Università Commerciale "Luigi Bocconi"

PhD School

PhD program in Economics and Finance

Cycle: XXXI

Disciplinary Field: SECS-P/09

Essays on Finance and Corporate Innovation

Advisor: Alberto MANCONI

Co-Advisor: Stefano ROSSI

PhD Thesis by

Ekaterina GAVRILOVA

ID number: 3006780

Academic Year: 2019/2020

PhD THESIS DECLARATION

I, the undersigned

SURNAME	GAVRILOVA
NAME	EKATERINA
Student ID no.	3006780

Thesis title:

ESSAYS ON FINANCE AND CORPORATE INNOVATION

PhD in	Economics and Finance (Curriculum: Finance)
Cycle	XXXI

DECLARE

under my responsibility:

1. that, according to Italian Republic Presidential Decree no. 445, 28th December 2000, mendacious declarations, falsifying records and the use of false records are punishable under the Italian penal code and related special laws. Should any of the above prove true, all benefits included in this declaration and those of the temporary "embargo" are automatically forfeited from the beginning;
2. that the University has the obligation, according to art. 6, par. 11, Ministerial Decree no. 224, 30th April 1999, to keep a copy of the thesis on deposit at the "Biblioteche Nazionali Centrali" (Italian National Libraries) in Rome and Florence, where consultation will be permitted, unless there is a temporary "embargo" protecting the rights of external bodies and the industrial/commercial exploitation of the thesis;
3. that I will submit the thesis online in unalterable format to Bocconi University, that, by means of "Institutional Research Information System (IRIS)", will permits online

consultation of the complete text (except in cases of temporary "embargo");

4. the thesis is protected by the regulations governing copyright (Italian law no. 633, 22nd April 1941 and subsequent modifications). The exception is the right of Università Commerciale "Luigi Bocconi" to reproduce the same, quoting the source, for research and teaching purposes;
5. that the copy of the thesis submitted online is identical to the copies handed in/sent to the members of the Thesis Board and to any other paper or digital copy deposited at the University offices, and, as a consequence, the University is absolved from any responsibility regarding errors, inaccuracy or omissions in the contents of the thesis;
6. that the contents and organization of the thesis is an original work carried out by the undersigned and does not in any way compromise the rights of third parties (Italian law, no. 633, 22nd April 1941 and subsequent integrations and modifications), including those regarding security of personal details; therefore the University is in any case absolved from any responsibility whatsoever, civil, administrative or penal, and shall be exempt from any requests or claims from third parties;
7. that the thesis is not subject to "embargo", i.e. that it is not the result of work included in the regulations governing industrial property; it was not written as part of a project financed by public or private bodies with restrictions on the diffusion of the results; is not subject to patent or protection registrations.

Date: July 20, 2020

Acknowledgements

I thank my advisors, Alberto Manconi and Stefano Rossi, for their continuous support and encouragement. They supplied me with enough guidance and knowledge to stay on the right path, but also enough freedom to feel empowered by the journey. I am grateful for their tremendous time, energy, and wisdom that they invested in steering my research. Their support and guidance allowed me to learn, grow, and find my own values and interests in research.

I also thank Stefan Zeume who has hosted me for one year at the Ross School of Business (University of Michigan). Discussions with Stefan inspire me for new achievements and motivate me to work even harder.

Likewise, I thank finance faculty, colleagues, and friends at Bocconi University and the Ross School of Business for interesting discussions, insightful comments, and helpful suggestions.

I thank my family for the unconditional love and support. I especially thank my mother who never doubts in my strengths and supports all my new undertakings. Last, but not least, I thank my boyfriend Daniele for his love and patience.

Abstract

"Innovation distinguishes between leaders and followers."

— Steve Jobs

Innovation shapes corporate life. Companies innovate in order to keep their competitive advantage on the market. Over the long run, if companies do not innovate, they lose their position on the market and may even go bankrupt if their peers continue to innovate. Corporate innovation affects many companies' decisions – from the choice of corporate innovation strategy itself to the firms' interaction with their peers and banks. My dissertation aims to stress the importance of innovation in corporate life by showing the impact of innovation on firm boundaries, corporate disclosure policy, and lending.

In the first chapter, I study how firms' choices of M&A, licensing, collaboration, and their performance depend on the extent of their innovation linkages. I find that innovation matters for firm boundaries. Companies integrate more tightly with peers with closer follow-on innovation. Based on patent citations, I construct a measure capturing what firms are the innovation originators and what firms are the followers, which I call innovation proximity. I find that companies are more likely to acquire peers with closer follow-on innovation rather than to create strategic alliances with them or license/buy their patents. My measure of innovation proximity does not affect firms' combined announcement returns but only the way they are split. In M&A transactions with the target with closer follow-on innovation, the bidder pays a lower premium and exhibits greater announcement returns. On the other hand, in licensing and strategic alliance deals with patent holder with closer follow-on innovation, the patent seeker obtains lower returns. These results are

consistent with the hold-up theory where companies bargain over type and terms of the contract.

In the second chapter, I focus on corporate nondisclosure and firm value. The evidences are based on the confidential treatment (CT) of corporate information. CT can exacerbate information asymmetry and agency problems but may also protect trade secrets; therefore whether it is valuable for shareholders is an empirical question. I address this question using novel, hand-collected data, studying the market reaction to CT requests. I document that companies with strong governance experience positive or no market reaction to redacted filings, whereas firms with weak governance obtain negative returns. I also examine whether and what types of information redaction might have negative effect on the market. Companies mostly redact information in collaboration, supply, license, and asset purchase agreements. Vis-à-vis fully disclosed filings, the market responds positively to redacted product-related information and negatively to redacted investor-sensitive information, such as settlement agreements. Taken together, this evidence is consistent with the various channels through which CT may affect firm value.

The third chapter presents a joint work with Alberto Manconi and Ekaterina Neretina. We analyze the use and valuation of patents as collateral in syndicated loans to large, publicly listed U.S. firms. We provide novel stylized facts about the use and valuation of collateralized patents. Firms that pledge patents are larger than the typical Compustat firm, but smaller than other syndicated loan borrowers; they obtain smaller loans, and pledge their less valuable patents; lenders that accept patent collateral tend to be larger and have bigger market shares. The use of patents as collateral could reflect an expansion of the set of pledgeable assets, suggesting a relaxation of financial constraints; but the opacity of intangible collateral such as patents may also create room for lenders to extract rents from borrowers, lending a smaller amount per dollar value of collateral. Preliminary evidence supports the latter view.

Contents

List of Figures

List of Tables

Chapter 1

Corporate innovation linkages and firm boundaries

"The nature of the business is that the revenues are dependent on patent protections. That means at some point you face a decline in that revenue stream. The replacement has either got to come from your own labs or from outside."

— Drew Burch, head of healthcare M&A at Barclays

(Financial Times, 2012)

1.1 Introduction

How does innovation shape firm boundaries? Historically most firms kept this core and strategic activity in house so they could maintain competitive advantage. Firms progressively have also been adopting alternative innovation strategies such as M&As, patent acquisition/licensing deals, strategic alliances, and patent infringement. Every year about 5% of all in-force patents changed their owner. For example, Apple allocated over $13 billion for R&D spending in 2019. Along with in-house innovation, Apple obtained new knowledge through acquisitions (Intel's modem business (2019)), and patent acquisition/licensing deals (Lighthouse AI (2018)).[1]

The firm's choice of innovation strategy depends on the costs and benefits of asset ownership (Grossman and Hart (1986), Hart and Moore (1988, 1990)). Strategies that involve a lower degree of integration (e.g. licensing deals) are usually less costly but the risks associated with the loss of competitive advantage are potentially high. To choose a certain level of integration with peers, companies take many aspects into consideration. I focus on one of the aspects: firms' innovation linkages.

Firms' innovation linkages could affect firm boundaries in two ways. First, innovation linkages could create synergies that impact companies' willingness to integrate. Second,

[1] Apple to acquire the majority of Intel's smartphone modem business. *Apple's press release.* July 25, 2019; Apple Acquires Lighthouse AI's Patent Portfolio in Possible Home Security Push. *Fortune.* March 5, 2019.

corporate innovation linkages could give rise to dependence between firms, and thus relate to their bargaining power. Yet, the existing literature mainly focuses on analyzing single organizational structures rather than examining the trade-off between them. I fill this gap in the literature, by building a theoretical model that predicts how firms' innovation linkages determine the choice between M&As, strategic alliances, and patent acquisition/licensing deals, and affect their performance. I also test theoretical predictions empirically.

The main challenge is to measure firms' innovation proximity. I use patents to capture corporate innovation. Patents usually incorporate innovation from the patents they cite (Jaffe et al. (2000)); so in order to exploit follow-on patents companies have to license the original patents. Companies with original innovation could in turn decide whether to allow others to exploit their innovation. Consider a *patent seeker*, i.e. a firm that is seeking the innovation, and a *patent holder*, i.e. a firm with such innovation. I construct a measure of innovation proximity based on patent citations between the patent seeker and the patent holder. Suppose that the patent holder closely cites the patent seeker, whereas the patent seeker does not cite the patent holder. In this case, the patent seeker's innovation is original and he decides whether to allow the patent holder to use his innovation. So the patent holder is the "follower" and she is in the dependent position. According to the hold-up theory, the patent holder is expected to have less bargaining power than the patent seeker in the contracting. In the reverse scenario where the patent seeker closely cites the patent holder, he has closer follow-on innovation and the patent holder has original innovation. In this case, the patent seeker is more likely to be willing to exploit patent holder's innovation in his production so he is in the dependent position.

To test how patent portfolio proximity impacts the firms' choice to innovate and deal gain splits, I articulate my analysis in two steps. In the first part, I study the determinants and the firms' choice between M&As, patent acquisition/licensing deals, strategic alliances, and patent infringement. I find that patent seekers are more likely to acquire peers with closer follow-on innovation rather than to agree on strategic alliances or patent acquisition/licensing deals. On the other hand, patent seekers are more likely to license patents from peers with closely original patents or alternatively infringe their patents. Overall, closer patent holder proximity is associated with a higher degree of integration, consistent with the hold-up theory's predictions.

In the second part, I study whether corporate innovation linkages determine the integration gains, and their split. By examining announcement returns of companies involved in the integration, I show that innovation linkages have no impact on combined returns but only how the deal gains are split. I find that in M&As a patent seeker (bidder) with closer follow-on innovation pays a greater premium to a patent holder (target) and exhibits lower announcement returns. In particular, one standard deviation decrease in *patent holder relative proximity* is associated with \$1.9 million greater premium and 59.2 bps lower patent seeker announcement returns. The results also hold in the relative dollar gains; one standard deviation decrease in *patent holder relative proximity* on average leads to an additional \$14.7 million gain for the patent holder.

An alternative innovation strategy is to form a strategic alliance. Using an approach similar to Robinson (2008), I identify the patent seeker as a firm that operates in an industry different from the alliance industry, and the patent holder as a firm that operates in the same industry as the alliance. I find that the patent seeker with closer follow-on innovation obtains larger announcement returns. One standard deviation decrease in *patent holder relative proximity* translates into 41.5 bps greater patent seeker announcement returns. This suggests that the patent seeker with more dependent patents benefits more from the strategic alliance.

In licensing deals the market reacts more positively when the patent holder licenses its patents to a peer with closely original innovation. This suggests that the patent holder's follow-on innovation is valuable and that the patent seeker's position is weaker. On the other hand, the market reacts less positively when the patent holder licenses its original patents as it might create an additional competition and the patent holder's competitive advantage might weaken. One standard deviation decrease in *patent holder (assignor) relative proximity* is associated with 49 bps increase in patent seeker (assignee) announcement returns and 40.5 bps decrease in patent holder returns compared to their average returns. The reader can notice that *patent holder relative proximity* has an inverse impact on the companies in licensing and strategic alliance agreements compared to M&As.

In the post-deal period, I find no effect of corporate innovation linkages on the stock market performance for any type of the firm's integration. This suggests that all gains associated with firms' innovation connections are priced correctly at the announcement date. Focusing on the operating performance, I do not find any evidence of an increase in productivity. This confirms that my measure captures only the gains split.

Overall, my results are consistent with the hold-up theory. Closer follow-on innovation is associated with a greater dependence from peers, meaning that the firm has weaker bargaining power. I show that companies are more likely to buy peers with closer follow-on innovation rather than to license innovation from them. The merger performance analysis suggests that bidder pays a greater compensation to firms whose innovation he closely depends on and so he obtains lower announcement returns. In licensing deals the market reacts more positively when the firm licenses its innovation to the peer on which it depends. This is in line with theoretical predictions that bargaining power plays a crucial role in contracting. In M&As bidders with weaker bargaining power have to pay a greater premia and experience lower announcement returns (Lambrecht (2004), Gorton et al. (2009) and Edmans et al. (2012)).

I address four possible alternative explanations of my findings. First, the source of bargaining power might not be innovation dependence but the value of firm's innovation portfolios. I consider two measures of innovation portfolio value – citation weighted (Hall et al. (2005)) and stock market weighted innovation portfolio output (Kogan et al. (2017)). Controlling for firms' innovation portfolio values, I still find innovation connections to matter in the split of merger gains. Compared to the baseline results, the magnitude of the effect remains the same when I control for stock market weighted innovation output, whereas it increases by 26 percent, controlling for citation weighted innovation output. Second, patents are not the only output of firm's innovation process. To control for other types of innovation output, I control for capital expenditure and the value of intangible capital (Ewens et al. (2020)); the magnitude of the effect of my measure on the degree of firms' integration remains unchanged. Third, industry concentration could impact corporate innovation strategies. Larger firms usually have greater power and they could have more aggressive innovation strategy. I run several tests to check whether industry concentration has an impact on my measure. I find no significant correlation between these two measures. Controlling for industry concentration, the results are almost identical to the baseline results. Fourth, I rule out the alternative explanation that *patent holder relative proximity* simply captures geographic distance. I divide the sample by the median of geographic distance between firm headquarters. I find no difference in patent holder relative proximity between two subsamples.

I make three main contributions to the literature. First, my paper is related to the literature on innovation and corporate strategy. Innovation affects many aspects of corporate life. So far, the main focus of the literature is to understand the optimal intensity and frequency of innovation (Aghion and Tirole (1994), Barker III and Mueller (2002), Hall et al. (2010)) and whether to develop it in house or obtain it externally (Pisano (1990), David et al. (2000)). I propose a new measure of firms' innovation connectedness that characterizes firms' relative dependence.

Second, my paper contributes to the literature on firm boundaries. Theoretical studies construct incomplete contracting models where they analyze how costs and benefits of asset ownership affect boundaries of the firm (Grossman and Hart (1986), Hart and Moore (1988, 1990), Fauli-Oller and Sandonis (2003), Anosova (2018)). Yet, the empirical studies mostly focus on single organizational structures[2] rather than examining the trade-off between them (Villalonga and McGahan (2005)). I find that companies are more likely to acquire peers with closer follow-on innovation, and create strategic alliances with firms with original innovation or to buy/license their patents. To the best of my knowledge, mine is the first study that empirically analyzes how innovation affects the determinant of and the choice between M&A, strategic alliance, patent acquisition/licensing deal, and patent infringement.

Third, the paper contributes to the literature on mergers and acquisitions. Combining firms' innovation could create synergies. One strand of the M&A literature studies whether innovation linkages favor the post-merger innovation output (Ahuja and Katila (2001), Bena and Li (2014), Sevilir and Tian (2012), Sears and Hoetker (2014), Seru (2014)). Other strand of M&A literature claims that bidders with weaker bargaining power have to pay a greater premium, which is associated with additional costs for the bidders and so they observe lower announcement returns (Lambrecht (2004), Gorton et al. (2009), Edmans et al. (2012), Anosova (2018)). Though, it is difficult to test it empirically because bargaining power is unobservable. Ahern (2012) proxies bargaining power using relative industry dependence based on input-output matrix. He finds that greater bargaining power is associated with larger relative gains in the vertical mergers. In my sample only 3% of M&A deals have previous customer-supplier relationships. So something else is driving mergers that involve innovation portfolio transfers. I analyze corporate innovation linkages and find that they drive M&A gains split as opposed to value creation. Hence I can conclude that it captures bargaining power.

The rest of the paper is organized as follows. Section 1.2 provides a simple theoretical model and lays out theoretical predictions. In Section 1.3 I provide details of data collection and define the measure of firms' innovation proximity. Section 1.4 examines how firm's

[2] M&As – Rhodes-Kropf and Robinson (2008), Phillips and Zhdanov (2013) and Hoberg and Phillips (2010, 2016); patent acquisition/licensing deals – Bowen III (2016); collaboration/joint ventures – Gomes-Casseres et al. (2006), Lindsey (2008), Robinson (2008); patent infringement lawsuits – Reitzig and Wagner (2010); corporate ventures capital investments – Ma (2020).

relative proximity affects firm boundaries. Section 1.5 presents the empirical results on firms' interaction performance. Section 1.6 discusses possible alternative explanations and presents robustness checks. The final section concludes the paper.

1.2 Theoretical framework

This section builds theoretical predictions on how innovation linkages impact firm boundaries. My model identifies what innovation strategy firms choose, depending on their innovation proximity. I consider five most common corporate innovation strategies: 1) in-house innovation (no cooperation); 2) acquisition; 3) strategic alliance; 4) licensing deal and 5) infringement.

Consider two firms A and B; they compete in quantities (Cournot competition). The demand for the good is $P(Q) = a - Q$. The cost function is linear with marginal cost equal to c_i. Marginal cost depends on the innovation a firm uses. Firm B has innovation that allows it to produce at marginal cost c_B. Firm A has two innovations – old and new. Using old (new) innovation firm A produces the good at cost c_H (c_L), where $c_H > c_B > c_L$ and $a > c_B$. The novelty of the model is that firm A cannot exploit the new innovation without firm B's innovation. Assume $\mu \in [0, 1]$ to be a level which firm A's new innovation depends on firm B's innovation. When $\mu = 0$ two innovation are independent. When $\mu = 1$ firm A's new innovation is almost identical of firm B's innovation. In-between values shows to which extent firm A's new innovation depends on firm B's innovation. The higher the level of μ is, the more likely firm B wins the infringement cases and could bargain more on the contract terms.

In this framework the following strategies are possible:

1. Competition – firm A uses old technology and competes with firm B;

2. M&A – firms merge and produce using the new technology;[3]
3. Strategic alliance – firm A and firm B cooperate, produce together and share their surplus equally;
4. Licensing – firm A obtains a license from firm B, and competes with firm B, by producing using new technology;
5. Infringement – firm A produces using its new innovation by infringing firm B's innovation. Firm A competes with firm B. Firm B could file an infringement lawsuit against firm A.

I assume that firms use Nash bargaining to share the merger surplus. Firm B's bargaining parameter is $\gamma(\mu)$ and firm A's bargaining parameter is $(1-\gamma(\mu))$, where $\gamma(\mu) = \mu^2$. I also assume that strategic alliance agreement is constructed as a merger of equals and when firms agree to build strategic alliance they act as a monopolist. In the first stage they decide how much to produce; in the second stage companies divide their surplus equally.

The licensing agreement defines royalty rate $Royalty = f_{base} + \mu f$, where one part of the fee (f_{base}) is independent from μ and another one (f) is strictly increasing in μ.

In case of infringement both firms bear sunk costs ψ, where $\psi > f_{base}$. The expected settlement amount is $P(\mu)\Phi$, where $P(\mu) = \mu$ is the probability of reaching settlement and Φ is settlement amount.

The table below reports all the payoff of both firms under all strategies:

[3] Here I assume that firm that has more power acquires its peer. For example, an extreme case where firm A has no power is when competition and infringement is not feasible for firm A.

Firm A's payoff

Competition	$\pi_A^{Comp} = \dfrac{(a + c_B - 2c_H)^2}{9}$
Infringement	$\pi_A^{Inf} = \dfrac{(a + c_B - 2c_L)^2}{9} - \mu\Phi - \psi$
Merger	$\pi_A^{Acq} = \pi_A^{Comp} + (1 - \mu^2)(\dfrac{(a - c_L)^2}{4} - \pi_A^{Comp} - \pi_B^{Comp})$
Strategic alliance	$\pi_A^{Alliance} = \pi_A^{Comp} + \dfrac{1}{2}(\dfrac{(a - c_L)^2}{4} - \pi_A^{Comp} - \pi_B^{Comp})$
License	$\pi_A^{License} = \dfrac{(a + c_B - 2c_L)^2}{9} - f_{base} - \mu f$

Firm B's payoff

Competition	$\pi_B^{Comp} = \dfrac{(a + c_H - 2c_B)^2}{9}$
Infringement	$\pi_B^{Inf} = \dfrac{(a + c_L - 2c_B)^2}{9} + \mu\Phi - \psi$
Merger	$\pi_B^{Acq} = \pi_B^{Comp} + \mu^2(\dfrac{(a - c_L)^2}{4} - \pi_A^{Comp} - \pi_B^{Comp})$
Strategic alliance	$\pi_B^{Alliance} = \pi_B^{Comp} + \dfrac{1}{2}(\dfrac{(a - c_L)^2}{4} - \pi_A^{Comp} - \pi_B^{Comp})$
License	$\pi_B^{License} = \dfrac{(a + c_L - 2c_B)^2}{9} + f_{base} + \mu f$

Firm A can choose between strategies competition and infringement without firm B's approval, while other strategies (licensing, strategic alliance and M&A) can be only chosen only if both firms agree. Firms accept any form of cooperation if they both are better off compared to their outside feasible options.

In the Appendix I provide the solution to the theoretical model while below I present a numeral example that illustrates the mechanism identifying firm boundaries. Assume the following parameters: $a = 2$, $c_H = 0.7$, $c_B = 0.6$, $c_L = 0.3$, $f_{base} = 0.02$, $f = 0.5$, $\Phi = 0.3$, $\psi = 0.05$.

In Figure 1.2 first two graphs report the payoff of firm A and firm B under their different strategies, whereas the third graph summarizes the overall firms' strategy. In the first step, I identify firm A's outside option for each μ. Comparing firm A's output in case competition and infringement, I find that when μ is lower than 0.78, firm A's outside option is infringement. When μ is greater than 0.78, firm A's outside option is competition.

In the second step, I focus on studying firms' overall strategy. In region, where $\mu \leq 0.15$, firm A is better off to obtain a license rather than to infringe firm B's innovation, its outside strategy. Firm B compares its outputs of licensing and infringement strategies; it is clear from the graph that firm B prefers to license compared to the infringement. So for $\mu \leq 0.15$ the optimal strategy for both firms is to agree on license. The intuition behind this is that the firm B's innovation almost does not depend on firm A's innovation and it is very difficult for firm B to win infringement lawsuit in this case. Now, consider the region where $0.1 < \mu < 0.36$. Firm A's infringement strategy dominates other strategies; and firm B cannot do anything but only files a lawsuit. In the region, where $0.36 \leq \mu \leq 0.54$, Firm A prefers merger compared to infringement; other strategies would not be considered by firm A because infringement dominates them. Firm B prefers merger compared to infringement so firms agree on a merger. In the region, where $0.54 < \mu < 0.78$, firm A's first best is merger, second best is strategic alliance and third best is infringement. Firm B prefers strategic alliance among three feasible strategies so firms sign strategic alliance. In the region, where $\mu \geq 0.78$, firm A's outside option is competition, while strategic alliance is preferred over merger that in its turn preferred by competition. Firm B prefers merger over strategic alliance and competition, so firm A agrees on merger. Above you could see the example that explains the mechanism of firms' different strategies depending firm A's dependence.

In short, the theoretical predictions are as follows. A firm with original innovation chooses to:

1. acquire firms with closely follow-on innovation;
2. build strategic alliance or merge with peers whose innovation depends on the firm but not very much;

3. license to peers whose innovation is less dependent on the firm;
4. face infringement if the firm and its peers cannot agree on any of the above strategies.

In this theoretical framework I consider just one innovation linkage between firms. In reality companies could have multiple innovation linkages that go in both directions. To measure corporate innovation dependence, I create a measure of patent holder relative proximity in next section.

1.3 Data and innovation proximity

This section aims to overview the existing measures of bargaining power, define a new measure of innovation proximity. The section also highlights the data sources that are used to test theoretical predictions.

1.3.1 Existing literature on bargaining power

There exist different proxies of bargaining power but they are not perfect. So far the widely used measure of bargaining power is the relative deal size. Moeller et al. (2004) claim that larger companies have greater bargaining power so they obtain larger share of the total gains. Alexandridis et al. (2013) show that relative size is associated with the level of uncertainty of the merger outcome. So the relative deal size also drives the total merger gains. Schneider and Spalt (2017) show that "size" should not be considered as a proxy measure. They demonstrate that the size can be both good and bad for the bidder announcement returns depending on the sample selection.

Despite the "size" measure, the companies might have other competitive advantages that impact bargaining power. Rhodes-Kropf and Robinson (2008) find that firms tend to acquire peers with similar market-to-book values. Ahern (2012) identifies the relative industry dependence based on the input-output matrix. In case of technological M&As firm's innovation plays a crucial role. If the target does not accept the merger, she can produce by herself and compete with the bidder. The innovation dependence determines the importance of the target's innovation portfolio for the bidder. When the bidder closely cites the target, the bidder's innovation is based on the target's innovation portfolios and so the bidder depends more on the target. Similar logic holds in the reverse direction. The bidder has greater bargaining power when he cites less the target and is cited more by the target. I propose a new measure of bargaining power based on the firm's innovation linkages. It captures to which extent the patent seeker depends on the patent holder.

1.3.2 Measuring innovation proximity

The goal is to construct a relative measure of innovation proximity between two companies before the announcement of their integration. I proceed in five steps.

First, I identify patent seeker and patent holder in each deal. I define the patent seeker as the firm that obtains the innovation from the deal, and the patent holder as the firm that owns the innovation. The patent seeker is the bidder in M&As, the assignee in licensing deals, and the infringer in patent infringement lawsuits. The patent holder is the target in M&As, the assignor in licensing deals, and the plaintiff in patent infringement lawsuits. In strategic alliances firms usually have equal status so it is challenging to identify patent holder and patent seeker. To overcome this challenge, I use an approach similar to Robinson (2008). I claim that a firm that operates in the industry different from the alliance's industry seeks the expertise from the firm that is an expert in that field. I call the patent holder to be the firm that operates in the same industry as the alliance, and the patent seeker to be the firm that operates in the industry different from the alliance industry.

Second, I construct firm's innovation portfolios over time. I observe innovation on the firm level through the patent database collected by Kogan et al. (2017). Each patent has information of its filing, publication and grant dates, technological class, citations, and assignee. A firm's patent portfolio includes all of the firm's patents filed before the deal announcement.[4]

Third, using patent citations I build direct and indirect patent connections between the patent portfolios of the patent holder and the patent seeker. I use two notions of patent citations: direction and degree. A directed link (X, Y) means that patent X cites patents Y but patent Y does not cite patent X; so I can observe which patent is the originator and which patent is the follower. Each patent cites some patents that in turn cite other patents. I consider up to the fourth degree citations because patent's protection lasts maximum 20 years from the filing date and the time lag between citing patent and cited patent is on average 5.5 years. That means that if I have considered fifth degree connections I would observe mostly expired patents.

Fourth, I construct the firms' innovation dependence from the patent holder and patent seeker perspectives. Suppose that the patent holder has K patents and the patent seeker has N patents. From the patent seeker's perspective, define:

$$Patent\ seeker\ proximity = \frac{1}{K}\sum_{k=1}^{K}(5 - Connection\ degree_{k,N}), \tag{1.1}$$

where $Connection\ degree_{k,N}$ is the closest degree of citation of the patent seeker's patent k to any patent assigned to patent holder before the deal announcement. First-degree connections (direct citations) have the score of 1; the second-, third- and fourth-degree connections have the score of 2, 3 and 4, respectively. Higher degree connections are

[4] I consider all of the firm's patents filed not and not prior to 20 years before the deal announcement, which is the maximum duration of the patent protection. Patents filed and granted before June 8, 1995 have the protection period for maximum of 17 years from the issued date. Patents filed before June 8, 1995 but not approved until after June 8, 1995 are valid for the greater of 20 years from filing date or 17 years from the grant date.

assigned the score of 5. From the patent holder's perspective:

$$Patent\ holder\ proximity = \frac{1}{N}\sum_{n=1}^{N}(5 - Connection\ degree_{n,K}), \tag{1.2}$$

Fifth, I compute the patent holder relative proximity as the difference between patent holder proximity and patent seeker proximity:

$$Patent\ holder\ relative\ proximity = Patent\ holder\ proximity - Patent\ seeker\ proximity \tag{1.3}$$

Patent holder relative proximity varies from -4 to 4. I standardize it so that it ranges from 0 (none of the patent holder's patents cite the patent seeker's patent portfolio and all of the patent seeker's patents directly cite patent holder's patent portfolio) to 1 (all of the patent holder's patents directly cite patent seeker's patent portfolio and none of the patent seeker's patents cite patent holder's patent portfolio). *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal.

1.3.3 Data

I merge data from a number of sources. First, I define firm boundaries by identifying completed mergers and acquisitions, strategic alliances, patent acquisition/licensing deals and patent infringement lawsuits. I require firms involved in transactions to be U.S. public companies whose stock return data is available on CRSP. Moreover, utilities (SIC codes $4000 - 4999$) and financial firms (SIC codes $6000 - 6999$) are excluded.

The sample of M&A transactions comes from Thomson One's Mergers and Acquisitions database. Buybacks are excluded from the sample. I restrict the sample to M&A transactions where the bidder buys at least 51% of target shares.

The United States Patent and Trademark Office (USPTO) Patent Assignment dataset is the source for patent acquisition and licensing deals. The database contains all patent assignments reported to the USPTO from 1980 to 2017. It provides information on the changes of patent ownership, security agreements, patent acquisitions, licensing, inventor-employee assignment etc. To retrieve patent acquisition and licensing deals I adapt the strategies of Serrano (2010), Bowen III (2016), and Ma (2020). The database sometimes reports multiple transaction dates per transaction, where the average lag between the first and the last date is 37 days. I consider the announcement date of patent acquisition/licensing deals to be the first date when the companies register a transaction in the USPTO. Multiple filings between the same parties filed on the same day are considered as a single transaction.

I use SDC Platinum to assemble a sample of strategic alliance deals that spans from 1975 to 2010. I restrict the sample to strategic alliances that involve only two parties. I also exclude strategic alliances between different subsidiaries of the same company. I restrict the sample to the deals where two parties operate in different two-digit SIC code industry; one firm operates in the same industry as alliance.[5]

The sources of patent infringement data are Stanford NPE litigation database and Patent litigation docket reports data (Marco et al. (2017)). They include all patent infringement lawsuits filed in U.S. courts from 1985 to 2015. Parties can settle the dispute both in and out of court.

Second, I calculate my measure of firms' relative innovation proximity using the U.S. patent database collected by Kogan et al. (2017) and available on Professor Noah Stoffman's website. It contains the information about patents issued by USPTO from 1926 to 2010. I require both parties of an agreement to have at least one issued patent before the firms' interaction announcement.

The final sample consists of 932 M&A transactions, 2,479 patent acquisition and licensing

[5]Otherwise, I am not able to distinguish patent seeker and patent holder in a deal.

agreements, 2,166 patent infringement lawsuits, and 1,922 strategic alliances that span over the period from 1975 to 2010. 1975 is the first year when a deal meets all the criteria described above and 2010 is the last year when the Kogan et al. (2017) patent dataset is available.

I also include several additional variables as controls (all retrieved from Compustat and Thomson's One). Firm size is proxied by the logarithm of market equity. To measure profitability, I include the operating income, scaled by the firm book value. I also control for the leverage (ratio of debt to assets), and Tobin's Q. In the M&A sample I also control for the relative deal size (transaction value, scaled by the bidder's market equity), means of payment and deal attitude.

1.4 Innovation and firm boundaries

In this section, I study how corporate innovation linkages determine companies' innovation strategy. I examine which companies are more likely to integrate with each other and how innovation connections impact the probability of signing an agreement.

I consider four main strategies of obtaining external innovation (Figure 1.1). The first option is to acquire a firm with innovation. The second alternative is to collaborate with other companies though strategic alliance. The third possibility is to sign patent acquisition or licensing agreement.[6] As for the fourth alternative, firms might decide to infringe patents of other companies that in their turn can file a lawsuit against the infringer. I observe the filing of patent infringement lawsuits.

Companies might have different strategies and aims for obtaining innovation. It is not clear whether and how innovation linkages affect firm's decision to innovate. Having connected innovation portfolios between two companies may improve their market power.

[6] Unfortunately, I cannot distinguish patent acquisition from patent licensing deals. From now on, I call them licensing deals but they also include patent acquisition deals.

This can happen through a number of channels: 1) operating on the same market, the buyer has enough experience to integrate the target's innovation (Bena and Li (2014)); 2) if in the pre-deal period potential buyer already uses the target's innovation, after the deal he obtains exclusive rights for the acquired patents. While merging two different innovation portfolios might lead to a wider scope of future innovation. For example, by acquiring OraPharma Inc., a specialty pharmaceutical company, Johnson&Johnson was able to enter to the new professional products market of the oral health products and create new therapies in that field.

First, I test whether there is something specific about companies that interact from the innovation network perspective. I compare *patent holder relative proximity* between placebo firm pairs to the pairs of the exact deals. In my analysis I consider only public companies with at least one patent in their innovation portfolio. Using Kogan et al. (2017) database, I identify 7,545 potential companies that respect this requirement. I calculate the degree of separation for each pair from both perspectives over time. Some firm pairs are very unlikely to integrate; so considering all firms' pairs is not the best counterfactual to the actual interaction between firms as they might create additional noise. So I run a matching procedure to identify comparable potential pairs. I require company to meet the following criteria in order to be a potential pair:

1. Its market value is 70%-130% of the actual firm's market value two months before the transaction announcement;
2. The company has at least one patent issued before the transaction;
3. The company operates in the same Fama-French 12 industry as the actual company.

I identify the top 10 closest potential firms for each company involved in an actual transaction, using 10-nearest neighbors matching with no replacement. Then, I construct firm pairs; for each transaction I have 120 potential firm pairs and 1 actual pair. I sometimes cannot identify all 10 similar firms so my final sample is a bit smaller.

I regress firms' interaction announcement indicator on *patent holder relative proximity*. I include firms' industry and year fixed effects. Standard errors are clustered by patent holder $\times$ patent seeker industries. I also control for characteristics of firms involved in the transaction. The estimations reported in Panel A of Table 1.3 show that companies are more likely to use patents of firms on which they depend more. One standard deviation increase in *patent holder relative proximity* leads to 10.8 percent ($= 0.018 \times 0.08/1.335\%$) lower probability of patent seeker to integrate with patent holder compared to the average deal probability. Next, I examine the deal probability by each type separately. Panel B shows that one standard deviation increase in *patent holder relative proximity* is associated with 49.5 percent ($= 0.074 \times 0.066/0.986\%$) higher merger probability compared to the mean merger probability in the sample. Panels C and D show that one standard deviation increase in *patent holder relative proximity* leads to 22.4 percent ($= 0.037 \times 0.090/1.486\%$) higher probability of strategic alliance compared to the average strategic alliance probability. Panels D reports that one standard deviation increase in *patent holder relative proximity* lowers the probability of licensing deal by 37.7 percent compared to the average probability. The results suggest that greater *patent holder relative proximity* is associated with a higher degree of firms' integration.

As an alternative strategy, companies might decide to exploit new advances without paying any royalties and fees, by infringing patent holder's rights. In this case the patent holder can file a patent infringement litigation lawsuits. Panel E of Table 1.3 shows that infringers are more likely to face a lawsuit if their innovation closely cites plaintiff's patents (*patent holder relative proximity* is lower). This confirms that firms depend on the innovation they cite, which gives an economic intuition and validation of my measure as bargaining power.

Second, I randomly select 1 out of 120 potential matches for each firm and estimate a multinomial logistic regression. Figure 1.3 shows the likelihood of the each integration type to happen with respect to *patent holder relative proximity*. When patent holder depends less on patent seeker, licensing deals and patent infringement are more likely to happen.

On the other hand, when the patent holder closely depends on the patent seeker, they are more likely to create a strategic alliance or agree on a merger. In sum, the figure shows that as *patent holder relative proximity* increases the patent seeker integrates more tightly with the patent holder.

Third, I focus on completed interactions between firms. I explore whether *patent holder relative proximity* affects the firms' choice of integration type. First, I conduct a univariate analysis by comparing *patent holder relative proximity* in different types of deals. Table 1.1 shows that it equals 0.55 in M&As and it is statistically different from licensing agreements (*patent holder relative proximity*= 0.46). Second, I run a multinomial logistic regression examining the impact of *patent holder relative proximity* on the degree of integration. I find that when the patent holder has follow-on innovation, the patent seeker interacts more tightly with the patent holder (Table 1.4). To understand the effect of proximity on the degree of integration I examine the coefficients for comparisons among all pairs of outcomes. I calculate odds ratio for each pair of the outcomes (Panel B of Table 1.4). I find that the coefficients of all pairs are statistically different from each other.

1.5 Deal performance

1.5.1 Announcement returns

To measure the effect of the deal on the value of the parties involved in the deal, I estimate cumulative abnormal returns (CARs). The abnormal return is defined as the difference between stock return and value weighted market return. I cumulate the abnormal returns over an event window around the deal announcement, to obtain the X-day CAR. I use 3-day $[-1,+1]$ window for M&A and strategic alliance samples as we know the actual date of deal announcement. I use 21-day $[-10,+10]$ window for licensing deals and patent infringement lawsuits due to the following reasons: 1) most of the transactions are not covered by newspapers; 2) I do not know exactly when the market observes the information related to licensing deal or infringement lawsuit. Combined returns are defined as value weighted returns around the announcement date, where the weights are based on the companies' market value two months prior to announcement date.

Table 1.1 summarizes the mean CARs of the firms and their combined returns. Column 1 of Panel A reports mean CARs for the M&A sample. Mean bidder and combined abnormal returns are -1.35% and 1.70%, respectively, and statistically different from zero at the 1% level. The CARs are consistent with the literature (Andrade et al. (2001) and Fuller et al. (2002), for example). Panel C of Table 1.1 presents the CARs for patent licensing deals. The average of assignee and combined abnormal returns is 0.33% and 0.44%, respectively. Panel E reports average returns for infringer equal to 0.93 and combined returns equal to 0.78% in the patent infringement lawsuits. There is a great heterogeneity of returns both for licensing deals and infringement lawsuits as the standard deviations of the CARs is greater than 8.15.

I investigate how *patent holder relative proximity* affects announcement returns in multivariate context:

$$CAR_{ik} = \alpha + \beta Patent\ holder\ relative\ proximity_{ijk} + \epsilon_{ijk} \tag{1.4}$$

The dependent variable is CAR_{ijk}, firm i's cumulative abnormal returns in deal k that involves firms i and j. *Patent holder relative proximity* is the variable of interest. In all specifications standard errors are clustered by firm i $\times$ firm j industries that follow 12 Fama-French industry classification (Fama and French (1997)). In specifications (2) and (3) I add year, firm i and firm j fixed effects. Specification (3) also includes a vector of deal and firms' characteristics.

Table 1.5 reports the estimates of patent seeker announcement returns. In M&As one standard deviation increase in *patent holder relative proximity* is associated with 59.2 bps

($= 4.231\% \times 0.140$) increase in bidder announcement returns (Panel A). This is a large effect relative to the mean of -135 bps. In Panel C I examine assignee announcement returns. I find that one standard deviation of *patent holder relative proximity* leads to 48.6 bps ($= 3.078\% \times 0.161$) lower assignee returns. The opposite effect compared to M&A sample could be noticed.

Next, I study the patent holder returns (Table 1.6). I find no difference in percentage announcement returns for target in M&As. Whereas in licensing deals assignor returns are greater by 40.5 bps ($= 2.517\% \times 0.161$) with an increase of *patent holder relative proximity* by one standard deviation. The size of firms involved in the interaction may differ considerably; so it might be difficult to infer the split of the gains from the cumulative percentage abnormal returns of two parties of the deal. I follow the strategy of Ahern (2012) to calculate how much money the patent holder extracts more from the patent seeker for each dollar of their combined market value than the patent seeker does. I find that in M&As one standard deviation decrease of *patent holder relative proximity* is associated with additional \$14.7 million ($= 4.833\% \times 0.140 \times \$2,200$) gain for the target (Table 1.7). Whereas, assignor loses on average \$28.6 million ($= 0.34\% \times \$8,400$) with the decrease of *patent holder relative proximity* by one standard deviation.

The results are consistent with bargaining power hypothesis, where greater *patent holder relative proximity* is associated with weaker bargaining power. I find that patent holders with independent innovation (lower *patent holder relative proximity*) are more likely to license their patents rather than to sell their business. In M&As such patent holders are able to extract a greater premium and dollar announcement returns. Whereas, in licensing deals the market punishes patent holders that have independent patent portfolio and license their patents. By doing this, patent holders may lose their bargaining power and potentially create an additional competition in the supply market. That is why the market reacts negatively to such licensing deals.

According to theoretical predictions, bargaining power has no impact on the total deal gains but only on their split. So to validate my measure, I regress *patent holder relative proximity*, the variable of interest, on the combined returns. Table 1.8 shows no significant relationship between *patent holder relative proximity* and the combined returns.

1.5.2 Premium

Next I analyze takeover premiums. Theoretical models (Lambrecht (2004), for example) predict that a target with greater bargaining power is able to bargain over price so that the bidder has to pay a greater compensation. I calculate the premium as the deal value, scaled by the target market value two months before the M&A announcement, minus one.

Table 1.9 presents the estimates from the premium regressions. One standard deviation decrease in *patent holder relative proximity* is associated with a $1.9 million higher premium paid by the bidder. This has an impact on bidder returns that decrease by 43.9 percentage points compared to the average bidder announcement returns.

Unfortunately, due to data limitations I cannot calculate a premium for licensing deals and patent infringement lawsuits, as I do not observe licensing royalties and patent infringement lawsuit costs.

1.5.3 Post-deal performance

So far I have examined the impact of *patent holder relative proximity* on the market. I find that the less dependent the patent holder's innovation is (*patent holder relative proximity* is lower), the lower the patent seeker returns in M&As are and the greater the patent seeker returns in licensing deals are. This sub-section focuses on the post-deal performance. Under the market efficient hypothesis the market incorporates the news of deals immediately and we should not observe abnormal returns in the long run.

To test this hypothesis, I analyze long-turn returns using calendar-time approach (Fama (1998)) with 4-factor models (Fama and French (1993) and Carhart (1997)) and Fama and MacBeth (1973) approach. Table 1.10 reports the results based on the calendar time and Fama and MacBeth (1973) approach. In both approaches I do not find any statistical difference between deals with *patent holder relative proximity* < 0.5 and *patent holder relative proximity* ≥ 0.5.

Next, I analyze the operating performance in the post-deal period. I find no evidence of the change in the operation performance, measured by ROA (Table 1.11). This confirms that my measure of *patent holder relative proximity* captures only the deal gains split and not synergy effects.

1.6 Robustness

In this section I rule out alternative explanations. First, firms' patent proximity captures the average connectedness of the firm and it depends on the number of patents the firms have. If a patent holder has a small patent portfolio, the probability that a patent seeker cites the patent holder patents is lower. So the measure might be biased by the size of the patent portfolio. To address this possibility, I look at alternative variables that capture the value of firm innovation output. The first measure is the citation weighted value of the patents (Hall et al. (2005)), a widely proxy used in the literature. After controlling for the absolute value of the patents, I find that my innovation proximity measures still matter and become even more statistically significant (Table 1.12). The second measure, proposed by Kogan et al. (2017), is the value of the patents weighted by the stock market. Taking into account this measure, I find that my innovation measures survive. These all suggest that it is important to look at the innovation interaction between the companies and not just their absolute innovation outputs.

Second, patents are not the only output of firm's innovation process. For example, trade secrets and know-how could be an alternative to patents. I take into account other types of innovation output, by controlling for capital expenditures and the change in intangible value, measured by Ewens et al. (2020). The magnitude of the effects of patent holder relative proximity on the degree of firms' integration remains the same (Table 1.13).

Third, in my main analysis I calculate patent holder relative proximity using firm's innovation portfolios that consist of up to 20-year old patents, which is the maximum life of their patent. Older patents are closer to the expiration so their value should be lower compared to the newly issued patents. In the M&A transaction the bidder should value more the newly target's patents. In the Appendix, I run regressions considering only up to 7- (10- or 15-) year patents. I find that the effect is always statistically significant and the magnitude of the effect is increasing with considering only more recent patents.

Fourth, relative proximity and integration decisions might correlate with industry concentration. Larger firms usually have greater bargaining power. To check whether that is the case, I examine the correlation between patent holder relative proximity and industry concentration. I find the correlation to be less than 5% in absolute values. I also control for firms' industry concentration in multivariate analysis. The coefficients of patent holder relative proximity remain almost unchanged (Table 1.14).

Fifth, I rule out that *patent holder relative proximity* captures geographic distance. Previous studies point out that geographic proximity increases the merger likelihood (Uysal et al. (2008), Ozcan (2015)). Connected innovation is more likely to be concentrated within the same state or even the same county (Jaffe et al. (1993), Audretsch and Feldman (1996)). I address this question by dividing the patent holder relative proximity by the median of geographic proximity. I find no difference in means between two subsamples (Table 1.15).

1.7 Conclusion

I analyze the impact of corporate innovation linkages on firm boundaries. First, I show that companies integrate more tightly with peers with closely follow-on innovation. This suggests that companies actually bargain over type, terms and conditions of the agreements.

Second, I study market reaction around the firms' deals. I find that my bargaining power measure facilitates how the interaction gains are split as opposed to drive the total deal performance. In M&As patent seekers obtain lower returns in the deals with greater patent holder relative proximity. This holds both in percentage points and dollar value. On the other hand, patent seekers experience greater announcement returns when they are able to sign strategic alliance or license patents from the peers with closely original patents (greater bargaining power).

I find that my measure of patent holder relative proximity is consistent with the bargaining power hypothesis, where greater patent holder relative proximity translates into weaker bargaining power. I use patent holder relative proximity in the context of contracting to acquire external innovation. Potentially, the application can extended to a more general case. Future research can focus on other corporate activities such as customer-supplier relationships and asset purchases. It might also be promising to study how firm's bargaining power impacts the litigation lawsuit settlement outcome.

Figure 1.1: Continuum of transaction types and degree of firms' integration

The figure shows the transaction types with respect to the degree of firms' integration.

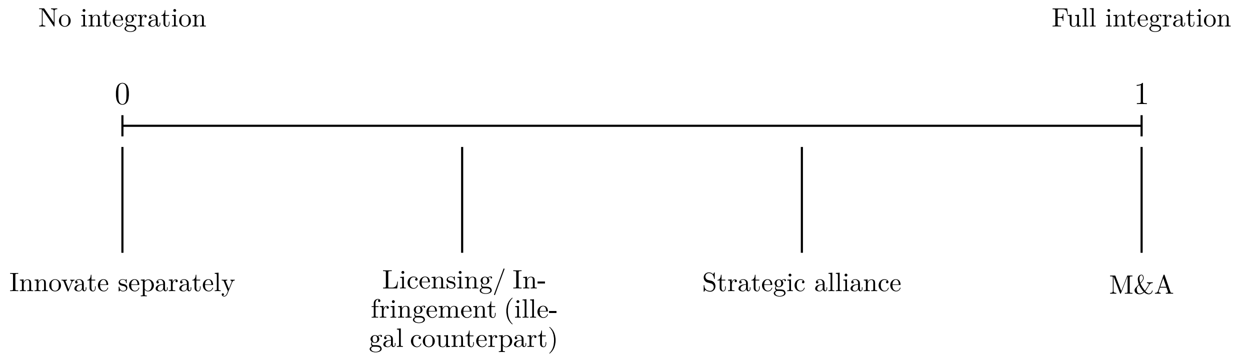


Figure 1.2: Numerical example of the model

The figure presents a numerical example of the model described in Section 1.2. Plots A and B show firms A's and B's output using different integration strategies, respectively. Plot C reports firms' combined strategy. The values of parameters of the model are the following: $a = 2$, $c_H = 0.7$, $c_B = 0.6$, $c_L = 0.3$, $f_{base} = 0.02$, $f = 0.5$, $\Phi = 0.3$, $\psi = 0.05$.

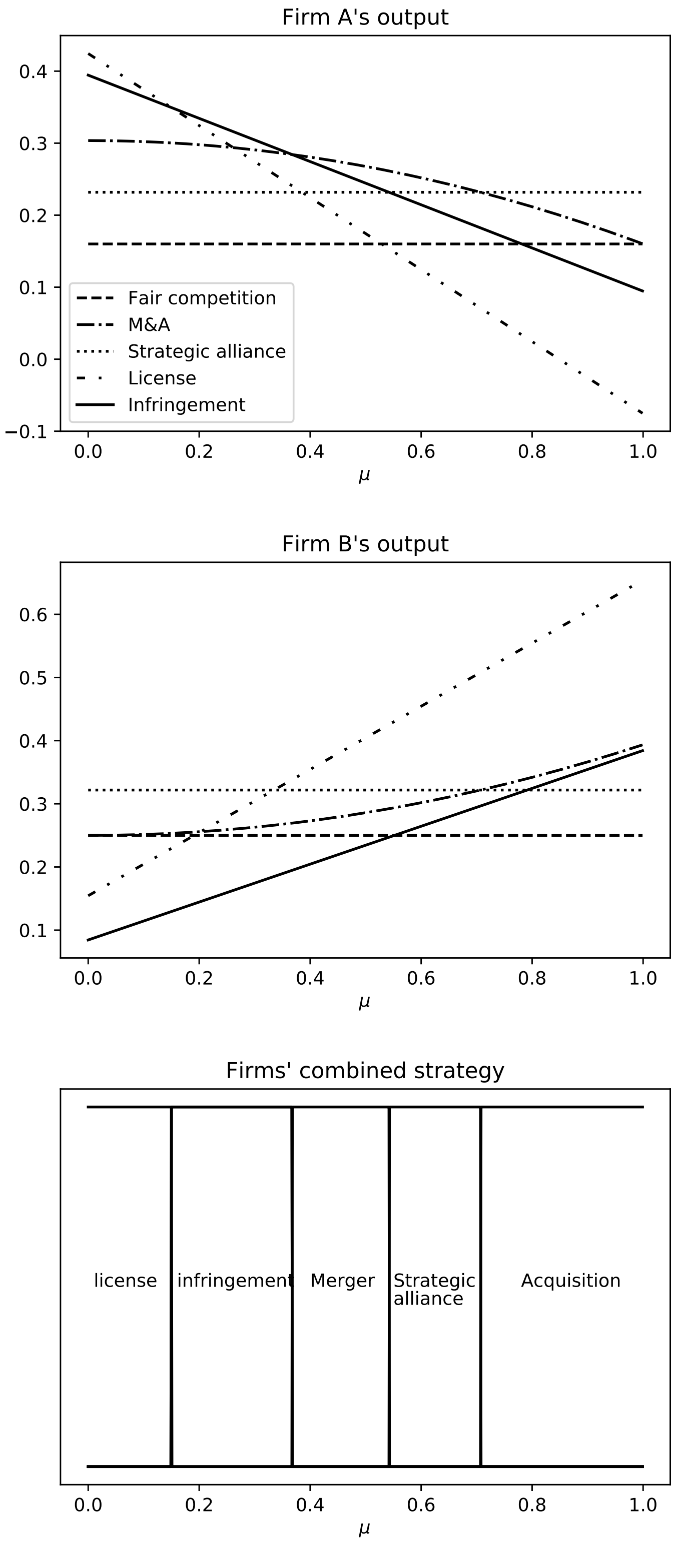


Figure 1.3: Probability of firms' integration, by type

The figure plots the probability of firms' integration (by type) with respect to patent holder relative proximity. The probabilities are calculated using multinomial logistic regression. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. In the graph the probability of no integration is suppressed.

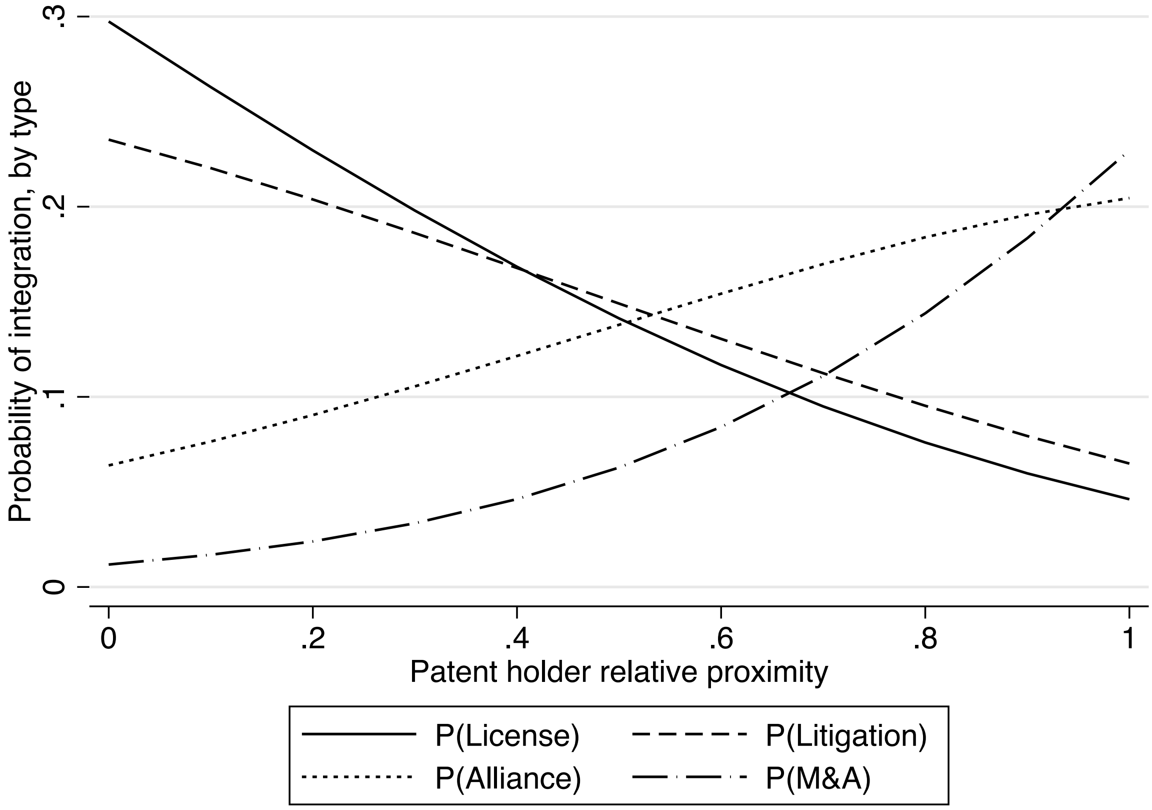


Table 1.1: Summary statistics

This table reports summary statistics of the sample based on the intersection of Thomson's One M&A dataset, SDC Platinum, USPTO patent assignment dataset, Stanford NPE litigation database, Patent litigation docket reports data, Kogan et al. (2017), CRSP and Compustat databases. Patent seeker is a firm that is willing to obtain the innovation, and patent holder is a firm with such innovation. All variables are defined in Table 1.16.

Panel A: Completed M&As

	Mean	St.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.557	0.140	0.000	0.500	0.500	0.610	1.000	932
Deal performance								
Patent seeker CAR (%)	-1.350	7.162	-25.517	-4.393	-0.777	2.266	19.832	932
Patent holder CAR (%)	25.601	30.073	-99.219	8.376	20.733	36.640	299.832	927
Combined CAR (%)	1.702	6.966	-18.600	-1.691	1.006	5.185	25.183	927
Δ\$CAR	3.782	7.010	-26.005	-0.417	2.492	6.957	37.181	927
Premium	0.669	0.420	0.001	0.354	0.587	0.906	1.993	814
ROA, 1-year	0.123	0.118	-0.393	0.084	0.134	0.187	0.355	886
ROA, 2-year	0.120	0.123	-0.434	0.084	0.137	0.188	0.330	854
ROA, 3-year	0.120	0.118	-0.466	0.084	0.134	0.183	0.312	798
Patent seeker (bidder) characteristics								
Patent seeker market equity	7.635	2.183	2.721	5.952	7.542	9.179	12.175	932
Patent seeker Tobin's Q	2.331	2.512	0.198	0.837	1.519	2.657	14.735	932
Patent seeker leverage	0.138	0.143	0.000	0.017	0.110	0.203	0.968	932
Patent seeker ROA	0.135	0.143	-0.529	0.095	0.154	0.211	0.395	927
Patent holder (target) characteristics								
Patent holder market equity	5.169	1.721	1.505	3.956	5.161	6.336	9.390	932
Patent holder Tobin's Q	1.898	2.915	0.057	0.617	1.110	2.055	48.515	932
Patent holder leverage	0.125	0.159	0.000	0.000	0.057	0.214	0.812	926
Patent holder ROA	0.025	0.265	-1.253	-0.011	0.105	0.164	0.349	925
Deal characteristics								
Relative deal size	0.400	0.610	0.000	0.048	0.186	0.534	6.944	925
Same industry	0.746	0.436	0.000	0.000	1.000	1.000	1.000	932
Hostile	0.033	0.179	0.000	0.000	0.000	0.000	1.000	932
Cash	0.424	0.494	0.000	0.000	0.000	1.000	1.000	932
Alternative bargaining power measures								
Patent seeker CW patent output	2.880	2.285	0.000	0.330	2.867	4.780	7.765	932
Patent holder CW patent output	1.413	1.516	0.000	0.000	1.075	2.523	5.631	932
Patent seeker SM patent output	3.724	3.159	0.000	0.592	3.423	6.234	10.149	932
Patent holder SM patent output	1.295	1.654	0.000	0.000	0.563	2.133	7.057	932

(continued on next page)

(Continued)

Panel B: Potential M&As

	Mean	Sd.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.516	0.064	0.000	0.500	0.500	0.500	1.000	97,627
Patent seeker (bidder) characteristics								
Patent seeker market equity	7.217	1.965	2.985	5.758	7.140	8.530	11.903	97,489
Patent seeker Tobin's Q	2.650	2.377	0.748	1.286	1.836	2.964	15.306	97,489
Patent seeker leverage	0.178	0.163	0.000	0.027	0.156	0.272	0.779	97,627
Patent seeker ROA	0.113	0.167	-0.774	0.080	0.140	0.200	0.370	97,200
Patent holder (target) characteristics								
Patent holder market equity	5.115	1.681	2.237	3.863	5.046	6.195	11.952	97,436
Patent holder Tobin's Q	2.373	2.296	0.701	1.122	1.561	2.583	14.406	97,436
Patent holder leverage	0.167	0.183	0.000	0.004	0.112	0.276	0.771	97,627
Patent holder ROA	0.012	0.263	-0.987	-0.026	0.093	0.160	0.366	97,365
Deal characteristics								
Same industry	0.537	0.499	0.000	0.000	1.000	1.000	1.000	97,627

Panel C: Completed patent acquisition/licensing deals

	Mean	St.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.463	0.161	0.000	0.380	0.500	0.518	1.000	2,479
Deal performance								
Patent seeker CAR (%)	0.339	11.431	-36.707	-5.180	0.166	5.846	37.062	2,479
Patent holder CAR (%)	0.702	10.680	-32.366	-4.521	0.482	5.440	36.785	2,479
Combined CAR (%)	0.439	8.151	-25.920	-3.784	0.342	4.508	25.401	2,471
Δ\$CAR	0.004	7.463	-24.442	-3.987	0.228	3.918	22.225	2,471
Patent seeker (assignee) characteristics								
Patent seeker market equity	8.403	2.330	2.590	6.731	8.673	10.200	12.814	2,476
Patent seeker Tobin's Q	2.126	1.550	0.755	1.168	1.601	2.405	9.356	2,476
Patent seeker leverage	0.204	0.155	0.000	0.083	0.193	0.280	0.647	2,479
Patent seeker ROA	0.113	0.133	-0.512	0.074	0.127	0.179	0.361	2,474
Patent holder (assignor) characteristics								
Patent holder market equity	8.473	2.608	2.364	6.637	8.820	10.526	12.894	2,474
Patent holder Tobin's Q	1.812	1.122	0.709	1.169	1.420	2.028	7.506	2,474
Patent holder leverage	0.238	0.158	0.000	0.132	0.217	0.313	0.674	2,479
Patent holder ROA	0.094	0.143	-0.682	0.069	0.113	0.163	0.346	2,478
Deal characteristics								
Same industry	0.435	0.496	0.000	0.000	0.000	1.000	1.000	2,479

(continued on next page)

(Continued)

Panel D: Potential patent acquisition/licensing deals

	Mean	St.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.497	0.088	0.000	0.500	0.500	0.500	1.000	172,836
Patent seeker (assignee) characteristics								
Patent seeker market equity	7.360	2.122	2.985	5.828	7.285	8.953	11.903	172,684
Patent seeker Tobin's Q	2.489	2.165	0.748	1.262	1.752	2.817	15.306	172,684
Patent seeker leverage	0.182	0.169	0.000	0.021	0.161	0.283	0.779	172,836
Patent seeker ROA	0.102	0.165	-0.774	0.069	0.128	0.186	0.370	172,139
Patent holder (assignor) characteristics								
Patent holder market equity	7.220	2.247	2.237	5.639	7.239	8.717	11.952	172,567
Patent holder Tobin's Q	2.376	2.050	0.701	1.235	1.685	2.683	14.406	172,567
Patent holder leverage	0.189	0.171	0.000	0.028	0.167	0.291	0.771	172,836
Patent holder ROA	0.090	0.187	-0.987	0.065	0.124	0.181	0.366	172,032
Deal characteristics								
Same industry	0.439	0.496	0.000	0.000	0.000	1.000	1.000	172,836

Panel E: Filed patent infringement lawsuits

	Mean	St.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.475	0.181	0.000	0.373	0.500	0.541	1.000	2,166
Lawsuit performance								
Patent seeker CAR (%)	1.127	12.605	-37.744	-5.013	0.770	7.103	42.656	2,166
Patent holder CAR (%)	0.903	12.221	-36.809	-5.332	0.704	6.446	41.179	2,166
Combined CAR (%)	0.925	9.293	-28.773	-3.771	0.763	5.563	29.785	2,166
Δ\$CAR	-0.430	8.639	-33.111	-4.587	-0.149	4.005	25.158	2,166
Patent seeker (infringer) characteristics								
Patent seeker market equity	8.253	2.103	3.311	6.903	8.339	9.831	12.355	2,166
Patent seeker Tobin's Q	2.747	2.069	0.845	1.454	2.100	3.196	13.492	2,166
Patent seeker leverage	0.186	0.164	0.000	0.031	0.163	0.286	0.691	2,166
Patent seeker ROA	0.123	0.139	-0.495	0.087	0.135	0.193	0.387	2,160
Patent holder (plaintiff) characteristics								
Patent holder market equity	8.435	2.376	2.751	6.667	8.524	10.573	12.285	2,166
Patent holder Tobin's Q	2.713	1.870	0.803	1.464	2.069	3.249	10.883	2,166
Patent holder leverage	0.175	0.153	0.000	0.044	0.157	0.255	0.789	2,166
Patent holder ROA	0.124	0.143	-0.501	0.085	0.143	0.205	0.383	2,166
Deal characteristics								
Same industry	0.771	0.420	0.000	1.000	1.000	1.000	1.000	2,166

(continued on next page)

(Continued)

Panel F: Potential patent infringement lawsuits

	Mean	St.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.495	0.083	0.000	0.500	0.500	0.500	1.000	207,316
Patent seeker (infringer) characteristics								
Patent seeker market equity	7.669	2.010	2.985	6.219	7.755	9.086	11.903	207,130
Patent seeker Tobin's Q	2.954	2.465	0.748	1.480	2.136	3.462	15.306	207,130
Patent seeker leverage	0.177	0.175	0.000	0.012	0.144	0.283	0.779	207,316
Patent seeker ROA	0.089	0.188	-0.774	0.060	0.128	0.191	0.370	206,738
Patent holder (plaintiff) characteristics								
Patent holder market equity	7.786	2.144	2.237	6.284	7.954	9.253	11.952	207,184
Patent holder Tobin's Q	2.905	2.377	0.701	1.470	2.137	3.302	14.406	207,184
Patent holder leverage	0.182	0.173	0.000	0.021	0.156	0.280	0.771	207,316
Patent holder ROA	0.095	0.193	-0.987	0.067	0.135	0.195	0.366	206,691
Deal characteristics								
Same industry	0.612	0.487	0.000	0.000	1.000	1.000	1.000	207,316

Panel G: Completed strategic alliances

	Mean	St.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.517	0.160	0.000	0.473	0.500	0.556	1.000	1,922
Strategic alliance performance								
Patent seeker CAR (%)	2.680	21.322	-53.128	-9.600	1.692	13.238	72.965	1,922
Patent holder CAR (%)	4.412	24.755	-61.859	-9.169	2.924	16.011	82.859	1,922
Combined CAR (%)	3.055	16.757	-44.592	-6.418	2.631	11.530	55.560	1,919
Δ\$CAR	0.465	15.250	-40.207	-8.529	-0.009	9.098	46.335	1,919
Patent seeker characteristics								
Patent seeker market equity	8.368	2.374	2.661	6.621	8.756	10.266	12.037	1,921
Patent seeker Tobin's Q	2.894	2.807	0.827	1.310	1.876	3.226	16.138	1,921
Patent seeker leverage	0.167	0.149	0.000	0.030	0.145	0.265	0.646	1,922
Patent seeker ROA	0.101	0.181	-0.648	0.074	0.135	0.193	0.418	1,920
Patent holder characteristics								
Patent holder market equity	7.815	2.312	2.479	6.058	7.946	9.742	11.628	1,920
Patent holder Tobin's Q	3.619	3.352	0.782	1.516	2.383	4.209	18.461	1,920
Patent holder leverage	0.137	0.151	0.000	0.002	0.098	0.222	0.729	1,922
Patent holder ROA	0.106	0.205	-0.856	0.064	0.139	0.224	0.418	1,920
Deal characteristics								
Same industry	0.724	0.447	0.000	0.000	1.000	1.000	1.000	1,922

(continued on next page)

(Continued)

Panel H: Potential strategic alliances

	Mean	St.dev.	Min	p25	Median	p75	Max	N
Patent holder relative proximity	0.497	0.085	0.000	0.500	0.500	0.500	1.000	129,286
Patent seeker characteristics								
Patent seeker market equity	7.286	2.274	2.661	5.471	7.393	9.021	12.037	129,043
Patent seeker Tobin's Q	3.044	2.818	0.827	1.379	2.006	3.472	16.138	129,043
Patent seeker leverage	0.158	0.157	0.000	0.013	0.122	0.254	0.646	129,286
Patent seeker ROA	0.108	0.183	-0.648	0.074	0.142	0.204	0.418	128,798
Patent holder characteristics								
Patent holder market equity	6.894	2.101	2.479	5.378	6.865	8.410	11.628	129,088
Patent holder Tobin's Q	3.036	2.892	0.782	1.374	2.029	3.487	18.461	129,088
Patent holder leverage	0.149	0.162	0.000	0.006	0.103	0.241	0.729	129,286
Patent holder ROA	0.099	0.197	-0.856	0.066	0.135	0.202	0.418	128,586
Deal characteristics								
Same industry	0.536	0.499	0.000	0.000	1.000	1.000	1.000	129,286

Table 1.2: Firm's innovation strategies, by year

This table reports the number of M&As, strategic alliances, licensing deals and patent litigation lawsuits, by year.

Year	License (1)	Lawsuit (2)	Alliance (3)	M&A (4)
1975	2	0	0	0
1978	0	0	0	4
1979	0	0	0	2
1980	9	0	0	6
1981	29	0	0	16
1982	26	0	0	11
1983	41	0	0	13
1984	25	0	0	12
1985	28	1	0	25
1986	33	1	12	31
1987	33	1	15	21
1988	36	2	12	20
1989	26	7	36	25
1990	43	28	41	10
1991	27	34	94	9
1992	31	45	119	12
1993	43	54	117	12
1994	70	47	162	29
1995	67	49	146	41
1996	52	49	117	34
1997	81	71	169	53
1998	94	95	156	70
1999	91	61	150	62
2000	90	125	99	55
2001	140	169	65	49
2002	191	162	73	30
2003	187	202	63	34
2004	182	189	48	32
2005	134	135	67	44
2006	148	105	58	40
2007	143	123	30	34
2008	168	166	38	36
2009	110	127	22	33
2010	99	118	13	27
Total	2,479	2,166	1,922	932

Table 1.3: Prediction of firms' integration

In specifications (1)–(2), the table reports the estimates of linear probability model:

$$\mathbb{1}\{interaction_{ijt}\} = \alpha + \beta Patent\ holder\ relative\ proximity_{ijt} + \epsilon_{ijt}$$

where $\mathbb{1}\{interaction_{ijt}\}$ equals one when the interaction between firms i (patent holder) and j (patent seeker) is announced at time t, and zero when the interaction does not take place. In specification (4), the table reports the estimates of logistic regression. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. Potential interactions are identified thought the matching procedure: (1) their market value is 70%-130% of the actual firms' market value two months before the interaction; (2) they have at least one patent issued before the interaction; (3) they are active firms in the year of the interaction; (4) they operate in the same industry as the actual firms. I identify top 10 potential firms for each actual firm that respect (1)-(4) criteria above and create all possible pairs among potential firms. t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: Predicting firm interaction

	LPM (1)	LPM (2)	LPM (3)	Logit (4)
Patent holder relative proximity	-0.016	-0.016	-0.018**	-0.828***
	(-1.42)	(-1.50)	(-1.99)	(-2.61)
Controls	N	N	Y	Y
Year FE	N	Y	Y	Y
Industry FE	N	Y	Y	Y
N	550,366	550,366	545,268	545,268
R^2	0.000	0.001	0.008	0.055

Panel B: Predicting M&A transactions

	LPM (1)	LPM (2)	LPM (3)	Logit (4)
Patent holder relative proximity	0.075***	0.077***	0.074***	4.282***
	(4.15)	(4.15)	(3.99)	(5.87)
Controls	N	N	Y	Y
Year FE	N	Y	Y	Y
Industry FE	N	Y	Y	Y
N	93,550	93,550	92,680	92,680
R^2	0.003	0.003	0.005	0.042

(continued on next page)

(Continued)

Panel C: Predicting strategic alliances

	LPM (1)	LPM (2)	LPM (3)	Logit (4)
Patent holder relative proximity	0.040**	0.039***	0.037***	0.968***
	(2.60)	(2.68)	(2.88)	(3.70)
Controls	N	N	Y	Y
Year FE	N	Y	Y	Y
Industry FE	N	Y	Y	Y
N	124,334	124,334	122,886	122,886
R^2	0.001	0.003	0.013	0.084

Panel D: Predicting licensing transactions

	LPM (1)	LPM (2)	LPM (3)	Logit (4)
Patent holder relative proximity	-0.063***	-0.063***	-0.059***	-2.195***
	(-2.72)	(-3.15)	(-3.36)	(-3.56)
Controls	N	N	Y	Y
Year FE	N	Y	Y	Y
Industry FE	N	Y	Y	Y
N	161,955	161,955	160,469	160,469
R^2	0.002	0.005	0.016	0.103

Panel E: Predicting patent infringement lawsuits

	LPM (1)	LPM (2)	LPM (3)	Logit (4)
Patent holder relative proximity	-0.030***	-0.030***	-0.031***	-1.699***
	(-3.64)	(-3.65)	(-4.58)	(-4.39)
Controls	N	N	Y	Y
Year FE	N	Y	Y	Y
Industry FE	N	Y	Y	Y
N	170,527	170,527	169,233	169,233
R^2	0.001	0.001	0.007	0.049

Table 1.4: Prediction of firms' degree of integration using multinomial logistic regression

In specifications (1)–(2) of Panel A, the table reports the estimates of multinomial logistic regression:

$$Degree\ of\ Interaction_{i,j,k} = \alpha + \beta Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{ijt}$$

where $Degree\ of\ Interaction_{i,j,k}$ equals one if there is no integration between firms i and j, 2 in case of licensing agreement, 3 in case of patent infringement lawsuit, 4 in case of strategic alliance, and 5 in case of merge and acquisition. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: multinomial logistic regression on firms' integration types

Dependent variable		Mlogit (1)	Mlogit (2)	Mlogit (3)
1 (No integration)	Patent holder relative proximity		(Base outcome)	
2 (License)	Patent holder relative proximity	-4.380***	-4.610***	-2.189***
		(-4.08)	(-4.37)	(-3.07)
3 (Litigation)	Patent holder relative proximity	-3.044***	-2.868***	-1.290***
		(-4.14)	(-4.41)	(-3.48)
4 (Strategic alliance)	Patent holder relative proximity	2.172***	1.813***	0.854**
		(2.84)	(2.63)	(2.18)
5 (M&A)	Patent holder relative proximity	5.098***	5.418***	4.454***
		(7.12)	(6.53)	(8.26)
	Controls	N	N	Y
	Industry FE	N	Y	Y
	N	550,366	550,366	545,268
	pseudo R^2	0.010	0.032	0.083

(continued on next page)

(Continued)

Panel B: Factor change in the odds of “integration degree"

			b	z	$P > \|z\|$	e^b	$e^b StdX$
No Integration	vs	License	2.1805	10.385	0.000	8.851	1.209
No Integration	vs	Infringement	1.2831	6.021	0.000	3.608	1.118
Infringement	vs	License	0.8974	3.015	0.003	2.453	1.081
Strategic alliance	vs	No Integration	0.8628	3.935	0.000	2.37	1.078
Strategic alliance	vs	License	3.0433	10.058	0.000	20.975	1.304
Strategic alliance	vs	Infringement	2.1459	7.042	0.000	8.55	1.206
M&A	vs	No Integration	4.4504	13.073	0.000	85.659	1.474
M&A	vs	License	6.6309	16.592	0.000	758.17	1.782
M&A	vs	Infringement	5.7335	14.29	0.000	309.046	1.648
M&A	vs	Strategic alliance	3.5876	8.878	0.000	36.146	1.367

Table 1.5: Patent seeker announcement returns

In Panel A (B) the table reports the estimates of:

$$CAR_{j,k} = \alpha + \beta Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{i,j,k}$$

where $CAR_{j,k}$ is the three-day $[-1, +1]$ window patent seeker percentage abnormal returns around the M&A (strategic alliance) announcement date. In Panel C (Panel D) $CAR_{j,k}$ is the $[-10, +10]$ window assignee (infringer) percentage abnormal returns around the licensing signed date (patent infringement lawsuit filing date). *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: M&A deals (Bidder side)

	(1)	(2)	(3)
Patent holder relative proximity	5.218***	5.905***	4.231**
	(4.14)	(5.16)	(2.42)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	932	932	907
R^2	0.010	0.084	0.142

Panel B: Strategic alliances (Patent seeker side)

	(1)	(2)	(3)
Patent holder relative proximity	-4.453***	-4.856***	-2.596**
	(-6.82)	(-9.23)	(-2.32)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	1,922	1,922	1,915
R^2	0.014	0.032	0.069

(continued on next page)

(Continued)

Panel C: Licensing deals (Assignee side)

	(1)	(2)	(3)
Patent holder relative proximity	-2.188	-2.872**	-3.078**
	(-1.50)	(-2.40)	(-2.27)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,479	2,478	2,464
R^2	0.001	0.031	0.038

Panel D: Patent infringement lawsuits (Infringer side)

	(1)	(2)	(3)
Patent holder relative proximity	-0.002	-0.003	-0.000
	(-0.12)	(-0.27)	(-0.02)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,166	2,163	2,157
R^2	0.000	0.031	0.041

Table 1.6: Patent holder announcement returns

In Panel A (B) the table reports the estimates of:

$$CAR_{i,k} = \alpha + \beta Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{i,j,k}$$

where $CAR_{i,k}$ is the three-day $[-1, +1]$ window patent holder percentage abnormal returns around the M&A (strategic alliance) announcement date. In Panel C (Panel D) $CAR_{i,k}$ is the $[-10, +10]$ window assignor (plaintiff) percentage abnormal returns around the licensing signed date (patent infringement lawsuit filing date). *Patent holder relative proximity*$_{i,j,t}$ is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around firm $i \times$ firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: M&A deals (Target side)

	(1)	(2)	(3)
Patent holder relative proximity	25.071***	19.374***	-2.650
	(5.16)	(5.19)	(-0.34)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
Observations	927	927	906
R^2	0.018	0.097	0.192

Panel B: Strategic alliances (Patent holder side)

	(1)	(2)	(3)
Patent holder relative proximity	2.309***	2.716***	-1.330**
	(3.75)	(3.45)	(-2.21)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	1,922	1,922	1,915
R^2	0.003	0.027	0.074

(continued on next page)

(Continued)

Panel C: Licensing deals (Assignor side)

	(1)	(2)	(3)
Patent holder relative proximity	3.806***	3.037**	2.517**
	(3.56)	(2.50)	(2.01)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,479	2,478	2,464
R^2	0.003	0.030	0.034

Panel D: Patent infringement lawsuits (Plaintiff side)

	(1)	(2)	(3)
Patent holder relative proximity	0.003	0.007	0.025
	(0.12)	(0.27)	(0.74)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,166	2,163	2,157
R^2	0.000	0.035	0.042

Table 1.7: Patent holder relative dollar gains

The table reports the estimates of:

$$\Delta\$CAR_{i,j,k} = \alpha + Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{i,j,k}$$

where the dependent variable is $\Delta\$CAR_{i,j,k}$ defined as the difference between dollar value of patent holder announcement returns and patent seeker announcement returns, scaled by the sum of patent holder and patent seeker market equity two months prior to the announcement of interaction k. *Patent holder relative proximity*$_{i,j,k}$ is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: M&A deals

	(1)	(2)	(3)
Patent holder relative proximity	-9.438***	- 9.495***	-4.833**
	(-6.35)	(-7.12)	(-2.54)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
Observations	927	927	906
R^2	0.039	0.105	0.176

Panel B: Strategic alliances

	(1)	(2)	(3)
Patent holder relative proximity	-0.679***	-0.817***	-0.873***
	(-3.29)	(-5.46)	(-2.67)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	1,909	1,909	1,905
R^2	0.001	0.010	0.020

(continued on next page)

(Continued)

Panel C: Licensing deals

	(1)	(2)	(3)
Patent holder relative proximity	1.060	0.821	2.119**
	(1.00)	(0.86)	(2.32)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,471	2,470	2,464
R^2	0.001	0.022	0.027

Panel D: Patent infringement lawsuits

	(1)	(2)	(3)
Patent holder relative proximity	1.485**	1.774**	1.796
	(2.07)	(2.32)	(1.58)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,166	2,163	2,157
R^2	0.001	0.023	0.033

Table 1.8: Combined announcement returns

Panel A (B) reports the estimates of

$$CAR_{i,j,k} = \alpha + \beta Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{i,j,k}$$

where $CAR_{i,j,k}$ is the three-day $[-1, +1]$ window combined cumulative abnormal percentage returns (CARs) around M&A (strategic alliance) announcement date. In Panels C and D $CAR_{i,j,k}$ is calculated over the $[-10, +10]$ day window. The weights are based on the companies' market value two months prior to interaction announcement. *Patent holder relative proximity*$_{i,j,k}$ is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: M&A deals

	(1)	(2)	(3)
Patent holder relative proximity	-1.740*	-1.048	1.365
	(-1.87)	(-1.05)	(0.96)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
Observations	927	927	906
R^2	0.001	0.080	0.181

Panel B: Strategic alliances

	(1)	(2)	(3)
Patent holder relative proximity	-0.002	-0.001	0.001
	(-0.90)	(-0.55)	(0.23)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	1,919	1,919	1,915
R^2	0.000	0.020	0.025

(continued on next page)

(Continued)

Panel C: Licensing deals

	(1)	(2)	(3)
Patent holder relative proximity	0.905	0.157	-0.183
	(1.21)	(0.21)	(-0.21)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,471	2,470	2,464
R^2	0.000	0.033	0.041

Panel D: Patent infringement lawsuits

	(1)	(2)	(3)
Patent holder relative proximity	0.002	0.003	0.013
	(0.12)	(0.30)	(0.88)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
N	2,166	2,163	2,157
R^2	0.000	0.037	0.045

Table 1.9: Premiums

The table reports the estimates of:

$$Premium_{i,j,k} = \alpha + \beta Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{i,j,k}$$

where *Premium* is the value of the merger transaction, scaled by the target's market value 43 trading days prior to the M&A announcement, minus 1 (Officer (2003)). *Patent holder relative proximity*$_{i,j,k}$ is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: M&A deals

	(1)	(2)	(3)
Patent holder relative proximity	-1.053***	-0.899***	-0.068*
	(-12.76)	(-17.00)	(-1.81)
Controls	N	N	Y
Year FE	N	Y	Y
Industry FE	N	Y	Y
Observations	925	925	907
R^2	0.082	0.166	0.932

Table 1.10: Long-term returns

The table reports the estimates of the patent seeker average monthly abnormal returns using Fama-French (1993) 3-factor model and Fama-Macbeth regression. Monthly abnormal returns are based on the daily average of abnormal returns over 1 (2 or 3) years (depending on the specification) followed the deal announcement date. The market return is the value-weighted return. Panel A (C) estimates are based on three portfolios. The first portfolio consists of the full sample of the M&A (licensing) deals. The second (third) one includes all the M&A (licensing) deals with patent holder relative proximity less (greater or equal) than 0.5. Panels C and D use Fama-French approach. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. *t*-statistics, reported in parentheses, are based on robust errors. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: M&A deals. Calendar-time approach

	1 year (1)	2 years (2)	3 years (3)
Full sample	0.224	0.192	0.181
	(1.39)	(1.33)	(1.26)
M&As with low patent holder relative proximity	0.368*	0.225	0.209
	(1.82)	(1.40)	(1.27)
M&As with high patent holder relative proximity	0.135	0.176	0.172
	(0.73)	(1.04)	(1.08)
Wald test	0.39	0.83	0.87

Panel B: M&A deals. Fama-MacBeth regression

	1 year (1)	2 years (2)	3 years (3)
Patent holder relative proximity	0.757	0.573	0.072
	(1.45)	(1.08)	(0.14)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Observations	10,560	20,757	30,496
R^2	0.027	0.025	0.023

(continued on next page)

(Continued)

Panel C: Licensing deals. Calendar-time approach

	1 year (1)	2 years (2)	3 years (3)
Full sample	0.366***	0.331***	0.340***
	(2.90)	(2.94)	(3.18)
License with low patent holder relative proximity	0.462***	0.453***	0.411***
	(2.72)	(3.09)	(2.94)
License with high patent holder relative proximity	0.289***	0.228*	0.281***
	(2.14)	(1.94)	(2.60)
Wald test	0.51	0.32	0.54

Panel D: Licensing deals. Fama-MacBeth regression

	1 year (1)	2 years (2)	3 years (3)
Patent holder relative proximity	-0.188	-0.774	-0.319
	(-0.20)	(-1.18)	(-0.59)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
N	14,102	27,730	39,934
R^2	0.076	0.073	0.072

Table 1.11: Post-deal operating performance

The table reports the estimates of the post-deal operating performance, ROA. Firm portfolios include all patents, that are filed before the M&A (licensing) announcement and issued not prior that 20 years to the merger announcement, depending on the specification. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around bidder × target industry (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: M&A deals

	1 year (1)	2 years (2)	3 years (3)
Patent holder relative proximity	-0.008	0.009	-0.016
	(-0.57)	(0.86)	(-0.91)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
N	863	831	777
R^2	0.682	0.598	0.542

Panel B: Licensing deals

	1 year (1)	2 years (2)	3 years (3)
Patent holder relative proximity	-0.002	-0.010	-0.016
	(-0.16)	(-0.93)	(-1.50)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
N	2,280	2,187	2,098
R^2	0.631	0.601	0.554

Table 1.12: Bidder announcement returns using alternative measures

The table reports the estimates of bidder cumulative abnormal percentage returns (CARs) using alternative measures of bargaining power. *SM innovation output* is the logarithm of the firm's innovation output that weighs patents using stock market reaction (Kogan et al. (2017)). *CW innovation output* is the logarithm of the citation-weighted patent portfolio of the firm. Both SM and CW innovation outputs are measured one year before the M&A announcement and are taken from Kogan et al. (2017) dataset. t-statistics, reported in parentheses, are based on standard errors clustered around bidder × target industry (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)
Patent holder relative proximity	4.231**	4.358**	5.332***	4.477**
	(2.42)	(2.13)	(3.09)	(2.62)
Bidder SM innovation output		-0.180		0.411
		(-1.24)		(1.00)
Target SM innovation output		-0.230		-0.613***
		(-1.44)		(-4.81)
Bidder CW innovation output			-0.336***	-0.706*
			(-2.89)	(-1.87)
Target CW innovation output			-0.067	0.437**
			(-0.38)	(2.50)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
N	907	907	907	907
R^2	0.142	0.146	0.147	0.152

Table 1.13: Prediction of firms' degree of integration., controlling for other types of intangibles

The table reports the estimates of multinomial logistic regression:

$$Degree\ of\ Interaction_{i,j,k} = \alpha + \beta Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{ijt}$$

where $Degree\ of\ Interaction_{i,j,k}$ equals one if there is no integration between firms i and j, 2 in case of licensing agreement, 3 in case of patent infringement lawsuit, 4 in case of strategic alliance, and 5 in case of merge and acquisition. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. In specification (1) I report baseline results, while in specifications (2), (3) and (4) I control for CAPEX or/and change in knowledge value calculated by Ewens et al. (2020). t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A: multinomial logistic regressions

	(1)	(2)	(3)	(4)
1 (No integration)	Baseline			
2 (License)				
Patent holder relative proximity	-2.181***	-2.315***	-2.102***	-2.219***
	(-3.06)	(-3.28)	(-3.59)	(-3.74)
Patent seeker's CAPEX		4.201***		3.704***
		(4.10)		(3.65)
Patent holder's CAPEX		3.401***		2.879***
		(5.17)		(3.78)
Patent seeker's knowledge capital			0.278***	0.262***
			(2.76)	(2.63)
Patent holder's knowledge capital			0.301***	0.275***
			(4.05)	(3.82)
3 (Infringement)				
Patent holder relative proximity	-1.283***	-1.234***	-1.101***	-1.042***
	(-3.45)	(-3.41)	(-3.30)	(-3.19)
Patent seeker's CAPEX		1.413**		0.871*
		(2.22)		(1.82)
Patent holder's CAPEX		-0.268		-0.929
		(-0.36)		(-1.24)
Patent seeker's knowledge capital			0.181***	0.176***
			(3.55)	(3.56)
Patent holder's knowledge capital			0.154**	0.155**
			(2.14)	(2.09)

(continued on next page)

(Continued)

4 (Strategic alliance)				
Patent holder relative proximity	0.863**	0.771**	0.665**	0.596**
	(2.20)	(2.25)	(2.53)	(2.33)
Patent seeker's CAPEX		5.294***		4.763***
		(13.85)		(9.57)
Patent holder's CAPEX		5.589***		5.177***
		(12.58)		(7.48)
Patent seeker's knowledge capital			0.417**	0.380**
			(2.22)	(2.11)
Patent holder's knowledge capital			0.460***	0.443***
			(5.56)	(5.91)
5 (M&A)				
Patent holder relative proximity	4.450***	4.437***	4.331***	4.306***
	(8.23)	(7.45)	(7.41)	(6.66)
Patent seeker's CAPEX		-4.397***		-4.560***
		(-5.17)		(-4.81)
Patent holder's CAPEX		1.525***		1.169*
		(2.76)		(1.69)
Patent seeker's knowledge capital			0.022	0.026
			(0.97)	(1.10)
Patent holder's knowledge capital			0.076**	0.089**
			(2.48)	(2.45)
N	540,514	530,338	469,301	460,407

Panel B: Factor change in the odds of "integration degree"

			b	z	$P > \|z\|$	e^b	$e^b StdX$
No Integration	vs	License	2.219	10.615	0.000	9.200	1.225
No Integration	vs	Infringement	1.043	4.861	0.000	2.836	1.100
Infringement	vs	License	1.177	3.952	0.000	3.244	1.114
Strategic alliance	vs	No Integration	0.596	2.731	0.006	1.815	1.056
Strategic alliance	vs	License	2.815	9.360	0.000	16.695	1.294
Strategic alliance	vs	Infringement	1.638	5.376	0.000	5.147	1.162
M&A	vs	No Integration	4.306	11.846	0.000	74.123	1.483
M&A	vs	License	6.525	15.573	0.000	681.909	1.817
M&A	vs	Infringement	5.348	12.686	0.000	210.231	1.632
M&A	vs	Strategic alliance	3.710	8.768	0.000	40.845	1.404

Table 1.14: Prediction of firms' degree of integration, controlling for industry competition

The table reports the estimates of multinomial logistic regression:

$$Degree\ of\ Interaction_{i,j,k} = \alpha + \beta Patent\ holder\ relative\ proximity_{i,j,k} + \epsilon_{ijt}$$

where $Degree\ of\ Interaction_{i,j,k}$ equals one if there is no integration between firms i and j, 2 in case of licensing agreement, 3 in case of patent infringement lawsuit, 4 in case of strategic alliance, and 5 in case of merge and acquisition. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. In specification (1) I report baseline results, while in specification (2) I control for market concentration in patent holder and patent seeker industries. I define industry according to 48 Fama-French industry classification. t-statistics, reported in parentheses, are based on standard errors clustered around firm i × firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)
1 (No integration)	Baseline	
2 (License)		
Patent holder relative proximity	-2.181***	-2.081***
	(-3.06)	(-2.93)
Patent holder's industry HHI		0.089
		(0.11)
Patent seeker's industry HHI		3.560***
		(3.07)
3 (Infringement)		
Patent holder relative proximity	-1.283***	-1.279***
	(-3.45)	(-3.49)
Patent holder's industry HHI		0.874
		(1.26)
Patent seeker's industry HHI		0.167
		(0.19)
4 (Strategic alliance)		
Patent holder relative proximity	0.863**	0.754**
	(2.20)	(2.24)
Patent holder's industry HHI		4.191***
		(2.85)
Patent seeker's industry HHI		4.002***
		(3.54)
5 (M&A)		
Patent holder relative proximity	4.450***	4.448***
	(8.23)	(8.29)
Patent holder's industry HHI		0.291
		(0.28)
Patent seeker's industry HHI		-0.075
		(-0.11)
N	540,514	540,514

Table 1.15: Geography

The table reports sample splits of *patent holder relative proximity* by geographic distance. Geographic distance is the geodetic distance between firms' headquarters. I divide the sample by the median of geographic distance. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. t-statistics, reported in parentheses, are based on standard errors clustered around firm $i \times$ firm j industries (12 Fama-French industry). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

	High (1)	Low (2)	t-stat (3)
Patent holder relative proximity			
Full sample	0.503	0.503	-0.47
Completed deals	0.516	0.516	0.02
Potential deals	0.503	0.503	-0.56

Table 1.16: Variable definitions

Variable	Definition
Key variable of interest	
Patent holder relative proximity	Difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. Sources: CRSP, Kogan et al. (2017), Thomson One.
Deal performance	
Firm i's CAR (%)	Cumulative abnormal percentage return of firm i around the deal announcement date. Three-day window $[-1,+1]$ is used for M&As and strategic alliances; 21-day window $[-10,+10]$ is used for license and patent infringement lawsuits. Source: CRSP.
Combined CAR (%)	Cumulative abnormal percentage return of value-weighted portfolio around the interaction announcement date. The weights are based on the companies' market value two months prior to the interaction announcement. Source: CRSP.
$\Delta\$CAR$	The difference between patent holder \$CAR and patent seeker \$CAR, scaled by the sum of patent holder and patent seeker market equities two months before the deal announcement (Ahern (2012)). \$CAR is the three-day dollar abnormal return for M&As and strategic alliances, and the 21-day dollar abnormal returns for licensing deals and patent infringement lawsuits. Market return is the value weighted market return. Source: CRSP.
Premium	Transaction value, scaled by the patent holder market equity of 43 trading days prior to interaction announcement, minus 1 (Officer (2003)). Sources: CRSP, Thomson One.
Firm Characteristics	
Market equity	Natural logarithm of firm's market value in millions two months prior to the deal announcement date. Source: CRSP.
Tobin's Q	Market value over book value of assets. Source: Compustat.
Leverage	Book value of debt over book value of assets. Source: Compustat.
ROA	Operating income before depreciation, normalized by book value of assets. Source: Compustat.

(continued on next page)

(Continued)

Integration characteristics	
Relative deal size	Deal value, scaled by the patent seeker market equity. Sources: CRSP, Thomson One.
Same industry	Equal one if both firms are from the same industry, and zero, otherwise. Industry is defined according 12 Fama-French industry classification. Source: Thomson One.
Attitude	Equal one when there is a hostile takeover, and zero, otherwise. Source: Thomson One.
Cash	Equal one if cash is the term of payment that the patent seeker uses, and zero, otherwise. Source: Thomson One.
Alternative measures	
SM innovation output	Natural logarithm of the sum of one and the total dollar value of innovation produced by the firm in year t, based on the stock market. Source: Kogan et al. (2017).
CW innovation output	Natural logarithm of the firm's citation weighted patent value. Source: Kogan et al. (2017).
Geographic distance	Geodetic distance between the headquarters of two firms. Source: Compustat.

Appendix

1.A Solution of theoretical model

Firm A can choose between strategies competition and infringement without firm B's approval, while other strategies (licensing, strategic alliance and M&A) can be only chosen if only both firms agree. Firms accept any form of cooperation if they both are better off compared to their outside feasible options.

I first find the conditions when Firm A prefers competition over infringement. As π_A^{Comp} is constant in μ and π_A^{Inf} is strictly decreasing in μ there exists $\bar{\mu}$, below which infringement is the outside option of firm A, and above which competition is the outside option of firm A.

$$\bar{\mu} = \frac{(a+c_B-2c_L)^2-(a+c_B-2c_H)^2}{9\Phi} - \frac{\psi}{\Phi} = \frac{4(c_H-c_L)(a+c_B-c_H-c_L)}{9\Phi} - \frac{\psi}{\Phi}$$

If $\bar{\mu} > 1$, firm A's outside option is always to infringe. If $\bar{\mu} \leq 0$, firm A's outside option is always to fairly compete. If $0 < \bar{\mu} \leq 1$, firm A's outside option is to infringe for $\mu < \bar{\mu}$ and to fairly compete $\mu \geq \bar{\mu}$.

Theorem A.1. Suppose competition and infringement are feasible ($c_H > a$ and $\mu \leq \dfrac{(a+c_B-2c_L)^2}{9\Phi} - \dfrac{\psi}{\Phi}$).

Case 1. Firm A infringes firm B if $\mu < \bar{\mu}$ and one of the two conditions holds [1) $\Phi < f$ and $\mu > \dfrac{\psi - f_{base}}{f-\Phi}$; 2) $\Phi \geq f$ and $\mu > \dfrac{\psi + f_{base}}{\Phi - f}$] and if at least one condition is satisfied:

1. $\pi_A^{Inf} > \pi_A^{Alliance}$ and $\pi_A^{Inf} > \pi_A^{Acq}$;
2. $\pi_A^{Acq} \geq \pi_A^{Inf} > \pi_A^{Alliance}$ and $\pi_B^{Inf} > \pi_B^{Acq}$;
3. $\pi_A^{Alliance} \geq \pi_A^{Inf} > \pi_A^{Acq}$ and $\pi_B^{Inf} > \pi_B^{Alliance}$;
4. $\pi_B^{Inf} > \pi_B^{Alliance}$ and $\pi_B^{Inf} > \pi_B^{Acq}$.

Case 2. Firms agree on licensing agreement if:

- If $\mu \geq \bar{\mu}$, $\mu < \dfrac{4(c_H-c_L)(a+c_B-c_H-c_L)}{9f} - \dfrac{f_{base}}{f}$ and any of two conditions is satisfied: 1) $\mu \geq \frac{1}{\sqrt{2}}$ and $\pi_B^{Acq} < \pi_B^{License}$ or 2) $\mu < \frac{1}{\sqrt{2}}$ and $\pi_B^{Alliance} < \pi_B^{License}$.

- If $\mu < \bar{\mu}$ and one of the two conditions holds [1)$\Phi < f$ and $\mu \leq \frac{\psi - f_{base}}{f - \Phi}$; 2) $\Phi \geq f$ and $\mu \leq \frac{\psi + f_{base}}{\Phi - f}$] and if at least one condition is satisfied:
  1. $\pi_A^{Inf} > \pi_A^{Acq}$ and $\pi_A^{Inf} > \pi_A^{Alliance}$;
  2. $\pi_A^{Alliance} \geq \pi_A^{Inf} > \pi_A^{Acq}$ and $\pi_B^{License} \geq \pi_B^{Alliance}$;
  3. $\pi_A^{Acq} \geq \pi_A^{Inf} > \pi_A^{Alliance}$ and $\pi_B^{License} \geq \pi_B^{Acq}$;
  4. $\pi_B^{License} \geq \pi_B^{Alliance}$ and $\pi_B^{License} \geq \pi_B^{Acq}$.

Case 3. Firms build strategic alliance if

- $\mu \geq \bar{\mu}$, $\mu \geq \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$ and $\mu < \frac{1}{\sqrt{2}}$;
- $\mu \geq \bar{\mu}$, $\mu < \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$ and $\mu < \frac{1}{\sqrt{2}}$ and $\pi_B^{Alliance} \geq \pi_B^{License}$;
- If $\mu < \bar{\mu}$ and at least one condition is satisfied:
  1. $\pi_A^{Alliance} \geq \pi_A^{Inf} > \pi_A^{Acq}$, $\pi_B^{Alliance} \geq \pi_B^{License}$ and $\pi_B^{Alliance} \geq \pi_B^{Inf}$;
  2. $\pi_A^{Inf} \leq \pi_A^{Alliance}$, $\pi_B^{Alliance} \geq \pi_B^{License}$, $\pi_B^{Alliance} \geq \pi_B^{Inf}$ and $\mu < \frac{1}{\sqrt{2}}$.

Case 4. Firms agree on merger if

- $\mu \geq \bar{\mu}$, $\mu \geq \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$ and $\mu \geq \frac{1}{\sqrt{2}}$;
- $\mu \geq \bar{\mu}$, $\mu < \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$, $\mu \geq \frac{1}{\sqrt{2}}$ and $\pi_B^{Acq} \geq \pi_B^{License}$;
- $\mu < \bar{\mu}$ and at least one of two conditions is satisfied:
  1. $\pi_A^{Acq} \geq \pi_A^{Inf} > \pi_A^{Alliance}$, $\pi_B^{Acq} \geq \pi_B^{License}$ and $\pi_B^{Acq} \geq \pi_B^{Inf}$
  2. $\pi_A^{Acq} \geq \pi_A^{Inf}$, $\pi_B^{Acq} \geq \pi_B^{License}$, $\pi_B^{Acq} \geq \pi_B^{Inf}$ and $\mu \geq \frac{1}{\sqrt{2}}$.

Theorem A.2. Suppose infringement is not feasible ($\mu > \frac{(a + c_B - 2c_L)^2}{9\Phi} - \frac{\psi}{\Phi}$).

1. Firms agree on licensing agreement if $\mu < \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$, $\pi_B^{Acq} \leq \pi_B^{License}$, and $\pi_B^{Alliance} \leq \pi_B^{License}$.
2. Firms build strategic alliance if:

- $\mu < \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$, $\mu < \frac{1}{\sqrt{2}}$ and $\pi_B^{Alliance} \geq \pi_B^{License}$
- $\mu \geq \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$ and $\mu < \frac{1}{\sqrt{2}}$

3. Firms agree on merger if $\mu \geq \frac{4(c_H - c_L)(a + c_B - c_H - c_L)}{9f} - \frac{f_{base}}{f}$ and $\mu \geq \frac{1}{\sqrt{2}}$.

Theorem A.3. If fair competition is not feasible ($c_H > a$), then:

1. Firm A infringes firm B if one of the conditions is satisfied [1) $\Phi < f$ and $\mu > \frac{\psi - f_{base}}{f - \Phi}$; or 2) $\Phi \geq f$ and $\mu > \frac{\psi + f_{base}}{\Phi - f}$] and at least one condition holds:
   (a) $\pi_A^{Inf} > \pi_A^{Alliance}$ and $\pi_A^{Inf} > \pi_A^{Acq}$;
   (b) $\pi_A^{Inf} > \pi_A^{Alliance}$, $\pi_A^{Inf} \leq \pi_A^{Acq}$ and $\pi_B^{Inf} > \pi_B^{Acq}$;
   (c) $\pi_A^{Inf} > \pi_A^{Acq}$, $\pi_A^{Inf} \leq \pi_A^{Alliance}$ and $\pi_B^{Inf} > \pi_B^{Alliance}$;
   (d) $\pi_B^{Inf} > \pi_B^{Alliance}$ and $\pi_B^{Inf} > \pi_B^{Acq}$.
2. Firms agree on licensing contract if one the conditions are satisfied [1) $\Phi < f$ and $\mu \leq \frac{\psi - f_{base}}{f - \Phi}$ or 2) $\Phi \geq f$ and $\mu \leq \frac{\psi + f_{base}}{\Phi - f}$] and at least one condition holds:
   (a) $\pi_A^{Inf} > \pi_A^{Acq}$ and $\pi_A^{Inf} > \pi_A^{Alliance}$
   (b) $\pi_A^{Inf} \leq \pi_A^{Alliance}$, $\pi_A^{Inf} > \pi_A^{Acq}$ and $\pi_B^{License} > \pi_B^{Alliance}$
   (c) $\pi_A^{Inf} \leq \pi_A^{Acq}$, $\pi_A^{Inf} > \pi_A^{Alliance}$ and $\pi_B^{License} > \pi_B^{Acq}$
   (d) $\pi_B^{License} > \pi_B^{Alliance}$ and $\pi_B^{License} > \pi_B^{Acq}$
3. Firms build strategic alliance if at least one condition is satisfied:
   (a) $\pi_A^{Alliance} \geq \pi_A^{Inf} > \pi_A^{Acq}$, $\pi_B^{Alliance} \geq \pi_B^{License}$ and $\pi_B^{Alliance} \geq \pi_B^{Inf}$;
   (b) $\pi_A^{Inf} \leq \pi_A^{Alliance}$, $\pi_B^{Alliance} \geq \pi_B^{License}$, $\pi_B^{Alliance} \geq \pi_B^{Inf}$ and $\mu < \frac{1}{\sqrt{2}}$.
4. Firms agree on merger if at least one condition is satisfied:
   (a) $\pi_A^{Acq} \geq \pi_A^{Inf} > \pi_A^{Alliance}$, $\pi_B^{Acq} \geq \pi_B^{License}$ and $\pi_B^{Acq} \geq \pi_B^{Inf}$
   (b) $\pi_A^{Acq} \geq \pi_A^{Inf}$, $\pi_B^{Acq} \geq \pi_B^{License}$, $\pi_B^{Acq} \geq \pi_B^{Inf}$ and $\mu \geq \frac{1}{\sqrt{2}}$.

Theorem A.4. If infringement and fair competition are not feasible then:

1. Firms agree on licensing agreement if $\mu > \frac{(a + c_B - 2c_L)^2}{9f} - \frac{f_{base}}{f}$, $\pi_B^{Acq} \leq \pi_B^{License}$, and $\pi_B^{Alliance} \leq \pi_B^{License}$.
2. Firms build strategic alliance if one of two conditions holds:

- $\mu \leq \dfrac{(a + c_B - 2c_L)^2}{9f} - \dfrac{f_{base}}{f}$ and $\mu < \dfrac{1}{\sqrt{2}}$
- $\mu > \dfrac{(a + c_B - 2c_L)^2}{9f} - \dfrac{f_{base}}{f}$, $\mu < \dfrac{1}{\sqrt{2}}$ and $\pi_B^{Alliance} \geq \pi_B^{License}$

3. Firm B acquires firm A if one of two conditions holds:
   - $\mu \leq \dfrac{(a + c_B - 2c_L)^2}{9f} - \dfrac{f_{base}}{f}$ and $\mu \geq \dfrac{1}{\sqrt{2}}$
   - $\mu > \dfrac{(a + c_B - 2c_L)^2}{9f} - \dfrac{f_{base}}{f}$ and $\mu \geq \dfrac{1}{\sqrt{2}}$ and $\pi_B^{Acq} \geq \pi_B^{License}$

1.B Matching names to PERMNO

USPTO Assignment dataset, Stanford NPE litigation database and Patent litigation docket reports data do not have any firm identifier. So I build an algorithm that standardizes firm names and matches them to PERMNO.

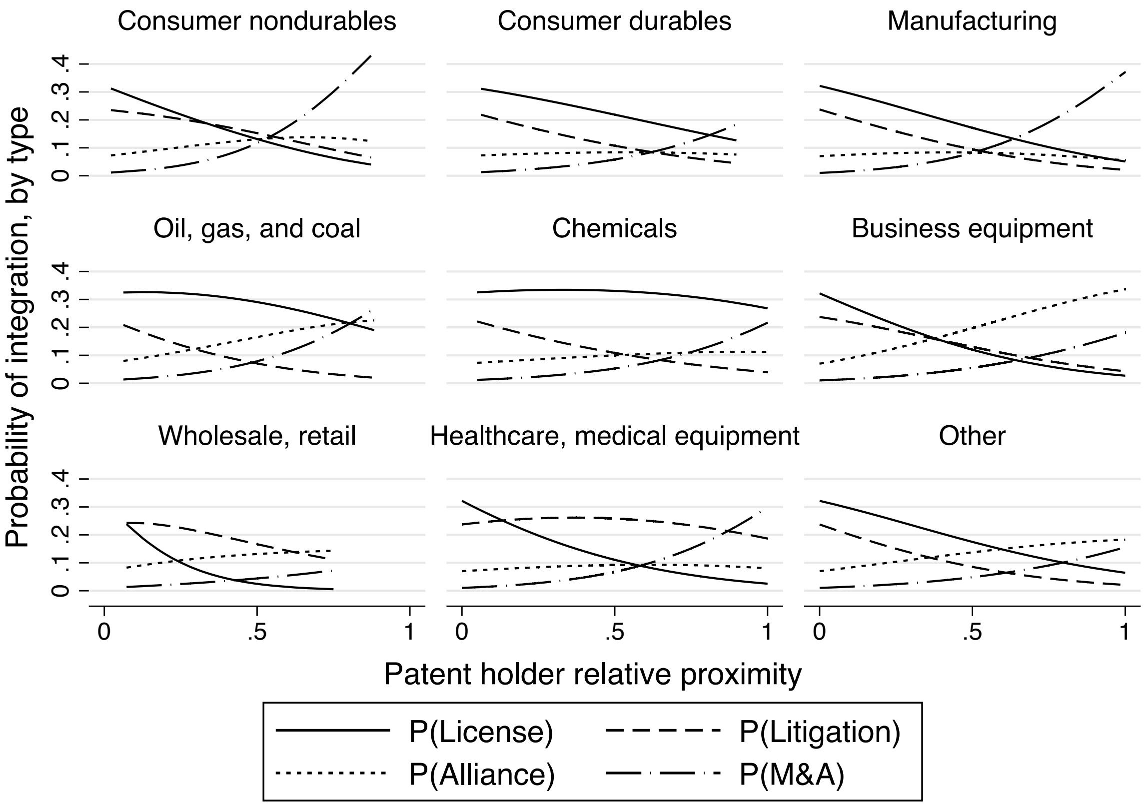
First, I apply strategies of Serrano (2010), Bowen III (2016) and Ma (2020) to identify patent acquisition and licensing agreements in USPTO Assignment dataset. Then I process for all licensing and litigation databases in the following order:

1. I eliminate most common misspellings. For example, I find 96 different versions of misspelling of word “corporation".
2. I build an algorithm to standardize most common words like Corporation (CORP), International (INTL), Pharmaceutical (PHARMA) etc.
3. I eliminate entity indicators such as “LLC”, “CORP”, “INC” etc.
4. I download CRSP database and identify all firm names with PERMNO. I standardize them using (1)-(3)
5. I match firm’s names of USPTO Assignment dataset, NPE litigation database and Patent litigation docket reports data to standardized names from CRSP database
6. I eliminate if both parties of transactions have the same PERMNO

1.C Additional plots

Figure 1.C.1: Probability of firms' integration, by type and patent seeker industry

The figure plots the probability of firms' integration (by type and patent seeker industry) with respect to patent holder relative proximity. The probabilities are calculated using multinomial logistic regression. *Patent holder relative proximity* is the difference between patent holder proximity and patent seeker proximity, where patent holder (seeker) proximity measures to what extent patent holder's (seeker's) patents cite patent seeker's (holder's) patent portfolio. *Patent holder relative proximity* ranges from 0, indicating that all patent holder's patents do not cite patent seeker's patent portfolio and all patent seeker's patents directly cite patent holder's patent portfolio, to 1, meaning that all patent holder's patents directly cite patent seeker's patent portfolio and all patent seeker's patents do not cite patent holder's patent portfolio. *Patent holder relative proximity* equals 0.5 when patent holder and patent seeker proximity measures are equal. In the graph the probability of no integration is suppressed.



References

Aghion, P. and Tirole, J. (1994). The management of innovation. *Quarterly Journal of Economics*, 109(4):1185–1209.

Ahern, K. R. (2012). Bargaining power and industry dependence in mergers. *Journal of Financial Economics*, 103(3):530–550.

Ahuja, G. and Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, 22(3):197–220.

Alexandridis, G., Fuller, K. P., Terhaar, L., and Travlos, N. G. (2013). Deal size, acquisition premia and shareholder gains. *Journal of Corporate Finance*, 20:1–13.

Andrade, G., Mitchell, M. L., and Stafford, E. (2001). New evidence and perspectives on mergers. *Journal of Economic Perspectives*, 15:103–120.

Anosova, D. (2018). Organizational structures and innovation. *Working Paper*, Stanford University.

Audretsch, D. B. and Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review*, 86(3):630–640.

Barker III, V. L. and Mueller, G. C. (2002). Ceo characteristics and firm r&d spending. *Management Science*, 48(6):782–801.

Bena, J. and Li, K. (2014). Corporate innovations and mergers and acquisitions. *Journal of Finance*, 69(5):1923–1960.

Bowen III, D. E. (2016). Patent acquisition, investment, and contracting. *Robert H. Smith School Research Paper No.*, 2870112.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52(1):57–82.

David, P. A., Hall, B. H., and Toole, A. A. (2000). Is public r&d a complement or substitute for private r&d? a review of the econometric evidence. *Research Policy*, 29(4-5):497–529.

Edmans, A., Goldstein, I., and Jiang, W. (2012). The real effects of financial markets: The impact of prices on takeovers. *Journal of Finance*, 67(3):933–971.

Ewens, M., Peters, R., and Wang, S. (2020). Measuring intangible capital with market prices. *Working Paper*.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49(3):283–306.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, 43(2):153–193.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Fauli-Oller, R. and Sandonis, J. (2003). To merge or to license: implications for competition policy. *International Journal of Industrial Organization*, 21(5):655–672.

Fuller, K., Netter, J., and Stegemoller, M. (2002). What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. *Journal of Finance*, 57(4):1763–1793.

Gomes-Casseres, B., Hagedoorn, J., and Jaffe, A. B. (2006). Do alliances promote knowledge flows? *Journal of Financial Economics*, 80(1):5–33.

Gorton, G., Kahl, M., and Rosen, R. J. (2009). Eat or be eaten: A theory of mergers and firm size. *Journal of Finance*, 64(3):1291–1344.

Grossman, S. J. and Hart, O. D. (1986). The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of Political Economy*, 94(4):691–719.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, 36(1):16–38.

Hall, B. H., Mairesse, J., and Mohnen, P. (2010). Measuring the returns to r&d. In *Handbook of Economics of Innovation*, volume 2, pages 1033–1082. Elsevier.

Hart, O. and Moore, J. (1988). Incomplete contracts and renegotiation. *Econometrica*, 56(4):755–785.

Hart, O. and Moore, J. (1990). Property rights and the nature of the firm. *Journal of Political Economy*, 98(6):1119–1158.

Hoberg, G. and Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies*, 23(10):3773–3811.

Hoberg, G. and Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465.

Jaffe, A. B., Trajtenberg, M., and Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *American Economic Review*, 90(2):215–218.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):577–598.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2):665–712.

Lambrecht, B. M. (2004). The timing and terms of mergers motivated by economies of scale. *Journal of Financial Economics*, 72(1):41–62.

Lindsey, L. (2008). Blurring firm boundaries: The role of venture capital in strategic alliances. *Journal of Finance*, 63(3):1137–1168.

Ma, S. (2020). The life cycle of corporate venture capital. *Review of Financial Studies*, 33(1):358–394.

Marco, A. C., Tesfayesus, A., and Toole, A. A. (2017). Patent Litigation Data from US District Court Electronic Records (1963-2015). *USPTO Economic Working Paper*.

Moeller, S. B., Schlingemann, F. P., and Stulz, R. M. (2004). Firm size and the gains from acquisitions. *Journal of Financial Economics*, 73(2):201–228.

Officer, M. S. (2003). Termination fees in mergers and acquisitions. *Journal of Financial Economics*, 69(3):431–467.

Ozcan, Y. (2015). Innovation and acquisition: Two'sided matching in M&A markets. *Working paper*, Kellogg School of Management, Northwestern University.

Phillips, G. M. and Zhdanov, A. (2013). R&D and the incentives from merger and acquisition activity. *Review of Financial Studies*, 26(1):34–78.

Pisano, G. P. (1990). The R&D boundaries of the firm: an empirical analysis. *Administrative Science Quarterly*, 35(1):153–176.

Reitzig, M. and Wagner, S. (2010). The hidden costs of outsourcing: Evidence from patent data. *Strategic Management Journal*, 31(11):1183–1201.

Rhodes-Kropf, M. and Robinson, D. T. (2008). The market for mergers and the boundaries of the firm. *Journal of Finance*, 63(3):1169–1211.

Robinson, D. T. (2008). Strategic alliances and the boundaries of the firm. *Review of Financial Studies*, 21(2):649–681.

Schneider, C. and Spalt, O. G. (2017). Why does size matter so much for bidder announcement returns? *Working Paper*.

Sears, J. and Hoetker, G. (2014). Technological overlap, technological capabilities, and resource recombination in technological acquisitions. *Strategic Management Journal*, 35(1):48–67.

Serrano, C. J. (2010). The dynamics of the transfer and renewal of patents. *RAND Journal of Economics*, 41(4):686–708.

Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and r&d activity. *Journal of Financial Economics*, 111(2):381–405.

Sevilir, M. and Tian, X. (2012). Acquiring innovation. *Working paper*, Indiana University.

Uysal, V. B., Kedia, S., and Panchapagesan, V. (2008). Geography and acquirer returns. *Journal of Financial Intermediation*, 17(2):256–275.

Villalonga, B. and McGahan, A. M. (2005). The choice among acquisitions, alliances, and divestitures. *Strategic Management Journal*, 26(13):1183–1208.

Chapter 2

Information (non)disclosure and firm value: Evidence from confidential treatment orders

2.1 Introduction

Corporate financial scandals and financial crisis undermined trust in financial system. Regulation (Dodd-Frank Act, Regulation FD and Sarbannes-Oxley Act) was introduced and updated to remedy that. Yet, SEC allows companies to redact proprietary information, by filing confidential treatment (CT) requests. This diminishes firm's transparency, which may lead to an increase in asymmetric information and agency problems between firm, its shareholders, and the general public.

Public companies are required to disclose financial documents (such as 10-K, 10-Q, 8-K etc.). But disclosing certain information might undermine their competitive advantages so companies could request to redact certain portion of information by filling CT requests. On the one hand, CT protects the firm from its rivals and potential lawsuits as it does not disclose certain information and builds less expectations. The firm also signals that it is careful of not leaking the information. On the other hand, CT might increase information asymmetry and opaqueness.

There are mixed findings whether protecting proprietary information is actually good or bad. Theoretical papers (Grossman (1981) and Milgrom (1981)) predict that when firms do not disclose information, the market expects that something bad is happening. Whereas empirical papers (Verrecchia and Weber (2006), Cao et al. (2018), Tian and Yu (2018)) find that companies that redact their information experience greater market share growth and bid-ask spread. My paper aims to understand the importance of nondisclosure and in particular to identify when redacting information is actually beneficial for shareholders.

The main challenge is that an unredacted version of the agreements is not unobservable. To analyze whether corporate redaction is valuable for shareholders, I need to find the counterfactuals and identify an empirical strategy . First, I examine the market reaction to redacted filings by different firms. In particular, I study how the reaction differs between firms with high/low institutional ownership, with(out) blockholders and with strong/weak governance. Second, I focus on the type of information companies redact. As I cannot observe unredacted version of filings, I categorize corporate agreements by type such as license, asset purchase, supply agreements etc. By doing this, I distinguish information related to product competition, corporate R&D, corporate governance etc. If redacted information has some value in the product market, companies would gain competitive advantage by redacting some portion of information. In this case I would expect a positive shareholders' reaction. Though, when the company redacts investor-sensitive information (e.g. settlement agreement) then its shareholders expect something bad. Third, I examine market reaction in different industries. In particular, healthcare gives us a unique set-up where we can observe the introduction of new drugs. This allows me to test whether the market can distinguish the quality of redacted information.

I conduct the analysis on a comprehensive dataset that I collect by scraping firm's filings from EDGAR website. By analysing "CT ORDER" documents, I obtain 11,375 redacted filings that contain 16,606 redacted agreements. I identify similar fully disclosed agreements for every redacted agreement. To do this, I scrape all material contracts that companies filed between 2008 and 2018. Writing a Python algorithm, I categorize 242,426 firm's agreements by type. To my knowledge, this is the first work that uses such a comprehensive and detailed dataset.

My main results are as follows. The reaction to the redacted information in contracts differs across firms. In general, *good* companies experience larger abnormal returns compared to *bad* firms, where the incentives between agents and principal are less aligned. I use various proxy of the firm's quality - institutional ownership level, presence of blockholders, governance indexes (CEO-Chair separation, dollar value of director's ownership, directors' independence). Firms with higher level of institutional ownership experience greater returns compared to the firms with lower institutional ownership. Likewise, firms with the presence of blockholders have no market reaction to the redacted filings; whereas firms without blockholders experience negative reaction. I also look at corporate governance indexes.

CEO-Chair separation, greater director's ownership and greater director's independence are associated with stronger governance. Using the above measures, I divide the sample by companies with strong and weak corporate governance. I find that when a company with strong corporate governance files redacted agreements it experiences positive market reaction. However, firms with weak governance always observe no reaction or negative market reaction.

These all results suggest that when the market has a positive prior of firm's quality and there is a trust between shareholders and the managers, the market does not react badly to redacted information. However, companies that have bad reputation and redact the information experience negative returns.

Next, I examine the information content of the agreements. I divide all firm's agreements by type, e.g. license, development/collaboration, settlement agreements etc. I compare market reaction to redacted and fully disclosed agreements for each agreement type. I find that when companies redact product sensitive information, the proprietary costs are lower than the benefits. Whereas when firms hide information regarding lawsuits, the shareholders assume worst things to happen. Nevertheless, the market has a negative reaction but it does not collapse.

Dividing the sample by industry, I find that healthcare industry is a good example of successful redaction. Healthcare firms that redact information experience positive market reaction. By looking at the composition of the redacted agreements, we can notice that companies redact more often license agreements and supply agreements. These contracts are associated with products and innovation. Next, I examine whether redacted information is associated with the introduction of new drugs. Using Drugs@FDA database, I find that companies are more likely to redact information before the introduction of new drugs. I also test whether the market reacts differently to redacted agreements prior to the introduction of new drugs and not. I find that the market is able to distinguish the quality of redacted agreements and reacts more positively to the redaction prior to the introduction of new drugs compared to redacted agreements where the introduction of new drugs is not followed.

To rule out alternative explanation, I run additional tests. First, nondisclosure might increase agency problems between the firm and its shareholders, which may lead to a potential class action litigation lawsuit. To test this, I study whether nondisclosure impacts the probability of lawsuit. Intersecting my hand-collected database of redacted filings with Stanford Securities Clearinghouse database and Factiva, I find that companies that redact are more likely to be sued in the following year. This supplies us with an additional insight to the cost of redacting information.

Second, I examine whether the company does not disclose just in one area of business or in multiple settings. Cao et al. (2018) claim that competition and disclosure are multidimensional. They show that competition provokes lower disclosure related to product and investment and increases voluntary disclosure about future earnings forecasts. I test whether the company systematically does not disclose certain type of information. In particular, whether the decision comes from the counterpart or the company itself. To completed this test, I need to collect the parties involved in each contract. The goal is to see whether certain companies hide more information. In particular, I would like to find which firms are successful in hiding the information.

Finally, I would like to see the difference in the disclosure behavior between financially constrained and unconstrained firms. Potentially, the firms that are lack of money are more transparent to their investors so they can hope for the additional capital to arrive.

The rest of the paper is organized as follows. In Section 2.2 discusses institutional background of CT process and related literature. Section 2.3 describes the data and presents summary statistics. In Section 2.4 I present my main results. The final section concludes the paper.

2.2 Related literature and institutional background

2.2.1 Related literature

Since May, 2008 SEC has been publishing documents of type “CT ORDER” that provide the information of granted confidential treatment requests. They contain information about redacted exhibits and the duration of redaction period. Thompson (2011) focuses on the confidential treatment process.

Boone et al. (2016) research relates to the initial public offerings. They find that companies that redact some information in the initial public offerings (IPO) experience underpricing. In the post-IPO period they have better performance.

The majority of the nondisclosure papers focuses on the competition aspect. Verrecchia and Weber (2006) and Tian and Yu (2018) study how market conditions affect companies' decision to redact. When the market is more competitive, companies tend to hide more information. What is more, the firm that redacts innovation related information on average has greater market share growth, rise in bid-ask spread, and market power. Verrecchia and Weber (2006) also point out that companies disclose more before raising long-term financing. Cao et al. (2018) claim that competition and disclosure are multidimensional, by showing that competition provokes lower disclosure related to product and investment and increases voluntary disclosure about the future earnings forecast.

Bourveau et al. (2019) find that companies tend to share more proprietary information in the presence of cartel enforcement. In particular, they share the information about their counterparts (customers, suppliers etc.) and their products.

Kankanhalli and Kwan (2018) and Kankanhalli et al. (2019) focus on the intellectual property licensing agreements. They find that companies tend to redact portions of agreements when royalty rates are lower. This suggests that companies redact the information strategically so they could sign future contracts on more favorable conditions. Consistent with Tian and Yu (2018), Kankanhalli and Kwan (2018) find that companies that redact the information have greater growth and are more likely to file new patents.

By disclosing more corporate R&D related information companies are more likely to find more suitable counterparts (Ettredge et al. (2018)). This has a positive impact on interfirm technology flow. In order to not disclose very valuable information, companies substitute the decrease in mandatory disclosure to an increase in voluntary disclosure (Heinle et al. (2018), Glaeser (2018)).

The literature also examines the effect of disclosure on corporate life. Diamond and Verrecchia (1991) argue that larger companies extract more benefits from the disclosure. By disclosing corporate information companies decrease the asymmetric information; this has a positive effect on the liquidity of their stocks and the price of the stock. Greater disclosure also has an impact on governance (Hermalin and Weisbach (2012))

2.2.2 Institutional background about CT

In this subsection I focus on the institutional background of confidential treatment process (Figure 2.1).

A company signs an agreement with other firm. It has notify its shareholders about the contracts that are sufficiently important for the company's future. Different types of contracts have different thresholds. For example, agreements that involve buying or selling of assets for more than 15% of the reporting company's fixed assets. It usually takes around four working days for the company to file the copy of the agreement to SEC. The company has the possibility redact some portion of immaterial information from the contract that might harm the company's competitive advantage. It does by filing redacted documents on EDGAR platform and submitting CT request together with unredacted version of the filing to SEC. Everyone can access the redacted version of the contracts that is available online on EDGAR platform. SEC has then 28 working days to decide whether to accept or reject the CT request. SEC communicates its decision by filing a document of type "CT ORDER". Figure 2.2 reports an example of such filing. It contains the following information: date of CT order, company's name, original date of redacted filing, form number, redacted exhibit numbers and their confidential treatment period. I build a Python code to automatically extract the above information from each filing. Each CT order may contain multiple redacted exhibits. For example, CT order of Figure 2.2 has four exhibits. In my analysis I refer to filings when I refer to "CT ORDER" filing, whereas I refer to agreements when I study each exhibit separately. Figure 2.3 reports the example an redacted agreement. As some parts of the agreement are redacted completely it is difficult to infer what exactly has been redacted.

In case of CT request approval, SEC decides the CT period, where 10 years is the maximum. Companies can file another CT request to prolong the CT duration period. Once it is expired, the information is public under request.

In case of CT request denial, the company has 21 working days to file a petition. If the CT request is still rejected, the company has to disclose an unredacted version of the document by filing an amendment. Since then, the information is public. As of January 2020, CT requests are denied in less than 5% of all cases.

This procedure has been used from May, 2008 to April, 2019. Since FAST Act was updated on March 22, 2019 with taken into force on April 3, 2019, companies can redact immaterial information from material agreements without filing CT request if the information might be potentially harmful for the competition. Under this update companies no longer need to submit CT request and unredacted version of the document to SEC. SEC still retains the possibility to request the unredacted information. Under new regulation the redacted information will be never public. This change may increase asymmetric information and agency problems between company and its shareholders.

2.3 Data and summary statistics

2.3.1 Data

To identify redacted filings I collect by scraping all filings of type "CT ORDER" from EDGAR database from May 2008 to December 2018. I obtain 11,375 CT order filings that have been filed by 3,448 unique firms. Number of filings over time remains quite stable (Figure 2.4). The example of CT order filing is in Figure 2.2. I build a Python code to automatically extract filing date of CT order, company's name, original date of redacted filing, form number, redacted exhibit numbers and their confidential treatment period.

Next, I restrict my sample to 10-K, 10-Q and 8-K filings. This accounts for 79% of all redacted filings. The remaining 21% is IPO agreements. I do not consider them in my analysis. I also exclude all filings that are filed prior to May 1, 2008.

The following step is to download all the exhibits of type "Exh-10", which are material contracts, from EDGAR database. I focus on material contracts as they represent significant agreements for a company, which should be disclosed on EDGAR platform. I extract the title of each agreement. I classify the filings into following categories: asset purchase, supply, licensing, settlement agreement etc. Detailed classification is described in the Appendix. The distribution of each type of agreement is presented in Panel A of Table 2.2.

Then I identify which agreements are redacted. Percentage of redacted agreements varies considerably across different types of agreements (Figure 2.5). Healthcare is the industry with higher level of redacted agreements, both in percentage and absolute values. Around 13% of all filings are redacted in the healthcare. Next two most active industries are telecommunication and business equipment. All three industries are associated with high level of R&D.

To identify firm's governance characteristics I use different sources. I proxy corporate governance based on ISS database. Following Bebchuk et al. (2008) and Bhagat and Bolton (2008), I calculate the level of directors' independence, level of median director ownership, and the presence of CEO-Chair duality. The second set of proxies is the level of institutional ownership and the presence of block shareholders. They are calculated using Thomson Reuters Institutional Ownership database. The third set of proxies is regarding analyst coverage (IBES).

Drugs@FDA database reports FDA-approved brand-name and generics drugs since 1939. The data is comprehensive since 1998. The database contains the information about the drug name, the date of drug approval, name of drug producer. There is no link to any firm's identifier. So I build an algorithm to standardize company's names and match them to CIK. Details are in the Appendix.

I obtain the information on class action litigation lawsuits through Stanford Securities Class Action Clearinghouse. Using Factiva, I manually identify the date when lawsuit is first mentioned. To identify stock market reaction and firm's control variables I use CRSP and Compustat, accordingly.

2.3.2 Summary statistics

I start by describing what information companies actually redact. As unredacted version of the agreements are not publicly available I cannot analyze the redacted information itself. Nevertheless, I can infer from the redacted version of agreements what kind of information is redacted more often. I analyze 60 random redacted agreements (Table 2.1). I find that most frequent redactions are price and payment scheme (67%), quantity and quality of the product (40%), and the duration of the agreements (35%). These redactions are related to the products and terms of contract. Companies may use the prices and royalty fee redaction as an instrument of bargaining power. They usually do not disclose lower price so they could bargain better with other customers (Kankanhalli and Kwan

(2018)).

Next, I compare what companies that redact to companies that do not redact (Table 2.2). I find that companies that redact are smaller but growing firms, having on average $0.48 bn compared to $1 bn; their sales growth is 21% compared to 9%. Companies that redact spend more than on R&D (13.3% in comparison to 3.9%).

Figure 2.5 presents sample splits along two dimensions: agreement type and industry. Panels A and B focus on agreement type dimension. Companies redact most frequently product and innovation related contracts such as supply, license, collaboration and R&D agreements. Panels C and D analyze the sample by industry. Healthcare is the industry where companies redact the most, both in absolute and percentage terms. More than 5,000 healthcare agreements are redacted, which means that one in eight contracts filed with SEC is redacted. The second most frequent industry for the reduction is business equipment. Around 1,500 agreements has been redacted from 2008 to 2018; this accounts for about 4.6% of all contracts filed in this industry. These two industries are technologically intensive and are associated with dynamic and competitive markets. On the contrary, monopolistic industries (e.g. oil, gas, coal and utilities) redact considerably less.

2.4 Baseline

In this section I describe main results. First, I examine whether there is a variation of how the market reacts to the redaction made by companies with different corporate governance. Second, I look whether companies redact different information and how the market perceives it.

The first part of the analysis aims to understand whether the reaction to redacted information in contracts differs across firms. I argue that firms with different quality should observe different market reaction to their corporate disclosure redactions. To test this hypothesis, I run the following regression:

$$CAR_{i,f} = \beta_0 + \beta_1 Firm's\ quality_{f,t-1} + \mu' x_{f,t-1} + \epsilon_{i,f},$$

where $CAR_{i,f}$ is the market reaction to the filing i of firm i. $Firm's\ quality_{f,t-1}$, the variable of interest, is measured using different proxies: (i) corporate governance measures (director ownership, director independence, and CEO-Chair separation); (ii) institutional ownership (level or the indicator of its presence); (iii) block shareholders (level or the indicator of its presence); and (iv) analyst coverage. $x_{f,t-1}$ is the vector of controls. The regression includes 12 Fama-French industry and year fixed effects. The t-statistics are based on standard errors clustered around firm.

Figure 2.7 reports the results on corporate governance measures. Companies with stronger governance receive positive market reaction to the redaction. The effect varies from 0.6% to 1%, depending on the specifications. Companies with weaker governance experience no reaction or slightly negative market reaction.

Figure 2.6 and Tables 2.3 and 2.4 report the results on institutional, block shareholders, and analyst dimensions. The coefficients of $Firm's\ quality_{f,t-1}$ are positive and significantly associated with market reaction. This indicates that firms with a better quality have greater trust in the eyes of shareholders.

The second part of the analysis studies whether companies with different quality redact similar information. In order to answer this question, I sort agreements by type. Panel A of Table 2.2 splits agreements by type and institutional ownership. Companies with low institutional ownership redact on average 4.62% of their documents compared to 3.44% of documents redacted by companies with high institutional ownership (IO). Supply agreements are the most frequent type where the redaction takes place (47% in low IO vs 61% in high IO). Licensing deals are the second most frequent type for redaction (41% in low IO vs 52% in high IO). Whereas, the redaction happens less frequently in merger and employment agreements for both firms with low and high IO.

Healthcare industry represents an unique setting that allows to distinguish innovation related redactions from other type of redaction. Federal drug approvals are very important for the companies and are associated with large positive market reaction. Combining FDA data on drugs and SEC data on redaction agreements allows us to see the timing of the drug approvals and redactions (Table 2.10). I find that the market reacts positively to the redaction when the public associates the redaction with the introduction of new drug. The effect is around 0.5 percentage points. On the contrary, the market reacts negatively when the reduction occurs one quarter before the introduction of new drug. In-process clinic trials are covered closely by the press. In this moment the redaction is perceived as company hide something from the public and so the shareholders assume the worst. The firm value decreases by 2.7 percentage points around filing date of the redacted agreement.

CT may create misalignment between shareholders and managers so security class action lawsuits are more likely to occur. To understand whether this is the case, I run a regression that examines the effect of corporate redaction on the class action lawsuits. I find positive correlation (Table 2.5). This may happen due to two reasons. One reason is that shareholders learn that managers are not transparent to them and assume the worst; so they sue the company. Another reason is that managers expect the lawsuit to be filed soon and they redact strategically some portion for the information. As it is hard to disentangle two stories so I do not claim any causality.

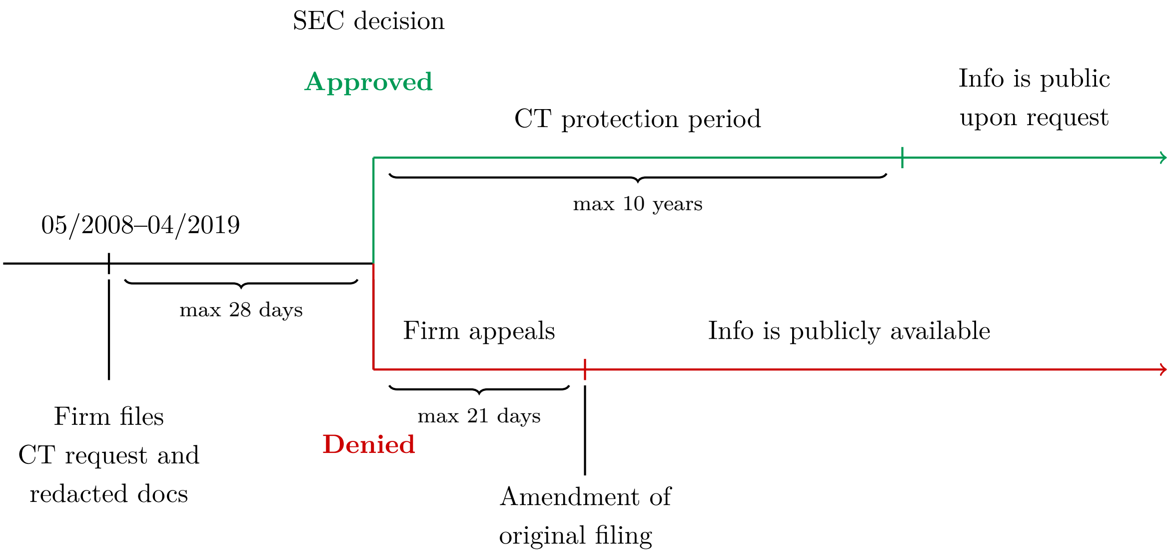
2.5 Conclusion

CT allows companies to keep product related secrets but also may cause an increase in asymmetric information and agency problems between the company and its shareholders. This paper analyzes costs and benefits of the redaction. First, I analyze the market reaction to redacted agreements, by exploring company's characteristics. I find that companies with stronger corporate governance experience positive reaction or no reaction to redacted filings, whereas firms with weaker governance have negative reaction. Second, I extend the analysis to all material agreements, comparing redacted agreements to the fully disclosed documents. As subject of agreements may vary from supply and license agreements to asset purchase and settlement contracts, I categorize the agreements into 13 different categories. Vis-à-vis fully disclosed filings, the market responds positively to redacted product-related information and negatively to redacted investor-sensitive information, such as settlement agreements. Third, I run a cross-industry analysis. I identify that healthcare industry is an example of successful redaction.

The results of the paper suggest that CT is a valuable tool for companies and their shareholders as it protects product-related secrets but does not support bad practices.

Figure 2.1: CT request process

A. Before FAST Act Update



B. After FAST Act Update

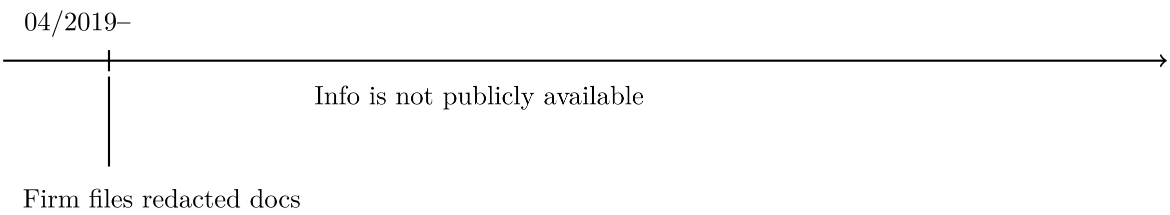


Figure 2.2: Example of "CT ORDER" filing

UNITED STATES
SECURITIES AND EXCHANGE COMMISSION
March 22, 2017

ORDER GRANTING CONFIDENTIAL TREATMENT
UNDER THE SECURITIES EXCHANGE ACT OF 1934

SolarCity Corporation

File No. 1-35758 - CF#34829

SolarCity Corporation submitted an application under Rule 24b-2 requesting confidential treatment for information it excluded from the Exhibits to a Form 10-K filed on March 1, 2017.

Based on representations by SolarCity Corporation that this information qualifies as confidential commercial or financial information under the Freedom of Information Act, 5 U.S.C. 552(b)(4), the Division of Corporation Finance has determined not to publicly disclose it. Accordingly, excluded information from the following exhibit(s) will not be released to the public for the time period(s) specified:

Exhibit 10.19z	through December 31, 2018
Exhibit 10.19aa	through December 31, 2018
Exhibit 10.19bb	through December 31, 2018
Exhibit 10.19cc	through December 31, 2018
Exhibit 10.25	through December 31, 2026

For the Commission, by the Division of Corporation Finance, pursuant to delegated authority:

Brent J. Fields
Secretary

Figure 2.3: Example of redacted filing

Exhibit 10.25

CONFIDENTIAL TREATMENT REQUESTED

Certain portions of this document have been omitted pursuant to a request for Confidential Treatment and, where applicable, have been marked with "[***]" to indicate where omissions have been made. The confidential material has been filed separately with the Securities and Exchange Commission.

Production Pricing Agreement: Phases 1-3
("Phase 1-3 Agreement")

Date: December 31, 2016

Pricing Validity Period: January 1, 2017 through December 31, 2026

Annual Forecasted Production Volume:
- [***] MW (Phase 1 Modules);
- [***] MW (Phase 2 PV Cells), with Modules;
- [***] MW (Phase 3 PV Cells), with Modules;
- *1 GW (Total PV Cells) plus Modules.*

Payment Terms: Net 60 Days

1. This Phase 1-3 Agreement is entered as of the first date set forth above (the "Phase 1-3 Effective Date") by and between Tesla Motors, Inc. and SolarCity Corporation (collectively with their Affiliates, "Tesla"), on the one hand, and Panasonic Corporation, Sanyo Electric Co., Ltd., and Panasonic Corporation of North America, by and through their respective Solar System Business Units (collectively, "Seller"), on the other hand. The Parties agree to this Phase 1-3 Agreement in consideration of the mutual promises and agreements contained herein, and for other good and valuable consideration, the receipt and adequacy of which are hereby acknowledged. Any capitalized term not separately defined in this Phase 1-3 Agreement shall have the meaning ascribed to it in the GTC (as defined below).

2. *Sourcing and Manufacturing*.

   a. Seller shall develop, manufacture, deliver, and sell best-in-class, high-efficiency photovoltaic cells ("PV Cells"), and photovoltaic panels or modules (collectively, "Modules") pursuant to mutually-agreed Specifications (collectively, "Goods") to Tesla and Tesla's Authorized Purchasers in accordance with this Phase 1-3 Agreement.

   b. *Production Phases*. Seller shall produce Goods as follows in distinct production phases (each, a "Phase"). The Parties shall determine, based on a good faith discussion, (i) whether Seller will build [***] PV Cells, [***] PV Cells, or a combination thereof for each Phase, as applicable, and (ii) the required Module design(s) for each Phase. The Parties will also discuss in good faith whether to [***].

Production Pricing Agreement: Phases 1-3

Page **1**

[***] Confidential treatment has been requested for the bracketed portions. The confidential redacted portion has been omitted and filed separately with the Securities and Exchange Commission.

iv. [***]

v. [***]

d. License Rights.

i. Tesla hereby grants to Seller a limited, non-exclusive, non-assignable, non-sublicensable, royalty-free license to the Background IP and Foreground IP owned by Tesla or an Affiliate of Tesla solely to the extent necessary for Seller to produce, make, offer for sale, test, evaluate, and sell Goods under this Phase 1-3 Agreement to Tesla, Tesla's Affiliates, or Tesla's Authorized Purchasers.

ii. Unless expressly agreed otherwise in writing by Tesla, Seller agrees that it will not engage in, nor will it authorize or allow others to engage in, reverse engineering, disassembly or decompilation of any information or technology in which Tesla has any Intellectual Property Rights.

iii. Except as expressly provided in this Phase 1-3 Agreement, no other rights or licenses are granted to Seller, including by way of implication, waiver, or estoppel.

e. [***].

i. [***]

ii. [***]

iii. [***]

iv. [***]

v. [***]

vi. [***]

f. [***].

i. [***]

ii. [***]

iii. [***]

g. [***]

i. [***]

ii. [***]

iii. [***]

Production Pricing Agreement: Phases 1-3

Page **9**

[***] Confidential treatment has been requested for the bracketed portions. The confidential redacted portion has been omitted and filed separately with the Securities and Exchange Commission.

Figure 2.4: Number of CT requests per quarter

The figure reports the frequency of CT requests per quarter. Source: EDGAR.

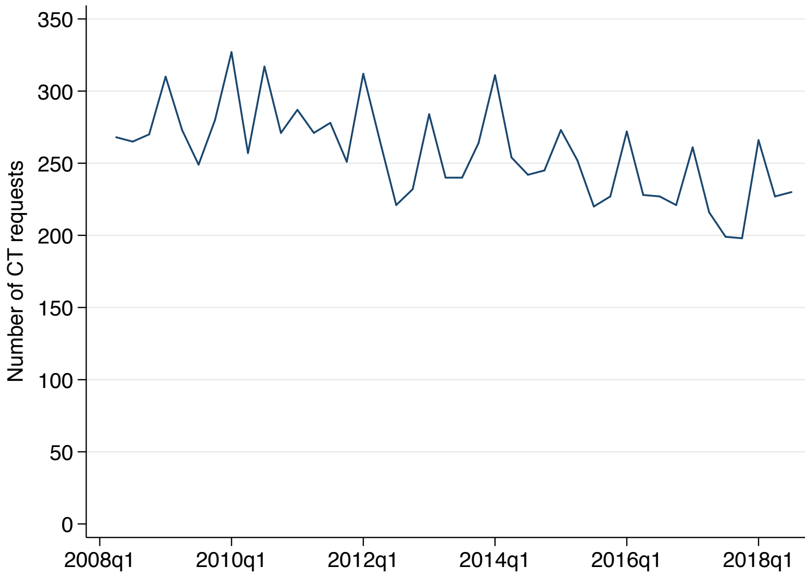
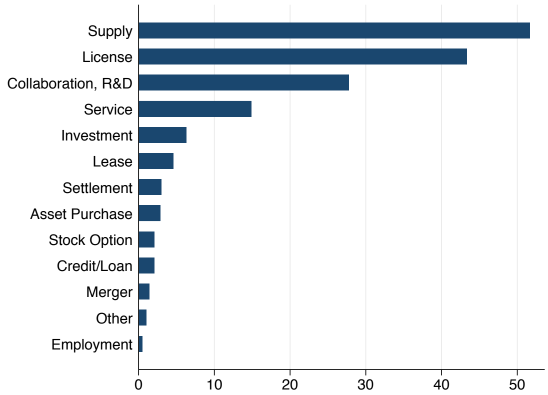


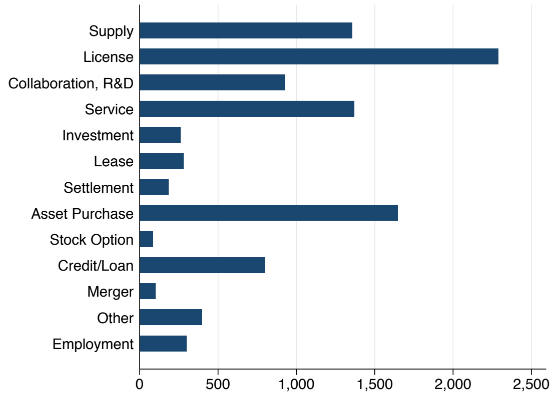
Figure 2.5: Sample sorts

The figure presents sample sorts by agreement types and by industry. Panels A reports percentage of redacted agreements by agreement type, and Panel B presents the total number of redacted agreement by type. Classification of agreements by type is described in Appendix X. Panels C and D sort agreements using 12 Fama-French industry classification. Panel C reports the percentage of redacted agreement by industry, whereas Panel D reports the number of redacted agreements by type.

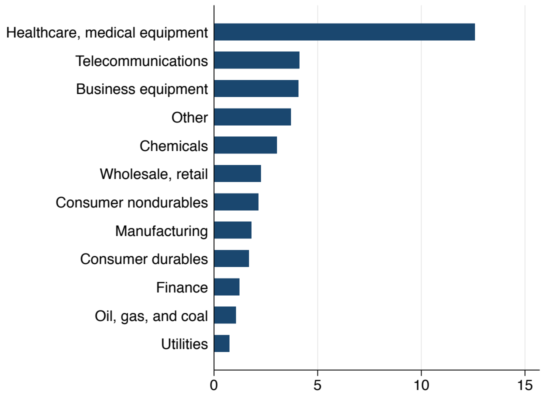
A. % of redacted agreements by agreement type



B. Number of redacted agreements by agreement type



C. % of redacted agreements by industry



D. Number of redacted agreements by industry

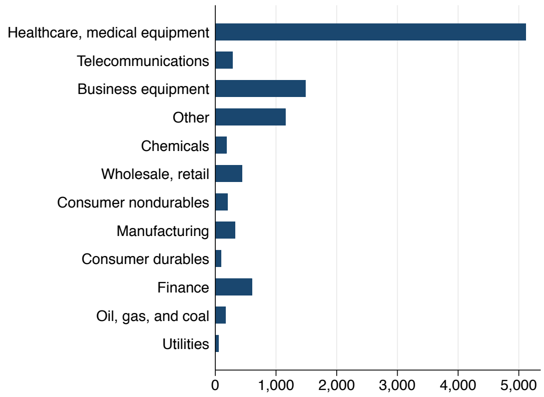
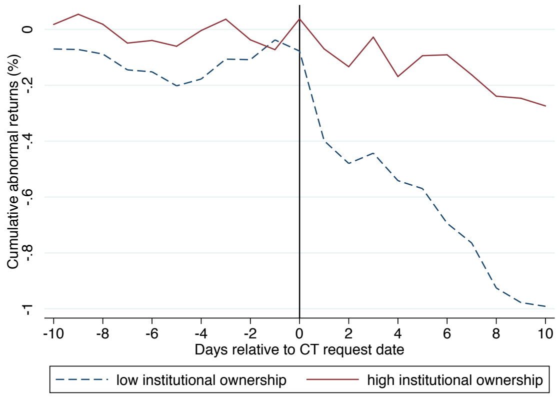


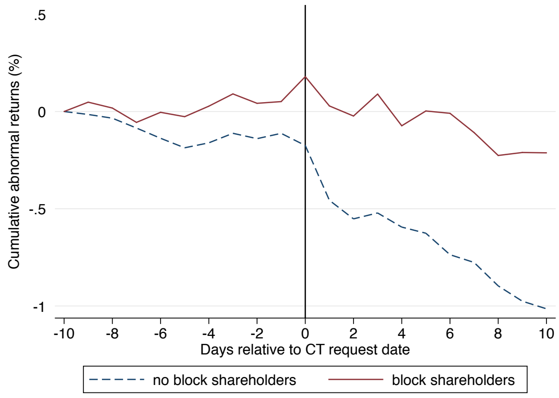
Figure 2.6: Market reaction to the CT requests

The figure reports the cumulative abnormal returns around the CT request date. Panel A divides firms by the level of the institutional ownership - low (less than 25%) and high (greater than 25%). Panel B plots market reaction to redacted filings separately for the firms with and without the presence of block shareholders. Panel C divides the sample by the median of analyst coverage. The abnormal returns are calculated using three-factor model.

A. By the level of institutional ownership



B. By the presence of blockholders



C. By the level of analyst coverage

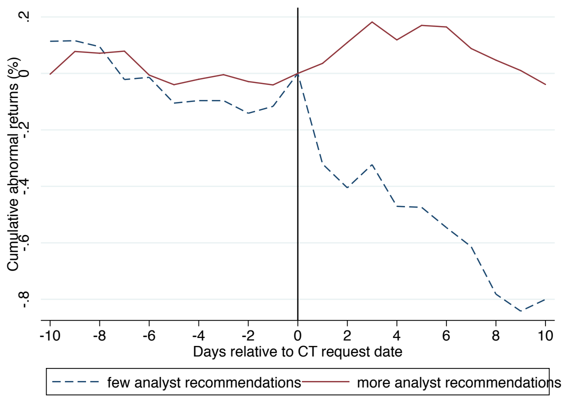


Figure 2.7: Market reaction to the CT requests, by corporate governance

The figure reports the cumulative abnormal returns around the CT request date. I divide the sample by quality corporate governance. Corporate governance proxies are director ownership, directors' independence, and CEO-Chair duality. In all graphs blue line shows bad corporate governance and red line shows good governance . The abnormal returns are calculated using three-factor model.

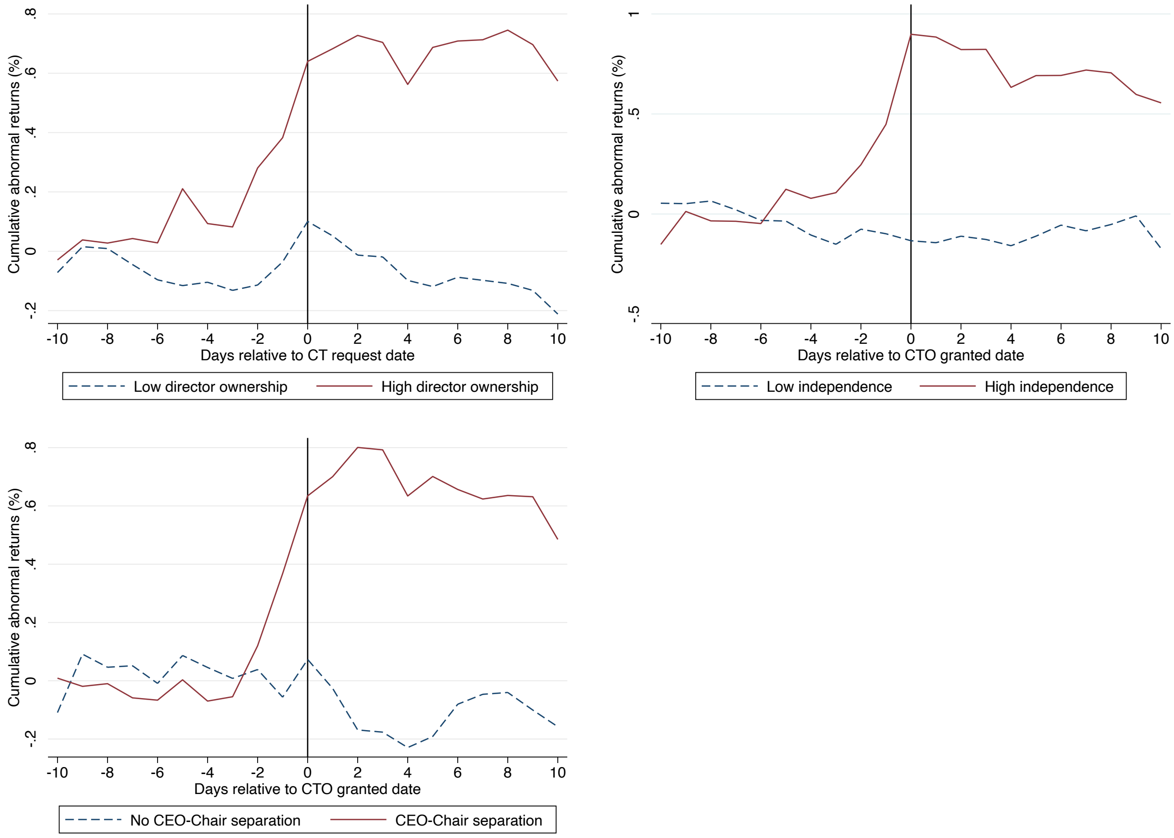


Figure 2.8: Market reaction to the agreement filing, by agreement type

The figure reports the cumulative abnormal returns around the contract filling date. I divide the material contacts by type. The abnormal returns are calculated using three-factor model.

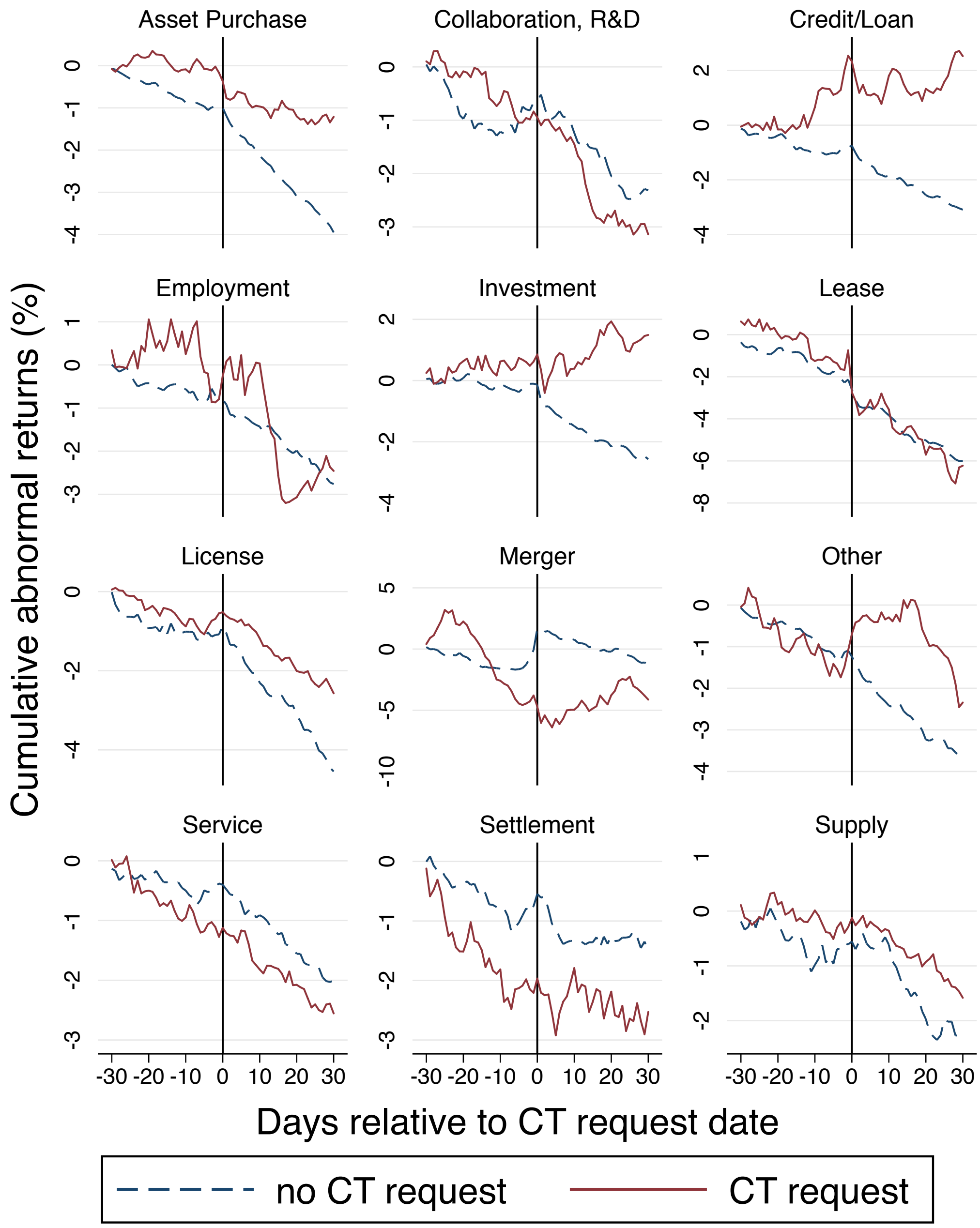


Figure 2.9: Market reaction to the agreement filing, by industry

The figure reports the cumulative abnormal returns around the agreement filing date by different industries. I include all industries that have at least 40 filings both redacted and fully disclosed agreements. The abnormal returns are calculated using three-factor model.

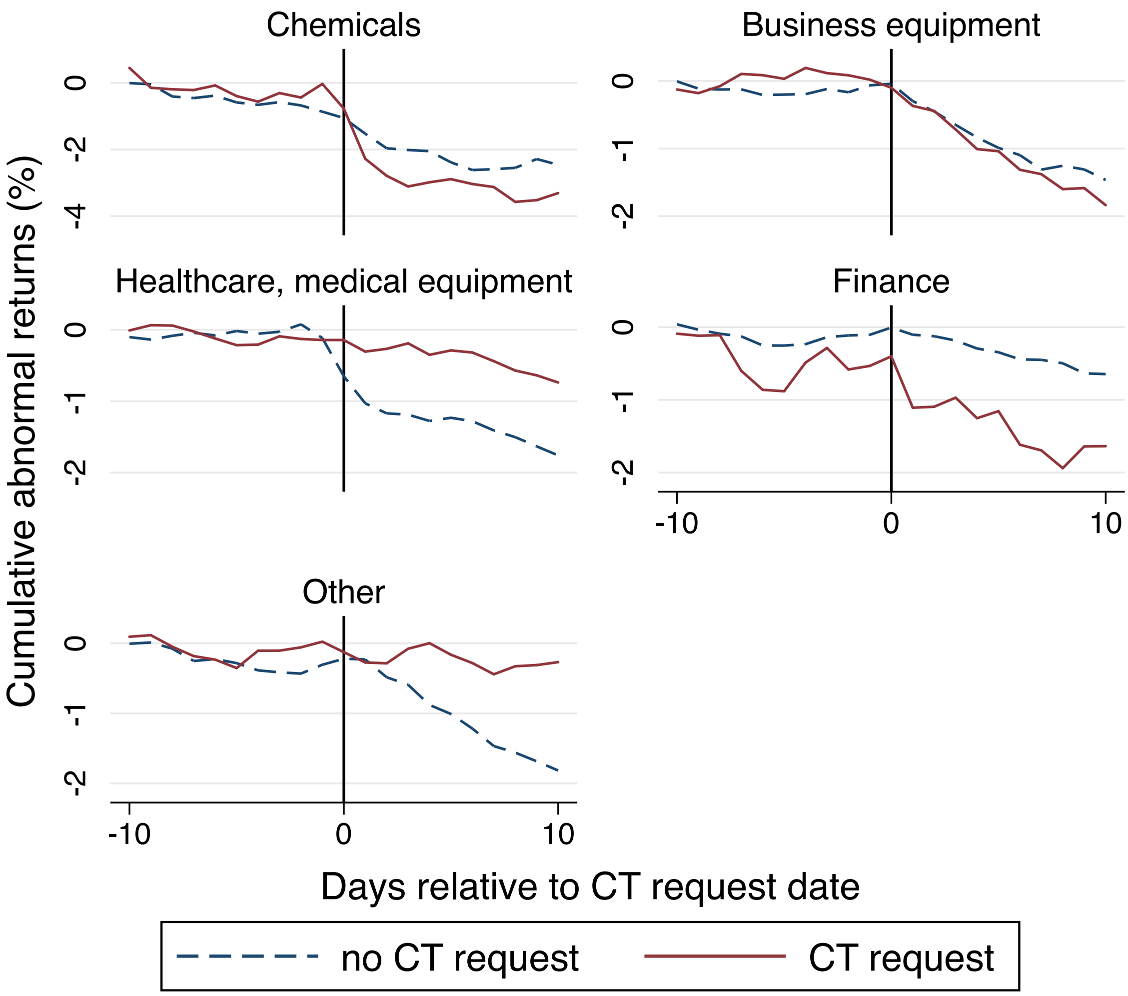
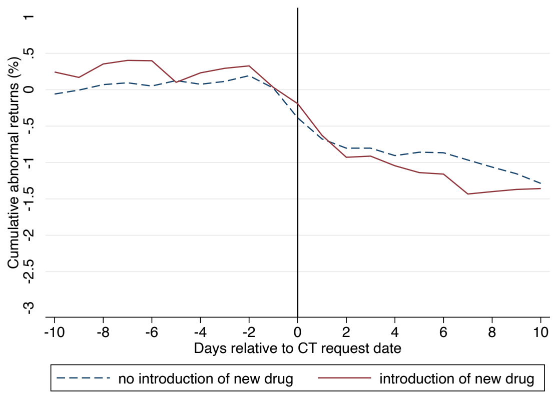


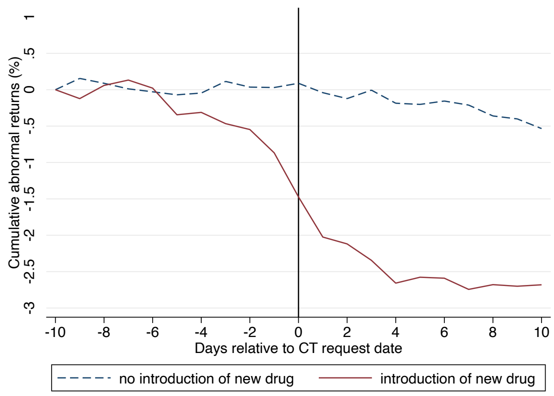
Figure 2.10: Market reaction to filings in healthcare industry, by introduction of new drugs

The figure reports the cumulative abnormal returns around the agreement filing date. Agreements should be filed by a healthcare company from 2008 to 2018. Panels A and B divide agreements by the introduction of new drug one quarter before and after the filing date of redacted agreement, respectively. Source of introduction of new drugs is Drugs@FDA database. The abnormal returns are calculated using three-factor model.

Panel A. One quarter prior to the introduction of new drugs

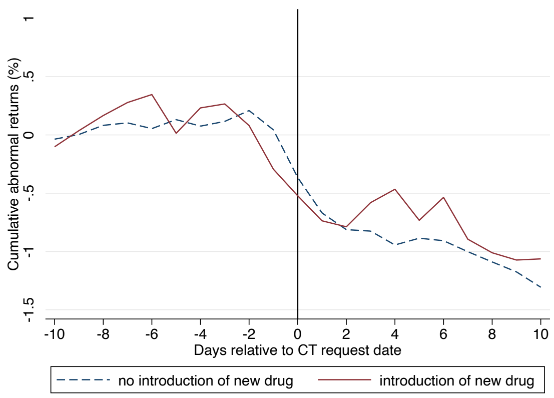


A.1. All agreements

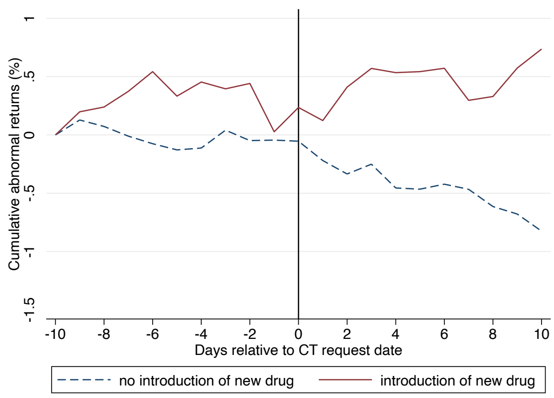


A.2 Redacted agreements

Panel B. One quarter after the introduction of new drugs



B.1. All agreements



B.2 Redacted agreements

Figure 2.11: Trading volume around agreement filing date

The figure reports trading volume around the filing date separately for redacted and fully disclosed filings. The trading volume is normalized by the trading volume 10 days prior to the filings for each firm.

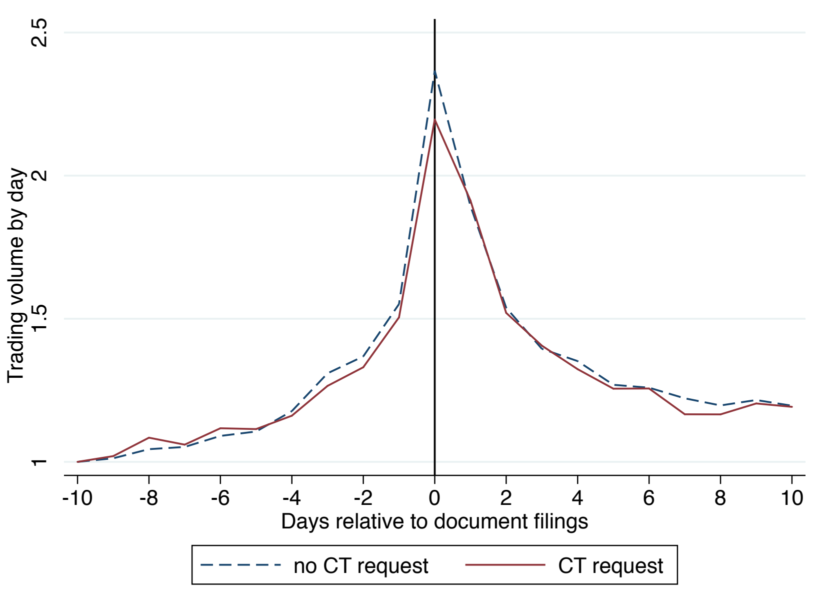


Table 2.1: Frequency of redacted clauses in a random sample of 60 redacted agreements

Contract term	Redacted (%)
Price/Payments	67.24
Appendix/Exhibits/Sections nondisclosed	41.38
Quantity	39.66
Duration/Timing	34.48
Other fees	32.76
Roalty rate	25.86
Identity of Product	20.69
Termination Clauses	18.97
Research Program/Development/CAPEX	18.97
License rate	15.52
Firm's info	15.52
Indetity of Patents (Grants)	15.52
Definition of terms	15.52
Territory of License	13.79
Signatories	13.79
Employees/Stockholders	12.07
Identitty of Patents (Application)	12.07
Minimum quantity	10.34
Identity of Non-Patent Intangible	10.34
Covernance	10.34
Milestone payments	8.62
Warranty Terms	8.62
Shipping details	8.62
Options	6.90
Objective/Bonuses	5.17
Everything is omitted	5.17
Exclusivity	3.45
Insurance	1.72

Table 2.2: Sample sorts

The table reports the proportion of the contracts with confidential treatment per contract type.

A. Agreements by type and institutional ownership (IO) level

	Total	Low IO		High IO	
	N	N	% redacted	N	% redacted
	(1)	(2)	(3)	(4)	(5)
Supply	2,626	1,761	47.02	865	61.16
License	5,283	4,061	40.75	1,222	51.88
Collaboration, R&D	3,342	2,108	29.03	1,234	25.61
Service	9,200	6,236	15.09	2,964	14.47
Investment	3,936	2,124	7.16	1,812	6.02
Lease	6,086	3,719	4.95	2,367	4.10
Asset Purchase	47,326	29,792	3.42	17,534	3.57
Settlement	6,116	3,736	2.44	2,380	3.95
Stock Option	3,983	2,033	3.00	1,950	1.13
Credit/Loan	38,607	22,734	2.14	15,873	1.97
Merger	7,066	4,271	1.10	2,795	1.93
Other	49,305	27,338	0.99	21,967	0.58
Employment	59,550	31,084	0.53	28,466	0.47
Total	242,426	140,997	4.62	101,429	3.44

B. Company characteristics

	No CT request		CT request		
	Mean	N	Mean	N	t-stat
	(1)	(2)	(3)	(4)	(5)
Log(size)	6.917	38,852	6.174	4,440	12.19***
Tobin's Q	1.212	38,852	1.943	4,440	-14.73***
ROA	-0.024	38,852	-0.152	4,440	16.50***
R&D expenditure	0.039	38,852	0.133	4,440	-19.40***
Turnover	6.131	37,951	5.435	4,208	9.53***
Sales growth	0.095	36,572	0.210	3,932	-10.05***
Cash	0.130	38,852	0.244	4,440	-19.65***
Leverage	0.179	38,852	0.178	4,440	0.10
Abnormal returns	0.001	38,852	0.003	4,440	-2.56***
IO	0.369	38,852	0.377	4,440	-0.72
Independence	0.794	12,539	0.794	1,137	-0.04
E-Index	3.951	13,771	4.087	1,349	-3.28***
CEO-Duality	0.514	12,539	0.484	1,137	1.21
DirectorOwn	13.953	12,394	14.018	1,128	-1.08

Table 2.3: Market reaction to redacted filings, by institutional ownership

The table reports the estimates of:

$$CAR_{i,f} = \beta_0 + \beta_1 IO_{f,t-1} + \mu' x_{f,t-1} + \alpha_{ind} + \alpha_t + \epsilon_{i,f,ind,t},$$

where $IO_{f,t-1}$ is *IO dummy by median* or *IO in %* , depending on the specification . *IO dummy by median* equal to one if institutional ownership level is greater than the median, and zero, otherwise. *IO in %* is the percentage of institutional ownership for a given firm. All control variable are lagged by one period. *t*-statistics, reported in parentheses, are based on standard errors clustered around firm. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)
IO dummy by median	0.471***	0.444**		
	(2.64)	(2.27)		
IO in %			0.008***	0.007***
			(3.49)	(2.80)
Cash		0.085		0.064
		(0.14)		(0.11)
Log(size)		0.079		0.070
		(0.78)		(0.69)
Leverage		-0.341		-0.366
		(-0.73)		(-0.78)
Tobin's Q		0.068		0.060
		(1.09)		(0.96)
ROA		0.268		0.247
		(0.49)		(0.45)
R&D expenditure		-0.384		-0.366
		(-0.38)		(-0.37)
Turnover		-0.055		-0.067
		(-0.59)		(-0.72)
Sales growth		-0.042		-0.036
		(-0.21)		(-0.17)
Constant	-0.369***	-0.480	-0.417***	-0.385
	(-2.91)	(-1.08)	(-3.43)	(-0.87)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6,984	6,118	6,984	6,118
R^2	0.005	0.006	0.006	0.006

Table 2.4: Market reaction to redacted filings, by block shareholders

The table reports the estimates of:

$$CAR_{i,f} = \beta_0 + \beta_1 Blockholder_{f,t-1} + \mu' x_{f,t-1} + \alpha_{ind} + \alpha_t + \epsilon_{i,f,ind,t},$$

where $Blockholder_{f,t-1}$ is $\mathbf{1}\{Blockholder\}$ or *N of blockholders*, depending on the specification. $\mathbf{1}\{Blockholder\}$ equal to one if a company has at least one block shareholder, and zero, otherwise. *N of blockholders* is the number of block shareholders for a given firm at a given year. All control variable are lagged by one period. t-statistics, reported in parentheses, are based on standard errors clustered around firm. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

	(1)	(2)	(3)	(4)
$\mathbf{1}\{Blockholder\}$	0.314**	0.291*		
	(1.96)	(1.74)		
N of blockholders			0.111***	0.106***
			(2.86)	(2.63)
Controls	N	Y	N	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6,984	6,118	6,984	6,118
R^2	0.005	0.005	0.005	0.006

Table 2.5: Probability of class action lawsuit once CT request is filed

The table reports the estimates of:

$$Class\ action\ lawsuit_{i,t} = \alpha + \beta\ CT\ request\ filing_{i,t-1} + \mu' X_{i,t-1} + \alpha_t + \alpha_{ind} + \epsilon_{i,t,ind},$$

where $CT\ request\ filing_{i,t-1}$ equals to one if CT request is filed by firm i in year $t-1$, and zero, otherwise. All control variable are lagged by one period. t-statistics, reported in parentheses, are based on standard errors clustered around firm. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

	All (1)	Merit (2)	No merit (3)	All (4)	Merit (5)	No merit (6)
CT request filing	0.012***	0.006***	0.005*	0.010***	0.005*	0.004
	(3.15)	(2.62)	(1.82)	(2.58)	(1.92)	(1.50)
Log(size)				0.007***	0.003***	0.004***
				(5.46)	(3.26)	(3.96)
Tobin's Q				0.007***	0.002***	0.004***
				(6.06)	(3.66)	(4.59)
ROA				-0.010	-0.007*	-0.002
				(-1.42)	(-1.68)	(-0.43)
R&D expenditure				-0.023	-0.021*	0.002
				(-1.37)	(-1.88)	(0.15)
Turnover				0.000	-0.001	0.001
				(0.32)	(-1.05)	(0.81)
Sales growth				0.008***	0.004*	0.005**
				(2.74)	(1.89)	(2.27)
Cash				0.017**	0.002	0.013*
				(1.96)	(0.47)	(1.91)
Leverage				-0.001	-0.002	-0.001
				(-0.28)	(-0.68)	(-0.15)
Abnormal returns				-0.118***	-0.039**	-0.065***
				(-4.24)	(-2.13)	(-3.22)
IO				-0.026***	-0.005***	-0.019***
				(-8.48)	(-3.12)	(-8.08)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	34,025	34,025	34,025	31,886	31,886	31,886
R^2	0.008	0.003	0.004	0.017	0.006	0.011

Appendix

2.A Agreement classification

I divide agreements into 9 categories. These groups are similar to Verrecchia and Weber (2006) and Boone et al. (2016).

Table 2.A.1: Definitions of most common material contracts

The table reports the definition of most common material contracts with CT requests.

Agreement	Definition
Asset purchase	Agreement between a buyer and a seller that finalizes terms and conditions related to the purchase and sale of a company's assets Key words: asset purchase, equity purchase, share purchase, asset transfer, asset sale
Collaboration and R&D	Agreement between two or more companies over research project, development of a product Key words: collaboration, R&D, research and development, (sponsored) research, co-co, clinical research, cooperative
Investment	Contract between channel partners that stipulates the responsibilities of both parties. It is usually signed between trust and fund distributor Key words: management trust, investment distribution, distribution date
License	Contract that deals with intellectual property rights. In a typical licensing agreement, the licensor grants the licensee the right to produce and sell goods, apply a brand name or trademark, or use patented technology owned by the licensor Key words: license, sublicense, intellectual property, franchise or/and omnibus.
Supply	Contracts related to sale and purchase of inventory, manufacture of products Key words: manufacturing, supply, supplier, distributor, reseller, construction or/and customer
Lease	Contract between a lessor and lessee that specifies the terms and rights under which lessee can use the leased asset. Key words: lease, leasing
Service	Agreement between two persons or businesses where one agrees to provide a specified service to the other. It can also be an express undertaking of employment signed by both the employer and the employee detailing therein the explicit terms and conditions of service Key words: service, servicing
Settlement	Binding and contractual agreement aimed to resolve legal disputes without having to go through court proceedings Key words: lawsuit, settlement, securities litigation
Stock option	Agreement between a company and holder of an option award, which defines the rights and obligations of the parties thereto Key words: stock option, (re)purchase option, exclusion option, call option, option plan.

2.B Matching company's names

Drugs@FDA database reports the drugs approved by FDA. The database does not include any firm identifier so I need to match firm's names to CIK code. To do so, I use build an algorithm that standardizes firm names and matches them to CIK:

1. I eliminate most common misspellings. For example, I find 96 different versions of misspelling of word "corporation".
2. I build an algorithm to standardize most common words like Corporation (CORP), International (INTL), Pharmaceutical (PHARMA) etc.
3. I eliminate entity indicators such as "LLC", "CORP", "INC" etc.
4. I download "Historical Company Names" and "GVKEY-CIK Link Table" from WRDS SEC Analytics Suite. I standardize them using (1)-(3).
5. I match firm's names of Drugs@FDA database to standardized names from WRDS SEC Analytics Suite.

References

Aragon, G. O., Hertzel, M., and Shi, Z. (2013). Why do hedge funds avoid disclosure? evidence from confidential 13f filings. *Journal of Financial and Quantitative Analysis*, pages 1499–1518.

Bebchuk, L., Cohen, A., and Ferrell, A. (2008). What matters in corporate governance? *Review of Financial Studies*, 22(2):783–827.

Bhagat, S. and Bolton, B. (2008). Corporate governance and firm performance. *Journal of corporate finance*, 14(3):257–273.

Boone, A. L., Floros, I. V., and Johnson, S. A. (2016). Redacting proprietary information at the initial public offering. *Journal of Financial Economics*, 120(1):102–123.

Bourveau, T., She, G., and Zaldokas, A. (2019). Corporate disclosure as a tacit coordination mechanism: Evidence from cartel enforcement regulations. *Working paper*.

Brown, S., Goetzmann, W., Liang, B., and Schwarz, C. (2008). Mandatory disclosure and operational risk: Evidence from hedge fund registration. *The journal of finance*, 63(6):2785–2815.

Cao, S. S., Ma, G., Tucker, J. W., and Wan, C. (2018). Technological peer pressure and product disclosure. *The Accounting Review*, 93(6):95–126.

Diamond, D. W. and Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *Journal of Finance*, 46(4):1325–1359.

Ettredge, M., Guo, F., Lisic, L. L., and Tseng, K. (2018). Technology spillover and corporate technology disclosures. *Available at SSRN 2727933.*

Glaeser, S. (2018). The effects of proprietary information on corporate disclosure and transparency: Evidence from trade secrets. *Journal of Accounting and Economics*, 66(1):163–193.

Grossman, S. J. (1981). The informational role of warranties and private disclosure about product quality. *The Journal of Law and Economics*, 24(3):461–483.

Heinle, M. S., Samuels, D., and Taylor, D. J. (2018). Proprietary costs and disclosure substitution: Theory and empirical evidence. *Working paper, University of Pennsylvania.*

Hermalin, B. E. and Weisbach, M. S. (2012). Information disclosure and corporate governance. *Journal of finance*, 67(1):195–233.

Kankanhalli, G. and Kwan, A. (2018). An empirical analysis of bargaining power in licensing contract terms. *Working paper, Cornell University.*

Kankanhalli, G., Kwan, A., and Merkley, K. J. (2019). Speech is silver, but silence is golden: Information suppression and the promotion of innovation. *Available at SSRN 2902341.*

Milgrom, P. R. (1981). Good news and bad news: Representation theorems and applications. *The Bell Journal of Economics*, pages 380–391.

Thompson, A. M. (2011). SEC confidential treatment orders: Balancing competing regulatory objectives. *Working paper, Texas A&M University.*

Tian, X. S. and Yu, M. (2018). Redact when competitors act-examining the threat of product market dynamics on information redaction. *Working paper. Ohio State University and Louisiana State University.*

Verrecchia, R. E. and Weber, J. (2006). Redacted disclosure. *Journal of Accounting Research*, 44(4):791–814.

Chapter 3

Lender Competition and Intangible Collateral in Syndicated Loans

joint with Alberto Manconi and Ekaterina Neretina[1]

[1]Manconi: Bocconi University, email: alberto.manconi@unibocconi.it, Neretina: USC Marshall School of Business, email: neretina@usc.marshall.edu. We thank Francesco Brunamonti for excellent research assistance.

3.1 Introduction

Intangibles play an increasingly central role in the U.S. corporate sector. As a share of book assets, intangible capital rose from 20% in 1970 to 90% in 2010 (Falato et al. (2018) and Figure 3.1.A). That has potential repercussions on corporate financing, as it affects the collateral that firms can pledge in a debt contract. Traditionally, tangible assets have been the main (if not the only) source of collateral, owing to their transparency and redeployability. Recent years, however, have witnessed a steady rise in the use of intangibles as collateral: as of 2013, nearly 40% of U.S. patenting firms had used their patents as collateral (Mann (2018)); and as we show in Figure 3.1.B, by 2020 around 15% of syndicated loans to large U.S. corporations are collateralized with patents.

The implications of this trend for corporate borrowers are not unambiguous. Greater use of intangible collateral could reflect the relaxation of a financial constraint: perhaps lenders are now more willing to accept intangibles as collateral, expanding firms' pledgeable assets and ability to raise financing. On the other hand, it could also stem from the fact that companies have relatively little tangible assets to pledge in the first place; and the opacity of intangibles could create room for rent extraction at the hands of lenders. This effect could be exacerbated if lenders have market power and borrowers have limited access to alternative sources of financing. In sum, whether or not the trend towards intangible collateral is beneficial for corporations is an empirical question—one that we attempt to address, to provide new evidence on intangible collateral.

Taking our research question to the data and disentangling the "relaxed financial constraint" and "lender market power" views can be challenging for two reasons. First, lender market power is hard to measure and can correlate with potentially relevant economic variables. A positive relationship between lender market power and collateralization might indicate rent extraction, but it could also arise from a more opaque/riskier borrower having to seek funding from a larger lender as a smaller one would not be able to bear the costs associated with information collection and monitoring. Second, and related, intangibles themselves are hard to value, which makes it difficult to assess if lenders extract rents from borrowers by undervaluing intangible collateral, and to what extent—presumably for that reason, much of the existing literature focuses on whether or not a given loan's collateral involves intangibles, rather than its value (Hochberg et al. (2018); Mann (2018)).

We address these challenges exploiting the unique features of our data and the setting of our test. First, we rely on a sample of syndicated loans to publicly listed, large U.S. corporations. Using intangibles as collateral in a loan is not uncommon among small, private, young companies (Hochberg et al. (2018)); but it happens with increasing frequency among more established firms too, as we show in Figure 3.1.B. Our sample firms are on average in the 7^{th} decile of the NYSE by size; and they are significantly larger than the typical firm in the CRSP/Compustat merged database. That attenuates the potential confounding effect of borrower opacity and monitoring costs. Second, we focus our analysis on patents, for which a widely-used measure of value is available from Kogan et al. (2017). Using a novel, hand-collected database combining information on patents used as collateral from the USPTO Patent Assignment database and the DealScan and SDC syndicated loans databases, we provide new evidence on the valuation of intangibles as collateral.

The first part of our analysis documents novel stylized facts about the use and valuation of patents as collateral in syndicated loans. We find that firms do not use their most valuable patents as collateral: the patents they do not pledge are typically worth about twice as much. Loans that have patent collateral are smaller, with average size $420m in comparison to $535m for other syndicated loans; they also have slightly longer maturity, and over twice as many covenants are attached to them. Corporate borrowers using patents as collateral are larger than the average Compustat firm, but smaller than other borrowers. Lenders accepting patents as collateral, on the other hand, are typically larger, lend to a broader range of borrowers, and have greater market share.

These findings lay out the ground for the second part of our analysis, where we study the relationship between lender market power and the use and valuation of patents as collateral. Our baseline finding is a strong, positive relationship between lender market share and the value of patents used as collateral in a given loan. That is consistent with lenders with larger market share demanding a higher amount of collateral for each dollar they lend, in line with the rent extraction hypothesis. The effect that we uncover is economically meaningful: A 10 percentage points higher lender market share is associated with a 4 to 8 percentage points higher value of patent collateral as a fraction of the loan's face value (henceforth, patents-to-loan ratio). This result is robust to a number of checks, such as alternative fixed effects, treatment of the standard errors, filters on the set of loans included in the analysis, and over different sub-samples.

We address three potential alternative explanations for our results. The first one is measurement error, arising from the fact that our baseline measure of patent value, the Kogan et al. (2017) value, is based on equity returns around the patent's grant date. That leads to two potential sources of measurement error: first, the loan is typically obtained some time after the patent grant date; and second, the lenders are debt holders and may thus value the patent differently from equity holders. To address the first issue, we depreciate patent values; to address the second one, we consider alternative measures of patent value that come closer to the perspective of debt holders, based on (i) the Merton (1974) model, (ii) the average resale value of patents, and (iii) a measure of recovery rate in bankruptcy from the results of Kermani and Ma (2020). In all cases, we find similar results as in our baseline.

The second potential explanation is constrained industry debt capacity (Shleifer and Vishny (1992)). Rather than obtaining a loan, a company may instead liquidate some of its assets—including intangibles—to an industry peer; the industry peer is expected to value them in a similar way as the liquidating firm, as they presumably have similar technology. If, however, industry peers have high leverage or face tighter financial constraints, the firm has to resort to borrowing, using the assets as collateral. But because the lender has no direct use for the collateralized assets (other than reselling them in the event of default), she is going to value them at a discount. We separate our sample loans into groups based on the leverage and financial constraints associated with their peers, defined based on the Hoberg and Phillips (2010, 2016) text-based industry classification. In all cases, we obtain similar results as in our baseline, suggesting that industry debt capacity is not behind our results.

The third potential explanation is assortative matching between lenders and borrowers. Prospective borrowers with relatively few tangible assets/more intangibles may only be able to secure a loan from a large, dominant lender, for instance because they are more opaque or more risky. Borrower opacity (or risk), in turn, requires a higher collateral value. This may drive the positive relationship between lender market share and patents-to-loan ratio that we document; the economic mechanism, however, would not be lender market power but the borrower's limited debt capacity, supporting the "relaxed financial constraint" view. Addressing this alternative explanation requires an instrument affecting lender market power for a given lender-borrower match without a separate effect on the value of patents used as collateral. In a future draft of the paper, we plan to use real estate prices as an instrument for the match between lenders and borrowers (following Adelino et al. (2015) and Luck and Santos (2019)).

Our paper makes two main contributions. First, it contributes to the literature on the use of intangibles as collateral, and patents specifically (Hochberg et al. (2018); Longman (2015); Ma et al. (2019); Mann (2018)). Loumioti (2012) argues that, in general, it alleviates a financing friction, to the benefit of borrowers. Nguyen and Hille (2018) and Nguyen and Keczkés (2018), on the other hand, find that banks are reluctant to lend against patent collateral. Our results are consistent with the opacity of intangibles creating room for rent extraction by dominant lenders, to the detriment of borrowers. We also provide new evidence on how intangible assets are valued as collateral; our findings indicate that the value of collateral is driven not only by its intrinsic characteristics, but also by the structure and degree of competition in credit markets.

Second, we contribute to the literature on capital structure and the rise of intangibles among U.S. firms (Lim et al. (2017), Falato et al. (2018), Ayyagari et al. (2019)). Prior studies have documented a secular trend towards intangible assets. Falato et al. (2018) argue that one consequence of it is that firms need to hold cash, as they have fewer tangible assets that can be used as debt collateral. Our results are consistent with the notion that intangibles are harder to collateralize, and that the dearth of tangible assets can present costs for borrowers.

The remainder of the paper is organized as follows. Section 3.2 describes our data sources. Section 3.3 presents a set of novel stylized facts about syndicated loans with patent collateral. Section 3.4 presents our tests. Section 3.5 concludes.

3.2 Data

3.2.1 Patent collateral in loans

We derive data on patents and their use as collateral from the USPTO Patent Assignment Database (Marco et al. (2015)). Starting from 2014, the U.S. Patent and Trademark Office (USPTO) made this dataset publicly available, linking patents to the organizations that own them, and reporting transactions, following the grant date, where the ownership of a patent is transferred, or "patent assignments."

A patent assignment transfers all or part of the right, title, and interest in a patent (or a patent application) from an existing owners (called assignor) to a recipient (called assignee). Patent assignments are voluntarily recorded with the USPTO by the parties in the transaction; although the filing of an assignment is not mandatory, the USPTO Patent

Assignment Database presents, as far as possible, a complete history of claimed interest in a patent (Longman (2015)). The data cover about 6 million patent assignments and other transactions, recorded between 1970 and 2014, and involving over 10 million U.S. patents and patent applications.

In particular, the USPTO permits recording other documents that affect title, such as certificates of name change and mergers, or are relevant to patent ownership, such as licensing agreements, security interests, mortgages, and liens. The database reports a patent assignment ID and date, the patent numbers for all patents involved in a given assignment, a description of the type of transaction, and strings identifying the assignor and assignee. Among the assignments in the USPTO database, we restrict the attention those related to loans, which we match to data on the syndicated loan market (described below).

We use the patent numbers to match these data to the Kogan et al. (2017) patent value database. This database reports, for a large number of U.S. patents, a link to the CRSP identifier of the firm that obtained the patent at the time it was granted. At the time of writing (June 2020) the link was available only for patents granted up to an including 2010, so we take that as the final year in our sample period.[2] The Kogan et al. (2017) data also report a measure of each patent's dollar value, based on the abnormal return on the patent owner's stock on the grant date.

The Kogan et al. (2017) value provides the input for our baseline measure of intangible collateral value. We express all patent values in constant 2010 dollars, and add up the value of all patents involved in a given assignment/loan. We then compute the ratio of that value to the size of the loan, or patents-to-loan ratio. The patents-to-loan ratio ranges between 0.00 and 13.59 in our data, with mean (median) 1.02 (0.13).

[2]In July 2020, an updated version of the Kogan et al. (2017) database was released, covering patents granted until 2019. In a future draft of the paper, we plan to expand our sample to include those patents as well.

3.2.2 Syndicated loans

We retrieve data on syndicated loans on U.S. publicly listed firms from the DealScan and SDC Platinum databases. Together, these databases cover loans over the period 1984–2010 overlapping our patent assignment and valuation data. DealScan and SDC report the names of the syndicate members and an indication of the lead bank(s) in the syndicate, as well as information regarding the size and date of the loan, contractual features such as interest rate, the presence of covenants, and maturity. They also report the share of the loan assigned to each syndicate member.

We match the DealScan borrowers to Compustat using the Chava and Roberts (2008) linking table; for the SDC data, we perform a manual screen. We also manually screen the data, to match the names of the borrower and lending bank(s) to assignor and assignee names in the USPTO Patent Assignment Database. The result is a set of 1,167 loans collateralized with patents, where for at least one collateralized patent we have value information from the Kogan et al. (2017) database. Although we cannot value all patents involved in a given loan (e.g. if the value information is missing, or if a given patent is not reported in the assignment data), robustness checks in Table 3.6 show that our results are not sensitive to requiring more complete information.

As our main proxy for lender market power, we compute the lead lender's market share on each loan following the approach of Liu and Ritter (2011). We partition the syndicated loan market into segments based on borrower rating (investment grade, speculative grade, or unrated) and loan maturity (shorter than 3 years, between 3 and 5 years, longer than 5 years).[3] For each loan in our data, we compute the lead bank's market share by aggregating all loans in the same segment over the preceding 5–year period (if there are multiple lead banks, the lender market share associated with the loan is an average of their market shares). The mean (median) market share among our sample loans is 7.9% (4.0%), with a

[3]We compute separate partitions for cash loans and lines of credit.

standard deviation of 9.4%.

3.2.3 Other sources

We supplement these data with information about the borrowing firms from the CRSP/Compustat merged database. In our tests we include controls for firm size (natural logarithm of market capitalization, expressed in millions of 2010 dollars), book-to-market ratio, ROA, and leverage (debt-to-total assets ratio). We also control for the borrower's creditworthiness by including corporate bond ratings, obtained as the average of the ratings from Standard & Poor's, Moody's, and Fitch on all bonds associated with the borrower in the Fixed Income Securities Database (FISD), where available, or Standard & Poor's long–term rating from Compustat.[4]

3.3 Stylized facts about collateralized patents

In this section, we describe a number of stylized facts about patents used as collateral in syndicated loans.

We start by comparing patents that are used as collateral to other patents, as follows. For each loan in our data, we identify the patents that the borrower uses as collateral on that loan, as well as other patents belonging to the borrower that are not collateralized. We then compare the two groups of patents along several observable characteristics. The results are reported in Table 3.1. Collateralized patents have slightly more citations (0.8 vs 0.5) and are very similar to other patents in terms of "originality" (the extent to which a patent builds on innovation from a broad range of technological classes, Hall et al. (2001); Jaffe et al. (1997)), residual life, and age. The only major difference between pledged

[4]To compute an average rating where multiple ratings are available, we convert ratings into a cardinal scale following Jorion and Zhang (2007).

and non-pledged patents is their value: the average pledged patent is worth nearly \$10 million, whereas the average non-pledge patents is worth over \$20 million.[5] In other words, borrowers tend to pledge their less valuable patents as collateral.

Loans with and without patent collateral are broadly similar, as we describe in Table 3.2. Loans with patent collateral have slightly longer maturity (55 vs 49 months), and a similar number of lead banks and syndicate size. They have, on the other hand, smaller size: the average loan with patent collateral is about \$420 million, compared to \$535 million for other loans in the union of the DealScan and SDC syndicated loans databases, i.e. a 20% difference. In addition, loans with patent collateral typically have about two covenants, in contrast to other loans, which have less than one covenant on average.

Next, in Table 3.3 we compare borrowers who pledge patents as collateral to (a) other borrowers and (b) publicly listed firms that do not obtain syndicated loans. Our sample borrowers are smaller than other borrowers in the union of the DealScan and SDC syndicated loans databases, having average market equity of \$1.7 Bn in comparison to \$3.0 Bn for other borrowers; but they are larger than the average CRSP/Compustat firm, which has market capitalization around \$1 Bn. They have also lower valuations than other borrowers, with average book-to-market 0.81 as opposed to 0.72 for other borrowers; in that dimension they are closer to the average CRSP/Compustat firm with book-to-market 0.82. Syndicated loan borrowers, whether they pledge patents or not, have higher leverage (debt-to-total assets ratio) than other CRSP/Compustat firms; patent pledgers are less profitable than other borrowers (ROA of 8.4%, in comparison to 11.4% for other borrowers), but more profitable than the average CRSP/Compustat firm (with ROA –5.7%).

Finally, Table 3.4 shows that lenders that accept patents as collateral are typically larger. They have a much larger loan portfolio than lenders that never accept collateralized patents (\$46 Bn vs \$0.7 Bn), they lend to firms belonging to a broader range of industrial sectors (Fama-French 12 industries, 9.1 vs 2.5), and they have a larger market share.

[5] All dollar values are expressed in constant 2010 dollars.

Some of these stylized facts align with the "relaxed financial constraint" view, some with the "lender market power" view. The fact that patent pledgers obtain smaller loans and have smaller market cap and higher book-to-market than other borrowers could indicate that they are more opaque and face tighter financial constraints. That said, they are still considerably larger and more profitable than the typical listed firm, suggesting that opacity is unlikely a big concern for these firms. The fact that lenders accepting collateralized patents are much larger and have a larger market share, on the other than, seems more in line with the "lender market power" view. In the remainder of the analysis, we attempt to disentangle these two views.

3.4 Lender market power and intangible collateral valuation

3.4.1 Baseline

Our baseline tests relate the valuation of patents used as collateral to lender market power. We gauge patent valuation by the patent-to-loan ratio, defined in Section 3.2. Lender market power is proxied by the market share of the syndicate leader, also defined in Section 3.2. Under the hypothesis that lenders with a dominant market position extract rents from borrowers, lending a smaller amount per dollar of collateral, we expect a positive relationship between patents to loan value and lender market share. Therefore, we estimate:

$$Patents\ to\ loan_i = \alpha + \beta Market\ share_i + \gamma' x_i + \varepsilon_i \tag{3.1}$$

The results are reported in Table 3.5. Column (1) reports the estimates of a baseline specification, where the patents to loan ratio is the sum of the Kogan et al. (2017) value of all patents pledged as collateral on a given loan, and the control variables in the vector

x are restricted to borrower rating and loan maturity. The standard errors are two–way clustered around lead bank and borrower Fama French 12-industry $\times$ year. We find a strong, positive relationship between lender market share and patents to loan ratio. A 10 percentage point increase in lender market share is associated with a 0.08 increase in the patents to loan ratio; compared to the mean (median) patents to loan ratio of about 1 (0.10), that effect also appears economically meaningful.

These estimates can be affected by two sources of measurement error, related to the fact that the Kogan et al. (2017) value is obtained based on the return on the stock of the patent holder at the time the patent is granted. That can lead to measurement error because (i) patents are typically pledged as collateral some time after they have been granted, and (ii) a creditor may value a patent differently than a shareholder.

To address the possibility of measurement error, we take two steps. First, we apply linear depreciation to the Kogan et al. (2017) patent values, assuming that when a patent expires it has a value of \$0 to its holder.[6]

Second, we apply three alternative approaches to adjust the pledged patents' value, to more closely reflect the way a creditor values them. Our first approach builds on the Merton (1974) structural model of credit risk, which treats equity as a call option on the total assets of a levered firm. Assuming that the relationship between the creditors' valuation of the patents and the Kogan et al. (2017) value is the same as the relationship between the values of debt and equity, straightforward algebra reveals that we can adjust the Kogan et al. (2017) value by a factor:

$$\frac{\sigma_E - \sigma_A}{\sigma_A - \sigma_D} \tag{3.2}$$

where σ_E, σ_A, and σ_D are the volatilities of the market values of equity, total assets, and

[6]Patents granted until 8 June 1995 have a validity of 17 years from the grant date; patents granted after 8 June 1995 have a validity of 20 years from the application date. We apply these criteria to determine the depreciation applied to each patent in our data.

debt. We estimate these quantities following the procedure developed by Bharath and Shumway (2008), and obtain for each patent in our data the corresponding value of the adjustment factor (3.2).[7]

As a second approach, we assume that the lender only values a patent to the extent that she is able to liquidate it in the event that the borrower defaults. We therefore estimate the probability that a given patent be sold in bankruptcy, by looking at the set of patents in the USPTO Patent Assigment dataset, previously pledged as collateral in a loan, that are liquidated following Chapter 7 and Chapter 11 bankruptcies. We obtain an average liquidation probability of 58%, implying that we apply an adjustment factor of 0.58 to the Kogan et al. (2017) value.

As a third approach, we also assume that the lender only values a patent to the extent that she can liquidate it. In this case we build on the estimates of Kermani and Ma (2020), who report recovery rates for different industries, which we apply as adjustment factors to the Kogan et al. (2017) value.

Columns (2)–(5) of Table 3.5 report the estimates of equation (3.1) where the dependent variable is the depreciated and adjusted patents to loan ratio. Across all approaches, we still find a positive and statistically significant relationship between lender market share and patents to loan ratio. The effects are in all cases economically significant, with a 1 percentage point increase in market share being associated with an increase in patents to loan ratio between 0.04 and 0.08. Measurement error, therefore, in unlikely to explain away our findings.

[7]Details about the derivation of the adjustment factor (3.2) and the estimation approach are provided in Appendix 3.A.

3.4.2 Robustness

We apply three sets of robustness checks, presented in Table 3.6, to the baseline tests described in the previous Section. In all cases, we follow the regression specification of column (3) of Table 3.5, including the full set of controls and adjusting the patents to loan ratio with the Merton (1974) factor, and we apply a given robustness check. First, we include in the regression fixed effects for each lead bank (or combination of lead banks where a loan has more than one), finding similar effects as in our baseline. Similarly, the statistical significance of the results is not affected if we apply three–way clustered standard errors, by lead bank, industry $\times$ date, and borrower.

Second, we require that the Kogan et al. (2017) patent value is known for at least a given fraction of all the patents pledged as collateral in a given loan. In separate checks, we require a known value for at least 25% and 50% of the pledged patents. In both cases, the estimated coefficient on lender market share in equation (3.1) is positive and statistically significant, and considerably larger in magnitude than in the baseline estimates of Table 3.5.

Third, we break the sample into an early period, including loans that are made up to and including the year 2002, and a late period, including all subsequent loans. We choose the year 2002 as a partition, because it splits the sample approximately in two; different years yield similar results. We find a positive relationship between lender market share and patents to loan ratio in both sub-samples. Although the coefficient on lender market share is not significantly different from zero in the early sub-sample, it is still close in magnitude to the baseline of Table 3.5, column (4). The relationship is statistically significant, and economically larger, in the late sub-sample.

3.4.3 Alternative explanations

We consider three potential explanations for our findings, based on (i) lender familiarity with the borrower's technology; (ii) industry debt capacity; and (iii) assortative matching between lender and borrowers.

The first potential alternative explanation is that lender market share could be related to the degree to which the lender is familiar with the borrower's technology; intuitively, one might expect that dominant, larger lenders are more likely to have lent to borrowers with a similar technology in the past. That, however, indicates that such a familiarity story is unlikely to explain our results—a greater familiarity suggests that the lender should be more willing to accept the borrower's patents as collateral, i.e. we should observe a lower patents to loan ratio.

The second potential alternative explanation is industry debt capacity Shleifer and Vishny (1992) can play a role. Suppose that an alternative to pledging patents as collateral is to sell the patents to an industry peer. Presumably the peer has similar technology, so that she is likely to find the patents valuable and to be willing to pay a fair price for them. In particular, the peer is likely to have a higher valuation of the patents, in comparison to a lender, who as an industry outsider only values the patents to the extent that they can be liquidated in the event of default. Building on this reasoning, it may be that borrowers only pledge patents as collateral when they are not able to sell them to a peer—that can happen, for instance, when the peers' debt capacity is also limited.

To address this potential explanation, for each borrower in our data we identify a set of five close peers based on Hoberg and Phillips (2010, 2016) text-based industry classification. We consider four proxies for peer debt capacity, computed as the average, across all five peers of leverage (debt-to-total assets ratio), three financial constraints indexes: the Kaplan and Zingales (1997) index, the Whited and Wu (2006) index, and the Hadlock and Pierce (2010) index. High leverage, or a high level of one of the financial constraints indexes, denotes peer with low debt capacity. We split the sample into borrowers whose peers have high (above the median) and low (below the median) debt capacity, and estimate regressions corresponding to the baseline of Table 3.5, column (4), on each sub-sample. In all cases, we find a positive relationship between lender market share and patents to loan ratio. In some cases the coefficient on lender market share is not statistically significant, possibly due to low power as the sample size shrinks. But importantly, we find a stronger relationship where the peers have higher, not lower, debt capacity—that suggests that tight industry debt capacity is not behind our baseline results.

The third potential alternative explanation is related to the "relaxed financial constraint" view discussed in the introduction, and relies of (negative) assortative matching between lenders and borrowers. Weaker borrowers might be firms characterized by opacity, more uncertain prospects, and lower tangible assets to pledge as collateral. It is thus possible that firms that tend to pledge patents are weaker borrowers, and that only larger, "dominant" lenders are able to bear the information collection and monitoring costs required to lend to them. In other words: the matching between borrowers who pledge patents and lenders with a large market share may be driven by an omitted variable, the borrower's weakness. Note that this explanation requires that the control variables already included in the regressions of Table 3.5, such as rating, maturity, the presence of covenants, and firm characteristics, do not adequately capture borrower weakness.

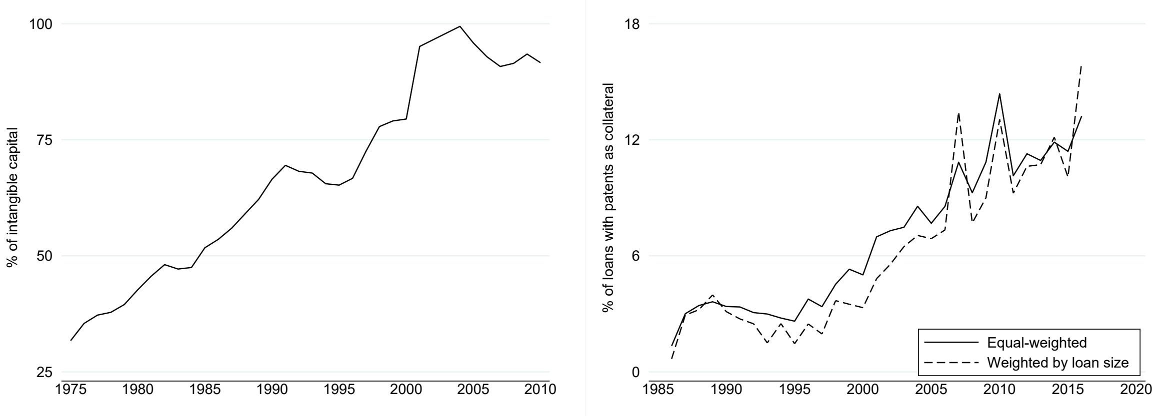
In a future draft of the paper, we plan to address the assortative matching alternative explanation with an instrument for the matching between lenders and borrowers. A candidate instrument is local real estate prices (e.g. Adelino et al. (2015)). A higher value of real estate may make the borrower's tangible assets more valuable, reducing the likelihood that the borrower pledges patents as collateral. At the same time, real estate prices do not, in general, affect the value of patents, so that the exclusion restriction should be satisfied. Data on real estate prices have already been collected, and this test will be included in the next draft of the paper.

3.5 Conclusion

We study the use and valuation of patents pledged as collateral in syndicated loans to large, publicly listed U.S. firms. We document a number of novel stylized facts about collateralized patents. Firms pledge their less valuable patents; loans with patent collateral tend to be smaller and have longer maturity; and patent pledgers are smaller than other syndicated loan borrowers, but larger than the average Compustat firm. Lenders that accept patent collateral tend to be larger and have a higher market share. We also find a positive relationship between lender market share and the patents to loan ratio, measuring the valuation of patents pledged as collateral: dominant lenders lend less per dollar value of collateral. This relationship is not explained by measurement error, lender familiarity with the borrower's technology, or borrower industry debt capacity. A possible explanation for our findings is that dominant lenders exploit the opacity and information asymmetry associated with patent valuation to extract rents, to the detriment of borrowers.

Figure 3.1: Shares of intangible capital and syndicated loans with patent collateral

In panel A, the graph plots the percentage of intangible capital for U.S. publicly listed firms from Falato et al. (2018). In panel B, the graph plots the percentage of syndicated loans with collateral that includes patents. The solid line assigns an equal weight to all loans; the dashed line assigns weights proportional to loan size. The sample consists of all loans in the union of the DealScan and SDC syndicated loans databases, over the period 1985–2019. Data on patents used as loan collateral are retrieved from the USPTO Patent Assignment database.



A. Intangible capital **B. Collateralized patents**

Table 3.1: Patents used/not used as collateral

The table compares patents that are used as collateral to other patents. For each loan, we separate the borrower's patents into a group used as collateral on the loan and a group that are not used as collateral. We then compare the two groups in terms of their characteristics, listed in the table. The sample consists of the intersection between the DealScan and SDC syndicated loans databases, the USPTO Patent Assignment database, the Kogan et al. (2017) patent value database, and the CRSP/Compustat merged database over the period 1985–2010.

	Used as collateral			
	Y	N	Difference	t
	(1)	(2)	(3)	(4)
Patent value at grant date ($MM)	9.853	23.115	–13.262	–2.93
Nr. citations	0.781	0.522	0.259	1.68
Originality	0.455	0.462	–0.007	–0.61
Residual life (years)	11.679	11.148	0.531	1.17
Age	7.369	8.011	–0.642	–1.29

Table 3.2: Loans with/without patent collateral

The table compares characteristics of loans with and without patent collateral. Columns (1) and (2) report the average loan characterics for loans whose collateral includes/does not include patents; column (3) the difference, and column (4) the associated t-statistic (based on standard errors clustered around borrower Fama-French 12 industry $\times$ year). The sample consists of the intersection between the DealScan and SDC syndicated loans databases, the USPTO Patent Assignment database, the Kogan et al. (2017) patent value database, and the CRSP/Compustat merged database over the period 1985–2010.

	Patent collateral			
	Y	N	Difference	t
	(1)	(2)	(3)	(4)
Loan size ($Bn)	0.424	0.535	–0.111	–5.33
Maturity (months)	55.045	49.194	5.851	6.56
Number of covenants	2.413	0.976	1.437	20.04
Number of lead banks in the syndicate	1.189	1.273	–0.084	–4.32
Syndicate size	6.494	6.609	–0.115	–0.73
Lead bank market share	0.078	0.076	0.002	0.52

Table 3.3: Borrowers using/not using patent collateral

The table compares borrowers that use patents as collateral to other borrowers (columns (2)–(4)), and firms that do not have outstanding syndicated loans (columns (5)–(7). The sample comprises all firms in the CRSP/Compustat merged database over the period 1985–2010. Column (1) restricts the sample to firms with a loan in the union of the DealScan and SDC syndicated loan databases and patent collateral information in the USPTO Patent Assignment database. Columns (2)–(4) restrict the sample to all other firms with a loan in the union of the DealScan and SDC syndicated loan databases, reporting the average characteristics, the difference relative to column (1), and the associated t-statistic (based on standard errors clustered around the firm's Fama-French 12 industry × year. Columns (5)–(7) restrict the sample to all CRSP/Compustat firms without a loan in the union of the DealScan and SDC syndicated loan databases, reporting the average characteristics, the difference relative to column (1), and the associated t-statistic.

	Sample	**Other borrowers**			**Non-borrowers**		
	firms	Avg.	Diff.	t	Avg.	Diff.	t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market equity ($Bn)	1.741	2.963	–1.222	–8.58	1.066	0.675	5.24
Book-to-market	0.805	0.721	0.084	2.59	0.816	–0.011	–0.36
Leverage	0.575	0.588	–0.013	–1.71	0.491	0.084	9.41
ROA	0.084	0.114	–0.030	–5.05	–0.057	0.141	13.91

Table 3.4: Lenders that take/never take patents as collateral

The table compares lenders that take/never take loans with patents as collateral. The sample consists of all the lenders in the union of the DealScan and SDC syndicated loan databases. Column (1) restricts the sample to lenders that make at least one loan with patents as collateral; column (2) to all other lenders; column (3) reports the difference between columns (1) and (2); and column (4) the associated t-statistic.

	Patent collateral			
	Y	N	Difference	t
	(1)	(2)	(3)	(4)
Loan portfolio ($Bn)	46.963	0.691	46.272	16.41
Number of sectors	9.089	2.536	6.553	25.28
Number of syndicates	4.602	5.278	–0.676	–1.09
Serve as lead (proportion)	0.364	0.557	–0.193	–7.16
Market share	0.003	0.000	0.003	16.45

Table 3.5: Lender market power and patent collateral valuation

The table reports the estimates of a regression the value of patents used as collateral in syndicated loans on lender marker power. Each observation corresponds to one syndicated loan. Patents used as collateral for the loan are valued based on the (depreciated) Kogan et al. (2017) value in column (1), and adjusting for the valuation from the point of view of creditors via the Merton (1974) model (columns (2)-(3)), via patent resale values (column (4)), and using the industry average recovery rates from Kermani and Ma (2020) (column (5)). Lender market power is proxied by the lead bank's market share. The t-statistics, reported in parentheses, are based on two-way clustered standard errors around lead bank and borrower Fama-French 12 industry × year. The sample consists of the intersection of the DealScan and SDC syndicated loans databases, the USPTO Patent Assignment database, the Kogan et al. (2017) patent value database, and the CRSP/Compustat merged database over the period 1985–2010.

Patent value	**Kogan et al. (2017)**	**Merton (1974)**		**Resale value**	**Recovery value**
	(1)	(2)	(3)	(4)	(5)
Lender market share	0.861	0.399	0.441	0.651	0.812
	(2.64)	(3.45)	(3.75)	(4.55)	(3.55)
log-Maturity	–0.743	–0.176	–0.077	–0.193	–0.122
	(–6.48)	(–4.46)	(–1.88)	(–2.38)	(–1.63)
log-Rating	0.466	0.279	0.139	0.163	0.158
	(1.27)	(2.28)	(3.09)	(2.20)	(1.61)
Unrated (Y/N)	1.075	0.643	0.342	0.501	0.504
	(1.08)	(1.94)	(2.57)	(2.78)	(2.08)
log-Market equity			0.017	0.071	0.083
			(0.46)	(0.98)	(1.10)
Leverage			0.077	0.213	0.280
			(0.37)	(0.62)	(0.77)
Book-to-market			–0.076	–0.109	–0.107
			(–2.95)	(–2.50)	(–2.04)
ROA			–0.783	–1.584	–1.708
			(–3.14)	(–3.66)	(–3.35)
# covenants			–0.023	–0.050	–0.061
			(–1.14)	(–1.70)	(–1.47)
Intercept	2.614	0.273	—	—	—
	(2.79)	(0.96)			
Industry and year f.e.			Y	Y	Y
R^2	0.04	0.02	0.13	0.15	0.19
N	1,167	1,167	1,053	1,053	1,032

Table 3.6: Robustness checks

The table reports the estimates of regressions with identical specification as in Table 3.5, columns (3)–(5), applying several robustness checks. Each row corresponds to one set of regression estimates; for brevity only the coefficient on lender market share, the associated t-statistic, the number of observations and the R^2 are reported. The column labelled "Check" describes the robustness check that each row applies.

Check	Coeff.	(t)	N	R^2
Bank f.e.	0.850	(2.53)	926	0.20
3-way clusters (bank, industry $\times$ year, borrower)	0.441	(2.74)	1,055	0.13
% collateralized patents with known value > 25%	0.758	(3.28)	747	0.15
% collateralized patents with known value > 50%	0.965	(3.24)	467	0.20
Pre-2002	0.348	(1.29)	582	0.15
Post-2002	0.497	(3.07)	472	0.14

Table 3.7: Industry peer debt capacity

The table reports the estimates of regressions with identical specification as in Table 3.5, columns (3)–(5), splitting the sample based on alternative indexes of industry debt capacity. All industry debt capacity indexes are based on average of the corresponding variables across the closest five industry peers of the borrower (identified based on the Hoberg and Phillips (2010, 2016) similarity index): leverage (high leverage implies low industry debt capacity) and the financial constraints indexes Kaplan and Zingales (1997), Whited and Wu (2006), and Hadlock and Pierce (2010, referred to as the SA index). For brevity, only the coefficients on the lender market share, the associated t-statistic, and the number of observations and R^2 are reported.

	High peer debt capacity			**Low peer debt capacity**		
Split by peer...	Coeff. (t-stat)	N	R^2	Coeff. (t-stat)	N	R^2
Leverage	0.534	423	0.16	0.459	422	0.22
	(1.13)			(2.23)		
KZ index	0.779	419	0.17	0.295	421	0.19
	(2.34)			(1.28)		
WW index	0.921	423	0.19	0.175	422	0.16
	(3.37)			(0.59)		
SA index	0.674	423	0.17	0.564	423	0.18
	(6.16)			(1.31)		

Appendix

3.A Valuing patents from the point of view of debt holders with the Merton (1974) model

We clarify how to apply a transformation to the Kogan et al. (2017) patent value to obtain an estimate of the patent's value from the point of view of debt holders. The starting point is the Merton (1974) model, where equity E is viewed as a European call option on the firm's total assets A, with strike price equal to the face value of debt K. Under these assumptions, equity can be valued by the Black–Scholes formula:

$$E = AN(d_1) - Ke^{-rT}N(d_2) \tag{3.A.1}$$

where r is the risk–free rate of return, T the maturity of debt, $d_1 = \frac{\ln(A/K)+(r+\sigma^2/2)T}{\sigma\sqrt{T}}$, $d_2 = d_1 - \sigma\sqrt{T}$, and $N(\cdot)$ denotes the normal cdf. Similarly, corporate debt is valued as a portfolio of risk–free debt and a short put:

$$D = Ke^{-rT}N(d_2) + A\left[1 - N(d_1)\right] \tag{3.A.2}$$

Finally, the volatilities of equity σ_E and debt σ_D are related to the volatility of total assets σ_A as:

$$\sigma_E E = N(d_1)\sigma_A A \tag{3.A.3}$$

$$\sigma_D D = \left[1 - N(d_1)\right]\sigma_A A \tag{3.A.4}$$

We apply the Merton (1974) logic to patent valuation. Kogan et al. (2017) value patents from the point of view of the equity holders, so we treat those values as E from (3.A.1), and seek the corresponding value of D implied by (3.A.2). We also match (3.A.3) and (3.A.4), so that we have four equations that can be solved for four unknowns: A, $N(d_1)$,

$Ke^{-rT}N(d_2)$, and D. The solution yields:

$$D = E\frac{\sigma_E - \sigma_A}{\sigma_A - \sigma_D} \tag{3.A.5}$$

Equation (3.A.5) implies that, to value a patent from the point of view of debt holders, we can multiply the Kogan et al. (2017) value by a factor that is a function of the volatilities of total assets, debt, and equity.

To take that to the data, we apply the procedure of Bharath and Shumway (2008) and obtain estimates of σ_A, σ_D, and σ_D. In our sample, the average (median) patent D/E implied by (3.A.5) is 34% (29%), ranging between 4% and 144%.

References

Adelino, M., Schoar, A., and Severino, F. (2015). House prices, collateral, and self-employment. *Journal of Financial Economics*, 117(2):288–306.

Ayyagari, M., Demirguc-Kunt, A., and Maksimovic, V. (2019). The rise of star firms: Intangible capital and competition. Working Paper, University of Maryland.

Bharath, S. T. and Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies*, 21(3):1339–1369.

Chava, S. and Roberts, M. R. (2008). How does financing impact investment? The role of debt covenants. *Journal of Finance*, 63(5):2085–2121.

Falato, A., Kadyrzhanova, D., Sim, J., and Steri, R. (2018). Rising intangible capital, shrinking debt capacity, and the U.S. corporate savings glut. Working paper, Board of Governors of the Federal Reserve System.

Hadlock, C. J. and Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the kz index. *Review of Financial Studies*, 23(5):1909–1940.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2001). The NBER patent citations data file: Lessons, insights and methodological tools. NBER Working Paper 8498.

Hoberg, G. and Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: a text-based analysis. *Review of Financial Studies*, 23(10):3773–3811.

Hoberg, G. and Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465.

Hochberg, Y. V., Serrano, C. J., and Ziedonis, R. H. (2018). Patent collateral, investor commitment, and the market for venture lending. *Journal of Financial Economics*, 130(1):74–94.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1997). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):577–598.

Jorion, P. and Zhang, G. (2007). Information effects of bond rating changes: the role of the rating prior to the announcement. *Journal of Fixed Income*, 16(4):45–59.

Kaplan, S. N. and Zingales, L. (1997). Do investment–cash flow sensitivities provide useful measures of financial constraints? *Quarterly Journal of Economics*, 112(1):169–215.

Kermani, A. and Ma, Y. (2020). Asset specificity of non-financial firms. Working paper, Berkeley Haas.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2):665–712.

Lim, S. C., Macias, A. J., and Moeller, T. (2017). Intangible assets and capital structure. Working Paper, Texas Christian University.

Liu, X. and Ritter, J. R. (2011). Lower underwriter oligopolies and ipo underpricing. *Journal of Financial Economics*, 102(3):579–601.

Longman, S. (2015). Intellectual assets and corporate finance. Unpublished PhD Dissertation, Ohio State University.

Loumioti, M. (2012). The use of intangible assets as collateral. Working Paper, UT Dallas.

Luck, S. A. and Santos, J. A. C. (2019). The valuation of collateral in bank lending. Working Paper, Federal Reserve Bank of New York.

Ma, S., Tong, J. T., and Wang, W. (2019). Selling innovation in bankruptcy. Working Paper, Yale University.

Mann, W. (2018). Creditor rights and innovation: evidence from patent collateral. *Journal of Financial Economics*, 130(1):25–47.

Marco, A. C., Myers, A. F., Graham, S., D'Agostino, P., and Apple, K. (2015). The USPTO patent assignment dataset: descriptions and analysis. USPTO Economic Working Paper 2015–2.

Merton, R. C. (1974). On the pricing of corporate debt: the risk structure of interest rates. *Journal of Finance*, 29(2):449–470.

Nguyen, P.-A. and Keczkés, A. (2018). Technology spillovers, asset redeployability, and corporate financial policies. Working paper, York University.

Nguyen, X.-T. and Hille, E. (2018). Patent aversion: an empirical study of patents collateral in bank lending, 1980-2016. *UC Irvine Law Review*, 9:141–176.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: a market equilibrium approach. *Journal of Finance*, 47(4):1343–1366.

Whited, T. and Wu, G. (2006). Financial constraints risk. *Review of Financial Studies*, 19(2):531–559.