]The Cooperative Patent Classification (CPC) is a classification system created collaboratively by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). Both offices jointly administer and update the CPC system, which is openly accessible to the public for classification purposes.

Table 2.2: Target-level Characteristics Summary Statistics

The table shows the summary statistic for the target-level characteristics. The *Compustat* measures are winsorized at 1%.*Actual* is a dummy equal to one, indicating whether the firm i actually part of a merger and equal to zero for the potential merger parties. *Citwpat* is the target's citation-weighted patents and *Patindex* is the target's patent index. The definition of the rest of the variables can be found in the variable definition section of the Appendix.

	n	mean	sd	min	Q0.25	median	Q0.75	max
Actual	144,838	0.169	0.375	0	0	0	0	1
Citwpat	144,838	1.935	2.673	0	0	0	4.220	13.323
Patindex	144,838	3.057	23.387	0	0	0	0.673	1,613.746
Sales (USD million)	144,532	658.878	2,740.922	0	15.362	65.424	283.839	39,906.410
Market Value	71,405	1,028.176	4,212.295	3.574	36.741	128.655	503.538	66,623.020
R&D intensity	144,838	0.071	0.121	0	0	0.010	0.093	0.588
ROA	144,575	-0.083	0.288	-1.388	-0.120	0.020	0.065	0.281
Tangibility	143,172	0.285	0.263	0	0.075	0.186	0.439	0.909
Leverage	144,381	0.190	0.215	0	0.004	0.108	0.319	0.923
Capx_asset	142,503	0.070	0.082	0	0.018	0.041	0.088	0.395
Q	144,838	1.957	1.639	0.577	1.090	1.410	2.114	11.217
B/M	144,838	0.631	0.453	-0.724	0.325	0.549	0.832	3.824
Size	144,838	4.680	1.925	0.999	3.294	4.443	5.856	11.537
Cash_liquidity	143,573	0.395	0.252	0.015	0.189	0.355	0.573	0.963
Sales growth(%)	128,210	31.483	108.221	-79.410	-4.014	9.492	29.712	729.799
Stock return(%)	130,613	20.806	90.187	-84.246	-31.465	0.752	39.766	461.926

data from Bowen et al. (2022) who assign patents to firms along with the *Compustat* identifiers. I construct two variables which capture the innovation output of all the firms, i.e., actual and potential merger parties. First, I construct *Patent Index* as the sum of scaled[9] number of awarded patents to each firm within the five years before the merger, i.e., $[-5, -1]$. Second, I construct *citation-weighted patents*, which is log of citation-weighted patents for each firm within the five year period before the merger, i.e., $[-5, -1]$.

Inventor Mobility I turn to PATSTAT database for mobility. PATSTAT records the names and location of inventors who file a patent and assign its rights to their employers. Therefore, I exploit this feature of PATSTAT to identify the acquirers who hired an inventor during the period of five years before the merger. Out of the 31,568 merger-acquirer observations in my sample, 9,519 (30%) hired at least one inventor in the five period before the merger. Furthermore, in order to see whether the hired employer brings new technology into the employer, I check the inventors' technology portfolio and compare with the technology portfolio of the acquirer. More specifically, an inventor is called a new technology (NT) inventor, if she meets the two following

[9]Each patent is scaled by the median number of patents filed in each technology class and application year

conditions; first, prior to the move, she has a patent in a technology class, which is totally new to the employer, and second, the intersection of her tech portfolio and the acquirer tech portfolio has a maximum of one element. In other words, an inventor is considered to be a *NT-inventor*, if she not only brings a new technology class to the employer, but also would not share a common technology class with the employer. If these conditions are not satisfied for the moving inventor, I classify her as an existing technology (ET) inventor.

Furthermore, in order to better categorize the hiring strategy of the firm into explorative or exploitative categories, I define a dummy variable, called *NT-employer* which is equal to one if the majority of an employer's pool of hired inventors in the period $[-5, -1]$ to the merger is of *NT-inventor* type and zero otherwise. Similarly, I define another dummy variable called *ET-employer* for each acquirer-employer whose majority of the pool of hire inventors are of *ET-inventors*. **Table 2.3** shows the summary statistics for these variables. While nearly 70% of the potential acquirers did not hire any inventors in $[-5, -1]$ before the merger (*Non-employer* with the mean of 71.6%), half of the rest of the potential acquirers (15.4%) mostly hired *NT-inventors* and the other half (13.3%) mostly hired *ET-inventors*.

Table 2.4 shows the differences in characteristics of the acquirers who hired at least one inventor in $[-5, -1]$ before the merger (first two columns with mean and SD of the respective feature) and those acquirers who did not hire any inventor (second two columns), and the difference in means in each characteristic (last two columns). Acquirer-employers are unconditionally more likely to become acquirers (27% compared to 16%), are more innovative measured by the citation-weighted and patent indexes (citation weighted of 5.6 compared to 0.89 and patent index of 25 compared to 0.39), and are nearly fourfold larger in terms of sales. All these differences are statistically significant and suggests that these two groups of firms are fundamentally different in nature.

Turning to the differences in the characteristics of the potential acquirers who mostly hire *NT-inventors* (i.e., *NT-employer* likely with exploratory motives) and those who do not (i.e., *ET-employer*). **Table 5** shows that the *NT-employer*s are less likely to actually become acquirers compared to the *ET-employer*s (22% vs. 33%). Fur-

Table 2.3: Summary Statistics on Acquirers' Hires and Technology Similarities

This table shows the summary statistics related to hiring decision of the **potential** acquirers, the technology similarity measures between acquirer-target pairs, and the tech similarity of different groups of hired inventors and the potential targets. *NT-employer* is a dummy variable equal to one if the majority of potential acquirer's pool of hired inventors is of NT-inventor type and zero otherwise. *NT-inventor*s have new technologies and no common technology class with the acquirer-employer. Similarly, *ET-employer* is a dummy for each acquirer-employer whose majority of the pool of hire inventors are of ET-inventors. *Jaffe-score* and *Mahal-scoree* measure the technology similarity of the acquirer-target pairs following the defitions in the Data section. *tar-invrep-jaffe* shows the technology similarity score of the potential target and the pool of newly hired inventors by the paired acquirer. Similarly, *tar-finvrep-jaffe*,*tar-nfinvrep-jaffe*, *tar-einvrep-jaffe*, and *tar-neinvrep-jaffe* is the tech similarity of fitting, non-fitting, expert, and non-expert group of newly hired inventors and the paired targets.

	mean	sd	min	Q0.25	median	Q0.75	max
Deals (unqiue)	9,560	0	–	–	–	–	–
Acquirers (unique)	10,528	0	–	–	–	–	–
Targets (unique)	11,879	0	–	–	–	–	–
Actual deal	0.018	0.133	0	0	0	0	1
Deal diversify	0.112	0.315	0	0	0	0	1
NT-employer	0.154	0.361	0	0	0	0	1
ET-employer	0.131	0.337	0	0	0	0	1
Non-employer	0.716	0.451	0	0	1	1	1
acq_n_inventor	6.158	44.907	0	0	0	1	1,600
jaffe_score	0.033	0.132	0	0	0	0	1
mahal_score	0.259	0.793	0	0	0	0	18.703
tar_invrep_jaffe	0.043	0.143	0	0	0	0	1
tar_invrep_mahal	0.484	1.298	0	0	0	0	27.434
tar_neinvrep_jaffe	0.013	0.078	0	0	0	0	1
tar_neinvrep_mahal	0.166	0.632	0	0	0	0	13.854
tar_einvrep_jaffe	0.019	0.091	0	0	0	0	1
tar_einvrep_mahal	0.255	0.757	0	0	0	0	14.224
tar_finvrep_jaffe	0.021	0.094	0	0	0	0	1
tar_finvrep_mahal	0.270	0.803	0	0	0	0	14.141
tar_nfinvrep_jaffe	0.008	0.062	0	0	0	0	1
tar_nfinvrep_mahal	0.099	0.483	0	0	0	0	14.907

Table 2.4: Differences in Characteristics of the Employer-acquirers and Non-employer-acquirers

Differences in characteristics of the acquirers who hired at least one inventor in $[-5, -1]$ before the merger, *Non-employer* $= 0$ and those who did not *Non-employer* $= 1$. *Citwpat* is the target's citation-weighted patents and *Patindex* is the target's patent index. The definition of the rest of the variables can be found in the variable definition section of the Appendix.

	Employer-acquirers *Non-employer* $= 0$		Non-employer-acquirers *Non-employer* $= 1$			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Actual	0.27	0.45	0.16	0.36	-0.12***	0.0025
Citwpat	5.6	2.5	0.89	1.8	-4.7***	0.014
Patindex	25	90	0.39	1.7	-25***	0.44
Sales (USD million)	2242	6515	632	2502	-1610***	33
Market Value	3560	11667	817	3052	-2743***	79
R&D intensity	0.13	0.14	0.049	0.1	-0.077***	0.00077
ROA	-0.089	0.3	-0.066	0.28	0.024***	0.0017
Tangibility	0.2	0.18	0.33	0.28	0.13***	0.0012
Leverage	0.12	0.16	0.21	0.22	0.092***	0.0011
Capx_asset	0.055	0.056	0.078	0.088	0.024***	0.00039
Q	2.4	1.9	1.9	1.7	-0.47***	0.011
B/M	0.51	0.37	0.62	0.43	0.1***	0.0022
Size	5.6	2.2	4.8	1.9	-0.79***	0.012
Cash liquidity	0.48	0.24	0.36	0.25	-0.12***	0.0014
Sales growth(%)	33	111	32	104	-0.88	0.67
Stock return(%)	19	84	24	90	4.2***	0.52

Table 2.5: Differences in Characteristics of the *ET-employers* and *NT-employers*

Differences in characteristics of the acquirers whose at least half of their hired inventors in $[-5, -1]$ are *NT-inventors*, i.e., *NT-employer* $= 1$ and the rest of the acquirers *ET-employer* $= 1$. *Citwpat* is the target's citation-weighted patents and *Patindex* is the target's patent index. The definition of the rest of the variables can be found in the variable definition section of the Appendix.

	ET-employer-acquirer *ET-employer* = 1		NT-employer-acquirer *NT-employer* = 1			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Actual	0.33	0.47	0.22	0.42	-0.1***	0.0044
Citwpat	6.6	2.3	4.7	2.3	-1.9***	0.023
Patindex	50	128	4.1	9.7	-46***	0.93
Sales (USD million)	3932	8692	805	3130	-3127***	67
Market Value	5827	15485	1387	5204	-4439***	155
R%D intensity	0.13	0.14	0.13	0.15	0.0012	0.0014
ROA	-0.066	0.28	-0.11	0.32	-0.044***	0.003
Tangibility	0.21	0.16	0.2	0.18	-0.0089***	0.0017
Leverage	0.13	0.16	0.11	0.16	-0.021***	0.0016
Capx_asset	0.052	0.051	0.057	0.059	0.0051***	0.00055
Q	2.2	1.7	2.5	2.1	0.31***	0.019
B/M	0.52	0.35	0.51	0.38	-0.016***	0.0036
Size	6.4	2.3	4.9	1.8	-1.5***	0.021
Cash liquidity	0.46	0.23	0.5	0.25	0.043***	0.0023
Sales growth(%)	27	101	39	119	12***	1.1
Stock return(%)	16	75	23	91	6.3***	0.85

thermore, *NT-employers* have much smaller innovation output and size compared to *ET-employers* (citation-weighted of 4.7 vs. 6.6, patent index of 4.1 vs. 50, sales of 800 million USD vs. nearly 4 billion USD). However, *NT-employer* have sizable differences in metrics that represent faster growth. For instance, they show statistically significant higher CapEx intensity (5.7% vs. 5.2%), growth in sales (39% vs. 27%), and higher growth opportunities measured by the Tobin's Q (2.5 vs. 2.2) relative to the *ET-employer*s. Furthermore, the *NT-employer*s have R%D intensity of 13% with no significant difference compared to the *ET-employer*s. All in all, *NT-employer*s seem to be R&D-intensive and fast growing, though smaller, firms who scout for new technologies to complement to their existing technology portfolio.

Technology similarity The level of technological similarity between firms is gauged by employing two measures, namely the Jaffe (1986) metric and the Mahalanobis generalization used in Bloom et al. (2013). These measures describe the proximity of patenting activities across different technology classes among pairs of firms. To calculate *Jaffe* technological proximity, I obtain all the awarded patents by the set of actuall and potential merger parties, each with their technology classification (666 number of four-digit CPC). This allocation is then used to define a vector, T_i, for each firm, where T_i represents the number of patents owned by the firm in the technology class T. The *Jaffe* measure of technological proximity between two firms, i and j, is determined by the following formula.

$$Jaffe_{ij} = \frac{T_i T_j^{'}}{(T_i T_i^{'})^{1/2} (T_j T_j^{'})^{1/2}} \tag{2.1}$$

Mahalanobis similarity is another useful measure, which in addition to the *Jaffe* technology similarity, captures the collocation of technology classes at the same firm. This is based on the notion that the collocation of technology classes at a firm is not random and those technologies are most probably similar to each other on some way which made the firm choose to work on them together. In order to explain the calculation of the Mahalanobis normalized measure, I need to define some notation. First, I create a matrix T where each column represents a firm's patent shares in the 666 technological classes. Second, I normalize T, denoted as $\tilde{T}$, in which each column is normalized by the firm's patent share dot product. Third, I define the matrix TECH, which is just the standard *Jaffe* uncentered correlation measure between firms i and j in a matrix form. Fourth, I define the matrix $\tilde{X}$, which is similar to $\tilde{T}$, except it is the normalized patent class shares across firms rather than firm shares across patent classes. Finally, the matrix Ω is defined, in which each element is the standard Jaffe (1986) uncentered correlation measure between patent classes. The *Mahalanobis* normalized technology similarity measure is defined as $Mahal = \tilde{T}' \tilde{\Omega} \tilde{T}$. This measure weights the overlap in patent shares between firms by how close their different patent shares are to each other. The same patent class in different firms is given a weight of 1, and different patent classes in different firms are given a weight between 0 and 1, depending on how frequently they overlap within firms across the whole sample. If Ω is equal to I, then *Mahal* is equal to *Jaffe*. Thus, if no patent class overlaps with any other patent class within the same firm, then the standard *Jaffe* measure is identical to the Mahalanobis normalized measure. On the other hand, if some patent classes tend to overlap frequently within firms, suggesting they have some kind of technological spillover, then the overlap between firms sharing these patent classes will be higher.

Since I want to examine the technology similarity between the pool of hired inventors and the potential targets, in addition to the acquirer-target technology similarity, I calculate the tech similarity of pool of the hired inventors and the targets. Thus, I construct an representative inventor (*invrep*) whose tech portfolio is the sum of number of patents filed by the pool of recently hired inventors. Subsequently, I consider this pool as a single entity and calculate the *Jaffe* and *Mahal* technology similarity scores, as explained above, between the representative inventors and the potential targets.

Next, in order to find out which type of *NT-inventors* influence the decision of the acquirer in selecting the target, I categorize the *NT-inventors* to *fitting-inventor*s and *expert-inventor*s to examine the *Experiment* and *expert* hypotheses, respectively. An *NT-inventor* is considered to be fitting to the employer, if she has an above median **growth** in her citation-weighted patents after the employment and before the merger, i.e., in $[-5, -1]$. Citation-weighted patents is a single metric that captures both the quantity and the quality of the patents and therefore, is an appropriate measure of fitness of the newly hired *NT-inventor* with the employer and its environment. Thus, I define a dummy variable called *tar-finvrep-jaffe/mahal* that measures the technology similarity of the group of fitting inventors with each potential target. Similarly, the group of non-fitting *NT-inventors* are those with below median growth in the pool of newly hired *NT-inventors*, whose tech similarity with the target is denoted by *tar-nfinvrep-jaffe/mahal.* Furthermore, I divide the pool of *NT-inventors* to expert and non-expert inventors based on their citation-weighted patents at the point of employment. Similar to *tar-finvrep-jaffe/mahal* and *tar-nfinvrep-jaffe/mahal*, I calculate the technology similarity measure for the group of expert *NT-inventors* with above (below) median citation-weighted patents and call it *tar-einvrep-jaffe/mahal* (*tar-neinvrep-jaffe/mahal*). **Table 2.3** shows the calculated tech similarity measures between acquirer-target pairs, pool of hired inventors and the targets (*tar-invrep-jaffe/mahal*), and between the fitting (non-fitting), expert (non-expert) groups of inventors and the target (*tar-finvrep-jaffe/mahal* and *tar-einvrep-jaffe/mahal*).

For investigating the effect of newly hired inventors on the target selection, I remove the potential acquirers from my general sample (summary in **Table 2.3**) and only keep the actual acquirers. **Table 2.6** is the counterpart of **Table 2.3** for the set of actual acquirers and potential targets. Thus, **Table 2.6** displays the summary statistics related to hiring decisions of **actual** acquirers, technology similarity measures between acquirer-target pairs, and the tech similarity of different groups of hired inventors and potential targets. The data set has a total of 27,288 observations and the unit of observation is acquirer-target pairs or potential mergers, from which 9,560 deals actually happened. There are 3,832 unique acquirers and unique targets 9,396 in the sample. The variable *deal-treated* is a dummy variable that is equal to one if the merger actually happens (target is the actual target) and is the 9.6% of the observations. The dummy variable *Non-employer* shows that nearly 60% of the actual acquirers hired no inventors in the five year period before the merger. However, those acquirers who hired at least one inventor in this period, have hired between 1 to 1,600 inventors with a mean of nearly 18 inventors *acq-n-inventor*. Moreover, the dummy variables *NT-employer* (*ET-employer*) show that 18% (23%) of the actual acquirers mostly hired *NT-inventors* (*ET-inventors*).

Table 2.6: Summary Statistics the **Actual** Acquirers' Hiring Decision and the Technology Similarity Measures

This table shows the summary statistics related to hiring decision of the **actual** acquirers, the technology similarity measures between acquirer-target pairs, and the tech similarity of different groups of hired inventors and the potential targets. *NT-employer* is a dummy variable equal to one if the majority of a acquirer's pool of hired inventors is of NT-inventor type and zero otherwise. *NT-inventor*s have new technologies and no common technology class with the acquirer-employer. Similarly, *ET-employer* is a dummy for each acquirer-employer whose majority of the pool of hire inventors are of ET-inventors. *Jaffe-score* and *Mahal-scoree* measure the technology similarity of the acquirer-target pairs following the definitions in the Data section. *tar-invrep-jaffe* shows the technology similarity score of the potential target and the pool of newly hired inventors by the paired acquirer. Similarly, *tar-finvrep-jaffe*,*tar-nfinvrep-jaffe*, *tar-einvrep-jaffe*, and *tar-neinvrep-jaffe* is the tech similarity of fitting, non-fitting, expert, and non-expert group of newly hired inventors and the paired targets.

	n	mean	sd	min	Q0.25	median	Q0.75	max
Deals (unique)	27,288	9,560	0	–	–	–	–	–
Acquirers (unique)	27,288	3,832	0	–	–	–	–	–
Targets (unique)	27,288	9,396	0	–	–	–	–	–
Actual deal	27,288	0.096	0.294	0	0	0	0	1
Deal diversify	27,288	0.153	0.360	0	0	0	0	1
NT-employer	27,288	0.183	0.387	0	0	0	0	1
ET-employer	27,288	0.228	0.419	0	0	0	0	1
Non-employer	27,288	0.589	0.492	0	0	1	1	1
acq_n_inventor	27,288	17.592	85.016	0	0	0	4	1,600
Jaffe_score	27,288	0.018	0.102	0	0	0	0	1
Mahal_score	27,288	0.143	0.686	0	0	0	0	14.088
Tar_invrep_jaffe	27,288	0.072	0.180	0	0	0	0	1
Tar_invrep_mahal	27,288	0.837	1.837	0	0	0	0.762	27.434
Tar_neinvrep_jaffe	27,288	0.021	0.092	0	0	0	0	1
Tar_neinvrep_mahal	27,288	0.303	0.861	0	0	0	0	13.500
Tar_einvrep_jaffe	27,288	0.027	0.102	0	0	0	0	1
Tar_einvrep_mahal	27,288	0.394	0.960	0	0	0	0	14.224
Tar_finvrep_jaffe	27,288	0.030	0.109	0	0	0	0	1
Tar_finvrep_mahal	27,288	0.433	1.053	0	0	0	0	14.141
Tar_nfinvrep_jaffe	27,288	0.009	0.061	0	0	0	0	1
Tar_nfinvrep_mahal	27,288	0.137	0.591	0	0	0	0	14.907

2.4 Analysis and Results

In this section, I investigate the effect of hiring behavior of potential acquirers on their target selection. Furthermore, I examine two channels that could explain the effect of learning-by-hiring on M&A: the experiment channel and the expert channel. The following section provides a detailed description of the research methodology, regression specifications, and the results of the regression analyses.

2.4.1 Does Hiring Behavior of the Potential Acquirers Affect Their Target Selection?

I categorize the potential acquirers to three categories; *Non-employer*, *ET-employer*, and *NT-employer*. The first group of potential acquirers are those firms who did not hire any inventor before their (potential) merger, while *ET-employer* mostly hire *ET-inventor*s and *NT-employer* mostly hired *NT-inventor*s in before the merger. This categorization helps to imply whether a firm has exploratory innovation strategy or seeks to strengthen its existing technologies, and subsequently, study their M&A activity. More specifically, I test first **H1-1**, which posits that *NT-employers* are more likely to become acquirer of a technologically distant targets, and conversely, *ET-employers* are more likely to acquire technologically similar targets. I Run a conditional logit regression using the cross-sectional data of macthed acquirer-targets pairs as of the fiscal year-end before the merger and test whether a firm being a *NT-employer* or a *NT-employer* affects the probability of becoming an acquirer. Moreover, using the interaction terms in the specification 2.2, I test if *NT-employer* (*ET-employer*) are more likely to pair with distant (similar) targets. In other words, I expect β_2, β_3, β_4 to be positive, and β_4 to be negative.

$$
\begin{aligned}
Acquirer - Target_{ijm,t} = \alpha + \beta_1 TechOverlap_{ijm,t-1} + \\
&\beta_2 ETemployer_{im,t\in[-5,-1]} + \beta_3 NTemployer_{im,t\in[-5,-1]} \\
&+ \beta_4 TechOverlap_{ijm,t-1} \times ETemployer_{im,t\in[-5,-1]} \\
&+ \beta_5 TechOverlap_{ijm,t-1} \times NTemployer_{im,t\in[-5,-1]} \\
&+ \beta_6 AcquirerInnovationChars_{im,t-1} + \beta_7 TargetInnovationChars_{jm,t-1} \\
&+ \beta_8 AcquirerChars_{im,t-1} + \beta_9 TargetChars_{jm,t-1} \\
&+ \beta_{10} SameState_{ijm} + DealFE_m + \epsilon_{ijmt}
\end{aligned}
\tag{2.2}
$$

Table 2.7 presents the results of a conditional logit regression analysis aimed at testing hypothesis H1-1, which posits that *NT-employers* are more likely to acquire technologically distant targets, while *ET-employers* are more likely to acquire technologically similar targets. The analysis uses cross-sectional data of matched acquirer-target pairs before the merger announcement. The coefficients of the main variables of interest, *NT-employer* and *ET-employer*, are both positive and statistically significant, indicating that both types of employers are more likely to become acquirers than the *non-employers*, who serve as a baseline in this regression. The odds of becoming an acquirer are 2.45 (exp(0.828) = 2.45) times higher for ET-employers than for non-employers, and The odds of becoming an acquirer are 1.57 (exp(0.455) = 1.57) times higher for NT-employers than for non-employers, holding all other variables constant. The estimated coefficient of the interaction term between *Jaffe* and *Mahal* scores and NT-employer dummy are both negative and statistically significant, while only the interaction term between *Mahal* score and ET-employer dummy is positive and statistically significant. These findings suggest that *NT-employers* are more likely to acquire technologically distant targets than *non-employers*, while there is less stronger evidence that *ET-employers* are more likely to acquire technologically similar targets than non-employers. Overall, the findings provide support for H1-1 and suggest that *ET-employers* are more likely to acquire technologically distant targets, while *ET-employers* are more likely to acquire technologically similar targets.

Table 2.7: Acquirer-Target Pairing and Acquirers' Hiring Decision

This table shows the results associated with **H1-1**. The results of running a conditional logit regression using cross-sectional data as of the fiscal year-end before the bid announcement, according to specification 2.2. The data is cross section of 1-12 potential acquirers (targets) by matching compustat universe with the actual acquirer (target) on industry, size, and B/m ratio. *Jaffe* and *Mahal* are measures of technology overlap. *NT-employer* (*ET-employer*) is a dummy equal to 1 for the potential acquirers who mostly hired *NT-inventors*(*ET-inventors*). The regressions includes acquirer and target level controls for innovation and firm characteristics. The extended version of the table is in the appendix. The standard errors are robust and clustered at the deal level.

	Dependent variable:	
	deal_treated	
	(1)	(2)
jaffe_score	-0.747	
	(0.650)	
mahal_score		-0.598^{***}
		(0.146)
ET-employer	0.893^{***}	0.828^{***}
	(0.135)	(0.137)
NT-employer	0.451^{***}	0.455^{***}
	(0.109)	(0.109)
jaffe_score×ET-employer	0.419	
	(0.705)	
jaffe_score×NT-employer	-0.236^{***}	
	(0.071)	
mahal_score×ET-employer		0.333^{**}
		(0.152)
mahal_score×NT-employer		-0.069^{**}
		(0.028)
Controls	Yes	Yes
Deal FE	Yes	Yes
Observations	134,881	134,881
R^2	0.013	0.014
Max. Possible R^2	0.085	0.085
Note:	*p<0.1; **p<0.05; ***p<0.01	

Next, I turn to target selection and I test **H1-2** which poses that both *NT-employers* and *ET-employers* are more likely to pair with targets who are similar to the pool of newly hired inventors. I run a conditional Logit model according to the specification 2.3. For this analysis, I drop the matched acquirers. However, the sample still includes the full set of targets, i.e., actual and potential targets. This reduces the sample size to nearly 26K potential acquirer-target pairs, whose acquirers are actual acquirers. Moreover, I split the sample to be able to compare *ET-employer*s and *NT-employers*, along with the full sample. According to specification 2.3, I expect β_2 to be positive for both *ET-employer*s and *NT-employer*s.

$$\begin{aligned}
Acquirer - Target_{ijm,t} = \alpha + \beta_1 TechOverlap_{ijm,t-1} + \\
\beta_2 Tar - Invrep - TechOverlap_{im,t-1} + \\
\beta_3 AcquirerInnovationChars_{im,t-1} + \beta_4 TargetInnovationChars_{jm,t-1} \\
+ \beta_5 AcquirerChars_{im,t-1} + \beta_6 TargetChars_{jm,t-1} \\
+ \beta_7 SameState_{ijm} + DealFE_m + \epsilon_{ijmt}
\end{aligned} \tag{2.3}$$

The results are reported in Table 2.8. The results also support the hypothesis that both *NT-employers* and *ET-employers* are more likely to pair with targets who are similar to the pool of newly hired inventors. The coefficient of the variable *tar-invrep-jaffe* is positive and statistically significant at the 1% level in all three samples (for All, *ET-employer*, and *NT-employer*), indicating that a higher degree of overlap between the target's inventors and the pool of inventors recently hired by the acquirer is positively associated with the likelihood of the target being chosen. The economic significance of this effect is also notable, as a one-unit increase in tar-invrep-jaffe (note that *Jaffe* score is between 0 and 1, by construct) is associated with an odds ratio of approximately 21.3 in the full sample, 18.5 for ET-employers, and 20.6 for NT-employers. Similar results applies also to the *Mahal* similarity score. In summary, the results suggest that acquirers are more likely to select targets that have technological expertise similar to those inventors recently hired by the acquirer. This effect holds for both *NT-employers* and *ET-employers*, indicating that the acquisition strategy and inventor hiring strategy of the acquirers are dependent. The findings are consistent with prior research that highlights the importance of technological similarity in merger and acquisition activity (e.g., Bena and Li (2014) and Ahuja and Katila (2001)).

Table 2.8: Acquirers' Target Selection and Technology Similarity to the Newly Hired Inventors

This table shows the result of actual acquirer's decision regarding target selection. I test **H1-2** expecting that both *NT-employers* and *ET-employers* choose targets similar to the pool of newly hired inventors. I run a conditional Logit model according to the specification 3. The data is cross section of 1-12 potential targets by matching compustat universe with the actual target on industry, size, and B/m ratio. *Jaffe* and *Mahal* are measures of technology overlap. The regressions includes acquirer and target level controls for innovation and firm characteristics. The extended version of the table is in the appendix. The standard errors are robust and clustered at the deal level.

	Dependent variable:					
	Target Chosen		Target Chosen		Target Chosen	
	(1)	(2)	(3)	(4)	(5)	(6)
jaffe_score	−0.731**		−1.007**		−0.906	
	(0.302)		(0.403)		(0.558)	
tar_invrep_jaffe	3.104***		2.858***		3.029***	
	(0.220)		(0.274)		(0.436)	
mahal_score		−0.224***		−0.216***		−0.271**
		(0.048)		(0.056)		(0.129)
tar_invrep_mahal		0.239***		0.199***		0.204***
		(0.025)		(0.030)		(0.069)
Sample	All	All	ET-employer	ET-employer	NT-employer	NT-employer
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,380	26,380	6,048	6,048	4,853	4,853
R^2	0.029	0.025	0.060	0.049	0.028	0.019
Max. Possible R^2	0.216	0.216	0.279	0.279	0.207	0.207
Note:						*p<0.1; **p<0.05; ***p<0.01

2.4.2 What Is the Channel; Experiment or Expert?

In order to test possible mechanisms explaining the effect of learning-by-hiring on M&A, I pose the following two channels; the **experiment** and the **expert** channel. The experiment channel posits that firms hire NT-inventors to engage in an explorative experiment that helps them extract information about potentially promising technologies. This information helps the firm shortlist a set of larger technologies that are worthy of pursuing further through acquisition. This channel is based on the idea of "learning-by-hiring," which suggests that firms can improve their innovative capabilities by hiring inventors who possess relevant knowledge in areas where the firm is lacking. Thus, according to the **experiment** channel, the employer-acquirer is more (less) likely to pair with a target who is technologically similar to the fitting (non-fitting) *NT-inventor*s.

The expert channel, on the other hand, assumes that firms hire NT-inventors to benefit from their expertise in a technology that is planned to be acquired in the near future. The higher the expertise of the hired inventor, the better they will be able to help the firm. Therefore, the firm is more likely to acquire targets that are technologically similar to the inventor with the most expertise. This hypothesis implies that the firm is more likely to base its target selection decision on the opinions of the most expert inventors, thereby choosing targets that are similar to them. Hence, according to the **expert** channel, the employer-acquirer is more likely to pair with a target who is technologically similar to the expert *NT-inventor*s.

Hence, I run another conditional Logit regression to examine the decision of acquirers on target selection using specification 2.4. As explained in the data section, *TarFinvrepTechOverlap* (*TarNFinvrepTechOverlap*) meaures the technologically similarity of a potential target with the group of fitting (non-fitting) *NT-inventors.* In the same manner, *TarEinvrepTechOverlap* (*TarNEinvrepTechOverlap*) measure the technology similarity of a target with the group of expert (non-expert) *NT-inventors.* The experiment channel predicts that β_2 is positive and β_3 is negative. The expert channel predicts that β_4 is positive.

$$\begin{aligned}
Acquirer-Target_{ijm,t} = \alpha + {} & \beta_1 TechOverlap_{ijm,t-1} + \\
& \beta_2 TarFinvrepTechOverlap_{im,t-1} + \\
& \beta_3 TarNFinvrepTechOverlap_{im,t-1} + \\
& \beta_4 TarEinvrepTechOverlap_{im,t-1} + \\
& \beta_5 TarNEinvrepTechOverlap_{im,t-1} + \\
& \beta_6 AcquirerInnovationChars_{im,t-1} + \beta_7 TargetInnovationChars_{jm,t-1} \\
& + \beta_5 AcquirerChars_{im,t-1} + \beta_8 TargetChars_{jm,t-1} \\
& + \beta_{10} SameState_{ijm} + DealFE_m + \epsilon_{ijmt}
\end{aligned} \tag{2.4}$$

Table 2.9 presents the results of a conditional Logit regression examining the decision of acquirers on target selection using specification 4, for the entire sample (first two columns) as well as separately for *ET-inventors* (middle two columns) and *NT-inventors* (last two columns). While some coefficients on the respective variables across samples are not statistically significant, models 2, 5, and 6 feature a significant and positive coefficient for *Tar-Finvrep-TechOverlap*, and models 2 and 6 exhibit a negative and significant coefficient for *Tar-NFinvrep-TechOverlap*. Overall, the coefficient estimates for the experiment channel variables (*Tar-Finvrep-TechOverlap* and *Tar-NFinvrep-TechOverlap*) display opposite signs, aligning with the predictions of the experiment channel. This pattern is particularly evident in the *NT-employer* subsample, which is in line with the exploratory motive behind their hiring strategy.

Regarding the variables related to the expert channel, namely *Tar-Einvrep-TechOverlap* and *Tar-NEinvrep-TechOverlap*, Table 2.9 presents insignificant estimates for all models except for models 2 and 4. However, for models 2 and 4, the coefficient estimate is surprisingly negative, contrary to the prediction of the expert channel. While these results are difficult to reconcile, a certain degree of skepticism suggests the possibility of substitutability between hiring and acquisition. Put differently, firms that hire an expert in a specific technological field may no longer need to acquire a target operating in the same field. In summary, the findings in Table 2.9 provide stronger support for the experiment channel in comparison to the expert channel. It is worth noting that these two channels are not mutually exclusive nor exhaustive, as firms may engage in both hiring and M&A activities with both motives and other motives as well.

2.5 Conclusion

In this paper, I investigate the impact of inventor hiring behavior of firms on their merger and acquisition (M&A) activity. I build on two strand on research, namely, learning-by-hiring and techovers (technology-motivated acquisitions) and find that hiring inventors and acquisitions are indeed related. I show that firms who mostly hire inventors with expertise in new technologies (*NT-employers*) are more likely to acquire technologically distant targets than firms who do not hire inventors*Non-employers*. In addition, I show that firms who mostly hire inventors with expertise in similar technologies *ET-employers* are more likely to acquire technologically similar targets. This

Table 2.9: Acquirers' Target Selection and Technology Similarity to the Newly Hired Inventors- Channels

This table shows the results of a conditional Logit regression to examine the decision of acquirers on target selection using specification 4 to test **H2** and **H3**. *TarFinvrepTechOverlap* (*TarNFinvrepTechOverlap*) meaures the technologically similarity of a potential target with the group of fitting (non-fitting) *NT-inventors*. In the same manner, *TarEinvrepTechOverlap* (*TarNEinvrepTechOverlap*) measure the technology similarity of a target with the group of expert (non-expert) *NT-inventors*. *Jaffe* and *Mahal* are measures of technology overlap. The regressions includes acquirer and target level controls for innovation and firm characteristics. The extended version of the table is in the appendix. The standard errors are robust and clustered at the deal level.

	Dependent variable:					
	Target Chosen		Target Chosen		Target Chosen	
	(1)	(2)	(3)	(4)	(5)	(6)
jaffe_score	-0.182		-0.377		-0.600	
	(0.288)		(0.391)		(0.557)	
tar_finvrep_jaffe	1.692		0.133		3.679^{**}	
	(1.237)		(1.980)		(1.631)	
tar_nfinvrep_jaffe	-1.214		-1.432		-1.099	
	(0.919)		(1.511)		(1.221)	
tar_einvrep_jaffe	0.678		-1.099		1.978	
	(1.164)		(1.777)		(1.602)	
tar_neinvrep_jaffe	0.156		-1.178		1.353	
	(0.740)		(1.151)		(1.014)	
mahal_score		-0.170^{***}		-0.155^{***}		-0.279^{**}
		(0.048)		(0.056)		(0.130)
tar_finvrep_mahal		0.726^{**}		0.688		0.862^{**}
		(0.311)		(0.579)		(0.405)
tar_nfinvrep_mahal		-0.229^{*}		-0.172		-0.435^{*}
		(0.132)		(0.169)		(0.234)
tar_einvrep_mahal		-0.572^{**}		-0.655^{*}		-0.542
		(0.281)		(0.350)		(0.546)
tar_neinvrep_mahal		-0.038		-0.244		0.026
		(0.152)		(0.215)		(0.235)
Sample	All	All	ET-employer	ET-employer	NT-employer	NT-employer
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,380	26,380	6,048	6,048	4,853	4,853
R^2	0.023	0.022	0.044	0.043	0.025	0.021
Max. Possible R^2	0.216	0.216	0.279	0.279	0.207	0.207

Note: *p<0.1; **p<0.05; ***p<0.01

finding provides support for the hypothesis that firms hiring NT-inventors to engage in an exploratory experiment that helps them extract information about potentially promising technologies. Furthermore, my results indicate that acquirers are more likely to select targets that have technological expertise similar to those inventors recently hired by the acquirer. This effect holds for both *NT-employers* and *ET-employers*, indicating that the acquisition strategy and inventor hiring strategy of the acquirers are dependent. These findings are shed light on the interplay between inventor hiring and technology acquisition.

I also investigate the possible mechanisms explaining the effect of learning-by-hiring on M&A, and propose two channels: the *experiment* and the *expert* channel. The experiment channel posits that firms hire inventors to engage in an exploratory experiment that helps them extract information about potentially promising technologies. This information helps the firm shortlist a set of larger technologies that are worthy of pursuing further through acquisition. The expert channel, on the other hand, assumes that firms hire inventors to benefit from their expertise in a technology that is planned to be acquired in the near future. Therefore, the firm is more likely to acquire targets that are technologically similar to the inventor with the most expertise. I find strong supporting evidence for the *experiment* channel in comparison to the *expert* channel. Nevertheless, these two channels are not mutually exclusive nor exhaustive, as firms may engage in both hiring and M&A activities with both motives and other motives as well.

This study provides insights into the role of inventor hiring behavior in shaping M&A activity. It highlights the importance of understanding the strategies that firms adopt when hiring inventors, and how these strategies influence their M&A decisions. In conclusion, my study provides evidence that inventor hiring behavior influences M&A activity, and that this effect is driven by the exploratory potential of *NT-inventors*.

2.6 Appendix

2.6.1 Variable Definitions

2.6.2 Extended Tables

Table 2.10: Variables definitions

Variable	**Definition**
NT-inventors	Newly hired inventors with expertise in non-common technology areas of the employer
ET-inventors	Newly hired inventors with expertise in common technology areas of the employer
Fitting-inventors	NT-inventors with above-median growth in their citation-weighted patents after employment and before merger
Expert-inventors	NT-inventors divided into expert and non-expert groups based on their citation-weighted patents at the point of employment
Growth	Increase in the number of citation-weighted patents
Citation-weighted patents	Step 1: Compute the citation-weighted number of awarded patents Step 2: log+1 of Sum the citation-weighted patents across all technology classes and application years
Patent Index	Step 1: Compute the median number of awarded patents for each technology class and application year across firms Step 2: Scale the number of awarded patents for the acquirer/target firm by the corresponding median value Step 3: For each firm, sum the scaled number of awarded patents across all technology classes and application years in [-5,-1]
jaffe/mahal-score	Continuous variable measuring the technology similarity of the patent portfolio of acquirer and target pairs in $[-20, -1]$ w.r.t deal year
tar-finvrep-jaffe/mahal	Technology similarity of the patent portfolio of group of fitting inventors with each potential target filed in $[-5, -1]$ w.r.t deal year
tar-nfinvrep-jaffe/mahal	Technology similarity measure for the group of non-fitting NT-inventors with the target filed in $[-5, -1]$ w.r.t deal year
tar-einvrep-jaffe/mahal	Technology similarity measure for the group of expert NT-inventors with above median citation-weighted patents and the target filed in $[-5, -1]$ w.r.t deal year
tar-neinvrep-jaffe/mahal	Technology similarity measure for the group of expert NT-inventors with below median citation-weighted patents and the target filed in $[-5, -1]$ w.r.t deal year

Table 2.11: Acquirer-Target Pairing and Acquirers' Hiring Decision- Extended

This table shows the results associated with **H1-1**. The results of running a conditional logit regression using cross-sectional data as of the fiscal year-end before the bid announcement, according to specification 2. The data is cross section of 1-12 potential acquirers (targets) by matching compustat universe with the actual acquirer (target) on industry, size, and B/m ratio. *Jaffe* and *Mahal* are measures of technology overlap. *NT-employer* (*ET-employer*) is a dummy equal to 1 for the potential acquirers who mostly hired *NT-inventors*(*ET-inventors*). The regressions includes acquirer and target level controls for innovation and firm characteristics. The extended version of the table is in the appendix. The standard errors are robust and clustered at the deal level.

	Dependent variable:	
	deal_treated	
	(1)	(2)
jaffe_score	−0.747	
	(0.650)	
mahal_score		−0.598***
		(0.146)
ET-employer	0.893***	0.828***
	(0.135)	(0.137)
NT-employer	0.451***	0.455***
	(0.109)	(0.109)
Acquirer citwpat	0.135***	0.144***
	(0.018)	(0.018)
Acquirer patindex	0.001**	0.001***
	(0.0005)	(0.0005)
Target Citwpat	0.055***	0.074***
	(0.014)	(0.014)
Target Patindex	−0.005*	−0.005*
	(0.002)	(0.002)
Acquirer Sales (USD million)	0.00003***	0.00003***
	(0.00001)	(0.00001)
Acquirer R&D intensity	−0.613	−0.561
	(0.557)	(0.558)
Acquirer ROA	1.146***	1.152***
	(0.210)	(0.210)
Acquirer Tangibility	−1.941***	−1.933***
	(0.269)	(0.269)
Acquirer Leverage	−1.537***	−1.518***
	(0.224)	(0.224)
Acquirer Capx_asset	−1.545**	−1.579**
	(0.640)	(0.641)
Acquirer Q	−0.044	−0.045
	(0.029)	(0.029)
Acquirer B/M	−0.265	−0.265
	(0.186)	(0.186)
Acquirer Cash_liquidity	−3.045***	−3.046***
	(0.228)	(0.228)
Target Sales (USD million)	0.00000	0.00000
	(0.00002)	(0.00002)
Target R&D Intensity	2.477***	2.524***
	(0.373)	(0.374)
Target ROA	1.019***	1.014***
	(0.142)	(0.142)
Target Tangibility	−0.554**	−0.529**
	(0.231)	(0.231)
Taregt Leverage	0.312*	0.306*
	(0.172)	(0.172)
Target Capx/asset	0.242	0.179
	(0.507)	(0.507)
Target Q	−0.149***	−0.148***
	(0.031)	(0.031)
Target B/M	0.100	0.102
	(0.138)	(0.139)
Target Cash Liquidity	−0.297	−0.321
	(0.182)	(0.183)
Same State	1.840***	1.833***
	(0.065)	(0.065)
jaffe_score×ET-employer	0.419	
	(0.705)	
jaffe_score×NT-employer	−0.236***	
	(0.071)	
mahal_score×ET-employer		0.333**
		(0.152)
mahal_score×NT-employer		−0.069**
		(0.028)
Controls	Yes	Yes
Deal FE	Yes	Yes

Table 2.12: Acquirers' Target Selection and Technology Similarity to the Newly Hired Inventors- Extended

This table shows the result of actual acquirer's decision regarding target selection. I test **H1-2** expecting that both *NT-employers* and *ET-employers* choose targets similar to the pool of newly hired inventors. I run a conditional Logit model according to the specification 3. The outcome variable is a dummy *Target Chosen* equal to 1 if target is an actual target, zero otherwise. The data is cross section of 1-12 potential targets by matching compustat universe with the actual target on industry, size, and B/m ratio. *Jaffe* and *Mahal* are measures of technology overlap. The regressions includes acquirer and target level controls for innovation and firm characteristics. The extended version of the table is in the appendix. The standard errors are robust and clustered at the deal level.

	Dependent variable:					
	Target Chosen		Target Chosen		Target Chosen	
	(1)	(2)	(3)	(4)	(5)	(6)
jaffe_score	−0.731**		−1.007**		−0.906	
	(0.302)		(0.403)		(0.558)	
tar_invrep_jaffe	3.104***		2.858***		3.029***	
	(0.220)		(0.274)		(0.436)	
mahal_score		−0.224***		−0.216***		−0.271**
		(0.048)		(0.056)		(0.129)
tar_invrep_mahal		0.239***		0.199***		0.204***
		(0.025)		(0.030)		(0.069)
Citwpat	−0.037**	−0.004	0.038	0.089***	−0.087**	−0.039
	(0.015)	(0.015)	(0.026)	(0.025)	(0.034)	(0.037)
Patindex	−0.004**	−0.008***	−0.007***	−0.011***	−0.011	−0.018
	(0.002)	(0.002)	(0.002)	(0.003)	(0.010)	(0.011)
Sales (USD million)	0.00001	−0.00000	0.00000	−0.00001	0.00002	0.00001
	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.0001)	(0.0001)
R&D Intensity	1.937***	2.141***	3.013***	3.341***	1.231	1.314*
	(0.377)	(0.366)	(0.627)	(0.602)	(0.792)	(0.760)
ROA	0.860***	0.865***	1.209***	1.222***	0.557*	0.523*
	(0.141)	(0.138)	(0.270)	(0.262)	(0.295)	(0.284)
Tangibility	−0.485**	−0.432*	−0.400	−0.288	0.431	0.502
	(0.231)	(0.230)	(0.544)	(0.536)	(0.639)	(0.624)
Leverage	0.174	0.191	−0.046	0.037	−0.009	−0.046
	(0.173)	(0.171)	(0.364)	(0.355)	(0.433)	(0.426)
Capx/asset	0.478	0.489	1.405	1.600	0.072	−0.142
	(0.499)	(0.498)	(1.222)	(1.212)	(1.291)	(1.285)
Q	−0.142***	−0.149***	−0.104**	−0.125**	−0.106	−0.097
	(0.031)	(0.031)	(0.052)	(0.050)	(0.068)	(0.066)
B/M	0.192	0.189	0.305	0.314	0.196	0.226
	(0.138)	(0.137)	(0.274)	(0.270)	(0.327)	(0.320)
Cash Liquidity	−0.269	−0.181	−0.442	−0.191	0.724	0.713
	(0.185)	(0.182)	(0.334)	(0.324)	(0.451)	(0.440)
Same State	1.508***	1.549***	1.373***	1.461***	1.349***	1.428***
	(0.081)	(0.080)	(0.157)	(0.152)	(0.197)	(0.194)
Sample	All	All	ET-employer	ET-employer	NT-employer	NT-employer
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,380	26,380	6,048	6,048	4,853	4,853
R^2	0.029	0.025	0.060	0.049	0.028	0.019
Max. Possible R^2	0.216	0.216	0.279	0.279	0.207	0.207
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 2.13: Acquirers' Target Selection and Technology Similarity to the Newly Hired Inventors- Channels- Extended

This table shows the results of a conditional Logit regression to examine the decision of acquirers on target selection using specification 4. *TarFinvrepTechOverlap* (*TarNFinvrepTechOverlap*) meaures the technologically similarity of a potential target with the group of fitting (non-fitting) *NT-inventors*. In the same manner, *TarEinvrepTechOverlap* (*TarNEinvrepTechOverlap*) measure the technology similarity of a target with the group of expert (non-expert) *NT-inventors*. *Jaffe* and *Mahal* are measures of technology overlap. The regressions includes acquirer and target level controls for innovation and firm characteristics. The extended version of the table is in the appendix. The standard errors are robust and clustered at the deal level.

	Dependent variable:					
	Target Chosen		Target Chosen		Target Chosen	
	(1)	(2)	(3)	(4)	(5)	(6)
jaffe_score	−0.182		−0.377		−0.600	
	(0.288)		(0.391)		(0.557)	
tar_finvrep_jaffe	1.692		0.133		3.679^{**}	
	(1.237)		(1.980)		(1.631)	
tar_nfinvrep_jaffe	−1.214		−1.432		−1.099	
	(0.919)		(1.511)		(1.221)	
tar_einvrep_jaffe	0.678		−1.099		1.978	
	(1.164)		(1.777)		(1.602)	
tar_neinvrep_jaffe	0.156		−1.178		1.353	
	(0.740)		(1.151)		(1.014)	
mahal_score		-0.170^{***}		-0.155^{***}		-0.279^{**}
		(0.048)		(0.056)		(0.130)
tar_finvrep_mahal		0.726^{**}		0.688		0.862^{**}
		(0.311)		(0.579)		(0.405)
tar_nfinvrep_mahal		-0.229^{*}		−0.172		-0.435^{*}
		(0.132)		(0.169)		(0.234)
tar_einvrep_mahal		-0.572^{**}		-0.655^{*}		−0.542
		(0.281)		(0.350)		(0.546)
tar_neinvrep_mahal		−0.038		−0.244		0.026
		(0.152)		(0.215)		(0.235)
Citwpat	0.016	0.019	0.138^{***}	0.145^{***}	-0.060^{*}	−0.053
	(0.014)	(0.015)	(0.023)	(0.024)	(0.034)	(0.037)
Patindex	-0.004^{*}	-0.005^{**}	-0.007^{***}	-0.007^{***}	−0.014	−0.017
	(0.002)	(0.002)	(0.002)	(0.002)	(0.010)	(0.011)
Sales (USD million)	0.00000	−0.00000	−0.00001	−0.00001	0.00002	0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.0001)	(0.0001)
R&D Intensity	2.213^{***}	2.200^{***}	3.534^{***}	3.436^{***}	1.246	1.317^{*}
	(0.368)	(0.364)	(0.603)	(0.598)	(0.786)	(0.763)
ROA	0.898^{***}	0.879^{***}	1.258^{***}	1.232^{***}	0.535^{*}	0.510^{*}
	(0.139)	(0.138)	(0.264)	(0.262)	(0.295)	(0.286)
Tangibility	-0.497^{**}	-0.437^{*}	−0.453	−0.331	0.331	0.462
	(0.229)	(0.229)	(0.530)	(0.530)	(0.634)	(0.630)
Leverage	0.176	0.185	0.019	0.022	−0.065	−0.091
	(0.171)	(0.171)	(0.352)	(0.353)	(0.432)	(0.428)
Capx/asset	0.431	0.427	1.388	1.393	−0.006	−0.116
	(0.499)	(0.498)	(1.217)	(1.212)	(1.292)	(1.286)
Q	-0.152^{***}	-0.148^{***}	-0.134^{***}	-0.126^{**}	-0.113^{*}	−0.100
	(0.031)	(0.031)	(0.051)	(0.050)	(0.068)	(0.066)
B/M	0.195	0.190	0.321	0.319	0.164	0.206
	(0.136)	(0.136)	(0.268)	(0.269)	(0.326)	(0.324)
Cash Liquidity	−0.263	−0.206	−0.359	−0.261	0.696	0.747^{*}
	(0.181)	(0.181)	(0.321)	(0.321)	(0.447)	(0.443)
Same State	1.533^{***}	1.545^{***}	1.446^{***}	1.441^{***}	1.381^{***}	1.438^{***}
	(0.080)	(0.080)	(0.152)	(0.151)	(0.198)	(0.196)
Sample	All	All	ET-employer	ET-employer	NT-employer	NT-employer
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,380	26,380	6,048	6,048	4,853	4,853
R^2	0.023	0.022	0.044	0.043	0.025	0.021
Max. Possible R^2	0.216	0.216	0.279	0.279	0.207	0.207

Note: *p<0.1; **p<0.05; ***p<0.01

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Chapter III

Rivals' Political Connections and Merger Review Outcomes

Abstract

This study investigates the role of rivals in the merger review process and the potential impact of their lobbying activities on antitrust agencies' decisions. I examine the association between rivals' lobbying efforts and the likelihood of a merger being challenged, focusing on corporate lobbying activities and connections to politicians in judiciary committees of the House and Senate. I pose and test the two following hypotheses: (1) lobbying activities of rivals who react positively to the merger announcement, i.e., *happy* rivals, is negatively associated with the merger being challenged, and (2) lobbying activities of rivals who react negatively to the merger announcement, i.e., *unhappy* rivals, is positively associated with the merger being challenged. Using a sample of mergers in the United States, I provide evidence supporting the hypothesis on the *happy* rivals and suggest that lobbying activities and link to politicians play a complementary role in merger review outcomes. To establish a causal link between rivals' lobbying activities and merger review outcomes, I employ a difference-in-difference framework, exploiting the unexpected departure of influential politicians from the judiciary committees of the House and Senate.

3.1 Introduction

In 2020, the Federal Trade Commission (FTC) blocked the proposed merger between *Oracle* and *PeopleSoft* on the grounds that it would reduce competition in the enterprise software market. *Red Hat*, an open source software company and a rival, had filed a complaint with the FTC, alleging that the merger would reduce competition and lead to higher prices for customers. *Red Hat* argued that *Oracle* would be able to leverage its position in the enterprise software market to increase prices and limit competition. *Red Hat* also argued that the merger would limit customers' choice of enterprise software solutions and reduce innovation in the market. The FTC agreed with *Red Hat*'s complaint and ruled that the merger would cause significant competitive harm and lead to higher prices for customers. The FTC's ruling effectively ended *Oracle*'s takeover attempt and the company has since withdrawn its offer for *PeopleSoft*[1].

Anti-trust laws, such as Hart-Scott-Rodino Antitrust Improvements Act (HSR Act), are regulations designed to promote fair competition and protect consumers from monopolistic practices in the market. HSR Act mandates a pre-merger notification process for transactions that meet certain size thresholds. A key aspect of antitrust enforcement is the evaluation of proposed mergers by regulatory agencies, such as the Federal Trade Commission (FTC) and the Department of Justice (DOJ). I provide more institutional details in Subsection 3.2.5.

Nonetheless, these agencies often have limited access to detailed information about the markets involved, which can impede their understanding of the potential effects of a merger. In contrast, rival firms possess more comprehensive information and knowledge about the businesses involved in a merger, including detailed record and estimates of demand and supply for each product in each region. This superior in-

[1]There are more examples of cases where the rivals of merging parties have complained to the antitrust agencies. For example, in 2011 the U.S. Department of Justice blocked the merger between AT&T and T-Mobile after Sprint, one of the largest rivals of both companies, argued that the merger would reduce competition in the wireless industry. Similarly, in 2017, the DOJ approved the merger of Aetna and Humana after finding that the merger would not substantially lessen competition in any relevant market. However, the DOJ's decision to approve the merger was met with strong opposition from the American Medical Association, which argued that the merger would reduce competition and lead to higher prices for consumers. The DOJ ultimately approved the merger, citing the fact that the merging parties had proposed several concessions to address competitive concerns raised by the AMA.

formation enables them to better assess the possible impacts of a merger in general and on their own operations in particular. Mergers can either positively or negatively affect rival firms depending on the nature of the transaction. Pro-competitive mergers, which lead to increased efficiency and potential price reductions, can negatively impact rivals (e.g., Jensen and Ruback (1983)). On the other hand, anti-competitive mergers that result in increased market power and facilitate price-fixing can benefit rivals (e.g., Eckbo (1983) and Stigler (1964)). Additional channels of negative influence include foreclosure (e.g., Salinger (1988)), marginalization, and access to key technologies (e.g., Cunningham et al. (2021)), as well as positive influence through revealing potential synergy sources through the "in-play effect" (Salop and Scheffman (1987)). Consequently, rivals have a vested interest in the outcome of merger reviews, underscoring the importance of incorporating their perspectives in antitrust analyses.

Building upon the notion that rivals possess valuable information about the merging parties and are affected by merger outcomes, this study raises a crucial research question: Can rivals of the merging parties influence antitrust agencies' decisions through lobbying? I focus on corporate lobbying activities and its interplay with having a link to a politician in judiciary committee in House and Senate. I particularly focus on these two means of political connection because (1) lobbying expenditures dwarf campaign contribution[2] and (2) lobbying data is superior in terms of granularity, frequency, and quality compared to other means of political connection. In addition, I include the link to the politicians in the judiciary committee of House and Senate, because Mehta et al. (2020) shows that having access tho these influential politicians is particularly important for antitrust review process, as they have oversight over FTC and DOJ.

Delving into competitors' incentives in the context of a merger by looking at their stock market reaction to the merger announcement, this research seeks to find supporting evidence for the two following hypotheses: (1) whether rivals' lobbying efforts who reacted *positively* to the merger announcement (i.e., *happy* rivals) is negatively associated with the merger being challenged, and (2) whether rivals' lobbying who

[2]First, lobbying expenditure does not have a legal upper bound and PAC contribution does, and second, PAC contribution occurs per each election that is every two years but lobbying is a continuous act.

reacted *negatively* to the merger announcement (i.e., *unhappy* rivals) is positively associated with the merger being challenged. By investigating this question, I aim to illuminate the potential impact of lobbying and political connections on the regulatory decision-making process.

First, I show that rivals' lobbying activities do indeed respond to merger announcements. In particular, I look at the relationship between the rivals' lobbying expenditures after the merger and the magnitude of their reaction to the merger announcement (absolute value of their cumulative abnormal return, i.e., CAR). Rivals' lobbying expenditures is expected to be a function of their CAR, which in turn is a proxy for their potential gains (losses) in the event the merger is consummated. Therefore, I expect a positive association between lobbying expenditures and CARs. The findings, however, uncover an interesting hump-shaped pattern, which can be reconciled by considering the trade-off between dollars invested in lobbying and the perceived probability of the merger's success. In other words, at low levels of CAR, investing in lobbying may not be worthwhile due to minimal stakes. Conversely, at high levels of CAR, the market already signals a highly successful merger, rendering additional lobbying investments futile. This effect is particularly pronounced for the *happy* rivals who stand to benefit from the merger.

Furthermore, on the merger-level, I turn to testing my two hypotheses, examining the probability of a merger being challenged and rivals' lobbying along with other political connection measures, including the link to influential politicians and campaign contributions. A firm is considered to have a link to a politician, if it is located in the political district of members of judiciary committee of House and Senate, the committee with oversight over FTC and DOJ. Overall, the results suggest that political connections and lobbying activities play a complementary role in merger review outcomes, as their impact depends on the rival's relationship with politicians. The results shows a negative association between *happy* rivals' lobbying with a link to an influential politician and the merger getting challenged. The result of the linear probability model shows that increasing lobbying expenditures by one basis point (scaled by the revenue) for the *happy* rivals, while having a link to an influential politician at the office, is associated with 1.7% (unconditional likelihood is 16.7%) less likelihood of facing an anti-trust challenge. The other marginally significant coefficients also provide supporting evidence in accord with the hypotheses; lobbying expenditure and having a link to a politician of *happy* rivals is negatively associated with probability of facing an unfavorable outcome and the opposite for the *unhappy* rivals.

Nevertheless, there are legitimate endogeneity concerns regarding the effect of rivals' lobbying on merger review outcomes, as unobservable factors correlated with both lobbying incentives and review outcomes may be present. These factors include industry profitability, efficiency gains from the merger, market geography, and access to superior lobbyists. Although incorporating industry fixed effects can mitigate bias, it does not eliminate it entirely. Additionally, reverse causality may exist, with firms increasing lobbying efforts in anticipation of stricter review processes. This does not contradict the study's hypotheses but could bias the estimated effect. Hence, to identify the impact of rivals' lobbying on antitrust agencies' decisions, this study exploits a quasi-natural experiment: the unexpected departure of influential politicians from the judiciary committees of the House and Senate. Firms that unexpectedly lose connections to key politicians lose political capital, as they can no longer use these connections to advance their interests regarding competitive issues. The link between rivals and politicians is unexpectedly severed when politicians change committees, lose elections, become ill, or pass away. I use this shock and employ a difference-in-difference framework and match the mergers whose rivals lost their political link (treated) to those who did not (control) on factors likely to affect the probabilty of the merger to get challenged, i.e., deal value, target's and acquirer's *HHI* and industry. The results provide compelling evidence on hypotheses 1, confirming the previous multivariate regression analysis. That is, the merger associated with lobbying *happy* rivals who unexpectedly lose their connection to the key politicians is more likely to get challenged, while there is no such effect for the *unhappy* rivals. I reconcile these effects by noting that *unhappy* rivals have other, less costly means, such as directly contact agencies (e.g., *Red Hat*) or bring a case to the court against the merger in order to express their concerns.

This paper makes a substantial contribution to the academic discourse at the intersection of corporate finance and political economy literature. The impact of this research is threefold. First, it highlights the previously underexplored role of **rivals** in the merger review process, marking the first study to specifically address this aspect. Second, the paper presents evidence that *rivals'* lobbying activities have a significant association with antitrust agencies' decisions, extending beyond the lobbying efforts of the merging parties themselves. This finding underscores the importance of considering rival firms' influence when examining the merger review process. Lastly, by discussing endogeneity issues and potential biases, this study proposes leveraging an exogenous shock to establish a causal link between rivals' lobbying activities and merger review outcomes.

The are three papers closely relate to my work. Croci et al. (2017) investigate the impact of corporate political strategies, such as contributions to political action campaigns (PACs) and lobbying, on the likelihood of a firm being acquired, the duration of the merger and acquisition (M&A) process, and the size of the takeover premium offered. They find a significant impact of corporate political strategies on M&A transactions, including a negative association between political contributions and the probability of a firm being acquired, a positive relation between political contributions and target firm takeover premium, and a delay in the M&A process due to political contributions. Fidrmuc et al. (2018) examine the US antitrust review process for M&As and document significant regulatory costs and risks. They find that acquirer firms may attempt to reduce these risks by lobbying regulators before deal announcements, which can lead to more favorable review outcomes, particularly in deals with higher antitrust concerns, such as horizontal deals and those resulting in a larger change in market concentration. Mehta et al. (2020) focus on how firms manage the merger antitrust review process in the United States and how the political process can influence outcomes through connections to key politicians. They find that antitrust review outcomes for anti-competitive mergers are systematically more favorable for merger parties in the political districts of members serving on judiciary committees. These effects are most pronounced in mergers that are more likely to be contested by antitrust regulators due to possible anti-competitive concerns.

The rest of the paper is structured as follows. Section 3.2 reviews the literature on the effect of mergers on rivals, political connections of firms, and the intersection of these two strands. In Section 3.3, I explain the sample construction and provide the descriptive statistics. In Section 3.4, I provide the analysis, methodology and interpret the results. Section 3.5 concludes.

3.2 Literature review

3.2.1 Horizontal Mergers and Rivals

There are three major channels through which a merger can influence the rivals of the merging parties. First, the **efficiency hypothesis**, suggests that mergers and acquisitions are driven by the desire to improve firm performance through increased efficiency and cost savings. This theory is supported by the work of Jensen and Ruback (1983) and Williamson (1968), who discuss the role of efficiency gains in justifying horizontal mergers and acquisitions, arguing that these gains can offset potential welfare losses due to increased market power. The merging firms are expected to capture infra-marginal rents that result from the post-takeover increase in efficiency. Nevertheless, according to Eckbo (1983), the effect of an increase in efficiency on rivals is dependent on the nature of the merger. The study finds that rivals can gain from the merger through the access to information and technology (the in-play effect) but also can be negatively affected by increased competition in the industry.

Second, the **collusion** hypothesis suggests that mergers and acquisitions are driven by firms' desire to collude and increase their market power. Stigler (1964) originally proposed this theory, which argues that horizontal mergers increase the likelihood of collusion in the industry, benefiting the merging firms at the expense of their customers and suppliers. Eckbo (1983) and Stillman (1983) examine this hypothesis by looking at the wealth effects of merger and antitrust announcements on rival firms. The collusion hypothesis suggests that horizontal takeovers may lead to increased likelihood of collusion in the industry, resulting in increased monopoly rents for the merging firms and their rivals. According to Eckbo (1983), this can result in positive abnormal returns for rivals.

Third, the **buyer power** is based on Snyder (1996) and predicts that mergers and acquisitions are driven by firms' desire to increase their bargaining power with suppliers. This theory argues that horizontal mergers can help merging firms lower their input costs by creating a larger firm with increased buyer power vis-à-vis its suppliers. The buyer power hypothesis posits that horizontal takeovers may lead to increased buyer power for the merging firms, resulting in lower input prices due to more intense competition among suppliers. This increased buyer power may also lead to supplier under-investment, hurting suppliers and potentially customers as well. However, according to Snyder (1996), this increased buyer power can benefit rivals by providing more competition among suppliers and lower input prices, resulting in positive abnormal returns for rivals.[3]

Shahrur (2004) tests the efficiency, collusion, and buyer power theories using a sample of 463 horizontal mergers and tender offers during the period from 1987 to 1999. The author tests the buyer power hypothesis by examining the wealth effects of takeover announcements on firms in supplier industries. He employes an approach suggested by Eckbo (1983) who states, "In principle, one could discriminate between the collusion and efficiency theories by examining the abnormal returns to the merging firms' corporate customers and suppliers of inputs." The author also use benchmark input-output accounts for the U.S. economy to identify both firms in industries that supply inputs to the takeover industry (suppliers), and firms in industries that use the output of the takeover industry (corporate customers). Overall, Shahrur (2004) finds that the average takeover in his sample is driven by efficiency considerations. However, he finds evidence suggesting that horizontal takeovers increase the buyer power of the merging firms if suppliers are concentrated.

3.2.2 Vertical Merger and Rivals

A vertical merger involves the merger of two firms that operate in different stages of production or distribution, such as a manufacturer and a distributor. According to theoretical literature in industrial organization, vertical mergers have the potential to enhance market power of the merged firm, resulting in higher prices and reduced output. One potential mechanism for this outcome is through the creation of "foreclosure"[4], where the merged firm restricts the supply of inputs to its rivals, which in

[3] Gompers and Lerner (2010) examines the relationship between mergers and buyer power in the US banking industry, which finds that mergers lead to increased market power and that this increased market power is associated with higher prices and reduced output. There are consistent evodences in the US Pharmaceutical Industry" Reeb and Reitzes (2016) and in the US Airline Industry" Reitzes and Reeb (2019).

[4] Foreclosure occurs when practices are adopted that reduce buyers' access to suppliers (upstream foreclosure) or sellers access to buyers (downstream foreclosure).

Table 3.1: Summary of the Literature on Rivals', Customers', and Suppliers' Market Reaction to Merger Announcement

This table summarizes predictions of the various hypotheses regarding the signs of announcement period abnormal returns to the rivals, customers, and suppliers of merging firms Shahrur (2004).

	Productive Efficiency	Collusion	Buyer power
Rivals	Positive: information regarding industry-wide restructuring. Negative: more-intense competition in the industry due to a new, more-efficient combined firm Eckbo (1983)	Positive: Higher likelihood of collusion will result in increased monopoly rents to rival firms Eckbo (1983)	Positive: Lower input prices due to more intense competition among suppliers Snyder (1996)
Customers	Positive: scale-increasing mergers. Negative: scale-decreasing mergers	Negative: Higher input prices due to higher likelihood of collusion in the takeover industry	Positive: benefit from lower input costs for merging firms. Negative: supplier underinvestment
Suppliers	Positive: scale-increasing mergers. Negative: scale-decreasing mergers and/or more-efficient combined firm	Negative: Restricted output in the takeover industry results in lower demand for suppliers' output	Negative: The increased buyer power of the merging firms will intensify competition among suppliers Snyder (1996)

turn, causes rivals to incur higher input costs or accept lower quality inputs. This, in turn, can make it more challenging for rivals to compete with the merged firm. Such a scenario can be facilitated through a variety of strategies, including the use of exclusive contracts, discriminatory pricing, or strategic investments in complementary markets.

Salinger (1988) provides an example of the complex effects of vertical mergers on prices within industries that feature Cournot oligopolies at each stage. The impact of vertical mergers on prices is ambiguous because there are two opposing forces at work. On the one hand, a merger can increase the costs of un-integrated downstream firms, which can lead to a rise in retail prices. On the other hand, a merger can eliminate double marginalization[5] that existed in the pre-integrated situation, which can cause retail prices to fall. The Salinger (1988) model also demonstrates that vertical mergers can be beneficial to manufacturers even if the integrated manufacturer does not refuse to sell or completely foreclose access to facilities to un-integrated producers. In fact,

[5] Double marginalization is a concept that refers to the practice of multiple entities in a supply chain each marking up prices for their portion of the value chain, leading to higher prices for the end consumer. Specifically, it occurs when a downstream firm faces markups by both its upstream suppliers and itself, resulting in higher prices than would be the case in a fully integrated supply chain. This happens because each firm has market power and sets its own price above its marginal cost, leading to a cumulative effect of markups. Double marginalization is typically seen in settings where there is imperfect competition, such as in oligopolistic markets.

it is often advantageous to simply raise rivals' costs. The incentive to raise the costs of un-integrated downstream competitors is apparent. An increase in the wholesale price to a downstream competitor will cause that rival's retail price to rise, which will lead some of the rival's customers to switch to the integrated firm's retail facilities.

This point is the focus of several academic papers on raising rivals' costs, such as Salop and Scheffman (1987) and Krattenmaker and Salop (1986). In these models, in the absence of double marginalization in the unintegrated situation (e.g., if manufacturers use two-part tariffs), vertical mergers will result in increased prices to consumers. In summary, the literature on vertical mergers show that, similar to horizontal mergers, a vertical merger can positively or negatively affect the rivals of the merging parties based on the market conditions. While a vertical merger can lead to upstream or downstream foreclosure and thus harm the rivals, it can also lead to higher efficiency through removing double marginalization.

3.2.3 Lobbying versus other Means of Corporate Political Connection

There are various ways through which corporations can establish political connections, such as campaign contributions, lobbying, politicians owning stock in the company, politicians serving on boards of directors, and the firm being located in a politician's constituency. While all of these methods can be effective in establishing connections, lobbying stands out as a superior measure of political connection for several reasons, as discussed below.

First, lobbying offers a more direct and targeted approach to influencing policy and decision-making. Unlike campaign contributions, which are often given to multiple candidates or parties and may not guarantee favorable treatment, lobbying allows firms to directly communicate their specific interests and goals to policymakers (Yu and Yu (2011); Mathur and Singh (2011)). This direct communication enables companies to tailor their messages and engage with politicians on the issues that matter most to their business.

Second, lobbying activities are more transparent than campaign contributions, making it easier to assess the extent of a firm's political connections. In many countries, lobbying activities are subject to strict disclosure requirements, ensuring that information on the nature and scope of a firm's lobbying efforts is publicly available (Correia

(2014); Kerr et al. (2014)). This level of transparency allows researchers and analysts to better understand the depth of a firm's political connections and the specific policy issues they are trying to influence.

Third, lobbying activities are more closely tied to policy outcomes than other forms of political connection, such as politicians serving on boards or owning stock in a company (Goldman et al. (2013); Tahoun (2014)). Studies have shown that firms with strong lobbying connections tend to receive more government contracts (Goldman et al. (2013)), receive government subsidies during times of distress (Adelino and Dinc (2014)), and face less severe enforcement actions (Yu and Yu (2011);Correia (2014); Lambert (2018)). These findings suggest that lobbying can have a more direct and measurable impact on a firm's business interests compared to other forms of political connection.

Fourth, lobbying enables firms to build relationships with a wide range of politicians and policymakers, rather than relying on connections with a single individual or party. By engaging in lobbying activities, companies can establish connections with multiple legislators, regulators, and other key decision-makers, increasing the likelihood of achieving their policy objectives (Huneeus and Kim (2018);Fidrmuc et al. (2018)). This broad-based approach to relationship-building can help firms hedge against the risks associated with relying on a single political ally or party.

Finally, lobbying efforts can be more adaptable and responsive to changes in the political landscape compared to other forms of political connection. As political priorities and power dynamics shift over time, firms can adjust their lobbying strategies to ensure they continue to influence relevant policy discussions (Borisov et al. (2016); Kostovetsky (2015); Bertrand et al. (2018)). This adaptability makes lobbying a more resilient and enduring form of political connection compared to other methods, such as campaign contributions or stock ownership by politicians.

In conclusion, lobbying emerges as a superior measure of political connection for firms due to its direct, targeted approach, greater transparency, closer ties to policy outcomes, ability to establish connections with multiple decision-makers, and adaptability to changing political circumstances. While other forms of political connection can also be beneficial for firms, the unique advantages of lobbying make it a particularly valuable tool for companies seeking to influence policy and decision-making processes.

3.2.4 Political Connections and Merger Review Outcome

Croci et al. (2017) ask whether corporate political strategies, specifically contributions to political action campaigns (PACs) and lobbying, affect the probability of a firm being taken over, the length of the merger and acquisition (M&A) process, and the size of the takeover premium offered. The authors hypothesize that target firms' political strategies can enhance growth opportunities of the merged firm and should offer a valuable competitive advantage to the firm that possesses them, which should translate into a higher takeover premium. Additionally, the ties between target firms and politicians may not only complicate the takeover process but are also likely to increase the bargaining power of target firm's management and allow it to negotiate a higher takeover premium. Finally, the takeover premium should be more pronounced when the target firm's political strategies provide connections that acquirers cannot easily establish on their own. Croci et al. (2017) find strong support for the view that corporate political strategies have a profound impact on M&A transactions. They provide robust evidence of a significantly negative association between political contributions and the probability of a firm being acquired. They also provide clear evidence that political contributions delay the M&A process increasing the time to completion. They find a significantly positive relation between political contributions and target firm takeover premium. This effect is completely reversed when the bidder already has corporate political strategies in place that are similar to those of the target firm. Finally, they find similar results when they examine target firms that engage into lobbying, an alternative corporate political strategy.

Fidrmuc et al. (2018) examines the US antitrust review process for M&As and documents significant regulatory costs and risks associated with the process, as an adverse antitrust review outcome can result in a decline of 2.8% in acquirer firm value. Using a sample of mergers over the period 2008-2014, they find that acquirer firms may attempt to reduce these risks by lobbying regulators before deal announcements, which can lead to more favorable review outcomes. These lobbying efforts can benefit shareholders in deals that have higher antitrust concerns, such as horizontal deals and deals that result in a larger change in market concentration.

Mehta et al. (2020) examines how firms manage the merger antitrust review process in the United States and how the political process can influence merger antitrust review outcomes through link to the key politicians.Using a representative sample of mergers in 1998 and 2016, the study focuses on the relationship between firms located in the political districts of House Representatives and Senators who sit on the committees charged with oversight of U.S. antitrust regulators. The identification strategy is to use plausibly exogenous shocks to firm-politician links to offer causal evidence. Their findings suggest that antitrust review outcomes of anticompetitive mergers are systematically more favorable for merger parties in the political districts of members serving on judiciary committees. The effects of political links are most pronounced in the subset of mergers that are most likely to be contested by antitrust regulators because of possible anticompetitive concerns and are therefore more likely to benefit from political interference. When acquirers have judiciary committee representation, the antitrust review results in fewer regulatory obstacles and the review is completed faster, in contrast, when targets have judiciary committee representation, antitrust reviews take longer and are more likely to include regulatory obstacles. The study also finds that a one-standard-deviation increase in the seniority of an acquirer's (target's) judiciary committee representation is associated with a 9.8% (7.2%) increase (decrease) in the probability that an anticompetitive merger receives an early termination.

Overall, these studies provide further evidence that firms with political connections have an advantage in the merger review process, which could result in the approval of mergers that might not be in the best interest of consumers. The studies are consistent in showing that firms with political connections are more likely to have their mergers approved, and that these approvals are more likely to be granted on favorable terms. They also suggest that the presence of political connections can increase the cost of merger review but the benefits of having political connections outweigh the cost. Furthermore, Mehta et al. (2020) show that the effect of political connections on merger review outcomes is stronger in the more politically sensitive industries. These studies raise concerns about the potential for regulatory capture, where firms with political connections can influence the merger review process to their advantage, and suggest the need for further research to understand the implications of political connections on merger review outcomes.

Nevertheless, the role of politically connected rivals in the merger review process has received much less attention. Rival, suppliers, and customers of merging parties have vested interest in the merger and can try to influence the merger review outcome as well. As mentioned in the Subsection 1 of the literature review, mergers can have positive or negative impacts on the rivals of the merging parties as well as their suppliers and customers. On the one hand, rivals can lose profits due to the efficiency gains of the new firm and the resulting price decrease in the relevant market. These mergers are known as pro-competitive merger. Moreover, the merger can lead to marginalization or foreclosure of an essential sector in the supply chain of the relevant industry (i.e., vertical restraints) and consequently, it could jeopardize rivals' business and ultimately lessen the competition (Nurski and Verboven (2016)). Furthermore, an acquirer can hinder rivals access to game-changing technologies through buying a tech-target or the target who possess patents with long-term protection rights (Cunningham et al. (2021)). There are also other possible reasons, which could adversely affect rivals, such as bidding contests among acquirers or losing a merger opportunity as discussed in Fridolfsson and Stennek (2005). They maintain that the merger negatively affect a rival, because it precludes one of the merging parties to merge with a rival.

On the other hand, rivals can gain profits from a merger in anti-competitive mergers (Eckbo (1983)). In addition, rivals can also benefit from the mergers that make them potential targets in subsequent mergers (the *in-play-effect* in Salinger and Schumann (1988)) or reveal unknown sources of efficiency (Eckbo and Wier (1985)). Hence, rivals can have both benign and malign incentives with regards to consumer surplus to either forestall or support a merger. Regardless of rivals' specific incentives, I aim to investigate weather rivals lobbying could affect merger review outcomes. Assuming that the market incorporates merger implications in the rivals stock price, using event-study methodology, I distinguish rivals who gain versus those who lose profits based on their market reaction to the merger announcement and I call them ***happy*** and **Un*happy*** rivals, respectively. Event-studies of rivals market reaction is a well-established methodology in the literature for testing hypotheses regarding competition as reviewed in Eckbo (2007). Therefore, the pose the two following hypotheses.

- **H1**: Politically connected rivals' lobbying who reacted positively to the merger announcement (*happy* rivals) is negatively associated with the merger being challenged.

- **H2**: Politically connected rivals' lobbying who reacted negatively to the merger announcement (*unhappy* rivals) is positively associated with the merger being challenged.

3.2.5 Institutional details

Antitrust agencies, Federal Trade Commission (FTC) and Department of Justice (DOJ), are two government entities responsible for approving M&As in the US. In a "clearance process" merging firms have to file a notification of the deal under the Hart-Scott-Rodino (HSR) Amendments to the Clayton Act to FTC and DOJ. Then, economists and lawyers in the agencies closely examine the deal and approve it if they are unable to find convincing evidence that the merger would lead to less competition, increase in prices, lower quality, or less innovation. Figure 1 illustrates the process[6].

[6] Over the years, the agencies have developed expertise in particular industries or markets. For example, the FTC devotes most of its resources to certain segments of the economy, including those where consumer spending is high: **health care, pharmaceuticals, professional services, food, energy, and certain high-tech industries like computer technology and internet services**. Before opening an investigation, the agencies consult with one another to avoid duplicating efforts. The FTC also may refer evidence of criminal antitrust violations to the DOJ. Only the DOJ can obtain criminal sanctions. The DOJ also has sole antitrust jurisdiction in certain industries, such as **telecommunications, banks, railroads, and airlines**.

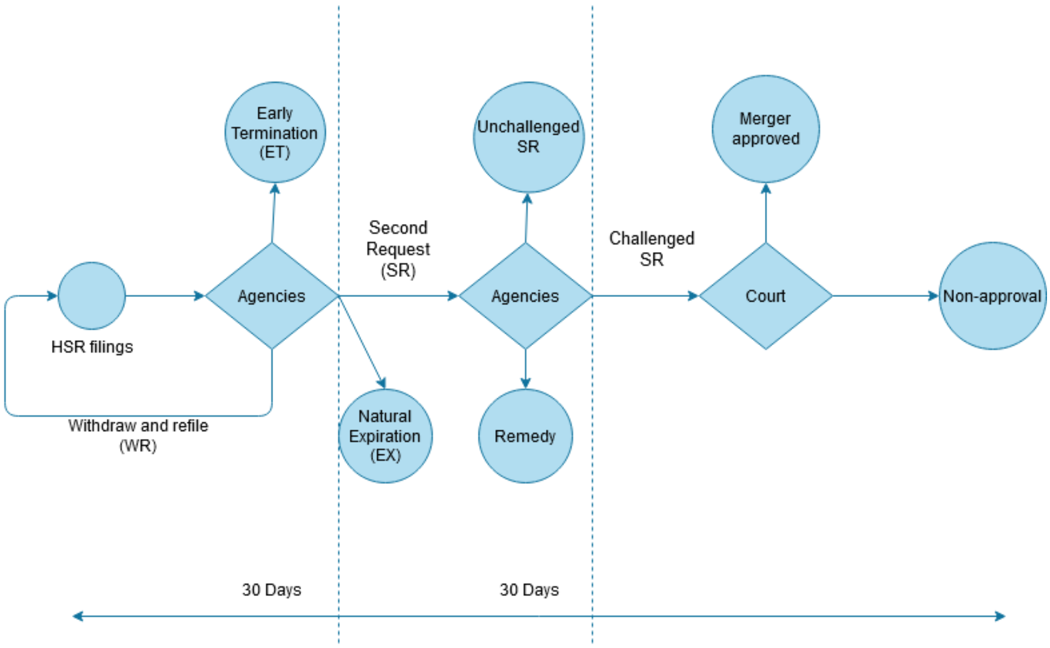

Figure 3.1: HSR act clearance process.

Days could be different in case of tender offers, cash payments, and bankruptcy.

Having notified the agencies, the agencies have 30 days (15 days in case of all cash deals) to assess the merger. Either the agencies approve the merger earlier than the deadline (i.e, early termination or "ET") or they let the waiting period to expire (i.e, "EX"), or they ask for further information (i.e., second request or "SR"). SR exposes the merger to the risk of disapproval and it is also costly to the merging parties as it delays the merger completion, even if the agencies approve it eventually. Fidrmuc et al. (2018) document a 2.8% loss of acquirer market value upon announcement of SR. Subsequent to receiving a SR, the merging parties and the agencies exchange information closely to make sure that the merger is not anti-competitive. This may include divestiture of some business lines or withdrawal of the merger altogether. At the end of the post-SR period, agencies decide to go to the court if the merging parties fail to address the agencies' concerns or refuse to seek for remedies, i.e., deal restructuring. This situation is called a challenged second request (i.e., "SRC")[7].

Private parties can also sue merging parties to enforce the antitrust laws. In fact, most antitrust suits are brought by businesses and individuals seeking damages for

[7]Still, even after the merger is consummated, the agencies can challenge a deal. This happens rather rarely and started to occur for the material public firms only recently. Thus, investigating any effects using these observations would be statistically problematic. I neglect these observations.

violations of the Sherman or Clayton Act. Private parties can also seek court orders preventing anti-competitive conduct (injunctive relief) or bring suits under state antitrust laws[8].

3.3 Data

In this section of discuss the sample construction. An overview of the sample and its sources can be seen in Section 1 of the Data Appendix.

To analyze the mergers and acquisitions, I use the SDC Platinum database to obtain merger data. I apply a series of filters to the dataset, including: (1) selecting deals with announcement dates between 1998 and 2018; (2) selecting public US acquirer and target firms; (3) imposing a minimum deal value of $100 million to focus on economically significant transactions; (4) excluding financial industry deals, spin-offs, self-tenders, repurchases, recapitalizations, privatizations, LBOs, and exchange offers; and (5) selecting deals where the acquirer owns more than 50% ownership after the deal. After applying these filters, I obtain a sample of 1738 mergers, consisting of 1734 unique targets and 1200 unique acquirers.

Since merger review outcomes are not reported in a standardized manner, I manually gather information on the merger review outcomes from the merging parties' Edgar filings. I search for relevant keywords, such as *"second request", "early termination", "FTC","DOJ", "HSR", "Hart-Scott-Rodino", "antitrust"*, to extract information on the agencies' decisions and decision dates (if available). I also use *Factiva* as a supplementary tool to find review outcomes for mergers not reported in Edgar filings. Furthermore, I consult the agencies' Joint Annual Competition Reports to Congress for information on challenged second requests. Out of 1738 mergers, 666 received *early termination* (**ET**) of the waiting period, 489 mergers had their waiting period expired (**EX**), 112 were requested to submit additional information (**SR**), 130 were challenged in court or sought remedies (**SRC**), and 48 were not reportable under the HSR act (**NRP**). However, I am unable to find review outcomes for 291 mergers. For mergers with known decisions, I define a dummy variable *challenged* as my main dependent variable, equal to one if the decision is **SR** or **SRC**, which represents 16.7% of the sample. I provide more explanation of the exaction of antitrust decisions in Subsection

[8] State attorney generals can also challenge a merger in a court.

of Data Appendix.

To identify rivals, I employ the firm-pairs similarity score developed by Hoberg and Phillips (2009) (Henceforth, HP). HP computes a similarity measure between two firms using textual analysis of product descriptions in 10-K filings, spanning from 1996 to 2017. I refer to this firm-pair similarity measure as the similarity score, which ranges from 0 to 1 and varies over time as firms change their product portfolios.

I adopt two approaches to identify rivals. First, I search for merging parties, either acquirer or target, in the *HP* dataset and consider firms in the top 10 percentile of similarity scores as rivals. Since the *HP* dataset is dynamic, with firm-pairs having time-varying similarity scores, I only choose rivals in the top 10% similarity score in the year prior to the merger. Using this approach, I find 4,894 unique firms, each of which could be rivals for multiple mergers, either from the acquirer or target side. In cases where a firm is a rival to both the acquirer and target, I remove duplicates. Second, I set a cutoff equal to 0.1 on the similarity score at the sample level, which corresponds to the 75% percentile of the score distribution in earlier years and the 64% percentile in later years. More information on this approach can be found in the Subsection 5 of Data Appendix.

These two rival identification approaches yield different sets of rivals. For less competitive industries, which include sparsely-populated firms, a similarity score of 0.1 may result in too few or no rivals. However, rivals with similarity scores below the cutoff might still have a vested interest in the merger, potentially attempting to influence the merger review outcome, which should be considered. To capture the rivals' interest in supporting or forestalling the merger, I match them to the CRSP database and categorize them as *happy* (*unhappy*) rivals if they experience a positive (negative) cumulative abnormal return (CAR) around the merger announcement.

Lobbying and campaign contribution data is sourced from the Center for Responsive Politics (henceforth, CRP). CRP reports lobbying activities of lobbying firms, which primarily act as intermediaries between various institutions, such as corporations, associations, interest groups, and universities, and agencies in the executive and legislative branches of the US government. After an extensive pre-cleaning process, I filter out corporations and employ fuzzy name matching to merge the lobbying dataset with the merging parties and their rivals. I merge lobbying expenditures of merging firms and their rivals who lobbied with the House of Representatives, the Senate, DOJ, and FTC.

Lastly, I link firms to influential politicians who have supervisory power over the DOJ and FTC. I match firms to politicians if the firms' headquarters are located in the politicians' political districts, following the methodology of Mehta et al. (2020). I use the merging firm's zip code in SDC and rival firms' zip code in Compustat to match them to political districts and subsequently to the respective politicians. For senators, I simply use the firm's state. The politician link is a dummy variable equal to one if the incumbent members of the judiciary committees come from the firm's headquarters location. Data on politicians, their political districts, their respective committees, and terms of service is obtained from Professor Charles Stewart's congressional data page.

Tables 3.1-3.4 show the summary stats for the deal and firm-level characteristics for acquirers, targets, and their respective rivals. Throughout the paper, I use two lobbying expenditure (lobbying exp.) figures, i.e., before and after the merger, to capture the dynamics behind the lobbying activity. Furthermore, in order to mitigate noisiness in lobbying and campaign contribution data, I normalize these expenditures with firm's revenue in the pre-merger year and report them in basis points. Therefore, I define *lobexp-ybefore* (*lobexp-yafter*) as sum of any lobbying expenditures by a firm during the year prior (post) to its corresponding merger, scaled by the firm's revenue at the same year. *Politician link* is an indicator equal to one, if the firm is located in the political district of influential politicians, i.e., those who are members of judiciary committee of house and senate and thus have supervisory power over *FTC* and *DOJ*. According to Tables 3.1-3.3, 26.7% of acquirers, 31.5% the targets, and 36.5% of the rivals have political connection(s)[9].

Tables 3.1-3.2 show that acquirers exhibit a negative *CAR* and the targets exhibit a positive *CAR*, on average. 28.4% of the acquirers, 13.4% of targets, and 11.8% of

[9]There might be multiple politicians (only senators) that get matched to a single firm. This is likely, because the matching criteria is the state level and if two senators from the same state happen to be in the judiciary committee, firms in that state get matched to multiple senators. This does not happen for the representatives though, as the matching criteria is the state and congressional district being the same. Thus, there are a handful of firms which are connected to 3 politicians (2 in the senate and 1 in the house) simultaneously, e.g., Ted Cruz and John Cornyn were both Texas senators and rep. Blake Farenthold was serving in Judiciary committee of the house, which makes it 3 political links for Susser holdings corp, in total.

the rivals have once lobbied during the whole sample period. The average acquirer spent roughly \$1.7 million (1.72 basis points scaled by revenues) before the merger and \$1.85 million (2.65 basis points scaled by revenues) after the merger. These numbers are \$0.6 million (3.39 scaled by revenues) and \$0.5 million (3.01 scaled by revenues) for the average target. As can be seen in Table 3.3, an average rival spends \$1.17 million (4.45 basis points of the revenue) before the merger and \$1.2 million (6.40 basis points of the revenue) after the merger, which shows an increase for the average rival.

Table 3.2: Acquirers Firm-level Summary Statistics

CAR is the cumulative abnormal return on a (-5,5) trading day window using the 3-factor Fama-French model. HHI in the text-based industry classification based on Hoberg and Phillips (2009). Total similarity measure captures the similarity of a given firm's product to its complete set of rivals, the higher the measure, the lower the market power, because the product could be more easily substituted with another firm's product. Revenue and total assets are in \$Billion. Size is log(revenue+1), lobbying expenditures are the sum of all lobbying expenditures of the firm to house, senate, DOJ, and FTC combined through out the year before and after the merger in \$ million. Scaled lobbying is lobbying expenditure scaled by the revenue in the pre-merger year. Contribution expenditure is the sum of firm's contributions to member of judiciary committee, who are in the office at the time of merger announcement. Political link is an indicator equal to 1, showing weather the firm's location (HQ) and constituency of judiciary committee members are the same.Scaled lobbying and contribution expenditures are winsorized at 5%.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
car	1,092	-0.021	0.108	-0.537	-0.074	-0.011	0.033	0.417
HHI	1,394	0.201	0.193	0.017	0.079	0.136	0.258	1
Total Similarity	1,394	4.827	5.577	0.383	1.422	2.609	5.726	55.816
Revenue($Bn)	1,622	8.552	13.666	0	0.591	2.231	9.116	51.258
Total assets($Bn)	1,624	12.542	20.677	0.006	0.905	3.292	13.391	81.843
Market-to-book	1,558	2.652	2.639	0.663	1.366	1.832	2.743	19.043
Leverage	1,551	0.199	0.193	0	0.044	0.144	0.292	0.986
Tangibility	1,621	0.281	0.242	0	0.087	0.189	0.447	0.950
Cash liquidity	1,610	0.294	0.204	0.0002	0.137	0.249	0.405	0.966
Size	1,622	7.630	2.088	0	6.384	7.711	9.118	12.960
Lobbying dummy	1,736	0.284	0.451	0	0	0	1	1
Before-merger lobbying exp.($Mn)	608	1.693	3.690	0	0.050	0.328	1.433	31.298
After-merger lobbying exp. ($Mn)	608	1.854	3.603	0	0.090	0.396	1.850	22.990
Contributions exp.($Mn)	339	1.437	4.626	-0.007	0.037	0.155	0.469	59.335
Scaled before-merger lobbying exp.(basis points.)	585	1.724	3.467	0	0.119	0.608	1.796	32.960
Scaled after-merger lobbying exp. (basis points.)	585	2.566	6.045	0	0.223	0.705	2.433	46.443
Scaled contribution	329	1.134	2.969	0.008	0.049	0.182	0.503	20.500
Politician link	1,736	0.267	0.442	0	0	0	1	1

Alas, there is no study that covers the same sample in order to compare the statistics, however Fidrmuc et al. (2018) who study the effect of acquirer lobbying on merger review outcomes in 2008-2014 and for 370 mergers report 16.8% challenged mergers, 80% lobbying acquirers, and around \$3 million lobbying expenditures. The difference is because their sample period starts from 2008, whereas this study starts from 1998, the time in which firms reported lower lobbying expenditure and was only three years

Table 3.3: Targets Firm-level Summary Statistics.

CAR is the cumulative abnormal return on a (-5,5) trading day window using the 3-factor Fama-French model. HHI in the text-based industry classification based on **?**. Total similarity measure captures the similarity of a given firm's product to its complete set of rivals, the higher the measure, the lower the market power, because the product could be more easily substituted with another firm's product. Revenue and total assets are in $Billion. Size is log(revenue+1), lobbying expenditures are the sum of all lobbying expenditures of the firm to house, senate, DOJ, and FTC combined through out the year before and after the merger in $ million. Scaled lobbying is lobbying expenditure scaled by the revenue in the pre-merger year. Contribution expenditure is the sum of firm's contributions to member of judiciary committee, who are in the office at the time of merger announcement. Political link is an indicator equal to 1, if the firm's location (HQ) and constituency of judiciary committee members are the same. Scaled lobbying and contribution expenditures are winsorized at 5%.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
car	1,439	0.234	0.246	-0.583	0.081	0.198	0.343	1.606
HHI	1,561	0.205	0.208	0.016	0.076	0.129	0.244	1
Total Similarity	1,561	5.197	5.960	1	1.440	2.890	6.407	62.584
Revenue ($Bn)	1,667	1.858	4.955	0	0.103	0.366	1.369	51.258
Total assets ($Bn)	1,667	2.534	6.517	0.006	0.149	0.471	1.816	77.965
Market-to-book	1,615	2.372	2.389	0.663	1.254	1.640	2.464	19.043
Leverage	1,608	0.216	0.231	0	0.005	0.153	0.357	0.998
Tangibility	1,662	0.279	0.258	0	0.073	0.169	0.436	0.970
Cash liquidity	1,660	0.358	0.249	0.002	0.147	0.299	0.534	1
Size	1,667	5.887	1.940	0	4.643	5.906	7.223	11.097
Lobbying dummy	1,736	0.134	0.341	0	0	0	0	1
Before-merger lobbying exp. ($Mn)	268	0.606	1.134	0	0.040	0.150	0.600	9.165
After-merger lobbying exp.($Mn)	268	0.540	1.110	0	0.020	0.120	0.485	8.020
Contributions exp.($Mn)	145	0.547	1.789	0.0001	0.012	0.050	0.196	14.436
Scaled before-merger lobbying exp. (basis points.)	262	3.389	6.307	0	0.280	1.169	3.181	32.960
Scaled after-merger lobbying exp. (basis points.)	261	3.077	7.353	0	0.075	0.729	2.468	46.443
Scaled contribution	143	1.694	4.362	0.008	0.048	0.175	0.968	20.500
Politician link	1,736	0.315	0.465	0	0	0	1	1

after passage of Lobbying Disclosure Act of 1995, which obligated lobbying firms to report their activities.

Before turning to the merger-level statistics, I need to define aggregate variables corresponding to *lobexp*, *Politician link*, and *Contributions*. A merger can have multiple *happy* and *unhappy* rivals, regardless of them being the target's or the acquirer's rival. Hence, all the rival-level variables need to be aggregated to merger-level. As such, I create the corresponding aggregate measures by taking a weighted average of the respective variable for the *happy* and *unhappy* rivals and by using similarity scores as weights. Using similarity scores is consistent with the hypothesis that rivals with more similarity in product market have more incentive to attempt affecting the agencies' decisions, both on the *happy* and *unhappy* sides. Since the specific purpose of rivals lobbying activity is unknown, the lobbying activity of a closer rival, i.e., higher similarity score, is more likely to be merger-related as compared to a farther rival. More specifically, I aggregate the firm-level scaled lobbying expenditures (i.e., *scaled lobexp-ybefore*) for the *happy* and *unhappy* rivals and call it *Aggregate before-merger scaled lobexp-happy* and *Aggregate before-merger scaled lobexp-unhappy*. I do the same for *Scaled lobexp-yafter* and construct *After-merger scaled lobexp-happy*. For each of the *happy* and *unhappy* groups of rivals, I construct a variable called *aggregate politician link* dummy, if any of the *happy* (or *unhappy*) rivals has a link to a politician.

Table 3.5 presents the descriptive statistics for the merger-level variables in the analysis. *Challenged*, is an indicator variable equal to one if the merger review outcome is either a second request (SR) or a challenged second request (SRC). In the sample of 1,445 mergers, 16.7% of them were challenged. Deal values range from $100 million to $164,746.9 million, with a mean of $3,609.1 million and a median of $843.9 million. The majority of the mergers in the sample are friendly (99%). The all-cash variable, which is only available for 1,004 observations, has a mean value of 0.501, indicating that half of these deals are all-cash transactions. Bidding contests are relatively rare, occurring in only 3.6% of the mergers. The average number of *happy* rivals per each merger is 7.63, while the average number of *unhappy* rivals is 8.80[10]. The *Aggregate*

[10]The number of rivals for each merger is dependent on the rival identification approach. For example, Table 4 shows that, using the top 10% approach and on average, nearly 8 *happy* and 9 *unhappy* rivals are identified, with a maximum number of 50 rivals on either side. The alternative approach, i.e., 0.1 cutoff on similarity score as shown in Table 16, roughly yields the same numbers

Table 3.4: Rivals-level Summary Statistics.

Car is the cumulative abnormal return on a (-5,5) trading day window using the 3-factor Fama-French model. HHI in the text-based industry classification based on Hoberg and Phillips (2009). Total similarity measure captures the similarity of a given firm's product to its complete set of rivals, the higher the measure, the lower the market power, because the product could be more easily substituted with another firm's product. Revenue and total assets are in $Billion. Size is log(revenue+1), lobbying expenditures are the sum of all lobbying expenditures of the firm to house, senate, DOJ, and FTC combined through out the year before and after the merger in $ million. Scaled lobbying is lobbying expenditure scaled by the revenue in the pre-merger year. Contribution expenditure is the sum of firm's contributions to member of judiciary committee, who are in the office at the time of merger announcement. Political link is an indicator equal to 1, if the firm's location (HQ) and constituency of judiciary committee members are the same. Scaled lobbying and contribution expenditures are winsorized at 5%.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
car	21,860	0.004	0.163	-1.472	-0.065	-0.0004	0.065	4.343
HHI	24,339	0.103	0.085	0.016	0.053	0.080	0.124	0.968
Total Similarity	24,339	12.663	11.477	1.006	4.858	9.332	17.563	121.688
Revenue ($Bn)	24,315	2.327	7.029	0	0.041	0.194	1.016	51.258
Total assets($Bn)	24,315	3.949	11.342	0.006	0.083	0.351	1.930	81.843
Market-to-book	24,063	2.926	2.961	0.663	1.289	1.880	3.294	19.043
Leverage	23,939	0.183	0.227	0	0.001	0.080	0.307	0.998
Tangibility	24,238	0.263	0.273	0	0.057	0.134	0.429	1
Cash liquidity	24,023	0.437	0.288	0	0.159	0.427	0.684	1
Size	24,304	5.319	2.407	-0.348	3.729	5.271	6.925	12.449
Lobbying dummy	24,339	0.118	0.323	0	0	0	0	1
Before-merger lobbying exp.($Mn)	3,646	1.166	3.123	0	0.020	0.127	0.700	48.680
After-merger lobbying exp.($Mn)	3,646	1.204	2.933	0	0.040	0.180	0.869	45.050
Contributions exp. ($Mn)	1,639	1.212	3.183	-0.007	0.028	0.130	0.445	22.248
Scaled before-merger lobbying exp.(basis points.)	3,633	4.564	8.694	0	0.095	1.003	3.694	32.960
Scaled after-merger lobbying exp.(basis points.)	3,641	6.388	12.221	0	0.333	1.425	4.645	46.443
Scaled contribution	1,638	2.473	5.388	0.008	0.105	0.268	1.126	20.500
Politician link	24,339	0.365	0.481	0	0	0	1	1

before-merger scaled lobbying expenditures for *happy* and *unhappy* rivals have means of 0.466 and 0.503, respectively. *Aggregate after-merger scaled lobbying expenditures* are slightly higher, with means of 0.584 and 0.642 for *happy* and *unhappy* rivals, respectively. In the sample, 12% of *happy* rivals and 13.7% of *unhappy* rivals have lobbied. *Aggregate scaled contribution expenditures (USD million)* have means of 0.141 and 0.147 for *happy* and *unhappy* rivals, respectively. Contribution dummies indicate that 7.5% of *happy* rivals and 7.4% of *unhappy* rivals have contributed to influential politicians. Finally, aggregate politician link dummies for *happy* and *unhappy* rivals have means of 0.56 and 0.67, respectively, suggesting that more than half of the rivals have a link to a politician.

Table 3.5: Merger-Level Summary Statistics

Merger review outcome is Early termination (ET) 666, Natural expiration (EX)489, Not required to report (NRP) 48, second request (112), Challenged second request (SRC)130, NA's 291. Challenged is an indicator equal to 1, if the outcome is SR or SRC. I create the corresponding aggregate measures by taking a weighted (similarity scores as weights) average of the respective variable for the *happy* and *unhappy* rivals. *Aggregate before-merger scaled lobexp-happy* and *Aggregate before-merger scaled lobexp-unhappy* are aggregated firm-level scaled lobbying expenditures (i.e., *scaled lobexp-ybefore*) for the *happy* and *unhappy* rivals, respectively.*Aggregate politician link* is a dummy equal to one, if any of the *happy* (or *unhappy*) rivals has a link to a politician. Similarly *Contribution* for the *happy* and *unhappy* rivals is a dummy equal to one, if any of the rivals has contributed to an influential politician.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
Challenged	1,445	0.167	0.374	0	0	0	0	1
Deal value ($Mil)	1,736	3,609.085	9,388.018	100	302.449	843.904	2,899.175	164,746.900
log deal value	1,736	6.926	1.490	4.605	5.712	6.738	7.972	12.012
Friendly	1,736	0.990	0.101	0	1	1	1	1
All cash	1,004	0.501	0.500	0	0	1	1	1
Bidding contest	1,736	0.036	0.187	0	0	0	0	1
Number of *happy* rivals	1,426	7.630	6.961	1	2	5	11	50
Number of *Unhappy* rivals	1,530	8.796	8.181	1	2	6	12	50
Aggregate before-merger scaled lobbying exp.(*happy*)	1,736	0.466	1.627	0	0	0	0.221	32.960
Aggregate before-merger scaled lobbying exp.(*Unhappy*)	1,736	0.503	1.296	0	0	0	0.377	21.078
Aggregate after-merger scaled lobbying exp.(*happy*)	1,736	0.584	1.782	0	0	0	0.322	26.502
Aggregate after-merger scaled lobbying exp.(*Unhappy*)	1,736	0.642	1.738	0	0	0	0.454	22.183
Lobbying dummy (*happy*)	1,736	0.120	0.326	0	0	0	0	1
Lobbying dummy (*Unhappy*)	1,736	0.137	0.343	0	0	0	0	1
Aggregate scaled contribution exp. (*happy*)	1,736	0.141	0.820	0	0	0	0.001	20.500
Aggregate scaled contribution exp. (*Unhappy*)	1,736	0.147	0.921	0	0	0	0.007	20.500
Contribution dummy (*happy*)	1,736	0.075	0.264	0	0	0	0	1
Contribution dummy (*Unhappy*)	1,736	0.074	0.262	0	0	0	0	1
Aggregate politician link dummy (*happy*)	1,736	0.56	0.230	0	0	0	0	1
Aggregate politician link dummy (*Unhappy*)	1,736	0.67	0.251	0	0	0	0	1

on average, namely, 10 un*happy* and 9 *happy* rivals, but totally different number of the maximum rivals, i.e., 300 *unhappy* and 167 *happy* rivals. In fact, the 0.1 cutoff approach cuts the distribution of similarity score irrespective of its density at the right tail and as such, it overweights highly fragmented industries, ignoring the industries with a couple of firms producing similar products, but not so similar as 0.1 cutoff demands. In contrast, the top 10% percentile approach picks a set of closest rivals for each target and acquirer and therefore provides a more balanced view of the rivals, which is more representative of the economy as well.

3.4 Analysis and results

A merger, irrespective of the rationale behind it, should have consequences in terms of profit or loss for the merging parties and their rivals. Studies like Eckbo (1983), Eckbo and Wier (1985), and Duso et al. (2007), among others, have used rivals' reaction to mergers in order to study competitive implications of a merger[11]. Following these studies, I employ the event study method to analyse rivals' reaction to the merger announcement. I calculate the rivals' cumulative abnormal returns (CAR) based on an 11-day trading window (-5,5) around the merger announcement, using Fama-French 3-Factor model. The rivals who experience a negative CAR arguably lose profits as a result of the merger and thus have incentives to forestall the merger. I categorize these rivals as *unhappy rivals* and the following the same argument for the rivals with a positive CAR, I categorize those with positive CAR as *happy rivals*.

3.4.1 What Makes a Rival Happy or Unhappy?

In order to see which variables have predictive power over the rivals' reaction, I run a linear probability model predicting if a rival is *happy* based on merger- and rival-level characteristics, according to specification 3.1. I construct a dummy variable equal to one for the rivals with positive CAR and zero otherwise and regress it, separately for target's rivals and acquirer's rivals, on rivals' and the merging parties characteristics. *CloseRival* variable indicates if a given rival is at the top 5% of the similarity score. I control for *HHI* of the merged firm and *total similarity* (Hoberg and Phillips (2009)), as measures of market structure and market power. *HHI* is positively associated with pricing power according to theory and *total similarity* is negatively related according to product differentiation theory. I also control for acquirer and targets *HHI* and a dummy indicating whether the rival is located at the same state as the acquirer or the target, and finally rival's characteristics.

[11] Eckbo (2007), in Chapter 15, Section 6.2, provides a comprehensive review of the empirical studies on merger effect on rivals.

$$\begin{aligned} happy - dummy_{it} = & \beta_1 AcquirerCloseRival_{it} + \beta_2 TargetCloseRival_{it} + \\ & \beta_3 HHI_{it} + \beta_4 TotalSimilarity_{it} + \\ & \beta_5 Size_{it} + \beta_6 TargetSize_{it} + \beta_7 AcquirerSize_{it} + \\ & \beta_8 AcquirerSameState_{it} + \beta_9 TargetSameState_{it} + \\ & \beta_{10} Tangibility_{it} + \beta_{11} Leverage_{it} + \beta_{12} CashLiquidity_{it} + \epsilon_{it} \end{aligned} \tag{3.1}$$

Table 3.6 displays the results. In columns (1) and (2), the *Acquirer close rival* variable is negative and statistically significant at the 5% level in column (2), suggesting that acquirer close rivals are less likely to be *happy* with the merger. Similarly, in columns (3) and (4), the *Target close rival* variable is negative and statistically significant at the 5% level, indicating that target close rivals are also less likely to be *happy* with the merger. The *Size* and *Acquirer size* variables are negative and significant in some specifications, suggesting that larger firms may be less likely to be *happy* with the merger. The *TargetSameState* variable is negative and statistically significant in columns (1), (2), and (3), indicating that rivals in the same state as the target are less likely to be *happy* with the merger. In contrast, the *AcquirerSameState* variable is positive and statistically significant across all specifications, suggesting that rivals in the same state as the acquirer are more likely to be *happy* with the merger. *TargetSameState* and *AcquirerSameState* capture the geographical dimensions of competition between the merging parties and the rivals. Interestingly, all these coefficient are highly significant and negative for the rivals that are in the same state as the target (e.g., -0.053 , $p = 0.0002$) and positive for those in the same state as the acquirer (e.g., 0.037 , $p = 0.006$). In other words, being in the same state with the target is negatively associated with being *happy* and being in the same state with the acquirer is positively associated with a being *happy* rival. These coefficients show that considering geographical dimensions are very important in examining rivals' reactions and thus incentives regarding the merger.

3.4.2 Is There a Relationship Between Rivals' Lobbying and Their Reaction to the Merger?

Next, I investigate whether rivals react in their lobbying activity to the magnitude of the *CAR*s. Assuming that the merger was not known to the rivals nor to the investors before the announcement, *CAR* should capture the rival potential gains or losses due to the merger and therefore, I expect to see a positive association between *CAR* magnitude and lobbying expenditure. Consequently, I regress rivals post-announcement lobbying expenditure (i.e., *lobexp-yafter* and similarly pre-announcement lobbying expenditure is *lobexp-ybefore*) on absolute value of *CAR* and its polynomials according to the following specifications in order to allow for a non-linear relationship. I control for industry, deal, and calendar-year fixed effects as well.

$$Lobexp\_yafter_{it} = \beta_1 CAR_{it} + \beta_2 lobexp\_ybefore_{it} + \beta_3 size_{it} + X_i + \epsilon_{it} \tag{3.2}$$

$$Lobexp\_yafter_{it} = \beta_1 CAR_{it} + \beta_2 CAR_{it}^2 + \beta_3 lobexp\_ybeforeit + \beta_4 size_{it} + X_i + \epsilon_{it} \tag{3.3}$$

$$Lobexp\_yafter_{it} = \beta_1 CAR_{it} + \beta_2 CAR_{it}^2 + \beta_3 CAR_{it}^3 + \beta_4 lobexp\_ybefore_{it} + \beta_5 size_{it} + X_i + \epsilon_{it} \tag{3.4}$$

Table 3.7 presents the results of the OLS regression models examining the relationship between the increase in lobbying expenditures (*lobexp-yafter*) and polynomials of cumulative abnormal return (*CAR*). The models control for lobbying expenditures in the year before (*lobexp-ybefore*), firm size (size), and industry, deal, and year fixed effects. The dataset is split into subgroups, separating *happy* and *unhappy* rivals.

Columns (1) to (3) use the full sample of rivals. In model (1), I find a negative and significant relationship between *CAR* and *lobexp-yafter* (coefficient = -0.621, $p<0.05$), suggesting that an increase in *CAR* is associated with a decrease in lobbying expenditures. This is in contrast to my expectation. Hence, in column (2), I add a quadratic term for *CAR* (CAR^2), and both *CAR* and CAR^2 are significant with opposite signs, suggesting a hump-shape relationship between CAR and *lobexp-yafter*. In column (3), the cubic term (CAR^3) is added, but it is not significant. Columns (4) to (6) focus on the *happy* subgroup. The results are qualitatively similar to those for the full sample, with the linear and quadratic terms for CAR being significant in columns (5) and (6) but not in column (4). The cubic term is not significant in Model (6). Models (7) to (9) use the *unhappy* subgroup. The results here are different from those for the full sample and the "*happy*" subgroup. Neither the linear nor the quadratic terms for CAR are significant in any of these models, and the cubic term is not significant in Model (9). For all models, *lobexp_ybefore* and *size* are positively and significantly associated with *lobexp_yafter*, indicating that larger firms and firms with higher lobbying expenditures in the year before the merger tend to have higher lobbying expenditures after the merger, consistent with the literature, e.g., Kerr et al. (2014).

In summary, the results suggest a nonlinear relationship between CAR and lobbying expenditures for the full sample and the *happy* subgroup, with lobbying expenditures decreasing as CAR increases initially and then increasing at higher levels of CAR. The relationship is not significant for the *Unhappy* subgroup. Explaining the hump-shape relationship between the lobbying expenditure and CAR is challenging, because there might be various, sometimes contradicting forces, at work, which is not the focus of this paper. For example, $CARs$ may include information about success probability of the merger, which in part expresses the investors opinion about anti-trust agencies' decision. If so, one would expect a negative association between the increase in lobbying expenditures and CAR magnitude, because investing in lobbying to change the agencies' decision while the market thinks that the merger would be successful might be ineffective and thus a waste altogether. This effect is in contrast to the effect which I am interested in, namely the larger the CAR, the more skin rivals have in the game and thus stronger incentive to try to affect the agencies' decision. Table 3.12 shows the same regression results for the rivals with above 0.1 similarity score and are qualitatively the same[12].

[12] Note, however, that merger-announcement $CARs$ themselves are very noisy and this noise is correlated with some firm characteristics, e.g., size or if the firm is active in multiple segments of the market. $CARs$ may not be able to capture potential sales loss or benefit due to the conglomerate effect discussed in McAfee and Williams (1988). McAfee and Williams (1988) in a paper called "Can event studies detect anti-competitive mergers?" examine a single anti-competitive case and check if

To delve deeper into the relationship between lobbying expenditure and cumulative abnormal returns (CAR), this study employs quantile regression as it allows for the examination of potential heterogeneous effects across different quantiles of lobbying expenditure. Quantile regression has been widely used in the literature to analyze relationships with varying effects across the distribution of a dependent variable (e.g., Koenker and Bassett (1978)).

I construct a new variable, *lobexp_change*, to represent the **change** in lobbying expenditure by calculating the difference between lobbying expenditure after the merger announcement and before the merger announcement. This variable is regressed on the absolute value of CAR, while controlling for firm size and calendar-year fixed effects for all rivals, as well as for *happy* and un*happy* rivals separately.

$$lobexp\_change_{it}^{p\%} = CAR_{it} + size_{it} + X_{it} + \epsilon_{it} \tag{3.5}$$

The graphical results, excluding the year fixed effects, are presented in Figure 2. The right column of the figure displays the coefficients for the intercept, CAR, and size of all the rivals' *lobexp_change* at each 5% step, along with their corresponding confidence intervals around the point estimates. The second and third columns represent the results for *happy* and *unhappy* rivals, respectively. The red flat lines indicate the OLS slope coefficients, while the dashed lines represent the corresponding confidence intervals. A closer look at the CAR graphs for all rivals, *happy* rivals, and *unhappy* rivals in the middle graph of Figure 3.2 reveals that the relationship between CAR and *lobexp_change* is generally insignificant, with the exception of *happy* rivals at the 65%, 70%, 75%, 80%, and 95% percentiles. However, the confidence intervals around the quantile point estimates tend to widen at the extremes of the distribution. This is expected for two reasons: first, there are fewer observations at the top and

an event-study shows a positive abnormal return for a single rival, namely M3. In fact, they find no effect and as a possible explanation, they argue that since the change in size of the market is negligible compared to the M3 revenue, the event study failed to capture the effect on M3 price. Conglomerate effect can explain the weak significance of the CAR coefficients. Nevertheless, $CARs$ still provide the best possible, objective tool for measuring merger effects on rivals.

bottom ranges of the dependent variable; and second, lobbying expenditures exhibit a high degree of persistence Kerr et al. (2014). While these two reasons share some commonalities, they are not entirely the same.

In summary, the quantile regression results provide evidence of a positive association between CAR and lobbying expenditure, but only for *happy* rivals. This highlights the value of using quantile regression to investigate relationships with potential heterogeneous effects across the distribution of a dependent variable.

Table 3.6: What Makes a Rival Happy?

This table shows the results of the linear probability model predicting if a rival is *happy* based on merger- and rival-level characteristics, according to specification 3.1. The dependent variable is a dummy indicating if the rival experienced a positive reaction to the merger announcement. *CloseRival* variable indicates if a given rival is at the top 5% of the similarity score. *HHI* is the Herfindahl–Hirschman index of the merged firm and total Similarity (Hoberg and Phillips (2009)) are measures of market structure and market power.

	Dependent variable:			
	happy dummy			
	(1)	(2)	(3)	(4)
Acquirer close rival	−0.014	−0.020**		
	p = 0.182	p = 0.046		
Target close rival			−0.023**	−0.022**
			p = 0.021	p = 0.023
HHI	0.004	0.048	−0.016	0.015
	p = 0.955	p = 0.626	p = 0.826	p = 0.867
Total simmilarity	0.001*	−0.0001	0.0001	−0.0002
	p = 0.065	p = 0.959	p = 0.912	p = 0.840
Acquirer HHI	−0.102	−2.434	0.063*	−1.557
	p = 0.146	p = 0.220	p = 0.066	p = 0.460
Target HHI	0.013	−2.944	−0.093	−1.448
	p = 0.706	p = 0.117	p = 0.172	p = 0.424
Size	−0.007**	−0.003	−0.002	−0.0004
	p = 0.014	p = 0.275	p = 0.432	p = 0.897
Acquirer size	−0.008***	−0.126	−0.007**	−0.051
	p = 0.009	p = 0.360	p = 0.011	p = 0.608
Target sizet	0.005	0.509	0.003	0.330
	p = 0.109	p = 0.195	p = 0.286	p = 0.428
Same state_target	−0.053***	−0.063***	−0.028**	−0.020
	p = 0.0002	p = 0.0002	p = 0.030	p = 0.187
Same state_acquirer	0.037***	0.046***	0.050***	0.043***
	p = 0.006	p = 0.005	p = 0.0002	p = 0.006
Tangibility	0.089**	0.044	0.073*	0.009
	p = 0.019	p = 0.336	p = 0.055	p = 0.850
Leverage	−0.010	0.001	−0.003	0.036
	p = 0.738	p = 0.972	p = 0.911	p = 0.274
Cash liquidity	−0.023	−0.012	0.016	0.033
	p = 0.498	p = 0.751	p = 0.626	p = 0.340
Industry FE	Yes	Yes	Yes	Yes
Deal FE	No	Yes	No	Yes
Subject	Acquirer rivals	Acquirer rivals	Target rivals	Target rivals
Observations	9,849	9,849	10,522	10,522
R^2	0.014	0.237	0.010	0.213
Adjusted R^2	0.008	0.138	0.004	0.121
Residual Std. Error	0.498	0.464	0.499	0.469
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.7: The Association between Reaction to the Merger and Lobbying Expenditure.

OLS regression results showing the association between the increase in lobbying expenditures and polynomials of cumulative abnormal return, CAR. Standard errors are robust and clustered at the merger level.

	Dependent variable:								
	lobexp_yafter								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CAR	-0.621^{**}	-1.997^{***}	-3.257^{***}	-0.935	-2.932^{*}	-3.110^{**}	-0.302	-1.623	-1.472
	p = 0.026	p = 0.004	p = 0.008	p = 0.114	p = 0.057	p = 0.044	p = 0.522	p = 0.174	p = 0.504
CAR^2		3.244^{**}	9.951^{**}		4.594^{*}	11.157^{**}		3.574	2.631
		p = 0.012	p = 0.042		p = 0.084	p = 0.050		p = 0.110	p = 0.792
CAR^3			-7.542			-8.923^{*}			1.246
			p = 0.124			p = 0.085			p = 0.914
lobexp_ybefore	0.586^{***}	0.585^{***}	0.585^{***}	0.516^{**}	0.515^{**}	0.709^{***}	0.516^{**}	0.515^{**}	0.515^{**}
	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.012	p = 0.013	p = 0.00000	p = 0.026	p = 0.026	p = 0.026
size	0.247^{***}	0.245^{***}	0.244^{***}	0.311^{***}	0.307^{***}	0.187^{***}	0.261^{**}	0.259^{**}	0.259^{**}
	p = 0.0003	p = 0.0003	p = 0.0003	p = 0.008	p = 0.009	p = 0.002	p = 0.032	p = 0.033	p = 0.033
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subject	Rivals	Rivals	Rivals	*happy*	*happy*	*happy*	Un*happy*	Un*happy*	Un*happy*
Observations	3,725	3,725	3,725	1,809	1,809	1,809	1,916	1,916	1,916
R^2	0.751	0.752	0.752	0.759	0.760	0.586	0.850	0.850	0.850
Adjusted R^2	0.640	0.640	0.640	0.544	0.544	0.584	0.729	0.729	0.728
Residual Std. Error	1.719	1.718	1.718	2.095	2.094	2.000	1.363	1.363	1.364
Note:									*p<0.1; **p<0.05; ***p<0.01

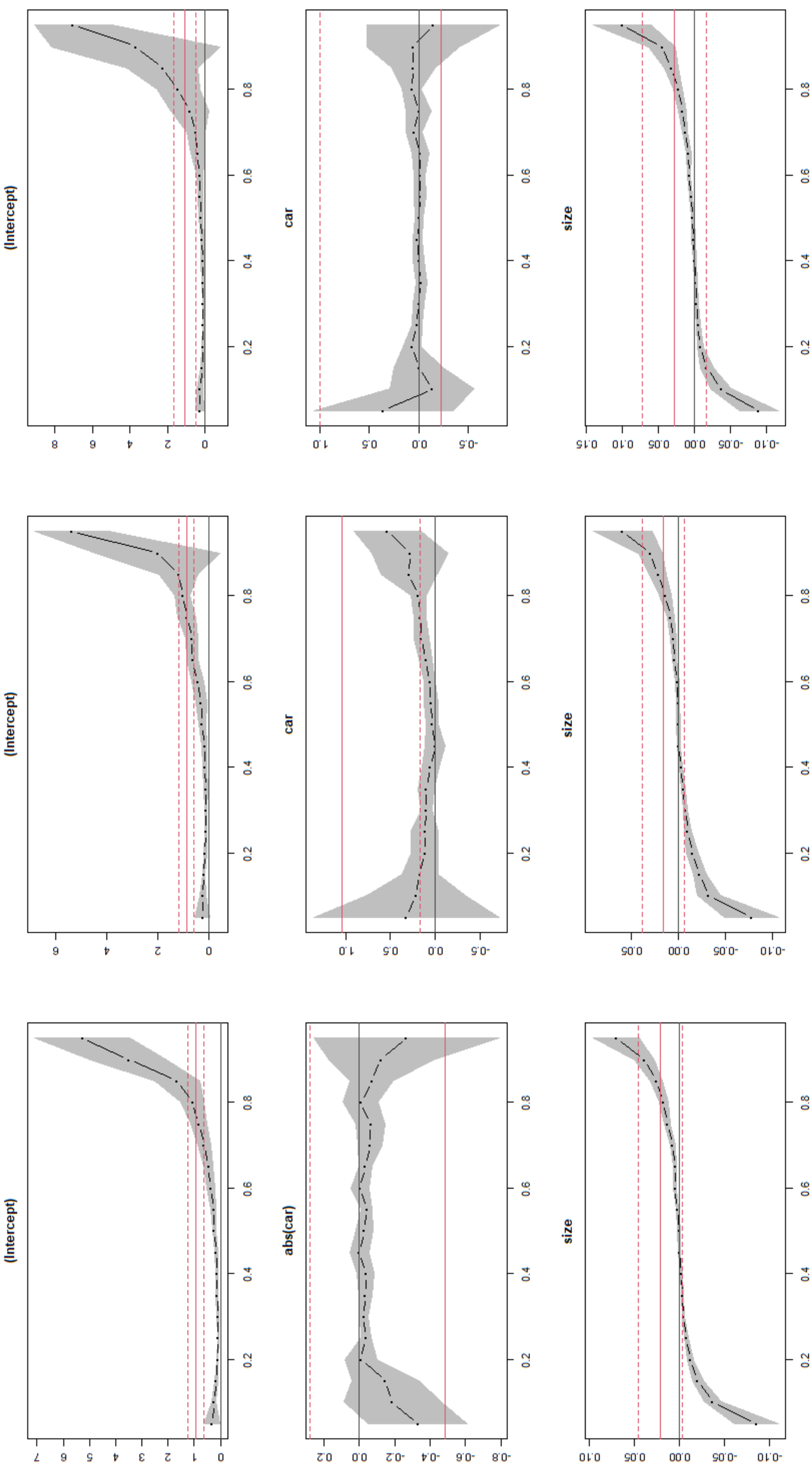

Figure 3.2: Quantile regression results, at 5% steps and controlling for calendar-year FE.

3.4.3 Can Rivals Influence the Merger Reivew Outcome?

I address my primary research question in this section, i.e., whether the lobbying activities of rivals influence the regulatory agencies' decision regarding a merger. To answer this question, it is necessary to aggregate the data from the firm-level to the merger-level. This aggregation process is challenging, as a single merger typically involves an average of 8 *happy* and 9 un*happy* rivals and may have as many as 50 rivals on both *happy* and *unhappy* sides. To aggregate lobbying expenditures and contributions, a weighted average is used, with similarity scores serving as weights. This assumes that higher similarity scores increase the likelihood that lobbying activities are related to the merger. Furthermore, the dummy variables, such as *lobbying dummy* and *politician link dummy*, the aggregated variable is set to one if any of the rivals has engaged in lobbying or has a link to a politician, respectively. The same aggregation method is applied to both sets of rivals, identified using the top 10% and 0.1 similarity score cutoff approaches. Moreover, lobbying and contribution expenditures are scaled by revenue to reduce skewness and mitigate measurement errors in reported amounts. Tables 3.4 and 3.12 present the summary statistics at the merger-level for both rival identification approaches.

I construct the key dependent variable, *"Challenged"*, as a dummy equal to one if the merger either got a *"Challenged Second Request"* or *"Second Request"*, and zero in *"Early Termination"* and *"Natural Expiration"* cases. There are 48 *"Not reportable"* cases along with 243 mergers for which I can not find any information and I exclude them all (291) from the sample, leaving 1445 merger-level observations.

In order to estimate the relationship between lobbying and merger review outcome, I use a linear probability model, which lets me to easily implement fixed effect models and more importantly, apply my identification strategy. Using multinomial choice models, e.g., logit or probit, would unnecessarily complicate the model with no benefit. I group *"Early Termination"* and *"Natural Expiration"* outcomes as zero and *"Challenged Second Request"* and *"Second Request"* outcomes as one to capture the main effect, leaving unnecessary nuances aside, because there is no effective difference between *"Early Termination"* and *"Natural expiration"*. Therefore, I estimate the following model, one with before-announcement lobbying activities and one with after-announcement, to investigate the dynamics of the link between the firms and politicians. Specifically, weather it is possible to establish a link in a short-run in order to affect the outcome or only an already established link could be utilized for this purpose.

$$\begin{aligned} Challenged_{it} = & scaled\ lobbying\ expenditure_{\,happy,\,unhappy} + \\ & scaled\ lobbying\ expenditure_{\,happy,\,unhappy} \times politician\ link_{\,happy,\,unhappy} + \\ & politician\ link_{\,acquirer,\,target,\,happy,\,unhappy} + \\ & lobbying\ dummy_{\,acquirer,\,target} + \\ & contribution\ dummy_{\,acquirer,\,target,\,happy,\,unhappy} + \\ & X^1_{it} + X^2_{it} + \epsilon_{it} \end{aligned} \tag{3.6}$$

In which, X^1 are firm-level characteristics, X^2 are merger-level characteristics, and regressions include acquirer's and target's industry fixed effects as well as calendar-year fixed effects.

Table 3.8 presents the results of an OLS regression analysis, regressing the challenged dummy variable on various political connection measures of the merging parties and their rivals, according to specification 6. The table is divided into two sections based on the rival identification approach explained in Data Section, with columns (1) and (2) displaying results for the top 10% similarity score, while columns (3) and (4) show results for the similarity score 0.1 cutoff. In general, the results indicate that the relationship between lobbying activities and the likelihood of a merger being challenged depends on the timing of the lobbying and the rival's relationship with politicians. For *unhappy* rivals, before-merger scaled lobbying expenditures are not statistically significant in any model. However, after-merger scaled lobbying expenditures are significant at the 10% level ($p = 0.065$) for the similarity score 0.1 cutoff (column 4). For the *happy* rivals, before-merger scaled lobbying expenditures are significant at the 10% level only for the similarity score 0.1 cutoff (column 3). After-merger scaled lobbying expenditures are not significant in either model.

The interaction between before-merger scaled lobbying expenditures and politician links, however, is negative and significant at the 10% level for *happy* rivals in the top 10% similarity score model (column 1, -0.026 (p-value = 0.057)) and at the 5% level for the similarity score 0.1 cutoff model (column 3, -0.017 (p-value = 0.02)). For un*happy* rivals, these interactions are not significant in either model. Conversely, the interaction between after-merger scaled lobbying expenditures and politician links is positive and significant at the 10% level for un*happy* rivals in the top 10% similarity score model (column 2) but not significant for the similarity score 0.1 cutoff model (column 4). For *happy* rivals, this interaction is negative and significant at the 10% level in the top 10% similarity score model (column 2) but not significant in the similarity score 0.1 cutoff model (column 4). Deal value is highly significant ($p < 0.01$) across all models, suggesting that larger deals are more likely to be challenged. The total similarity for acquirer and target is also significant and negative across all models, indicating that as similarity increases, the likelihood of a merger being challenged decreases.

Overall, the results suggest that political connections and lobbying activities play a complementary role in merger outcomes, as their impact depends on the timing of the lobbying, the type of rival (*happy* or *unhappy*), and the rival's relationship with politicians. Considering the 5% significance level, increasing lobbying expenditures by one basis point (w.r.t to the revenue) for the *happy* rivals, while having a link to an influential politician at the office, is associated with 1.7% (unconditional likelihood is 16.7%) less likelihood of facing an anti-trust challenge. The other marginally significant coefficients also provide supporting evidence in accord with the hypotheses; (1) lobbying expenditure and having a link to a politician of *happy* rivals is negatively

Table 3.8: The Association Between Rivals' Lobbying Expenditure and Merger Review Outcome

OLS regression results, regressing challenged dummy on political connections measure of the merging parties and the rivals. Merger-level, firm-level characteristics along with industry FE, and calendar-year FE are controlled for. Standard errors are robust and clustered at the merger-level.

	Top 10% similarity score		*Similarity score 0.1 cutoff*	
	challenged		challenged	
	(1)	(2)	(3)	(4)
Before-merger scaled lob. exp._Un*happy*	0.012		0.002	
	p = 0.181		p = 0.411	
Before-merger scaled lob. exp._*happy*	0.007		0.009*	
	p = 0.232		p = 0.072	
After-merger scaled lob. exp._Un*happy*		0.011		0.003*
		p = 0.143		p = 0.065
After-merger scaled lob. exp._*happy*		0.007		0.006
		p = 0.224		p = 0.120
Before-merger scaled lob. exp. × Politicain link_Un*happy*	−0.015		−0.0002	
	p = 0.531		p = 0.970	
Before-merger scaled lob. exp. ×Politicain link_*happy*	−0.026*		−0.017**	
	p = 0.057		p = 0.020	
After-merger scaled lob. exp. ×Politician link_Un*happy*		0.027*		−0.012
		p = 0.072		p = 0.212
After-merger scaled lob. exp. × Politician link_*happy*		−0.030*		−0.006
		p = 0.066		p = 0.335
Politician link_acquirer	0.011	0.012	0.033	0.033
	p = 0.619	p = 0.609	p = 0.166	p = 0.157
Politician link_*happy*	0.036	0.038	−0.029	−0.037
	p = 0.308	p = 0.287	p = 0.394	p = 0.287
Politician link_target	−0.001	0.0004	−0.026	−0.026
	p = 0.975	p = 0.985	p = 0.251	p = 0.261
Politician link_Un*happy*	0.018	0.024	0.033	0.041
	p = 0.619	p = 0.500	p = 0.362	p = 0.259
Lob dummy_target	−0.016	−0.015	0.059	0.058
	p = 0.633	p = 0.639	p = 0.154	p = 0.157
Lob dummy_acquirer	0.007	0.008	−0.004	−0.007
	p = 0.780	p = 0.776	p = 0.868	p = 0.782
Contribution dummy_acquirer	0.027	0.028	−0.001	0.001
	p = 0.381	p = 0.371	p = 0.973	p = 0.977
Contribution dummy_*happy*	0.048	0.052	0.003	0.004
	p = 0.213	p = 0.183	p = 0.937	p = 0.934
Contribution dummy_target	0.032	0.032	−0.025	−0.023
	p = 0.466	p = 0.465	p = 0.560	p = 0.591
Contribution dummy_Un*happy*	−0.001	0.002	0.030	0.028
	p = 0.974	p = 0.951	p = 0.509	p = 0.544
log deal value	0.069***	0.070***	0.073***	0.073***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Bidding contest	0.070	0.069	0.064	0.061
	p = 0.210	p = 0.215	p = 0.280	p = 0.302
Friendly	−0.033	−0.031	−0.038	−0.035
	p = 0.766	p = 0.781	p = 0.721	p = 0.744
Size_acquirer	0.0003	0.0003	−0.002	−0.002
	p = 0.931	p = 0.923	p = 0.695	p = 0.702
Size_target	0.013***	0.013***	0.015***	0.015***
	p = 0.003	p = 0.004	p = 0.005	p = 0.005
HHI_acquirer	−0.058	−0.065	−0.098	−0.097
	p = 0.270	p = 0.208	p = 0.107	p = 0.108
HHI_target	−0.031	−0.028	−0.074	−0.076
	p = 0.499	p = 0.542	p = 0.199	p = 0.189
Total similarity_acquirer	−0.006***	−0.006***	−0.007***	−0.007***
	p = 0.00002	p = 0.00001	p = 0.001	p = 0.0004
Total similarity_target	−0.004**	−0.004**	−0.004**	−0.004**
	p = 0.016	p = 0.017	p = 0.047	p = 0.049
Observations	1,445	1,445	1,445	1,445
R^2	0.156	0.156	0.229	0.229
Adjusted R^2	0.139	0.140	0.149	0.149
Residual Std. Error	0.347	0.346	0.344	0.344
Note:	*p<0.1; **p<0.05; ***p<0.01			

associated with probability of facing an unfavorable outcome, and (2) the opposite for the u*nhappy* rivals.

3.4.4 Identification

There are several reasons that the results in Table 8 might represent partial correlations rather than causal effects. Firstly, unobservable factors that are correlated with both rivals' incentives to lobby and the review outcome may be present, such as the profitability of the industry, the nature of efficiency gains arising from the merger, geographical aspects of the market that could not be captured by standard fixed effects, and access to superior lobbyists. For instance, a more profitable industry may result in rivals being more *willing and able* to lobby, and simultaneously, regulatory agencies may be more concerned about competition issues, leading to a higher likelihood of blocking the merger. Although incorporating industry fixed effects can improve the estimate, it does not entirely eliminate the bias. Secondly, the possibility of *reverse causality* exists, where firms anticipating more severe scrutiny in the review process may increase lobbying expenditures or hire better lobbyists to preempt unfavorable outcomes. This situation does not necessarily contradict the study's hypotheses but could potentially bias the estimated effect.

To identify the impact of rivals' lobbying on antitrust agencies' decisions, I exploit a quasi-natural experiment: the unexpected departure of influential politicians from the judiciary committees of the House and Senate, as examined by Mehta et al. (2020). Firms that unexpectedly lose their connections to key politicians effectively lose some of their political capital, as they can no longer use these connections to raise concerns or advance their interests regarding competitive issues. The link between rivals and politicians is unexpectedly severed when politicians change committees (thus losing power over antitrust agencies), lose elections, become ill, or pass away. In contrast to Mehta et al. (2020), I also consider election losses as unexpected turnover because it is unlikely that firms can predict election outcomes and redirect lobbying and campaign contribution efforts away from incumbent politicians.

Consequently, I identify 445 (393) mergers where un*happy* (*happy*) rivals unexpectedly lost their connections either two years before or after the merger. The top panel of Table 3.8 displays the matching details for the top 10% similarity score, while the bottom panel presents the same information using the 0.1 cutoff approach. Due to the inability to identify any rivals in some consolidated industries, I identify only 235 (189) mergers where *unhappy* (*happy*) rivals lost their political connections. These mergers are considered treated.

In order to find suitable control mergers to the set of mergers mentioned above, I use the optimal matching method, which finds the matched samples with the smallest average absolute distance across all the matched pairs. I match the mergers on *log of deal value*, *target HHI*, *acquirer HHI*, and *industry*, which are the most relevant factors in predicting the anti-trust agencies decision. The matched results are shown in Table 3.9. Next, I run two separate difference-in-difference regressions for mergers with treated *happy* and un*happy* rivals.

$$\begin{aligned} Challenged_{it} = &\beta_0 + \beta_1 Treated + \beta_2 Post + \beta_3 Lob\,dummy + \beta_4 Treated \times Post + \\ &\beta_5 Treated \times Lob\,dummy + \beta_6 Post \times Lob\,dummy + \\ &\beta_7 Treated \times Post \times Lob\,dummy + X_{it} + \epsilon_{it} \end{aligned}$$

Table 3.10 presents the results of a triple difference-in-difference regression analysis. The purpose of this analysis is to estimate the causal effect of a "treatment", i.e., loosing the link to an influential politician, on the merger being "Challenged". In line with hypotheses H1 and H2, I expect lobbying *happy* rivals who unexpectedly lose their political link to experience more challenged mergers. Conversely, I expect the lobbying *unhappy* rivals who lose their link to exhibit less challenged mergers. The table is split into two groups: rivals with top 10% similarity scores (Columns 1 and 2) and rivals with similarity scores above the 0.1 cutoff (Columns 3 and 4). For each group, the analysis is further broken down into "*Unhappy* rivals" (Columns 1 and 3)

Table 3.9: Matching Statistics for *Happy* and *Unhappy* Rivals

Matched sample for *happy* and *unhappy* rivals using nearest neighbour matching. For the two rival identification approaches. Top panel pertains to the Top 10% similarity score in *HP*, down panel pertains to rivals with similarity score above 0.1.

Top 10% similarity score	*Unhappy rivals (N = 445)*				*happy rivals (N = 393)*			
	Means Treated	Means Control	SD Control	Mean Diff	Means Treated	Means Control	SD Control	Mean Diff
-All Data								
ldealvalue	7.0797	7.1012	1.4653	-0.0215	7.0804	7.0485	1.4759	0.0319
tnic3hhi target	0.1357	0.1928	0.1967	-0.0571	0.1442	0.1880	0.1881	-0.0438
tnic3hhi acquirer	0.1356	0.1678	0.1817	-0.0322	0.1329	0.1688	0.1781	-0.0359
industry acquirer	28.2764	30.1179	10.9688	-1.8415	27.2214	30.4168	11.3449	-3.1954
-Matched Data								
ldealvalue	7.0797	7.0988	1.4273	-0.0191	7.0804	7.1152	1.4421	-0.0348
tnic3hhi target	0.1357	0.1404	0.1475	-0.0047	0.1442	0.1554	0.1548	-0.0112
tnic3hhi acquirer	0.1356	0.1393	0.1503	-0.0037	0.1329	0.1435	0.1449	-0.0106
industry acquirer	28.2764	28.2382	11.3595	0.0382	27.2214	26.4402	12.1727	0.7812
Similarity score cutoff 0.1	*Unhappy rivals (N = 235)*				*happy rivals (N = 189)*			
	Means Treated	Means Control	SD Control	Mean Diff	Means Treated	Means Control	SD Control	Mean Diff
-All Data								
ldealvalue	7.2770	7.0464	1.4636	0.2306	7.1722	7.0706	1.4949	0.1015
tnic3hhi target	0.0840	0.1889	0.2123	-0.1049	0.1134	0.1806	0.2099	-0.0672
tnic3hhi acquirer	0.0879	0.1635	0.1948	-0.0757	0.1173	0.1563	0.1936	-0.0390
industry acquirer	19.5660	24.1388	14.7015	-4.5729	23.1058	23.4387	14.9149	-0.3329
-Matched Data								
ldealvalue	7.2770	7.6044	1.4344	-0.3274	7.1722	7.6225	1.4164	-0.4503
tnic3hhi target	0.0840	0.0892	0.1168	-0.0052	0.1134	0.1162	0.1314	-0.0028
tnic3hhi acquirer	0.0879	0.0871	0.1091	0.0008	0.1173	0.1247	0.1457	-0.0074
industry acquirer	19.5660	19.2809	15.7853	0.2851	23.1058	23.4550	14.8038	-0.3492

and "*happy* rivals" (Columns 2 and 4). The regression controls for acquirer industry and calendar-year fixed effects (FE).

The coefficient I am interested in is the triple interaction $Post \times treated \times lobdummy$. The coefficient is significant only for the *happy* rivals with both rivals identification approaches, $0.371\,(p = 0.045)$ and $0.486\,(p = 0.069)$. These results reveal an important point; having a link to a politician does not seem to be enough, as none of the $post \times treated$ coefficients are significant, whereas, the effect of losing the link is important for the rivals who lobby as well. Note that this results only provides supporting evidence for effect of lobbying on merger review outcomes, as the shock only affects the politician link with the rival and not the lobbying itself. Nevertheless, since the triple interaction coefficient distinguishes the effect for lobbying rivals versus non-lobbying rivals, it supports the hypothesis that *happy* rivals lobbying can indeed affect the merger review outcomes.

Explaining why there is an effect for the *happy* rivals and no such effect for the *unhappy* rivals is challenging. However, considering and contrasting the legitimacy of

Table 3.10: Can Rivals' Affect Merger Review Outcomes: Quasi-natural Experiment

Triple Diff-in-diff regression results following $Challenged_{it} = \beta_0 + \beta_1 Treated + \beta_2 Post + \beta_3 Lobdummy + \beta_4 Treated \times Post + \beta_5 Treated \times Lobdummy + \beta_6 Post \times Lobdummy + \beta_7 Treated \times Post \times Lobdummy + X + \epsilon_{it}$.
Column 1 and 2 correspond to the rivals with top 10% similarity score. Columns 3 and 4 correspond to the rivals with similarity score above 0.1 cutoff. Acquirer industry and calendar-year FE are controlled for.

	Top 10% similarity score		*Similarity score cutoff 0.1*	
	Challenged		Challenged	
	(1)	(2)	(3)	(4)
Post	-0.098^{**}	-0.089^{**}	0.018	-0.095
	p = 0.020	p = 0.041	p =0.779	p = 0.151
Treated	0.056	0.090	-0.019	0.018
	p = 0.456	p = 0.322	p = 0.841	p = 0.873
Lob dummy	-0.020	0.020	-0.290^{***}	-0.028
	p = 0.809	p = 0.858	p = 0.0002	p = 0.883
Post ×lob dummy	0.100	-0.054	0.347^{**}	0.098
	p = 0.343	p = 0.675	p = 0.011	p = 0.654
Treated ×lob dummy	-0.003	-0.286^{*}	0.385^{**}	0.344
	p = 0.983	p = 0.082	p = 0.029	p = 0.147
Post ×treated	-0.029	-0.085	-0.058	0.063
	p = 0.720	p = 0.382	p = 0.585	p = 0.596
Post ×treated ×lob dummy	-0.082	0.371^{**}	-0.282	0.486^{*}
	p = 0.612	p = 0.045	p = 0.221	p = 0.069
log deal value	0.081^{***}	0.080^{***}	0.107^{***}	0.107^{***}
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Friendly	-0.085	-0.050	-0.040	0.015
	p = 0.623	p = 0.772	p = 0.761	p = 0.921
Lob dummy_acquirer	0.012	-0.024	-0.071	-0.040
	p = 0.710	p = 0.505	p = 0.152	p = 0.420
Lob dummy_target	0.022	-0.027	0.049	-0.027
	p = 0.584	p = 0.543	p = 0.488	p = 0.215
Contribution dummy_acquirer	0.042	0.069	0.097^{*}	0.099^{*}
	p = 0.293	p = 0.116	p = 0.090	p = 0.083
Contribution dummy_target	0.021	0.107	-0.037	-0.001
	p = 0.712	p = 0.118	p = 0.572	p = 0.985
Politician dummy_acquirer	-0.009	-0.030	0.055	0.037
	p = 0.757	p = 0.301	p = 0.313	p = 0.464
Politician dummy_target	-0.023	-0.019	-0.071	-0.016
	p = 0.330	p = 0.468	p = 0.113	p = 0.724
Observations	890	786	470	378
Subject	*unhappy* rivals	*happy* rivals	*unhappy* rivals	*happy* rivals
R^2	0.176	0.180	0.317	0.343
Adjusted R^2	0.117	0.115	0.202	0.195
Residual Std. Error	0.347	0.351	0.352	0.337
Note:	*p<0.1; **p<0.05; ***p<0.01			

concerns on either sides is helpful. Note that *unhappy* rivals, who are more likely to have concerns in line with the consumer and thus the agencies, have access to less costlier channels to communicate their concerns. Therefore, instead of investing in lobbying or using their link to the over-burden politicians, which they could reserve for other purposes, they could either directly contact agencies or bring a case to the court against the merger in order to express their concerns. My results resonates with those of Faccio and McConnell (2020) who, studying a sample covering 75 countries starting from 1910, find that big firms with political connections set forth regulations that restrict entry and therefore lessen the competition.

3.5 Conclusion

In conclusion, this paper investigates the role of political connections and lobbying activities of the rivals of the merging parties on merger review outcomes. By employing an event study method, I categorizes rivals as either *happy* or un*happy*, based on their reaction to the merger announcement as reflected by their cumulative abnormal returns (CAR).

The study further explores the association between lobbying expenditures and CAR, and documents a nonlinear relationship between these two variables. Furthermore, the paper examines whether the lobbying activities of rivals influence the regulatory agencies' decision regarding a merger. The results suggest that political connections and lobbying activities play a complementary role in merger outcomes, depending on the timing of the lobbying, the type of rival, and the rival's relationship with politicians.

However, the possibility of unobservable factors or reverse causality affecting the results cannot be dismissed. To address these concerns, the study exploits a quasi-natural experiment, namely the unexpected departure of influential politicians from the judiciary committees of the House and Senate. This approach aims to estimate the causal effect of losing a link to an influential politician on the merger being challenged.

The findings reveal that having a link to a politician through lobbying is not sufficient to affect merger outcomes, but having a sort of affinity (being located in the politician's political district) to the influential politicians is crucial for lobbying rivals. The triple difference-in-difference regression analysis provides supporting evidence for the effect of lobbying on merger review outcomes. The results show an effect for the *happy* rivals, while no such effect is observed for the *unhappy* rivals. This can be attributed to the fact that *unhappy* rivals may have access to less costly channels to communicate their concerns, such as directly contacting agencies or bringing a case to court against the merger.

3.6 Appendix

3.6.1 Similarity score 0.1 cutoff

Summary stats - Firm level

Table 3.11: Summary Statistics for the Rivals With Similarity Score Above 0.1.

CAR is the cumulative abnormal return on a (-5,5) trading day window using the 3-factor Fama-French model. HHI in the text-based industry classification based on Hoberg and Phillips (2009). Total similarity measure captures the similarity of a given firm's product to its complete set of rivals, the higher the measure, the lower the market power, because the product could be more easily substituted with another firm's product. Revenue and total assets are in $Billion. Size is log(revenue+1), lobbying expenditures are the sum of all lobbying expenditures of the firm to house, senate, DOJ, and FTC combined through out the year before and after the merger in $ million. Scaled lobbying is lobbying expenditure scaled by the revenue in the pre-merger year. Contribution expenditure is the sum of firm's contributions to member of judiciary committee, who are in the office at the time of merger announcement. Political link is an indicator equal to 1, if the firm's location (HQ) and constituency of judiciary committee members are the same. Scaled lobbying and contribution expenditures are winsorized at 5%.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
car	16,208	0.0003	0.168	-2.617	-0.067	-0.004	0.058	7.177
tnic3hhi	18,683	0.082	0.063	0.016	0.042	0.066	0.102	0.952
tnic3tsimm	18,683	19.077	14.245	0.398	8.873	16.250	24.207	95.963
revt	17,145	1.926	6.092	0	0.019	0.162	0.900	48.698
at	17,144	3.895	10.740	0.005	0.092	0.426	2.209	81.407
m2b	16,800	2.668	2.577	0.567	1.185	1.721	3.057	15.751
leverage	16,727	0.251	0.266	0	0.008	0.168	0.417	1.000
tangiblity	17,100	0.352	0.333	0	0.049	0.199	0.686	1
cashliquidity	16,784	0.408	0.332	0	0.087	0.315	0.738	1
size	17,125	4.876	2.693	-0.267	2.989	5.104	6.805	12.128
lob_dummy	18,683	0.123	0.329	0	0	0	0	1
lobexp_ybefore	2,814	0.873	2.610	0	0.010	0.100	0.500	48.680
lobexp_yafter	2,814	0.925	2.531	0	0.040	0.140	0.633	45.050
cntrbexp	1,428	8.768	11.359	0.001	0.245	3.243	14.805	71.317
lobexp_ybefore_scld	2,556	16.979	41.958	0	0.020	1.030	5.292	154.369
lobexp_yafter_scld	2,590	26.377	63.425	0	0.365	1.744	8.697	233.451
cntrbexp_scld	1,337	283.452	781.558	0.054	1.286	9.018	48.927	2,877.485
pollink	18,683	0.303	0.459	0	0	0	1	1

Table 3.12: Rivals' Reaction, Score Cutoff 0.1

OLS regression results showing the association between the increase in lobbying expenditures and polynomials of cumulative abnormal return, CAR. Standard errors are robust and clustered at the merger level.

	Dependent variable:								
	lobexp_yafter								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CAR	-0.573^{***}	-1.733^{***}	-2.570^{***}	-0.476^{*}	-1.671^{**}	-3.662^{**}	-1.177^{**}	-2.433^{***}	-3.562^{**}
	p = 0.007	p = 0.0001	p = 0.004	p = 0.098	p = 0.023	p = 0.017	p = 0.022	p = 0.005	p = 0.031
CAR^2		2.406^{***}	6.604^{*}		2.310^{**}	11.089^{**}		3.310^{***}	9.545
		p = 0.0002	p = 0.061		p = 0.021	p = 0.039		p = 0.010	p = 0.176
CAR^3			-4.070			-7.934^{*}			-6.150
			p = 0.199			p = 0.075			p = 0.319
lobexp_ybefore	0.581^{***}	0.580^{***}	0.580^{***}	0.619^{**}	0.617^{**}	0.770^{***}	0.401^{*}	0.400^{*}	0.400^{*}
	p = 0.0002	p = 0.0002	p = 0.0002	p = 0.011	p = 0.011	p = 0.00001	p = 0.076	p = 0.076	p = 0.077
size	0.199^{***}	0.197^{***}	0.196^{***}	0.175^{**}	0.172^{**}	0.129^{**}	0.231^{***}	0.229^{***}	0.228^{***}
	p = 0.0003	p = 0.0003	p = 0.0004	p = 0.046	p = 0.047	p = 0.012	p = 0.001	p = 0.001	p = 0.001
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subject	Rivals	Rivals	Rivals	*happy*	*happy*	*happy*	Un*happy*	Un*happy*	Un*happy*
Observations	3,242	3,242	3,242	1,591	1,591	1,591	1,651	1,651	1,651
R^2	0.655	0.656	0.656	0.677	0.677	0.516	0.775	0.776	0.776
Adjusted R^2	0.569	0.570	0.570	0.538	0.538	0.513	0.689	0.689	0.689
Residual Std. Error	1.650	1.650	1.650	1.938	1.938	1.988	1.195	1.194	1.195
Note:									*p<0.1; **p<0.05; ***p<0.01

3.6.2 Data Overview

Figure 3.3 is an overview how the data is collected and matched from various sources.

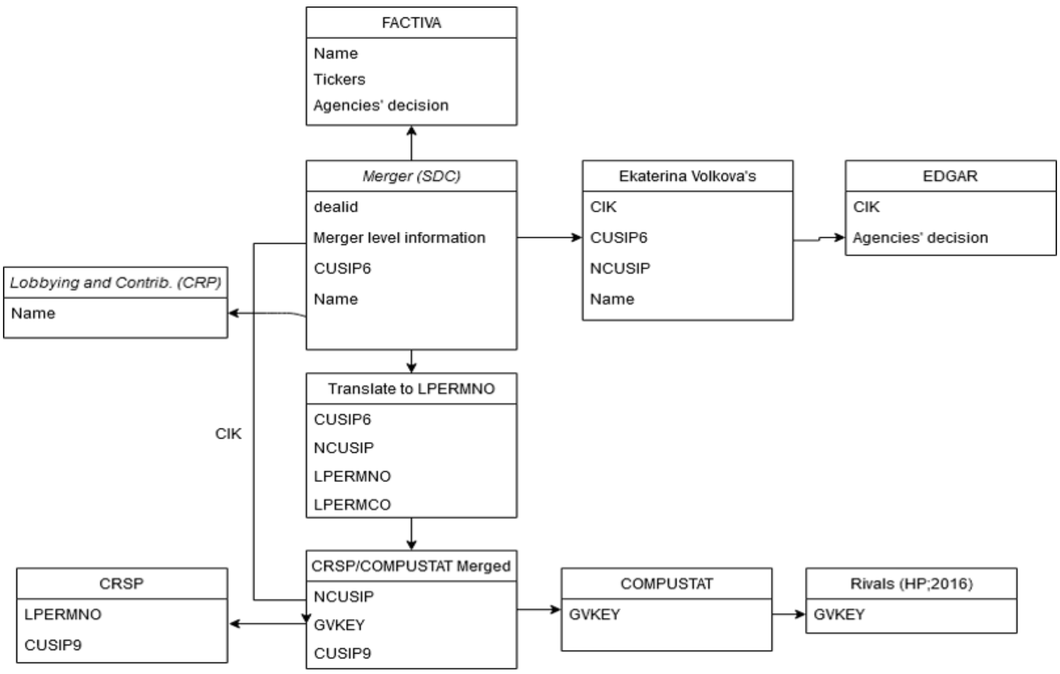

Figure 3.3: Data overview

Table 3.13: Merger-level Summary Statistics with Rivals With Above 0.1 Similarity Score.

Merger review outcome is Early termination (ET) 666, Natural expiration (EX)489, Not required to report (NRP) 48, second request (112), Challenged second request (SRC)130, NA's 291. Challenged is an indicator equal to 1, if the outcome is SR or SRC. I create the corresponding aggregate measures by taking a weighted (similarity scores as weights) average of the respective variable for the *happy* and *unhappy* rivals. *Aggregate before-merger scaled lobexp-happy* and *Aggregate before-merger scaled lobexp-unhappy* are aggregated firm-level scaled lobbying expenditures (i.e., *scaled lobexp-ybefore*) for the *happy* and *unhappy* rivals, respectively.*Aggregate politician link* is a dummy equal to one, if any of the *happy* (or *unhappy*) rivals has a link to a politician. Similarly *Contribution* for the *happy* and *unhappy* rivals is a dummy equal to one, if any of the rivals has contributed to an influential politician.

	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
dealvalue	1,736	3,609.085	9,388.018	100	302.449	843.904	2,899.175	164,746.900
ldealvalue	1,736	6.926	1.490	4.605	5.712	6.738	7.972	12.012
acquirortermfee	556	179.568	435.937	1	15	45	144.325	5,400
targettermfee	1,424	98.480	237.725	0.025	10	27.500	80	3,900
friendly	1,736	0.990	0.101	0	1	1	1	1
allcash	1,004	0.501	0.500	0	0	1	1	1
biddingcontest	1,736	0.036	0.187	0	0	0	0	1
count_parties_unhprvl	1,170	9.732	19.592	1	1	3	9	300
count_parties_hprvl	886	8.778	15.491	1	2	3	9	167
lobexp_ybefore_scld_agg_unhprvl	1,170	1.232	7.665	0	0	0	0.226	154.369
lobexp_ybefore_scld_agg_hprvl	886	1.283	8.283	0	0	0	0.224	154.369
lobexp_yafter_scld_agg_unhprvl	1,170	1.287	5.668	0	0	0	0.280	123.542
lobexp_yafter_scld_agg_hprvl	886	1.620	8.091	0	0	0	0.463	137.988
lob_dummy_unhprvl	1,170	0.139	0.346	0	0	0	0	1
lob_dummy_hprvl	886	0.167	0.373	0	0	0	0	1
cntrbexp_scld_agg_unhprvl	1,170	14.343	115.068	0	0	0	0.369	2,582.557
cntrbexp_scld_agg_hprvl	886	18.088	136.770	0	0	0	0.843	2,877.485
cntrb_dummy_unhprvl	1,170	0.087	0.282	0	0	0	0	1
cntrb_dummy_hprvl	886	0.117	0.322	0	0	0	0	1
pollink_agg_unhprvl	1,170	0.268	0.317	0	0	0.150	0.473	1
pollink_agg_hprvl	886	0.327	0.334	0	0	0.264	0.522	1
size_agg_unhprvl	1,170	49.978	113.120	0	6.804	17.055	44.851	1,035.119
size_agg_hprvl	886	46.175	86.810	0	8.577	19.558	46.321	1,136.570

3.6.3 SDC

I used SDC for merger data. I looked for US target that have been bought from 1/1/1998 until 12/31/2018. Then I filter only for public targets and acquirers. I excluded targets and acquirers at financial industry. I also filtered mergers with M100$ in value and above to focus only on economically significant mergers. Moreover, I exclude Spin-offs, Exclude spin-self tender, repurchases, recapitalization, privatization, LBO, and exchange offers. Lastly, I filter for the deals that acquirer owns more than 50% ownership after the deal.

Table 3.14: SDC request

SDC request		
Request	Hits	Request Description
0	-	DATABASES: Domestic Mergers, 1979-Present (MA, OMA)
1	-	Date Announced: 1/1/1998 to 12/31/2018 (Custom)
2	233857	Target Nation : US
3	33645	Target Public Status : P
4	25098	Acquiror Public Status : P
5	10372	Deal Value ($ Mil): 100 to HI
6	8008	Target Industry Sector : NOT DA, DC, DF, DE, DG, DD, DB
7	7878	Acquiror Industry Sector : NOT DA, DC, DF, DE, DG, DD, DB
8	2055	Deal Type : NOT 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
9	1736	Percent of Shares Owned after Transaction: 50 to HI

Out of 3472 (1736×2) merging parties, I have 2780 unique firms (unique cusip6s), 1734 unique targets[13], and 1200 unique acquirors. There are 288 acquirers (unique cusip6) that take over other firms at least twice. IBM Corp., *Oracle*, and Cisco are the three most frequent acquirers. Furthermore, around 300 acquirers (not necessarily unique) are HQ'ed outside of the US, followed by acquirers in California, Texas, and New York. All the targets are located in the US, by design, and the three top states are California, Texas, and New York.

3.6.4 SDC to CRSP/Compustat

Problem: SDC does not have permno, gvkey, and different cusip.

[13] Over the course of study, two firms, namely Keebler Foods Co and Stillwater Mining Co, have been acquired two times.

- Use 6-digit CUSIP codes.
  - Problem: CUSIP codes change over time, frequently after a merger has occurred.
  - ExecuComp or CRSP/Compustat only retain the latest CUSIP, leads to not matched (or, even worse, may matched to a different. company since CUSIPs can get reassigned to a different company).
  - Solution: use historical CUSIPs, i.e. CUSIPs valid at the exact time of each merger.
  - Use CRSP to obtain historical CUSIP (item NCUSIP) for each day of sample period.
  - Merge historical CUSIPs with compensation data

I have 6-digit CUSIPs for the merging parties and want to translate to 8 or 9 for use with CRSP and GVKEY in Compustat

In CRSP Tools there is a tool called "Translate to PERMCO/PERMNO" that accepts 6-digit cusip as input and produces permno, Company Name, Ticker, Exchange, and NCUSIP (8-digit cusip). I check all permno box to make sure I have the historical permno. Having PERMNO , I can use it to access CRSP. In addition, using "CRSP/COMPUSTAT Merged – Linking Table", I can PERMNO into a GVKEY and a 9-digit cusip.

Using the PERMNO link, I am not able to find the GVKEY for 636 acquirors (36.59 % of the acquirors) and 611 (35.15% of the targets).

In order to tackle this matching problem, I use the CIKs to find GVKEYs. I feed CIK to Compustat capital IQ in WRDS and ask for GVKEYs and filing date. Next, I match the firms with missing GVKEYs by CIKs and year (1 year before the merger). Using the second approach, link via CIKs, reduces the number of acquirors with missing GVKEYs to 282 and targets to 128.

SDC to CRSP/Compustat using CRSP/Compustat Merged Database - Linking Table

I download the entire table asking for GVKEY, Company name,CUSIP9, CIK, Historical PERMNO and PERMCO links to CRSP and COMPUSTAT, and check all the linking options.

I construct a cusip6 variable from the cusip9 and use it to match the this historical linking table to the merging parties. Matching cusip6 results into multiple GVKEY matches, I drop the duplicates whose merger is not between the date linking window. Still, there are duplicated GVKEYs I keep the duplicates that have closest names. This makes sure that I only have 1 GVKEY.

Next, I take care of the duplicated lpermno (they should exist because they are the security level identifiers), however, I need only the relevant securities. For this purpose, I drop duplicated permnos if they are missing or if the merger date is out of the data link window.

I merge the GVKEYs from the two approaches, namely the linking table and cusip6, permno, GVKEYs. Still there are 352 missing GVKEYs. For these cases I turn again to the linking table and use CIKs and for the remaining cases. Next, I use the tickers-year (fyear one year before the merger) combination for the remaining 330 cases. This reduces the missing GVKEYs to 104.

Lastly, for the remaining missing GVKEYs, I manually use the lookup function on WRDS and obtain comapnyid and thus firms' GVKEYs. Eventually, I am not able to find GVKEYs for 24 acquirers and 24 targets.

SDC to CRSP/Compustat via CIK

SDC main firm identifier is 6 digit cusip. This id is a firm identifier (issuer), but changes as soon as a given from stops reporting (e.g., gets merged into another firm). Thus, a given 6 digit cusip can belong to two different firms over time. Using a CUSIP-CIK mapping table constructed by Ekaterian Volkova (that has historical 6 digit cusip, 8 digit cusip, firm names under which they report and the year at which they report to SEC), I am able to map cusip6 to CIKs. Here is the matching process.

First, I match my 1736 *2 firms with Ekaterina's CUSIP-CIK table. Then, I compare the year in Ekaterina's to the year in announcement year from SDC. Since a given cusip6 can belong to two or more different firms over time, among the matched cusip6, I choose the closest year. Still, there are duplicate firms that report (to SEC) at the same year of the merger and have identical cusip6s. For these cases, per each deal and per firm, I keep only the one with closest name. I use Jaro-Winkler name matching algorithm in "Stringdist" package in R for this purpose.

For some missing CIK I use the search tool on Edgar CIK Search tool by entering names and/or tickers, in order to get CIKs. I use search_company() and cik_search() functions in edgarWebR package for this purpose.

Using this, for some I get no CIK and for some I get multiples. I drop the multiples and keep both the CIKs using Ekaterina's and Edgar search methods. Still, there are around 5% missing cases for acquirers and 3% missing for target. After doing company_search there are non-missing CIKs for acquirers and 9 (0.1% of the whole sample) cases for targets. Yet, for these cases I manually search their names on Edgar's "Company Search Tool" and find CIK for 3 more cases, but I cannot find anything for 6 cases[14].

3.6.5 Antitrust agencies' decisions

Matching merging parties with their CIKs, I am able to look up their filings in Edgar. I search for the acquirer's and target's filings that include "second request", "early termination", "FTC","DOJ", "HSR", "Hart-Scott-Rodino", or "antitrust" and are filed between merger announcement date and the date at which merger was effective. Both of the dates are taken from SDC. Next, I manually inspect the filings and extract the date at which the merging parties filed HSR filings to the agencies, agencies' decision and the decision date. Here are some examples of the passages that include the relevant information.

Regulatory and Other Governmental Approvals Antitrust/HSR

[14] Barry Wright Corp(Applied Power Inc) , RL Polk & Co, New Young Broadcasting Holding Co Inc, Blue Ridge Mountain Resources Inc, and Genzyme Tissue Repair.

The Merger is subject to review by the U.S. Antitrust Division of the Department of Justice (the “Antitrust Division”) and the U.S. Federal Trade Commission (“FTC”) under the HSR Act. The HSR Act provides that transactions like the Merger may not be completed until certain information and documents have been submitted to the Antitrust Division and the FTC and the applicable waiting period has expired or been terminated. On May 5, 2015, each of Parent and the Company made the requisite filings with the Antitrust Division and the FTC pursuant to the HSR Act and requested early termination of the initial thirty (30) day waiting period. Early termination of the applicable waiting period under the HSR Act was granted effective as of May 18, 2015 (link).

Regulatory Clearances for the Mergers

The mergers are subject to the requirements of the HSR Act, which prevents Sequential and MSLO from completing the mergers until the applicable waiting period under the HSR Act is terminated or expires. On July 7, 2015, Sequential and MSLO filed the requisite notification and report forms under the HSR Act with the Antitrust Division of the Department of Justice and the FTC. The FTC granted Sequential and MSLO early termination of the waiting period effective on July 17, 2015 (link).

HSR Act and U.S. Antitrust Matters

Under the HSR Act and the rules promulgated thereunder, the Merger cannot be completed until OmniVision and Investor file a notification and report form with the Federal Trade Commission (the "FTC") and the Antitrust Division of the Department of Justice (the "DOJ") under the HSR Act and the applicable waiting period has expired or been terminated. A transaction notifiable under the HSR Act may not be completed until the expiration of the waiting period following the parties' filing of their respective HSR Act notification forms (typically a 30 day period) or the early termination of that waiting period. OmniVision and Investor made the necessary filings with the FTC and the Antitrust Division of the DOJ on May 15, 2015. The Federal Trade Commission and the Department of Justice granted early termination of the waiting period under the HSR Act on May 26, 2015 link.

Alas, I was not able to retrieve the agencies' decision for a fraction of firms. The second source for extracting the decision is FACTIVA. I searched for the relevant firms and subject and looked up the agencies' decision. The third source, is the SDC item, *History file event*, which sometimes includes agencies' decision. This can be useful for two purposes, first, it reassures the decisions extracted from other sources, and second, can be used for those without any information from the other two sources.

For the cases which the agencies challenge the merger, either they accept consent orders for public comment, ask the merging parties to restructure the deal (some may abandon the deal altogether), or initiate administrative or federal court litigation. These cases are extracted from DOJ/FTC joint report to congress (link).

3.6.6 Hoberg&Phillips measures

Product similarity score

This data is based on web crawling and text parsing algorithms that process the text in the business descriptions of 10-K annual filings on the SEC Edgar website from 1996 to present. These product descriptions are legally required to be accurate, as Item 101 of Regulation S-K legally requires that firms describe the significant products they offer to the market, and these descriptions must also be updated and representative of the current fiscal year of the 10-K.

Step 1: Calculating the scores for each year (1996 - 2017)

$$SimilarityScore_{ij} = \begin{pmatrix} score_{11} & score_{12} & score_{13} & \dots & score_{1N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ score_{N1} & score_{N2} & score_{N3} & \dots & score_{NN} \end{pmatrix}$$

Table 3.15: Summary Statistics of Similarity Scores of Hober Sample

Similarity scores summary stats shows that across years the scores do change a bit on aggregate and the cutoff points are the same. The distribution is skewed to the right

year	n	mean	sd	min	Q0.1	Q0.2	Q0.3	Q0.4	median	Q0.6	Q0.7	Q0.8	Q0.9	max
1996	1,047,880	0.064	0.066	0	0.006	0.012	0.020	0.029	0.041	0.056	0.077	0.106	0.152	0.860
1997	1,124,746	0.061	0.064	0	0.005	0.012	0.019	0.028	0.040	0.054	0.074	0.102	0.146	0.866
1998	1,088,416	0.062	0.064	0	0.005	0.012	0.020	0.029	0.041	0.056	0.076	0.104	0.146	0.866
1999	1,170,600	0.067	0.067	0	0.006	0.013	0.021	0.031	0.044	0.062	0.084	0.115	0.160	0.843
2000	1,108,488	0.067	0.067	0	0.006	0.013	0.021	0.032	0.045	0.063	0.086	0.114	0.158	0.864
2001	952,870	0.065	0.063	0	0.006	0.013	0.022	0.032	0.046	0.062	0.084	0.110	0.149	0.865
2002	829,416	0.066	0.061	0	0.006	0.014	0.024	0.035	0.049	0.066	0.085	0.110	0.148	0.857
2003	773,048	0.066	0.059	0	0.007	0.015	0.025	0.037	0.051	0.067	0.086	0.109	0.144	0.856
2004	717,714	0.063	0.055	0	0.007	0.015	0.024	0.036	0.049	0.065	0.083	0.104	0.136	0.854
2005	677,858	0.067	0.057	0	0.007	0.016	0.026	0.039	0.054	0.071	0.089	0.111	0.142	0.856
2006	690,174	0.069	0.058	0	0.008	0.017	0.028	0.042	0.057	0.075	0.094	0.115	0.146	0.851
2007	662,024	0.069	0.059	0	0.007	0.016	0.027	0.040	0.056	0.073	0.092	0.114	0.146	0.855
2008	603,894	0.072	0.060	0	0.007	0.016	0.027	0.042	0.059	0.078	0.099	0.122	0.153	0.855
2009	526,824	0.071	0.058	0	0.008	0.017	0.029	0.043	0.060	0.078	0.097	0.118	0.148	0.856
2010	501,442	0.078	0.064	0	0.008	0.018	0.030	0.046	0.066	0.088	0.110	0.134	0.164	0.850
2011	490,440	0.078	0.064	0	0.008	0.017	0.029	0.045	0.065	0.087	0.109	0.133	0.164	0.846
2012	449,490	0.074	0.064	0	0.007	0.016	0.026	0.039	0.057	0.080	0.105	0.130	0.163	0.838
2013	502,216	0.077	0.065	0	0.008	0.017	0.028	0.043	0.062	0.085	0.109	0.134	0.165	0.842
2014	573,884	0.078	0.064	0	0.008	0.018	0.029	0.045	0.064	0.086	0.110	0.134	0.164	0.851
2015	559,278	0.074	0.063	0	0.008	0.017	0.027	0.041	0.058	0.079	0.103	0.129	0.161	0.850
2016	523,694	0.074	0.063	0	0.007	0.017	0.028	0.041	0.058	0.079	0.102	0.128	0.161	0.848
2017	499,722	0.076	0.064	0	0.008	0.017	0.029	0.043	0.061	0.083	0.107	0.132	0.164	0.849

Note that we have this matrix for each year, because the similarity scores are calculated based on pair-firms' 10K filings. On the diagonal there is 1 and the matrix is symmetric.

Step2[15]: Now let us sort the score from largest to smallest in each row and after a certain extent, HP set the score to 0 based on the coarseness level in SIC3 digit classification. The TNIC-3 classification data we are distributing only records firms having pairwise similarities with a given firm i that are above a threshold as required based on the coarseness of the three digit SIC classification. The level of coarseness of

[15] This is mostly quotes from Hoberg and Phillips (2009)

TNIC-3 thus matches that of three digit SIC codes, as both classifications result in the same number of firm pairs being deemed related. For example, if one picks two firms at random from the CRSP/COMPUSTAT universe, the likelihood of them being in the same three digit SIC code is 2.05%. Analogously, when the TNIC-3 cutoff is specified using our approach, the likelihood of two randomly drawn firms being deemed related in their TNIC-3 is also 2.05%. Hence, TNIC-3 is constructed to be "as coarse" as are three digit SIC codes. TNIC industries are also purged for vertical relationships from the input/output tables (see paper for details).

Identifying rivals (top 10% similarity)

The TNIC-3 data has four columns, year, gvkey1, gvkey2, and score. The last features the similarity score, a variable in [0,1].

I match firms gvkey with gvkey1 at one year prior to the merger in order to find the rivals with the given gvkey. I cound not find any rivals for 366 unique acquirors and 219 unique targets, but for all the mergers, I was able to find at least 1 rival either for the target or the acquirers. In other words, the missing rival does not occur for the target and acquirer for the same merger. Next, I cutoff the rivals at the top10% of the score to reach the close rivals who arguably have enough incentive or potential benefit/loss to react to the merger. Consequently, the mean (median) number of rivals per firm is 21 (22.21).

As I wrote in section2, I have 1200 unique acquirors and 1736 unique targets out of which I am able to match 1127 gvkeys to the acquirers (connectable to compustat) and 1709 unique gvkeys for targets. Using the method described above, I could find 4894 unique firms (gvkeys), each of which could be rivals for multiple mergers and from either acquirer or the target side. In these cases, I remove the duplicates.

Identifying rivals, SIC code

Yields too many rivals, I give up this method. Identifying rivals using HP has a couple of limitations. There are some merging parties for which I am not able to find GVKEY, thus it is not possible to match them with their rivals using HP's production similarity measure. In addition, even for some the known GVKEYs there is no corresponding rival on HP. Given that I am using similarity measures at year before the merger, it seems likely for the (at least a fraction of) foreign rivals not to file a 10-K and thus not being on HP dataset.

The alternative approach that does not use HP is using the standard SIC industry codes to find rivals. I download the whole compustat universe from 1997-01 until 2018-12 and match it with target and acquirer firms based on year (fyear for the rivals and announcement year - 1), SIC code, and the NAIC code. I drop the matched (year, SIC) firms with missing gkveys, foreign rivals (i.e., rivals with missing state and Canadian firms), and the rivals with missing financial.Table below shows the number of rivals per deal, or per firm. For the 3rd and 4th columns, I drop the rivals without CAR (probably because they were not active at the time of the merger). Rows 5th and 6th show the number of rivals after matching lobbying, contributions, and politicians. This is to make sure I did not drop any observation during the matching process.

Table 3.16: Summary Statistics of the Matched Rivals

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
# rivals per deal	1	130	183	214.641	288	680
# rivals per deal-role	1	111	166	185.491	220	518
# rivals with CAR (per deal)	1	67	92	105.463	150	311
# rivals with CAR (per deal-role)	1	35	63	77.197	102	235
# rivals after all matching (per deal)	1	66	92	105.1	150	311
# rivals after all matching (per deal-role)	1	34	62	76.84	102	235

3.6.7 Matching to Lobbying data

In order to match the lobbying data with firms data, I use name matching. I go through a very extensive precleaning and cleaning the names in lobbying ("clients") and I match it with the names from SDC for merging parties and the names from compustat for the rivals.

The precleaning phase includes omitting brotherhoods, sororities, unions, associations , schools, institutions, etc. that we know are not firms. Second, I omit punctuation ("[:punct:]") from both names to be matched. Then, I match them using the Jaro Winkler (JW) algorithm and check by eyeballing that those who have slight string distance are actually the same. JW gives the most weight to the longest sub string.

Next, I identify the lobbying reports that were reported in the time span one year before and one year after the merger. I take three important measures from each report, whether the report indicates employing an expert lobbyist, the agencies lobbied to, and the amount spent. I sum the amount spent on lobbying by each firm, 1 year before the merger announcement and one year after the merger announcement.

3.6.8 Link to influential politicians

I assume that the firms headquartered in the political district of the influential representatives and senators, i.e., those who sit in judiciary committee of house and senate, have better access to these politicians, who, given their oversight over DOJ and FTC, could potentially affect the agencies' decision. Both politicians and the firms have incentives to have a stronger connection with each other, that might involve money and information. However, politicians unexpectedly might change their committee, lose the election, die, or get sick. I use this quasi-natural experiment to see the effect of losing the link on merger review outcomes.

I match the firms to the key politicians if the firm is located at the politician's political restrict. I use merging firm's zipcode in SDC and rival firms' zipcode in COMPUSTAT in order to match them to political district and then to the respective politicians. As for the senators, I simply use firm's state.

I get the politicians' data from Charles Stwart page. The time span is 1998-2018.

There are 190 unique firms with missing zip-codes in set of 5899 unique firms, comprising merging parties and rivals. There are also around 300 acquirors and some rivals that are out side of the US and thus cannot be matched to the politicians. Above all, the politicians' incentives to get in contact with these firms are much weaker[16].

Throughout the study period, there are 447 (committee code 156) representative-term (committee code 358) for the house and 208 senator-term. Among these I count politicians turnover as those who had a note as in Table6 and those whose termination date was earlier than their cohort.

I match the firms using the variables mentioned above with the key politicians and keep those connections, which were around the merger announcement date, i.e., announcement date is between date of appointment and date of termination. There might be multiple politicians (only senators) that get matched to a single firm. This is likely, because the matching criteria is the state level and if two senators from the same state happen to be in the judiciary committee, firms in that state get matched to multiple senators. This does not happen for the representatives though, as the matching criteria is the state and congressional district being the same. Thus, there are a handful of firms which are connected to 3 politicians (2 in the senate and 1 in the house) simultaneously[17].

In sum, I get 3 main variables from the politicians:

- Pollink indicator=1 if the merger announcement in between appointment date and termination date of the matched politician.
- Treated=1 if the politician left earlier than the cohort or had note on transfer, losing election, etc. This is a politician's feature
- Post=1 if the merger announcement date is after the termination date.

[16]For matching the politicians to the rivals using the second approach, I get 1601 (around 15%) two matched reps for a single firm, meaning that some zip-codes are located in two distinct political district. E.g., zip-code 46268 in Indiana is both in political district 7 and 5, and if two representatives in the judiciary committee come from these two districts the firm could get two matched reps.

[17]e.g., Ted Cruz and John Cornyn were both Texas senators and rep. Blake Farenthold was serving in Judiciary committee of the house, which makes it 3 political links for Susser holdings corp, in total.

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Curriculum Vitae

Hamed Davari

Education

2017 - 2023	Doctoral Studies in Finance
	Graduate School of Social and Economic Sciences
	University of Mannheim, Germany
2013 - 2016	Master of Science in Technology Foresight
	Amirkabir University of Technology, Tehran, Iran
2008 - 2013	Bachelor of Science in industrial Engineering
	Sharif University of Technology, Tehran, Iran

Professional Experience

2015 - 2017	Co-founder & CFO
	Polytech Co., Tehran, Iran
2013 - 2015	Strategy Expert
	Hoze Honari, Tehran, Iran

Awards and Scholarships

2017 - 2019	Graduate School Scholarship,
	Graduate School for Economic and Social Sciences University of Mannheim