Essays On Innovation

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Abstract
This dissertation consists of two chapters on topics in innovation. The first chapter analyzes how alternative patent enforcement regimes affect inventors in the market. How does a change in enforcement costs influence the inventors' decisions to keep, sell to an intermediary, or enforce their patents through litigation? How much do inventors earn out of patent enforcement and trade under alternative cost structures? I combine publicly available litigation data with data on intermediaries to (i) document the impact of having tougher standards on the preliminary injunction on patent sale prices and incentives, (ii) calibrate a dynamic game, (iii) simulate counter-factual outcomes under different patent enforcement systems to quantify benefits on inventors. Reduced-form analysis of the data shows that small firms operating in high-risk litigation sectors are more likely to sell their patents after the implementation of tougher standards on the preliminary injunction. Moreover, such a change in standards decreases the price that inventors receive from the patent sale. To capture the impact of alternative regimes on inventors, I develop and calibrate a dynamic game played between an inventor, an intermediary and a licensee. In the model, inventors have the option to keep, litigate or sell their assets to an intermediary. An intermediary negotiates a price with inventors and chases licensees, picks the optimal time to enforce, and makes a take-it-or-leave-it offer to the licensee. The key point of this model is the difference between enforcement technologies of inventors and intermediaries in generating returns from enforcement. Intermediaries can settle the cases outside the courtroom and share the surplus with inventors. The quantitative analysis suggests that in equilibrium, the average litigation fees paid increases by 7.46 (no-intermediary world), 2.5 (British Rule), and 3.5 (intermediary-pays-all rule) percent. Additionally, the average earnings of inventors decrease by 15.23 (no-intermediary world), 2 (British Rule), 2.5 (intermediary-pays-all rule) percent. The findings of this chapter can help to inform future policy change on patent enforcement.

In the second chapter, which is based on research that I conducted with David S. Abrams, Ufuk Akcigit, I answer the following question: How do non-practicing entities (patent trolls) impact innovation and technological progress? The question has enormous importance to industrial policy, with little direct evidence to inform it. This chapter provides new evidence on the subject, both theoretically and empirically. In doing so, I inform the debate that has portrayed non-practicing entities (NPEs) alternatively as benign middlemen that help to reallocate IP to where it is most productive or stick-up artists that exploit the patent system to extract rents, thereby hurting innovation. I make use of unprecedented access to NPE-derived patent and financial data as well as a novel model that guides my data analysis. I find that NPEs target patents coming from small firms and those that are more litigation-prone, as well as ones that are not core to a company's business. When NPEs license patents, those that generate higher fees are closer to the licensee's business and more likely to be litigated. I also find that downstream innovation drops in fields where patents have been acquired by an NPE. Finally, my numerical analysis shows that the existence of the NPE encourages upstream innovation and discourages downstream innovation. I also find that the impact of an NPE on the overall innovation depends on the fraction of infringements coming from non-innovating producers. My results provide some support for both views of NPEs and suggest that a more nuanced perspective on NPEs as well as additional empirical work is necessary before informed policy decisions can be made.

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ESSAYS ON INNOVATION

Gokhan Oz

A DISSERTATION

in

Economics

Presented to the Faculties of the University of Pennsylvania in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

2018

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To my family for their unconditional love and support.
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In the second chapter, which is based on research that I conducted with David S. Abrams, Ufuk Akcigit, I answer the following question: How do non-practicing entities (patent trolls) impact innovation and technological progress? The question has enormous importance to industrial policy, with little direct evidence to inform it. This chapter provides new evidence on the subject, both theoretically and empirically. In doing so, I inform the debate that has portrayed non-practicing entities (NPEs) alternatively as benign middlemen that help to reallocate IP to where it is most productive or stick-up artists that exploit the patent system to extract rents, thereby hurting innovation. I make use of unprecedented access to NPE-derived patent and financial data as well as a novel model that guides my
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1.1 Introduction

The objective of this chapter is to answer the following questions: What is the impact of alternative patent enforcement regimes on inventors’ ability to generate revenue out of their assets? Specifically, how much do inventors earn out of patent enforcement and trade under alternative cost structures? To answer these questions, first, I document stylized empirical facts regarding the patent enforcement market in the U.S. Second, I calibrate a model of patent trade and enforcement in the presence of intermediaries\(^2\) to tackle this question building on Pakes [1986].

Due to the significant financial risk of patent litigation, there has been an effort to reform patent legislation in recent years. The debate on patent legislation is mainly centered around the impact of tougher standards of patent enforcement on

\(^2\)In this chapter, I use the term intermediaries or non-practicing entities (NPE) to refer to entities that are specialized in generating revenues out of patent licensing and damage awards. Since the primary purpose of this chapter is not to evaluate the business model of the intermediaries, interested readers can check Abrams et al. [2017] for extensive discussion on the role of non-practicing entities in the market.
the quality of patents enforced in the market. Proponents of such a reform claim that making enforcement costly can deter the enforcement of low quality patents. Opponents of the reform assert that such an increase in costs can deter inventors from enforcing their ideas altogether, which, in turn, leads to more infringement. It is important to note that policy propositions on patent enforcement do not increase enforcement costs equally for inventors and intermediaries. There are laws that aim to increase the enforcement costs for intermediaries, in addition to laws that aim to increase enforcement costs across the board for intermediaries and inventors. Much of the current debate ignores the impact of such a reform on the inventors’ opportunity to monetize their ideas in the market, as well as the revenue generated from patent trade.

The impact of alternative enforcement regimes on the monetization of ideas is ambiguous. A change in the enforcement regime can affect the costs of enforcement for both inventors and intermediaries, which impacts the patent sale price that inventors and intermediaries negotiate in the market. A policy change that increases the relative costs of enforcement for inventors can potentially facilitate the monetization of ideas via the sale to intermediaries. On the other hand, a policy change that increases the relative cost of enforcement for intermediaries decreases the incentives for trade and can potentially lead to the monetization of ideas via litigation by inventors.

An increase in enforcement costs across the board may affect inventors by making
it costly to litigate infringers. Without the means to litigate their patents, the benefits from patent trade depend largely on the bargaining power of inventors in negotiating prices in the patent sale market. Overall, an increase in enforcement costs may lead inventors to delegate the enforcement decision to intermediaries and seek compensation in exchange for selling their ideas in the market.

If intermediaries are better at generating revenue from enforcing property rights, they are more likely to acquire assets from inventors and enforce the patents on their behalf. This may reduce the total money spent on litigation fees if intermediaries are more efficient at patent enforcement. The overall effect on inventors, in turn, depends on the impact of the patent enforcement regime on the relative prices in the market.

For this chapter, I use data used in Abrams et al. [2017] to understand the impact of alternative patent enforcement regimes on inventors in the presence of intermediaries. Overall, the primary dataset covers patent licensing, acquisition data starting in early 2000. This dataset is first used by Abrams et al. [2013] to estimate the relationship between patent value and citations. Abrams et al. [2017] expand the data used in Abrams et al. [2013]. They combine previously unavailable data on intermediaries with several publicly available data sources retrieved from PTO, Compustat, and Lex Machina to compile rich information on the characteristics of the patents, licensees, and inventors. They try to determine whether non-practicing entities (NPEs) are merely middlemen or stick-up artists by providing empirical
stylized facts on the characteristics of patents that end up at the hands of intermediaries. They also analyze the determinants of patent acquisition and licensing prices in the market. They find that small firms more likely to sell their patents to intermediaries and are paid less in comparison to large firms. Licensees are willing to pay more for patents with higher litigation risk, all other variables being equal. Moreover, they find that licensing fees increase when the patent is closer to the operations of the licensee: the less distant the patent is, the more the licensee is willing to pay. Large firms, on the other hand, sell to intermediaries those patents that are not a good fit to their core business.

Patent enforcement and trade are highly connected markets and they are contingent on the legal system and frictions in the market for enforcement; therefore, it is necessary to analyze the effect of enforcement costs on the patent sale price and incentives. The Supreme Court verdict (eBay Inc. vs. MercExchange L.L.C.) caused an increase in the standards to obtain preliminary injunctions such that the plaintiff is required to invest more resources to prove the validity of the infringement claims. I show that such a change in enforcement standards have a substantial impact on the outside option of the inventors. My findings show that small entities operating in sectors exposed to high-risk litigation are more likely to sell their patents after the Supreme Court verdict. Additionally, the patent acquisition price diminishes after the seminal decision. Empirical facts suggest that tougher standards on enforcement push less capable firms to sell their ideas at a lower price. The price that
inventors receive is largely dependent on their negotiation power, which cannot be
observed directly from the data.

In order to establish the link between enforcement activity and the patent sale
market, I develop and calibrate a finite horizon dynamic game. The primary purpose
of the model is to quantify whether NPEs decrease legal fees paid and share the
surplus with inventors. The model has three entities: upstream (those who invent
the technology), downstream (those who implement the technology) and NPEs.
Upstream entities maximize the return out of their patent portfolio by choosing
to keep the patent, sell it to NPEs, or sue the infringers in the market. The value
of the patent to the upstream entity depends on its intrinsic value drawn from
Markov distribution and the proximity of the idea to the firm’s operation. In line
with the empirical regularities of the industry as it is shown in Abrams et al. [2017],
everything else equal, the higher the distance of the patent to the portfolio, the lower
the return is from keeping the patent. The return from enforcement for upstream
entities depends on the number of entrants in the field. The higher the number of
entrants, the higher the returns from enforcement.

The primary purpose of my model is to quantify whether delegation of enforce-
ment to the intermediaries decrease transaction costs and how much of the surplus
generated is transferred to the inventors and what would happen under alterna-
tive patent enforcement regimes. In my model, I extend the framework of Abrams
et al. [2017] by focusing on stick-up artists role of NPE-enforcement activities in
generating revenue for inventors by adding relevant dynamics into the model. In my model, patent value follows a Markov distribution à la Pakes [1986]. On the enforcement side, conditional on buying the patent, intermediary and downstream entities play the dynamic game where intermediary picks the settlement offer and time to enforce the patent. Intermediaries may offer a settlement fee which exceeds the intrinsic value of the patent to the licensee. Conditional on enforcement by intermediaries, the case can end up in court or settled outside the court depending on the preferences of the licensing entities.

The negotiation structure between intermediaries, downstream firms, and upstream firms are the key ingredients that enable the model to replicate the qualitative impact of the increase in enforcement cost for the calibrated parameters. Since the Supreme Court verdict caused an increase in the standards to obtain preliminary injunctions such that the plaintiff is required to invest more resources to prove the validity of the infringement claims, within the perspective of the model, this change has made enforcement relatively costlier for plaintiffs. An increase in enforcement costs decreases the value of enforcement for upstream entities. The increase in litigation costs affects intermediaries in the following way: Everything else equal, the cost increase reduces the expected payoff from patent enforcement and increases the probability of a case being resolved outside the court. Since settlement fees are determined endogenously, depending on how sensitive the licensees to the increase in settlement fees, intermediary can decrease the settlement fees and maximize the
expected return from enforcement by increasing the probability of the case to be settled outside the court. The price that intermediary offers to the upstream entities is determined through Nash Bargaining. Depending on the bargaining power of both parties, an increase in litigation costs can generate a decrease in acquisition prices. If inventors have nonzero bargaining power, then a drop in prices must be smaller than a reduction in the value of litigating the patent for upstream entities.

In order to understand the income that inventors generate out of enforcement in the market, I need to build the counter-factual outcomes for the patents that are ended up at the hands of intermediaries, had they not acquired by the intermediaries. There is a challenge in identifying this effect from the data. There is no way to predict whether patent holders would have enforced their patents by themselves if they did not sell their patent to intermediaries. The main reasons are counter-factual outcomes not observed in the data, and the patent acquisition, litigation, and licensing decisions are not random. Thus, the identification of these effects requires a structural model.

The model is calibrated via the simulated method of moments. The structural model allows me to conduct counterfactual policy analysis. The results show that patent trade is instrumental for innovating firms to earn returns out of their patents. Quantitative analysis shows that inventors and innovating firms earn 15.23 percent more on average out of their patents when they are allowed to sell their ideas in the market in comparison to the case where there is no sale in the market. Average
transaction costs decrease by 7.46 percent with intermediaries in comparison to the case where there is no intermediary.

In order to understand the impact of alternative policies on inventors, I need to build the counter-factual pricing schemes and outcomes for patents under alternative policy regimes. There is a significant challenge in identifying this effect only from the data. Prices and outcomes are functions of bargaining power which is not observed directly in the data. Empirical results shows that intermediaries are able to reduce the transaction costs by settling the large fraction of the cases outside the court and share the surplus with inventors. The analysis of alternative policy regimes shows that under British Rule average inventor earnings from enforcement and trade decreases by 2 percent, and average transaction costs increases by 2.5 percent and average profit margin of intermediaries from enforcement decreases by 3 percent. I find that under intermediary-pays-all rule average inventor earnings from enforcement and trade decreases by 2.5 percent, and average transaction costs in equilibrium increases by 3.5 percent and average profit margin of intermediaries from enforcement decreases by 4.2 percent.

The key takeaway from my analysis is that increasing enforcement costs for every type of agent in the market facilitates patent trade in the sense that less capable firms transfer their assets to intermediaries who is more efficient at enforcing patents. On top of that, such an increase in costs are translated into lower prices for inventors in the patent sale market. I show that the application of different
costs for each agent in the market yields dramatic results. A policy change where enforcement costs decrease for inventors and increase for the intermediaries leads to excessive enforcement by less capable entities. Furthermore, the policy change leads to higher litigation fees paid in equilibrium and lowers the price that they receive from intermediaries. Reduction in patent sale prices is mainly due to the fact that such policies decrease licensing fees in addition to the profit margin of intermediaries. Results from this chapter can inform the current debate on patent enforcement reform, specifically how to regulate intermediaries in the market.

The rest of the chapter is organized as follows: Section 1.2 discusses related literature. Section 1.3 describes background, data sources and stylized facts. Section 1.4 presents the model. Section 1.5 discusses identification and calibration of the model. Section 1.6 presents and discusses the quantitative findings from the model. Section 1.7 presents counterfactual policy analysis. Section 1.8 concludes.

1.2 Literature Review

This chapter relates to several strands of literature. My analysis touches upon the empirical literature on the effect of property rights on innovation incentives. Galasso et al. [2013] tries to understand whether patent rights facilitate or impede follow-on innovation. They formulate their empirical framework around the causal effect of removing patent rights by court invalidation on subsequent research related to the focal patent, as measured by later citation. They find that patent rights suppress
downstream innovation in computers, electronics, and medical instruments, but not in drugs, chemicals or mechanical technologies. Moreover, the effect is driven by an invalidation of patents belonging to large entities that give rise to more follow-on innovation by small entities. Mezzanotti [2016] attempts to quantify the impact of the change in patent enforcement on innovation activity. The chapter finds that making it more difficult for firms to get injunction restores the innovation incentives of large entities by employing difference-in-differences estimator around policy change. He finds that making it harder to get injunctions has a positive effect on innovation. A variety of other evidence proposes that policies governing access to knowledge appear to have substantial effects on follow-on innovation (Murray [2007], Williams [2013]). This growing body of empirical evidence shows that policy-relevant distinctions can be instrumental on both theoretical and empirical research agenda on innovation.

The second is the literature that assesses the business plan of the intermediaries. Several papers attempt to understand the effect of the specific intermediary called NPEs’ business plan on the economy.\textsuperscript{3} Abrams et al. [2017] overcomes the issue of limited data, which is a major problem of the literature. They try to understand the effect of NPEs on innovation by comparing two leading theories about NPEs by using data directly from NPEs. Their data is comprehensive, contrary to other studies, in the sense that they can keep track of NPE activities. They find a piece of

\textsuperscript{3}For a historical foundation of litigation intermediaries, please check Khan [2013], Khan [2014], Lamoreaux and Sokoloff [1996], Lamoreaux and Sokoloff [2001], Beaugrand [2016]).
evidence supporting the idea that the NPEs transfer assets from users that cannot use them effectively to those who can utilize. Moreover, they also show that NPE-activity may lead to a decline in innovation. Please check Abrams et al. [2017] for an extensive discussion.⁴

On the theory side, my analysis also builds upon the theoretical literature on settlement through bargaining versus resolving the disputes in court. Spier [2005] provides an excellent survey of the economics of litigation. My analysis follows the theoretical literature’s use of dynamic models to simulate the patent value. Pakes [1986] infers the patent value from patent renewal decisions. He employs a dynamic discrete choice model to estimate the patent value distributions. Lanjouw [1998] incorporates infringement in the patent renewal model. She formulated the infringement game with common knowledge. The most important feature of her litigation game from the perspective of the renewal model is the following: if the patentee is not willing to defend her rights when all potential infringers use her innovation, then it is an equilibrium for them to do so. In this such a case patent protection has no additional value. This means that nobody is willing to pay for the renewal. Hence, patent renewal decisions require that the originating firms are willing to prosecute if every firm were to infringe. It is important to note

⁴Current literature on NPEs includes the following papers:Lemley and Shapiro [2005], Bessen and Meurer [2008], Leychikis [2007], Ball and Kesan [2009], Galasso and Schankerman [2010], Bessen et al. [2011], Chien [2013a], Chien [2013b], Galasso and Schankerman [2014], Bessen and Meuer [2014], Choi and Gerlach [2014], Cotropia et al. [2014], Feldman [2014], Scott Morton and Shapiro [2014], Tucker [2014a], Feldman and Lemley [2015], Smeets [2015], Kiebzak et al. [2016], Feng and Jaravel [2015], Haber and Werfel [2016], Allison et al. [2017] and Sokol [2017], Cohen et al. [2017].
that Lanjouw [1998] does not allow for strategic litigation decisions. My analysis incorporates the intermediaries into such family of models to get the estimates of the patent value.

Abrams et al. [2017] attempts to understand the impact of NPEs on innovation by employing a model where inventors innovate ideas and have the option to sell the ideas to the NPEs while NPEs can engage in two different licensing activities. First, NPEs can license the ideas productively without engaging in any enforcement activities. Second, NPEs can threaten to sue licensees to extract more revenue and decrease innovation incentives of the licensees. Quantitative experiment suggests that NPE increases the innovation incentives of entrants while decreasing the innovation incentives of the licensees. My model differs from Abrams et al. [2017] in several respects. First, I focus on enforcement activity in a dynamic setting, which gives me more room for a detailed analysis of the enforcement with respect to optimal timing of licensing versus going to court. Second, primary aim of my model to quantify the costs and benefits of alternative patent enforcement regimes on inventors in the presence of intermediaries in the market.

On the empirical side, my analysis documents the impact of tougher standards on getting preliminary injunctions on inventors’ outside options. Moreover, contrary to current literature, my analysis attempts at estimating the bargaining power of the inventors and quantifying the benefits of the alternative patent enforcement regimes on inventors. Even though recent literature attempts to answer the same
question, my analysis tries to achieve this goal with the help of confidential data and the calibrated structural model.

1.3 Institutional Background, Data Sources, and Stylized Facts

1.3.1 Institutional Background

This section clarifies the institutional structure of the patent enforcement disputes and trade along with the role of intermediaries in this structure.

**Who Can Enforce Patents and Against Whom?** Patents give the patent holder the legal right to exclude others to use the idea in the form of a physical product. Any infringement claim should be based on physical products since ideas are materialized through physical products. Naturally, infringement suits involve firms producing physical products as defendants. Entities who do not produce any physical products cannot be part of infringement suits as defendants. Intermediaries fits into this market in the following way: As intermediaries do not produce any physical products, they can shield themselves against potential infringement suits.

If an infringement suit is not resolved outside the court or is dropped, then a court evaluates the claims from both parties. A judge or jury who decides in favor of the patent holder can award monetary damages and issue an injunction at the earlier stages of the case to prohibit further infringement.

**Type of Intermediaries and Restrictions** There can be different interme-
diaries with varying business plans. Due to the confidential nature of the data, there are mild restrictions on what I can disclose in my analysis. Although there is no limitation of the type of analysis that I can do, the number of observations and financial data cannot be disclosed without normalization.

1.3.2 Data Sources

**Patent Application Bibliographic Data (PAB)**

The database contains basic ‘front page’ data for patents issued from 1963 to 2014. The database is based on information from a custom extract DVD generated by the Electronic Information Products Division of the USPTO. The variables used from this dataset are defined extensively in the Appendix.

**Intermediary Data (ND)**

The confidential data set requires parsing through its many layers. Please see Abrams et al. [2017] for further details regarding the data.

**Lex Machina (LM)**

Data regarding patent litigation is retrieved from Lex Machina Database. The database lists the patent number, number of cases that a patent is asserted in court, number of infringements found in each case, number of findings of invalidity, total damages awarded involving each patent, legal fees, case start date, and end

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5 Please check Scott Morton and Shapiro [2014] for further details.
date, and the name of the parties involved in the dispute. The cases include only USPTO granted patents and covers cases filed after 1999.

**U.S. Patent Citation Data (USCIT)**

U.S. Patent Citation Data includes citations for utility patents issued between 1975-2014. Each observation is a citing-cited pair. The database is based on information from a custom extract DVD generated by the Electronic Information Products Division of the USPTO.  

**The Careers and Co-Authorship Networks of U.S. Patent Inventors (INV)**

Information on the inventors of patents granted in the United States is obtained from Lai et al. [2010] updated the dataset. These authors use inventor names and addresses as well as patent characteristics to generate unique inventor identifiers. I use these unique inventor identifiers for patents that are not identified in PAB.

### 1.3.3 Stylized Facts

My empirical analysis utilizes the recent Supreme Court verdict to analyze the impact of enforcement costs on patent sale incentives, prices. First, I describe the Supreme Court verdict briefly. Then, I present my empirical facts.

**Supreme Court Decision** The 2006 *(eBay Inc. vs. MercExchange L.L.C.)*

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6I complement our citation data with the citation data located at http://www.patentsview.org/web/.

7Individually owned patents do not have unique identifiers in PAB.

8The Details can also be checked from Lexis Nexis Database. Note that Bessen and Meurer
decision had a crucial impact on how courts interpret the issuance of permanent injunctions in disputes involving intellectual property. The injunction is simply a legal remedy that can be demanded by a plaintiff after infringement claim. If it is issued, injunction forces the infringer to stop the distribution of goods using any technology covered by the alleged patents, regardless of the magnitude of the infringement.

Before 2006, application of the law can be characterized by the automatic issuance of an injunction in case of infringement, regardless of the magnitude of infringement. Such a risk confers substantial bargaining power on plaintiff during the negotiations before the injunction is granted. Exceptions to the rule were uncommon before 2006. It is not surprising as the patent law was derived from property law, where an injunction is the standard method to resolve disputes.

The ruling (eBay Inc. vs. MercExchange L.L.C.) altered this landscape by granting courts more flexibility to decide when it is appropriate to issue an injunction. In particular, the decision stated clearly that the issuance of an injunction should not happen automatically. Instead, courts should decide on a case-by-case basis. A typical case should satisfy four different criteria to be able to be eligible for consideration. This is translated into more resources to be spent on filing the patent litigation lawsuits.

The Supreme Court aimed to set new norms that would improve the status of

[2008] and Shapiro [2010] argue that change was unexpected using different pieces of qualitative evidence from news sources and other public records.
patent enforcement, by eliminating abusive lawsuits and reducing the uncertainty in the patent system and increasing the amount of effort plaintiff puts in enforcement.

**Difference-in-Differences Analysis** My framework purports to document the changes in the incentives to trade after an exogenous increase in enforcement costs. To do so, I estimate the linear probability model specified in equation 1.3.1:

\[
\text{Patent Sale}_{i,t} = \alpha + \gamma_i + \eta_t + \beta \times \text{Exposure} \times \text{After} + \phi \times \text{Exposure} \times \text{Entity Size} \times \text{After} + \psi \times JU_{i,t} + \epsilon_{i,t}
\]

(1.3.1)

where \(\text{Patent Sale}_{i,t}\) is 1 if entity \(i\) sells its patent at time \(t\) to intermediaries, 0 otherwise. Equation 1.3.1 is a firm, time level regression which is estimated by OLS within a 3-year window before and after the law change. \(\text{After}\) takes 1 if year is after 2006 and 0 otherwise. We drop the year 2006 to neutralize the effect of year that we observe the law changed. \(JU_{i,t}\) is a vector consisting of firm level controls: \(\text{After} \times \text{Entity Size}\), where entity size is measured as the number of patents in the entities’ portfolio before the policy change period. \(\alpha\) is a constant, \(\gamma_i\) is the entity fixed effects while \(\eta_t\) is the time fixed effects. Robust standard errors are clustered at the entity level. Results are presented in Table 1.1.

The negative coefficient on \(\text{After} \times \text{Exposure} \times \text{Entity Size}\) implies that:

**Fact 1:** Small firms operating in high risk exposure sectors are more likely to sell their patents to intermediaries after Supreme Court verdict.

\(^9\)Please check identification section for details regarding Supreme Court Decision.
My second framework purports to document the response of intermediaries to the regime change by looking at the differential changes in patent acquisition fees and the quality of the acquired patents around the law change. I estimate the following the equation 1.3.2 by OLS:

\[ \text{Log Price}_{i,j,t} = \alpha + \theta_j + \eta_t + \beta \times \text{Exposure} \times \text{After} + \psi \times M_{i,j,t} + \epsilon_{i,j,t} \quad (1.3.2) \]

where \( \text{Log Price}_{i,j,t} \) represents acquisition price paid to deal i for technology category j at time t. Log Acquisition Fee is calculated as the log normalized acquisition prices\(^{10}\). Our main variable of interest is \( \text{After} \times \text{Exposure} \). I would like to un-

\(^{10}\)The details of normalization can be found in Appendix.
derstand whether intermediaries’ willingness to pay for patents has changed after the policy change. To isolate the effect of the main variable of interest, I need to introduce controls to account for acquired portfolio-specific characteristics. $M_{i,j,t}$ consisting of control variables including Exposure, Acquired Portfolio Size, Deal Age, Lifetime Forward Citations, Backward Citations, Entity Size. Control variables are calculated at the deal level. Standard errors are clustered at deal level. $\alpha$ is a constant, $\theta_j$ is technology category fixed effects and $\eta_t$ is time fixed effects.

Results are reported in Table 1.2.

The negative coefficient on After $x$ Exposure implies that:

**Fact 2:** Inventors are paid lower prices in upstream market after Supreme Court verdict.

To be able to understand how the Supreme Court verdict change affected the quality of acquired patents, I estimate the following 1.3.3 by OLS:

$$\text{Deal Quality}_{i,j,t} = \alpha + \gamma_j + \eta_t + \beta \times \text{Exposure} \times \text{After} + \psi \times MF_{i,t} + \epsilon_{i,t} \quad (1.3.3)$$

where $\text{Deal Quality}_{i,j,t}$ is measured by the mean of the lifetime forward citation of the deal $i$, technology category $j$ at time $t$. Time measures the acquisition year. Our main variable of interest is After $x$ Exposure. $MF_{i,j,t}$ is a vector consisting of control variables, consisting of Exposure, Acquisition Deal Size, Age, Backward Citations, Entity Size. Standard error are clustered at deal level. $\alpha$ is a constant,
Table 1.2: The Impact of Supreme Court Verdict on Acquisition Price

<table>
<thead>
<tr>
<th>Dependent Var:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Acquisition Fee</td>
<td>Log Acquisition Fee</td>
<td>Log Acquisition Fee</td>
<td>Log Acquisition Fee</td>
<td></td>
</tr>
<tr>
<td>After x Exposure x Entity Size</td>
<td>0.0001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>After x Exposure</td>
<td>-0.368** (0.001)</td>
<td>-0.382** (0.150)</td>
<td>-0.376** (0.158)</td>
<td>-0.356** (0.141)</td>
</tr>
<tr>
<td>Exposure</td>
<td>0.375** (0.168)</td>
<td>0.394*** (0.150)</td>
<td>0.385** (0.158)</td>
<td>0.354** (0.140)</td>
</tr>
<tr>
<td>After x Entity Size</td>
<td>-0.0001 (0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entity Size</td>
<td>0.002*** (0.001)</td>
<td>0.002** (0.001)</td>
<td>0.002** (0.001)</td>
<td></td>
</tr>
<tr>
<td>Acquisition Deal Size</td>
<td>0.022*** (0.003)</td>
<td>0.022*** (0.003)</td>
<td>0.021*** (0.003)</td>
<td>0.021*** (0.003)</td>
</tr>
<tr>
<td>Age</td>
<td>0.029 (0.030)</td>
<td>0.025 (0.030)</td>
<td>0.028 (0.030)</td>
<td></td>
</tr>
<tr>
<td>Age^2</td>
<td>-0.004** (0.002)</td>
<td>-0.003* (0.002)</td>
<td>-0.004** (0.002)</td>
<td></td>
</tr>
<tr>
<td>Lifetime Forward Citations</td>
<td>0.002*** (0.001)</td>
<td>0.002*** (0.001)</td>
<td>0.002*** (0.001)</td>
<td></td>
</tr>
<tr>
<td>Backward Citations</td>
<td>0.009*** (0.002)</td>
<td>0.010*** (0.001)</td>
<td>0.009*** (0.002)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.703*** (0.420)</td>
<td>3.458*** (0.462)</td>
<td>3.481*** (0.427)</td>
<td>3.472*** (0.435)</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>IPC Fixed Effects</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.296</td>
<td>0.301</td>
<td>0.349</td>
<td>0.350</td>
</tr>
</tbody>
</table>

Notes: Linear probability model with Log Acquisition Price as dependent variable. Robust standard errors clustered by deal level in parentheses. Please see the text and appendix for variable definitions and normalization.

and γ_j is technology category fixed effects while η_t is time fixed effects. Results are reported in Table 1.3.

The positive coefficient on After x Exposure implies that:

**Fact 3:** Intermediaries target higher quality patents after Supreme Court verdict.

In light of the facts above, I can claim that a researcher needs more data on
Table 1.3: The Impact of Supreme Court Verdict on Deal Quality

<table>
<thead>
<tr>
<th>Dependent Var: Deal Quality</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>After x Exposure x E. Size</td>
<td>0.004</td>
<td>(0.027)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>After x Exposure</td>
<td>3.708**</td>
<td>7.783***</td>
<td>7.587***</td>
<td>9.932*</td>
</tr>
<tr>
<td></td>
<td>(2.060)</td>
<td>(3.193)</td>
<td>(2.859)</td>
<td>(5.120)</td>
</tr>
<tr>
<td>Exposure</td>
<td>-4.274**</td>
<td>-8.276***</td>
<td>-8.135***</td>
<td>-10.546**</td>
</tr>
<tr>
<td></td>
<td>(2.029)</td>
<td>(3.187)</td>
<td>(2.851)</td>
<td>(5.007)</td>
</tr>
<tr>
<td>After x Entity Size</td>
<td>-0.124</td>
<td>(0.134)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entity Size</td>
<td>-0.076*</td>
<td>-0.044</td>
<td>0.045</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.052)</td>
<td>(0.144)</td>
<td></td>
</tr>
<tr>
<td>Acquisition Deal Size</td>
<td>-0.197***</td>
<td>-0.249***</td>
<td>-0.171**</td>
<td>-0.166**</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.075)</td>
<td>(0.067)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Age</td>
<td>6.891**</td>
<td>6.117*</td>
<td>5.999*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.077)</td>
<td>(3.282)</td>
<td>(3.279)</td>
<td></td>
</tr>
<tr>
<td>Age^2</td>
<td>0.018</td>
<td>0.075</td>
<td>0.081</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.223)</td>
<td>(0.239)</td>
<td>(0.239)</td>
<td></td>
</tr>
<tr>
<td>Backward Citations</td>
<td>0.307***</td>
<td>0.216***</td>
<td>0.218***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.099)</td>
<td>(0.099)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>55.015***</td>
<td>27.833*</td>
<td>28.907**</td>
<td>28.924**</td>
</tr>
<tr>
<td>Year Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>IPC Controls</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.094</td>
<td>0.124</td>
<td>0.191</td>
<td>0.194</td>
</tr>
</tbody>
</table>

Notes: Linear probability model with Lifetime Forward Citations (Deal Quality) as dependent variable. Robust standard errors clustered by deal level in parentheses. Please see the text and appendix for variable definitions and normalization.

financial transactions of an intermediary to be able to reach an economically sound conclusion regarding its impact on inventors. The current analysis, even if complemented with additional data on financial transactions of an intermediary is still going to be limited. Current analysis cannot reach any conclusions regarding the implications of a change in patent enforcement regime. For example, what would happen to the inventors’ income if court implements loser’s pay system? Answering such questions requires the knowledge of trade and enforcement activities under the new patent enforcement regime, which is a function of unobservable factor such as
the bargaining power of the inventors vis-a-vis intermediary.

In order to compare alternative patent enforcement regimes and their impact on outside options of inventors, it is necessary to know how intermediaries operates and how does it react to the possible modifications to the patent system. To do so, I develop and calibrate a dynamic game in the next section to answer these questions.

1.4 Model

I develop a dynamic model played between an intermediary, an inventor, and a licensee. Figure 1.1 provides a summary of the model. As figure 1.1 illustrates, the model takes the patent enforcement system as given. The upstream market consists of inventors and downstream market consists of licensees. The primary aim of the model is to quantify the impact of alternative patent enforcement regimes on inventors via the link between enforcement and patent trade market. The key parameter in the model is the bargaining power of the inventors in negotiating prices. This parameter help me to determine the costs and benefits of alternative patent enforcement regimes on patent sale incentives and prices.

1.4.1 Baseline Model

*Basic Setting* The game has $A < \infty$ periods, $a=1,2,..,A$. The baseline model includes three players an intermediary (N), firm (F) and licensee (l) and a patent
The patent period represents the age of the patent and increases yearly.

The patent (m) is characterized by its intrinsic value $r_a$, its distance to the operations of the player $i$ $\rho^i_m$, its utilization value to the player $i$ $(1 - \rho^i_m) \times r_a$, the number of firms working in similar technologies $n_{m,a}$ and a vector of preference shocks $\{\epsilon^i_{m,a}\}$ for $i \in \{F,l\}$. The licensee (l) is characterized by its revenue from sales $R^l_a$ and the number of ongoing cases in court $n^l_{\text{court},a}$ at a given period $a$. I discuss the details of the player characteristics in the parametrization section.

**Players and Strategies** At the beginning of each period, the firm (F) observes the characteristics of the patent $\{(1-\rho^F_m) \times r_a, n_{m,a}\}$, and the sale price of the patent $p_{m,a}$ denoted by vector $\Omega^F_a = \{(1 - \rho^F_m) \times r_a, n_{m,a}, p_{m,a}\}$. The determination of the sale price is going to be discussed in detail in the next section. The action space of
the firm in a given period $a$ is selling (S) the patent to intermediaries ($d_{S,m}^F \in \{0, 1\}$), keeping (K) the patent in the portfolio ($d_{K,m}^F \in \{0, 1\}$) or litigating (L) other firms working on similar technologies ($d_{L,m}^F \in \{0, 1\}$). I assume that the firm’s strategy depends on the firm-patent level characteristics and the sale price of the patent. Hence, the strategy space of the firm is given by:

$$d_{j,m}^F : \{1, ..., A\} \times \mathbb{R}_+ \times \mathbb{N} \times \mathbb{R}_+ \times \mathbb{R} \rightarrow \{0, 1\} \quad for \ j \in \{S, K, L\}$$

(1.4.1)

Here, $d_{S,m}^F(a, (1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}, \epsilon_{m,a}) = 1$ means that the firm’s action is to sell the patent (m) to intermediaries at period $a$, while $d_{S,m}^F(a, (1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}, \epsilon_{m,a}) = 0$ means the firm does not sell the patent (m) to intermediaries at period $a$. $d_{K,m}^F(a, (1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}, \epsilon_{m,a}) = 1$ means that the firm keeps the patent in portfolio at period $a$. $d_{K,m}^F(a, (1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}, \epsilon_{m,a}) = 0$ means, on the other hand, the firm does not keep the patent in portfolio at period $a$. Finally, $d_{L,m}^F(a, (1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}, \epsilon_{m,a}) = 1$ means that the firm litigates other players in the market using the patent at period $a$ while $d_{L,m}^F(a, (1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}, \epsilon_{m,a}) = 0$ means that the firm does not litigate any player in the market at period $a$. At a given period $a$, the choice specific flow utility that the firm (F) gets from the patent (m) with characteristics $\{(1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}\}$ is denoted by a continuous and bounded function $u_j^F((1 - \rho_m^F) \times r_a, n_{m,a}, p_{m,a}, \theta, \epsilon_{m,a})$ for $j \in \{S, K, L\}$. The flow utility can be written as the sum of choice specific
utilities:

\[
u_F((1 - \rho_m^E) \times r_a, n_{m,a}, p_{m,a}, d_{m}^E, \theta, \epsilon_{m,a}^E) = \sum_{j \in \{S,K,L\}} d_{j,m}^E u_{j,m}^F((1 - \rho_m^E) \times r_a, n_{m,a}, p_{m,a}, \theta, \epsilon_{m,a}^E).
\]

Please note that selling the patent to intermediaries is a terminal condition for the firm. Once the firm sells the patent at period \(a\), the flow utility of the patent to the firm is zero at period \(a+1\). Selling in this context means that the firm delegates all its rights to use the patent to intermediaries. Note that this characterization restricts the strategy space not to depend on history.

At the beginning of each period (\(a^*\)) after the sale of the patent to intermediaries, intermediaries (N) observes the characteristics of the patent and the licensee(l) denoted by vector \(\Omega_{a^*}^l = \{(1 - \rho_m^l) \times r_{a^*}, R_{a^*}, n_{court,a^*}^l\}\). The action space of intermediaries in a given period \(a^*\) is enforcing (E) the patent against the licensee \((d_{E,m}^N \in \{0, 1\})\) or waiting (W) for the next period \((d_{W,m}^N \in \{0, 1\})\).

\[
d_{j,m,j}^N : \{a^*, ..., A\} \times \mathbb{R}_+ \times \mathbb{R}_+ \times \mathbb{N} \rightarrow \{0, 1\} \text{ for } j \in \{E, W\}
\] (1.4.3)

Here, \(d_{E,m,j}^N(a^*, (1 - \rho_m^l)r_{a^*}, R_{a^*}^l, n_{court,a^*}^l) = 1\) means that intermediaries’ action is to enforce the patent against the licensee at period \(a^*\) while \(d_{E,m,j}^N(a^*, (1 - \rho_m^l)r_{a^*}, R_{a^*}^l, n_{court,a^*}^l) = 0\) means that intermediaries’ action is not to enforce the patent against the licensee at period \(a^*\). \(d_{W,m,j}^N(a^*, (1 - \rho_m^l)r_{a^*}, R_{a^*}^l, n_{court,a^*}^l) = 1\)
means that intermediaries’ action is wait at period $a^*$.

$$d^N_{W,m,l}(a^*, (1 - \rho_m^l)r_{a^*}, R_{a^*}^l, n_{court,a^*}^l) = 0$$ means, on the other hand, intermediaries’ action is not to wait to enforce the patent against licensee at period $a^*$.

Conditional on enforcing the patent ($d^N_{E,m} = 1$), intermediaries’ makes a take-it-or-leave-it settlement offer ($D^N$) to the licensee.

$$D^N_{m,l}: \{a^*, ..., A\} \times \mathbb{R}_+ \times \mathbb{R}_+ \times \mathbb{N} \times \{0, 1\} \times \{0, 1\} \rightarrow \mathbb{R}_+ \quad (1.4.4)$$

Here, $D^N_{m,l}(a^*, (1 - \rho_m^l)r_{a^*}, R_{a^*}^l, n_{court,a^*}^l, d^N_{W,m,l}, d^N_{E,m,l})$ means that intermediaries’ action is to offer the settlement fee to the licensee for the patent at period $a^*$.

After receiving the settlement offer from intermediaries, the licensee observes

$$\Omega_{a^*} = \{(1 - \rho_m^l) \times r_{a^*}, R_{a^*}^l, n_{court,a^*}^l\}$$ and the preference shocks $\{\epsilon_{m,a^*}\}$. The action space of the licensee in a given period is to take (T) the settlement offer ($d^T_{l,m} \in \{0, 1\}$) or to reject (R) the settlement offer ($d^R_{l,m} \in \{0, 1\}$).

$$d^l_{b,m}: \{a^*, ..., A\} \times \mathbb{R}_+ \times \mathbb{R}_+ \times \mathbb{N} \times \{0, 1\} \times \{0, 1\} \times \mathbb{R} \rightarrow \{0, 1\} \quad (1.4.5)$$

$$d^T_{l,m}(a^*, (1 - \rho_m^l)r_{a^*}, R_{a^*}^l, n_{court,a^*}^l, d^N_{W,m,l}, d^N_{E,m,l}; D^N_{m,l}; \epsilon_{m,a^*}) = 1$$ means that the licensee accept the settlement offer at period $a^*$ while

$$d^l_{m}(a^*, (1 - \rho_m^l)r_{a^*}, R_{a^*}^l, n_{court,a^*}^l, d^N_{W,m,l}, d^N_{E,m,l}; D^N_{m,l}; \epsilon_{m,a^*}) = 0$$ means licensee does not take the offer.
\[ d_{R,m}^l(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, q_m^N, q_m^N, D_m^N, \epsilon_m^l) = 1 \] means that the licensee rejects the offer in a given period \( a^* \) while
\[ d_{R,m}^l(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, q_m^N, q_m^N, D_m^N, \epsilon_m^l) = 0 \] means licensee does not reject the offer in a given period \( a^* \).

The choice specific flow utility that intermediaries’ and the licensee get from the patent at time \( a^* \) are denoted by a continuous and bounded function \( u_{j,m}^N(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, D^N, \theta) \) for \( j \in \{ E, W \} \) and \( u_{j,m}^l(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, \theta, \epsilon_m^l) \) for \( j \in \{ T, R \} \) respectively. The flow utilities that intermediaries and licensee get from strategy profile \( b = \{ \{ d_{r,m}^l \}, \{ d_{m,l}^N, D_{m,l}^N \} \} \) can be written as the sum of choice specific utilities:

\[
\begin{align*}
\sum_{j \in \{ T, R \}} d_{j,m}^l(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, b, \theta, \epsilon_m^l) = \sum_{j \in \{ T, R \}} d_{j,m}^l(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, b, \theta, \epsilon_m^l).
\end{align*}
\]

\[ (1.4.6) \]

\[
\begin{align*}
\sum_{j \in \{ E, W \}} d_{j,m}^N(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, \theta, \epsilon_m^l) = \sum_{j \in \{ E, W \}} d_{j,m}^N(a^*, (1 - \rho^l_m)r_{a^*}, R_{a^*}, n_{court,a^*}^l, D^N, b, \theta, \epsilon_m^l).
\end{align*}
\]

\[ (1.4.7) \]

**Information Sets and Transition** Let \( \pi \) denote the stochastic evolution of state variables \( \{ r_a, R_a, n_m, n_{court,a} \} \) at period \( a \), and \( G^i \) the distribution of preference shocks for player \( i \in \{ F, l \} \). As for the information set of players at time \( a \), I assume that player \( i \in \{ F, l \} \) knows the distribution \( \{ \pi^i, G^i \} \) and the current
draws. Player N observes \( \{ \pi^i, G^i \} \) for \( i \in \{ F, l \} \). The transition probabilities for \( i \in \{ F, l \} \) can be written as follows:

\[
\pi(r_{a+1}, R_{a+1}^l, n_{m,a+1}, n_{\text{court},a+1}^l | r_a, R_a^l, n_{m,a}, n_{\text{court},a}^l, \theta) \quad (1.4.8)
\]

The functional form of the transition probabilities is discussed in detail in the parametrization section.

**Terminal Value** The life of the patent is defined over \( A \) periods. Hence, the patent cannot generate any flow utility for any players after the age of \( A \). This can be defined formally as:

**Definition 1.** For every \( i \in \{ F, l \} \): \( u_i = 0 \) for \( a > A \).

The other terminal value depends on the firm’s decision to sell the patent. Once the firm sells its patent at period \( a^* \), it cannot gain any flow utility from the patent in the following periods, which can be written:

**Definition 2.** If \( d_F^F(a^*, .) = 1 \), then \( u_F = 0 \) for \( a > a^* \).

The last terminal value is concerning intermediaries’ decision to enforce the patent. Once intermediaries enforce the patent against the licensee, it cannot enforce the same patent against the same licensee in the future periods. Formally it can be written as:

**Assumption 1.** If \( d_N^E(a^*, .) = 1 \) for licensee (l) and patent (m), then \( u_N(\Omega_a^l, b, \theta) = 0 \) for \( a > a^* \).
This assumption ensures that intermediaries are not going to enforce the patent against the same licensee in the future conditional on having enforced the patent against the same licensee before.

**Figure 1.2: Time Line**

\[ e^t_{\text{realize}}, F \text{ and } N \text{ negotiate } \]
\[ t \]
\[ \text{Firm chooses } \{d^F, D^F\} \]
\[ \text{Intermediary chooses } \{d^N, D^N\} \]
\[ \text{Licensee chooses } \{d^L\} \]
\[ t+1 \]
\[ \text{State Transition}(\pi) \]

**Decision Problems**

Formally, I can state the decision problems of each player in the following fashion:

**Problem of the Licensee** The decision problem of licensee (l), given the strategies of player N, is:

\[
\max_{d^l_j \in \{0, 1\}} \left( \sum_{j \in \{T, R\}} d^l_j u^l_j (\Omega^l_a, d^N, D^N, d^l, \theta, \epsilon^l_a) \right). \tag{1.4.9}
\]

**Problem of the Intermediaries** The decision problem of the intermediaries (N), given the strategies of player l, is:

\[
\max_{\{d^N_j, D^N\}} \left( \sum_{a=\alpha^*} A^+ \beta^{a-1} [\sum_{j \in \{E, W\}} d^N_j u^N_j (\Omega^l_a, d^l, D^l, \theta)] \right). \tag{1.4.10}
\]

where the expectation is taken over future state transitions and subsequent characteristics.

**Problem of the Firm** The decision problem of the firm (F), given the strategies of player N, is:
\[
\max_{d_f^F} \left( \sum_{a=1}^{A+1} \beta^{a-1} E \left[ \sum_{j \in \{S,K,L\}} d_f^F u_j^F (\Omega_a^F, \theta, \epsilon_a^F) \right] \right)
\]

(1.4.11)

where the expectation is taken over future state transitions and subsequent characteristics.

**Determination of Prices** Given the strategies of players, price is determined through Nash Bargaining. Specifically, it is:

\[
\max_{p_a} \left( p_a - \sum_{a=1}^{A+1} \left( \beta^{a-1} E \left[ \sum_{j \in \{S,K,L\}} d_f^N u_j^N (\Omega_a^N, d_l^N, D_l^N, \theta, \epsilon_a^N) \right] - p_a \right) \right)^\eta \times \left( \sum_{a=1}^{A+1} \beta^{a-1} E \left[ \sum_{j \in \{E,W\}} d_f^N u_j^N (\Omega_a^N, d_l^N, D_l^N, \theta, \epsilon_a^N) \right] \right)^{1-\eta}
\]

(1.4.12)

where the expectation is taken over future state transitions and subsequent characteristics.

Since the game is a finite horizon, incomplete information game, one can solve it by backward induction.

**Assumption 2.** For any \((\Omega_a^l, \theta, \epsilon_a^l)\); \(u_T(\Omega_a^l, d_l^N, D_l^N, \theta, \epsilon_a^l)\) is strictly decreasing in \(D^N\) and \(u_R(\Omega_a^l, d_l^N, D_l^N, \theta, \epsilon_a^l)\) is constant in \(D^N\).

Assumption 2 ensures that increasing the settlement offer holding everything else constant decreases the utility of taking the offer in the perspective of the licensee. On the other hand, \(u_R\) being constant in \(D^N\) means that rejecting the offer can be seen as taking the outside option which does not depend upon the settlement offer.

**Assumption 3.** Assume \(u_i\) be a concave and bounded function for all \(i \in \{F,l,N\}\).

**Proposition 1.** Under Assumption 2, 3, player \(l\) has a cut-off strategy.
Proof. Given the period $a$ and the strategy of intermediaries, instantaneous utility of taking the offer is given by:

$$u_T^l(\Omega^l_a, d^N_l, D^N_l, \theta, \epsilon^l_a)$$  \hfill (1.4.13)

The instantaneous utility of rejecting the settlement offer ($D^N_l$) is given by:

$$u_R^l(\Omega^l_a, d^N_l, D^N_l, \theta, \epsilon^l_a)$$  \hfill (1.4.14)

Since $u_T^l$ is concave and strictly decreasing, its inverse exists. Equating the instantaneous utilities and inverting the function give us the cut-off value for accepting the settlement offer.

$$u_T^l(\Omega^l_a, d^N_l, D^N_l, \theta, \epsilon^l_a) = u_R^l(\Omega^l_a, d^N_l, D^N_l, \theta, \epsilon^l_a)$$  \hfill (1.4.15)

$$\bar{D}_N^l = \delta(\Omega^l_a, d^N_l, \theta, \epsilon^l_a)$$  \hfill (1.4.16)

The strategy profile $d^{l,*} = \{d^*_R, d^*_T\}$ can be summarized as:

$$d^*_R(a, \Omega^l_a, d^N_m, D^N_m, \epsilon^l_m|d^{-l}) = \begin{cases} 1 & \text{if } D^N_l \geq \bar{D}_N^l \\ 0 & \text{if } D^N_l < \bar{D}_N^l \end{cases}$$
\[ d^N_t(a, \Omega^l_a, d^N_{m,l}, D^N_{m,l}, \epsilon^l_{m,a}(d^{-l})) = \begin{cases} 0 & \text{if } D^N_t \geq \bar{D}^N_t, \\ 1 & \text{if } D^N_t < \bar{D}^N_t \end{cases} \]

Let \( V_a \) be the expected utility of enforcing the patent for player N in period \( a \):

\[ V_a = \left[ P(T|a, \Omega^l_a, d^N_t, D^N_t) u^N_E(\Omega^l_a, d^N_t, D^N_t, \theta) + P(R|a, \Omega^l_a, d^N_t, D^N_t) u^N_E(\Omega^l_a, d^N_t, D^N_t, \theta) \right] \quad (1.4.17) \]

**Assumption 4.** For any \((\Omega^l_a, \theta, d^N_t)\): \( V_a \) be strictly quasi-concave and bounded.

**Proposition 2.** Under Assumption 4, there exist a unique \( D^N, * \) which maximizes \( V_a \).

*Proof.* The proof is standard and follows the uniqueness of the maximizer for the strictly quasi-concave functions.

\[ V_a \geq 0 \quad (1.4.18) \]

At period \( A-1 \), player N enforces the patent today if expected utility of enforcing today is larger than the expected discounted value of enforcing the patent tomorrow:
\[ V_{A-1} \geq \beta \mathbb{E}(V_A) \]  

(1.4.19)

where the expectation is taken over the state variables and the time varying licensee characteristics. The strategy profile for intermediaries \( d^{N,*} = \{d_{E}^{N,*}, d_{W}^{N,*}\} \) can be summarized as follows:

\[
d_{E}^{N,*}(a, \Omega_{a}^{F}, d_{m,l}^{N}, D_{m,l}^{N,*}|d^{-N}) = \begin{cases} 
1 & \text{if } V_a \geq \beta \mathbb{E}(V_{a+1}) \\
0 & \text{if } V_a < \beta \mathbb{E}(V_{a+1}) 
\end{cases}
\]

\[
d_{W}^{N,*}(a, \Omega_{a}^{F}, d_{m,l}^{N}, D_{m,l}^{N,*}|d^{-N}) = \begin{cases} 
0 & \text{if } V_a \geq \beta \mathbb{E}(V_{a+1}) \\
1 & \text{if } V_a < \beta \mathbb{E}(V_{a+1}) 
\end{cases}
\]

Suppose the firm has the patent with characteristics \( \Omega_{A}^{F} \). Since the patent expires at period \( A+1 \), the future value of the patent to the firm is zero for every choice. Hence, the value of the patent to the firm (F) at period A is

\[
V_{S,A}^{F} = u_{S}^{F}(\Omega_{A}, \theta, \epsilon_{S,A}^{F}) \tag{1.4.20}
\]

\[
V_{K,A}^{F} = u_{K}^{F}(\Omega_{A}, \theta, \epsilon_{K,A}^{F}) \tag{1.4.21}
\]

\[
V_{L,A}^{F} = u_{L}^{F}(\Omega_{A}, \theta, \epsilon_{L,A}^{F}) \tag{1.4.22}
\]

where \( V_{S,A}^{F} \) denotes the value of selling the patent with characteristics \( \Omega_{A}^{F} \) at
period $A$, $V_{K,A}^F$ denotes the value of keeping the patent with characteristics $\Omega_A^F$ at period $A$, and $V_{L,A}^F$ denotes the value of litigating the patent with characteristics $\Omega_A^F$ at period $A$.

The firm is going to choose the option with the highest value at period $A$. The value of the optimal option is denoted ($V_A^F$).

$$V_A^F = \max\{V_{S,A}^F, V_{K,A}^F, V_{L,A}^F\}$$ \hspace{1cm} (1.4.23)

At period $A-1$, the firm makes the same decisions. The value of each option can be stated in a similar fashion:

$$V_{S,A-1}^F = u_S^F(\Omega_{A-1}^F, \theta, \epsilon_{S,A-1}^F)$$ \hspace{1cm} (1.4.24)

$$V_{K,A-1}^F = u_K^F(\Omega_{A-1}^F, \theta, \epsilon_{K,A-1}^F) + \beta \mathbb{E}[V_A^F(\Omega_A^F|d_{K,A-1}^F = 1)]$$ \hspace{1cm} (1.4.25)

$$V_{L,A-1}^F = u_L^F(\Omega_{A-1}^F, \theta, \epsilon_{L,A-1}^F) + \beta \mathbb{E}[V_A^F(\Omega_A^F|d_{L,A-1}^F = 1)]$$ \hspace{1cm} (1.4.26)

where the values are equal to flow utility of each option plus the discounted value of the future value of each option. Please note that if the firm sells the patent, its continuation value is zero. As I indicated before, selling means the delegation of all future rights of the patent to intermediaries.

In the same fashion, the value of the optimal option at period $A-1$ is
\[ V_{A-1}^F = \max \{ V_{S,A-1}^F, V_{K,A-1}^F, V_{L,A-1}^F \} \] (1.4.27)

Since \( u_F \) is a concave and bounded function, I can write the firm’s problem in recursive form.

\[ V_a^F = \max_{d_j^F \in \{0,1\}} \left\{ \sum_{j \in \{S,K,L\}} \{ d_j^F u^F(\Omega_a, d^F, \theta, \epsilon_j^F) \} + \mathbb{1}_{\{d_j^F \in \{K,L\}\}} \times \beta \mathbb{E}[V_{a+1}^F(\Omega_{a+1}|d_j^F)] \right\} \] (1.4.28)

The optimal strategy of the firm \( d^{F,*} = \{d^F_S, d^F_K, d^F_L\} \) can be written as follows:

\[
d^F_S(a, \Omega_a, \epsilon_S^F) = \begin{cases} 1 & \text{if } V_a^{F,S} \geq \max\{V_a^{F,K}, V_a^{F,L}\} \\ 0 & \text{if } V_a^{F,S} < \max\{V_a^{F,K}, V_a^{F,L}\} \end{cases}
\]

\[
d^F_K(a, \Omega_a, \epsilon_K^F) = \begin{cases} 1 & \text{if } V_a^{F,K} > \max\{V_a^{F,K}, V_a^{F,L}\} \\ 0 & \text{if } V_a^{F,K} \leq \max\{V_a^{F,S}, V_a^{F,L}\} \end{cases}
\]

\[
d^F_L(a, \Omega_a, \epsilon_L^F) = \begin{cases} 1 & \text{if } V_a^{F,L} > \max\{V_a^{F,S}, V_a^{F,K}\} \\ 0 & \text{if } V_a^{F,L} \leq \max\{V_a^{F,S}, V_a^{F,K}\} \end{cases}
\]

**Proposition 3.** Under Assumption 2, 3, 4, the sequential equilibrium of the game
is unique where strategies are \( \{d^{F,*}, d^{I,*}, d^{N,*}, D^{N,*}\} \) and beliefs are consistent with \( \{\pi, G^i\} \) for all \( i \in \{F, I\} \).

The idea behind uniqueness is simple. Inventors and intermediary solve a typical single-agent optimal stopping problem. Two optimal-stopping problems are combined into sequential one such that intermediary solves the optimal stopping problem of enforcement as soon as inventors reach their terminal condition. Notice that, when deciding, due to the concavity and monotonicity assumptions and the fact that players know the distribution of the characteristics and the evolution of the state variables, they only have one action for each draw given their beliefs. It constitutes the equilibrium of the game. No player has a profitable deviation as the off-equilibrium action always provides at most as much utility as the equilibrium action, given the beliefs.

1.4.2 Extension of the Model

For all practical purposes, the empirical application requires the game to be generalized for a larger number of players. The game has \( A < \infty, a=1,2,...,A \). The model includes the following players \( l \in \{1,...,L\}, F \in \{1,...,F\}, m \in \{1,...,M\} \) and intermediaries\((N)\).

**Assumption 5.** For any \((l,F,m)\in L \times F \times M : (l,F,m) \) and intermediaries\((N)\) play the baseline game defined in Definition 3 independently.

Here, independence means that strategies and payoffs of the players in different
games do not affect each other. For example, the Firm (F)’s pay-off from keeping the patent m is not going to influence the return of holding the patent m+1. It has slightly different implications for the payoff structure of intermediaries. As the game has only one intermediary, it can generate returns out of various licensees for each patent. The intermediaries’ valuation of the patent is going to be the sum of the utilities earned out of its interaction with each licensee. Its valuation is, in turn, going to affect the pricing of the patents. Under Assumption 5, I can modify the decision problem of intermediaries and the pricing as follows:

**Problem of the Intermediaries** The decision problem of the intermediaries (N), given the strategies of player l, is:

$$\max_{d^N(\cdot), D^N(\cdot)} \left( \sum_{l=1}^{A+1} \sum_{a=a^*}^{A+1} \beta^{a-1} \mathbb{E} \left[ \sum_{j \in \{E,W\}} d^N_{j} u^N_{j}(\Omega^l_a, d^l, D^N, \theta) \right] \right) \quad (1.4.29)$$

where the expectation is taken over future state transitions and subsequent characteristics.

**Pricing** Given the strategies of players, price is determined through Nash Bargaining. Specifically, it is:

$$\max_{p_a} \left( p_a - \sum_{n=1}^{n^*} \sum_{i \in \{E,K,L\}} \beta^{n-1} \mathbb{E} \left[ \sum_{j \in \{E,W\}} d^*_{j} u^*_{j}(\Omega^a_i, \theta, \epsilon^a_i) \right] \right)^{\eta} \times \left( \frac{1}{\sum_{n=1}^{n^*} \sum_{i \in \{E,K,L\}} \beta^{n-1} \mathbb{E} \left[ \sum_{j \in \{E,W\}} d^*_{j} u^*_{j}(\Omega^a_i, d^l, D^N, \theta) \right] - p_a \right)^{1-\eta} \quad (1.4.30)$$

where the expectation is taken over future state transitions and subsequent characteristics.
1.4.3 Parametrization

**Intrinsic Return** \( r_a \) denotes the period return of patent \((m)\) with age \(a\) and it follows log normal distribution at age zero and for \(a>0\) it is distributed as the following Markov Process\( (\Psi) \) at age \(a+1\):

\[
\begin{align*}
    r_{a+1} = & \begin{cases} 
        0, \text{ with prob. } \exp(-\theta r_a) \\
        \max\{\delta r_a, z\}, \text{ with prob. } 1 - \exp(-\theta r_a) 
    \end{cases} 
\end{align*}
\]  

(1.4.31)

\[
q_a(z) = \frac{1}{\phi^{a-1} \sigma} \exp\left(-\frac{\gamma + z}{\phi^{a-1} \sigma}\right) 
\]  

(1.4.32)

This process has the following economic interpretation. At each age, agents carry out experiments to increase the returns from their patented ideas. These tests can potentially result in three different outcomes. First, tests may reveal that the patented ideas can never generate any return. This event is realized with probability \(\exp(-\theta r_a)\). The second possible outcome is that the experiments do not culminate in a more profitable use for the patented ideas in comparison to the current one. In this case, current returns depreciate with \(\delta\). The last case is that the experiments can reveal a profitable use for the patented ideas which improves upon the current returns. The magnitude of the improvement on current returns depends on the realization of \(z\). This random variable has a two-parameter exponential distribution. \(z\) has a density which declines at the constant rate \(\phi^{a-1} \sigma\).
It means that probability of uncovering practical usage decreases with age.

The net value of the asset with age \((a)\) to the firm is determined by the distance of the idea \((\rho^F \in [0,1])\) to the firm \((F)\). The higher the distance, the lower the utilization of ideas for the firm. I can write the net value of the patent to the firm as:

\[
(1 - \rho^F) \times r_a \quad (1.4.33)
\]

The distance of ideas plays an important role for firms in deciding to sell their patents to the other entities. Several studies show that controlling for all other characteristics, the higher the distance, the greater the incentive to sell the patent.\(^{11}\)

Please check variable construction section for the details of the empirical counterpart of the measure.

**Utilities** I start by specifying expected utility function \(u_i\) for each \(i \in \{F,l,N\}\).

\[
u_F = \begin{cases} 
(1 - \rho^F) \times r_a - P^T \times C_{d,a} + \epsilon_{K,a}, & \text{if } d_K = 1 \\
(1 - P^I) \times (P^{w_F} \times (\sum_h ((1 - \rho^h) \times r_a)) - C_{p,a} - C_{d,a} + \epsilon_{L,a}), & \text{if } d_L = 1 \\
p_a + \epsilon_{S,a}, & \text{if } d_S = 1
\end{cases}
\]

(1.4.34)

where \(P^I\) is the probability that the patent is invalid. If the patent is invalid, the firm cannot generate any current and future returns regardless of its choice.

\(^{11}\)Please check Abrams et al. [2017] for details.
\((1 - \rho^F) \times r_a\) is the expected net return of the patent to the firm. \(P^T\) is the probability that an entity is going to litigate the firm \((F)\) by patent conflict. \(1 - P^T\) denotes the probability that the firm \((F)\) is not targeted as a part of any dispute in given period \(a\). \((1 - P^T) \times C_{d,a}\) denotes the expected defense cost as a result of being targeted in infringement dispute. \(\epsilon^{F}_{K,a}\) is preference shock that firm observes when it decides to keep the patent. \((1 - P^I) \times (1 - \rho^F) \times r_a - P^T \times C_{d,a} + \epsilon^F_{K,a}\) is the utility of maintaining the patent in the portfolio for the firm \((F)\).

Plaintiff faces the patent invalidity challenge when it enforces the patent in the court. The invalidity disputes usually accompany patent enforcement cases. The option to litigate should reflect these costs as well. \(C^I_{d,a}\) is the cost of defending itself in the invalidity dispute in the court, \(C_{p,a}\) is the cost of filing a complaint against other players on the court at a given period \(a\). Please note that litigation option both includes \(C_{p,a}\) and \(C^I_{d,a}\) because filing an infringement suit immediately follows invalidity challenges. Thus, the firm is the plaintiff in infringement dispute while the defendant in invalidity litigation. \(\rho^k\) measures the distance of firm \(F\)’s patent to the firms \((k)\) operating in the same technology space. The sum of the net value of the patent over firm \((k)\) yields the net value that can be captured by the firm \(F\). \(w_F\) is a parameter that captures the probability that the firm \((F)\) wins the case. \(\epsilon^{F,L}_a\) is the choice specific preference shock for \((L)\) at a given period \(a\).

\((1 - P^I) \times (P^{WF} \times (\sum_k((1 - \rho^k) \times r_a)) - C_{p,a} - C^I_{d,a} + \epsilon^{F}_{L,a}\) is the utility of enforcing the patent in the court.
The utility of selling the patent to intermediaries is just the sum of the selling price and the preference shock, which is $p_a + \epsilon_{S,a}^F$.

I specify linear choice specific utility for licensees and intermediaries (N) in the same fashion.

$$u_t = \begin{cases} 
\beta_1 D^N + \beta_2 R^l_a + \beta_3 n_{court} + \epsilon^l_T, & \text{if } d^l_T = 1 \\
-(1 - P^l) \times (P^\infty \times (1 - \rho^l) \times r_a) - C_{d,a} + \epsilon^l_R, & \text{if } d^l_R = 1 
\end{cases}$$

(1.4.35)

$$u_N = \begin{cases} 
D^N, & \text{if } \{d^l_T, d^N_E, D^N\} = \{1, 1, D^N\} \\
(1 - P^l) \times (P^\infty \times (1 - \rho^l) \times r_a) - C_{p,a} - C^I_{d,a}, & \text{if } \{d^l_R, d^N_E, D^N\} = \{1, 1, D^N\} \\
0, & \text{if } d^l_T \in \{0, 1\}, d^N_W = 1 
\end{cases}$$

(1.4.36)

where $D^N$ is the settlement offer made by intermediaries, $P^\infty$ is the probability that intermediaries wins when the case resolved in the court. $-\beta_1 D^N + \beta_2 R^l_a + \beta_3 n_{court} + \epsilon^l_T$ is the utility of accepting settlement offer (D) for licensee (l). $-(1 - P^l) \times (P^\infty \times (1 - \rho^l) \times r_a) - C_{d,a} + \epsilon^l_R$ is the utility of rejecting the offer (D) for licensee (l). $D^N$ is the utility of settling the case outside the court for intermediaries. $(1 - P^l) \times (P^\infty \times (1 - \rho^l) \times r_a) - C^I_{d,a} - C_{p,a}$ is the utility of resolving the case in the court for intermediaries.

Please note that $\{P^l, P^T\}$ are random variables drawn from a binomial distri-
bution with means imputed from the data and they are realized after decisions have been made.

**Preference Shocks** The choice specific preference shocks $\epsilon^i_a$ for each player $i \in \{F, l\}$ are iid over time and distributed as Extreme Value Type I.

**Transitions** Licensee specific revenues follow AR(1) process.

$$R^l_a = c + \varphi R^l_a + \epsilon_a \quad for \quad a = 1, ..., A$$  \hspace{1cm} (1.4.37)

The number of entrants follows Poisson distribution.

$$f(n_m) = \frac{\lambda_{entry}^{n_m} e^{-\lambda_{entry}}}{n_m!}$$ \hspace{1cm} (1.4.38)

The number of ongoing court cases follows a Poisson distribution.

$$f(n_{court}) = \frac{\lambda_{court}^{n_{court}} e^{-\lambda_{court}}}{n_{court}!}$$ \hspace{1cm} (1.4.39)

**1.4.4 Discussion**

In this section, some important issues related to the patents and the theoretical model will be discussed.

First, the model abstracts away from the patent trade between innovating firms. When intermediaries offer the price for a patent, it does not face competition from innovating firms. Even though patent sale transactions between the firms can have
an impact on intermediaries’ activities, the patent trade patterns of intermediaries and innovating firms exhibit stark differences. Akcigit et al. [2015] finds that the market for patents exhibits search costs and the innovating firms use the market for productive purposes. In other words, the firms try to find better ideas through patent agents to utilize under their business plan. Moreover, intermediaries data in this chapter shows that the firms having a transaction record with intermediaries do not use secondary markets extensively. This indicates that the functions of secondary markets for the innovating firms and the intermediaries are different. As the primary aim of this chapter is to understand the effect of the intermediaries on patent trade and enforcement, I abstract away from transactions between firms and their potential impact acquisitions of intermediaries.

The theoretical framework implies that the licensees do not have the option to buy the patents directly from the firms. Two reasons can justify this implicit assumption. First, finding the right patent for enforcement requires expertise and the skill to interpret the technical language of patent claims as well as the ability to map them to the consumer products. This requires substantial investment in expertise. The professional intermediaries combine big legal teams with industry experts to construct massive patent portfolios using the secondary markets. The literature shows that this option is limited for operating firms. Specifically, Akcigit et al. [2015] indicates that transactions among companies are for productive purposes. Moreover, Serrano [2010] suggests that the most of the patent transfers
occur between small firms. Licensees are big firms. They rely upon in-house R &D to construct their patent portfolios. This observation suggests that firms, thus intermediary licensees, do not use the secondary market for ideas extensively to complement their patent portfolios.

In a nutshell, the abstraction implies that the intermediary has the expertise, but the licensees do not have the expertise in finding the right patents in the secondary markets. On top of that, since intermediaries operates in disguise, licensees have little opportunity to anticipate intermediaries' strategy and buy the patents before intermediaries do. The implicit assumption of the model implies that licensees have to negotiate with intermediaries instead of anticipating their approach and buy the patents to avoid potential conflict. Given the empirical findings in the literature and the structure of the patent trade market, the negotiation structure between licensees and intermediaries capture the essential features of the patent enforcement market.

The expertise channel that the model implicitly implies can be achieved explicitly by adding costly search in the model. Suppose the licensee may search for patents that the intermediary plans to target for acquisition. First, since the licensee does not have any information regarding how intermediaries select the patents, the probability that intermediaries buy the patent is minuscule. Assume firm can draw random patents from the universe by paying the search cost and the price. Since the probability that intermediaries target the patent is very low, expected return from buying the patent is more likely to be negative. Given the low expected return,
the licensee decides not to purchase the patent endogenously. Thus, adding this additional layer does not change theoretical results of the model.

Second, the model implies that the firms do not have the option to settle the case outside the court. Empirical evidence regarding in-house firm licensing activity suggests that in-house licensing is not a well-developed market. The in-house licensing corresponds to 10 percent of the R&D expenditures of the firms. 12 The rate is much lower for the small firms. Lanjouw and Schankerman [2001] finds that small firms are more likely to end up in court during licensing negotiations. Considering the low rate of in-house licensing together with the increased visibility of small firms in court, one can say that small firms do not have the bargaining power to settle the cases outside the court. Much of the firms transacted with the intermediaries are small ones. 13 Thus, it is reasonable to assume that they do not have the bargaining power to settle the cases outside the court.

An obvious extension of the model can include the choice of settling the cases outside the court for the innovating firms. This option is less likely to be utilized by small firms as their capacity to enforce the patents outside the court are limited. Since small firms constitute the majority of the transactions with intermediaries, adding this option in the model is not going to change the value of the options they have. Thus, the main implications of the model are going to remain the same.

Third, the model implicitly assumes that intermediaries are the only entity buy-

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13 Abrams et al. [2017] shows that small firms comprise seventy percent
ing and enforcing patents in the market. Intermediaries in this study construct significant patent portfolios and specializes in certain technology fields. Competition among different intermediaries is ignored and not the primary focus of this analysis. One should keep in mind that different business plans may coexist in the same market.

1.5 Identification and Calibration, Model Fit

1.5.1 Identification

I present heuristic arguments for the identification of model parameters. The bargaining power of the inventors in upstream pricing negotiations are identified through the choice of entities with distant ideas and the Supreme Court Decision. Since entities with distant ideas do not have the option to enforce their patents in the court due to their lack of expertise, their choice is restricted to keep or sell the patent. An exogenous change in tougher standards on preliminary injunction grant is going to affect the acquisition prices only through its impact on intermediaries’ valuation depending on the relative bargaining power of intermediaries. Such a change in acquisition fees resulting from enforcement costs help me to recover the bargaining power of intermediaries in the upstream market. Ideally one can identify the bargaining parameter via indirect inference approach by targeting the differential decline in acquisition prices as a result of higher enforcement standards.\footnote{Due to computational burden of the procedure, indirect inference approach is not implemented in this analysis.}

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Now I discuss the identification of parameters governing patent value distribution. I identify the value distribution from patent acquisition and licensing transaction in both markets. Since I observe two transactions at different ages for the same patent, it gives me the power to identify the age-dependent parameters of the Markov distribution.

Last but not the least, identification of enforcement capacity of upstream entities comes from the variation in the proximity of the idea to the entrants and patent owners in the upstream market. Since the distance of the idea to the patent holders portfolio is fixed over time, the time series variation on the number of entrants and proximity of the idea to entrants changes the return to enforce the idea in the court relative to keeping it in the portfolio.

1.5.2 Calibration

Since I do not observe the intrinsic value of the patents from the real data, given the parameter values, I need to simulate the value paths for each patent before solving the model. Then, using these value paths, and a parameter guess, the model is solved backward in the upstream and downstream market simultaneously. Model is calibrated using the simulated method of moments. For a given vector of parameters, the model generates simulated data and fit the empirical moments generated by the real data.

For the calibration of the model, I discipline intermediaries in my model using
the Abrams et al. [2017] data that comes from some NPEs. I restrict my sample to the most essential patents\textsuperscript{15} in licensing deals. The sample covers the period early 2000s until 2014. I also focus my attention on the patents relevant to intermediary data.

I denote the vector of model parameters by $\Theta$. I group all of the model-simulated moments into the vector $\tilde{H}(\Theta)$ and the data moments into the vector $H$. I minimize the objective function $[\tilde{H}(\Theta) - H]'W[\tilde{H}(\Theta) - H]$, where $W$ is a diagonal weight matrix. As weights, I use the inverse of the variance of the data moments.

\textsuperscript{15}The most relevant patents have higher ranks in the deal. I focus my attention on the most important patents.
1.6 Empirical Results

I report the calibrated parameters in Table 1.4. Some of the model parameters can be easily interpreted, and I discuss them in turn. The probability that intermediary wins the case at court is calibrated to be 0.701 while the probability that firm wins the case at court is 0.145. The point estimates imply that intermediaries have a comparative advantage in patent enforcement relative to the innovating firms and inventors.

The point estimate of $\beta_2$ implies that the higher the revenue is, it is more likely that target firm fights at court.

The calibrated parameter that governs the bargaining power of intermediaries in the upstream market shows that intermediaries has substantial market power in price negotiations.

The results indicate that intermediaries can have significant profit margins due to their market power in both markets. Therefore, the total impact on market equilibrium is explored in the next section.

The success of the model in matching empirical moments is presented in Table 1.6. The model can replicate mean prices; however, there is a slight difference between model and data for average patent age moments.

1. Average Acquisition Price: I normalize mean acquisition price to 1 to be in accord with the confidentiality restrictions. Please note that acquisition prices
Table 1.4: Parameters In the Model

<table>
<thead>
<tr>
<th>Parameter Description</th>
<th>Notation</th>
<th>Parametrization</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Winning</td>
<td>( P^W ), ( P^W_N )</td>
<td>Binomial Distribution</td>
<td>Lex Machina</td>
</tr>
<tr>
<td>Preference Parameters</td>
<td>( \beta_1, \beta_2, \beta_3 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bargaining Power</td>
<td>( \eta )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Distribution</td>
<td>( \theta, \phi, \sigma, \delta )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1.5: Calibration Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P^W_F )</td>
<td>0.145</td>
</tr>
<tr>
<td>( P^W_N )</td>
<td>0.701</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>-0.678</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>-0.011</td>
</tr>
<tr>
<td>( \beta_3 )</td>
<td>0.001</td>
</tr>
<tr>
<td>( \eta )</td>
<td>0.266</td>
</tr>
<tr>
<td>( \theta )</td>
<td>0.741</td>
</tr>
<tr>
<td>( \phi )</td>
<td>0.378</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>50.212</td>
</tr>
<tr>
<td>( \delta )</td>
<td>0.923</td>
</tr>
</tbody>
</table>

are recorded at acquisition deal level.

2. Average Licensing Price for non-litigation License and Litigation License:

The licensing revenue of each patent is calculated based on licensing revenue type. Then I aggregate it for each acquisition deal. Licensing price is normalized relative to the average acquisition price.
Table 1.6: Calibration Target Moments

<table>
<thead>
<tr>
<th>Target</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Acquisition Price</td>
<td>1.50</td>
<td>1.451</td>
</tr>
<tr>
<td>Average Licensing Price for non-Litigation License</td>
<td>1.80</td>
<td>1.732</td>
</tr>
<tr>
<td>Average Licensing Price for Litigation License (Intermediary)</td>
<td>1.80</td>
<td>1.732</td>
</tr>
<tr>
<td>Average Damages Awarded to Firms at Court</td>
<td>1.35</td>
<td>1.30</td>
</tr>
<tr>
<td>Correlation between Acquisition Price and Distance</td>
<td>-0.0510</td>
<td>-0.0435</td>
</tr>
<tr>
<td>Correlation between Acquisition Price and Licensing Price</td>
<td>0.3150</td>
<td>0.301</td>
</tr>
<tr>
<td>Fraction of non-Litigation License (Intermediary)</td>
<td>0.701</td>
<td>0.682</td>
</tr>
<tr>
<td>Correlation between Acquisition Price and Distance</td>
<td>0.011</td>
<td>0.003</td>
</tr>
<tr>
<td>Fraction of Cases Brought Up by Firms</td>
<td>0.701</td>
<td>0.682</td>
</tr>
<tr>
<td>Fraction of Patents Sold to Intermediaries</td>
<td>0.0121</td>
<td>0.0521</td>
</tr>
<tr>
<td>Average Patent Acquisition Age (Intermediary)</td>
<td>8.2</td>
<td>4.812</td>
</tr>
<tr>
<td>Average Patent Age at Licensing for non-Litigation License</td>
<td>12.4</td>
<td>16.240</td>
</tr>
<tr>
<td>Average Patent Age at Licensing Deal for Litigation License (Intermediary)</td>
<td>14.320</td>
<td>15.1</td>
</tr>
<tr>
<td>Average Patent Age for Court Cases (Firm)</td>
<td>10.2</td>
<td>6.467</td>
</tr>
</tbody>
</table>

Notes: The most valuable patents in licensing negotiations are used to calculate the correlations, prices and characteristics.

3. **Average Damages Awarded to Firms at Court:** The damages awarded at court for firms is calculated using Lex Machina data set. Average Damages Awarded is normalized relative to the average acquisition price.

4. **Correlation between Acquisition Price and Distance:** I calculate the correlation between Acquisition Prices and Distance to the licensee at acquisition deal level for intermediary patents.

5. **Correlation between Acquisition Price and Intermediary Licensing Price:** I calculate the correlation between intermediary acquisition prices and licensing price. Intermediary licensing price includes both both non-litigation license and litigation license at acquisition deal level for intermediary patents.

6. **Fraction of non-litigation License:** This moment measures the mean fraction of cases licensed to the licensees without any court involvement.
7. Fraction of Cases Brought Up by Firms: This moment measures the fraction of patents brought up by firms relative to their portfolio size.

8. Fraction of Patents Sold to Intermediary: This moment measures the mean fraction of firms patents sold to intermediaries.

9. Average Patent Age at Licensing Deals for non-litigation Licensing: I calculated the mean age at the time of licensing for the cases settled outside the court.

10. Average Patent Age at Licensing Deal for Litigation License(Intermediary): I calculated the mean patent age for intermediary’s patents at the time of licensing for the cases settled at court.

11. Average Patent Age for Court Cases(Firm): I calculated the mean patent age for patents ended up at court at the time in which firms file infringement complaints.

In order to show how intermediary enforcement changes with respect to different parameter values, I simulated 1,000 patents at the calibrated value of the parameters. The results show that intermediaries is able to collect higher fees if licensee has a preference towards early settlement. In line with this result, larger fraction of the cases are resolved outside the court. Intuition behind this result is simple. An increase in \( \beta_1 \) means that the licensee is willing to pay more for settlement over going to the court. Intermediaries’ charge higher prices for the licensee’s preference
for the settlement by considering the trade-off between the increase in settlement offer and the reduction in choice probability.

I also explore the impact of intermediary’s enforcement technology on the fraction of cases settled outside the court and the fee they collect from the licensees. The results show that improvement in intermediary’s enforcement technology results in an increase in settlement fees collected and the fraction of cases settled outside the court. The intuition behind the results is simple. An increase in intermediary’s enforcement technology makes the option to go to the court is more expensive than not going to the court, intermediaries can re-optimize by considering the trade-off between the increase in settlement offer and the reduction in choice probability. Results show that the settlement offer is more likely to get accepted after the increase in $P_N$.

Figure 1.3: Comparative Statistics I
1.7 Policy Analysis

In this section, using the calibrated parameter values, several counterfactuals are conducted to understand the impact of alternative patent enforcement regimes on inventors. The quantitative analysis tries to explore the conditions and the patent enforcement system under which litigation fees paid in equilibrium decrease and inventors receive better prices in the patent sale market. Briefly, I would like to answer the following questions: Given the structural parameters of the model, what would happen to the transaction costs and inventor compensation if British Rule of patent enforcement regime is implemented in the market in comparison to the case in which American rule is implemented. Who benefits and losses? My answers to the questions above regarding the market micro-structure help me to propose potential policies which may have a tangible impact on inventors and affect patent enforcement and trade.
I consider the effects of different patent enforcement regimes on average inventor income, average transaction costs, average profits of intermediaries. To measure the effects on inventor compensation, I calculated average compensation that inventors receive from trade and enforcement in the presence of intermediaries under different regimes using the calibrated parameters. In the same fashion, I calculate the total licensing fees paid by target firms per patent under alternative regimes to calculate the effect on profits of intermediaries.

Table 1.7: Comparison of Alternative Patent Enforcement Systems

<table>
<thead>
<tr>
<th></th>
<th>No Intermediary World</th>
<th>British Rule</th>
<th>Intermediary Pays-all Rule</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in Average Inventor Income</td>
<td>-15.23%</td>
<td>-2%</td>
<td>-2.5%</td>
</tr>
<tr>
<td>Change in Average Transaction Costs</td>
<td>7.46%</td>
<td>2.5%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Change in Average Intermediary Profits</td>
<td>-3%</td>
<td>-4.2%</td>
<td></td>
</tr>
</tbody>
</table>

Empirical results indicates that intermediaries have comparative advantage in enforcement and reduce transaction costs in the market. They share the surplus with the inventors. Table 1.7 presents the results of the counterfactual analysis. The impact of British Rule and intermediary-pays-all rule and the counterfactual world without intermediaries is evaluated relative to the current system. Quantitative experiment suggests that in the no-intermediary world average transaction costs increases by 7.46 percent and average inventor income decreases by 15.23 percent. The key takeaway from the empirical results is that policies aiming at curtailing intermediary activity and profits can result in an increase in transaction costs and a
decrease in inventor earnings. Specifically, intermediary-pays-all rule culminates in reducing the average inventor income by 2.5 percent, increase transaction costs by 3.5 percent and decrease average profits by 4.2 percent in comparison to the current system. British Rule results in reducing the average inventor income by 2 percent, increase transaction costs by 2.5 percent and decrease average profits by 3 percent in comparison to the current system.

Intuition behind these results are simple. British Rule and intermediary-pays-all Rule increase the expected value of going to court for licensing entities. In the current system, each party has to pay their own litigation costs while under British Rule, loser pays the full cost of litigation and, under intermediary-pays-all Rule, intermediary pays all litigation fees if they are in dispute with innovating entities. This leads to a decline in expected litigation cost for licensees and inventors. Such a decline has two consequences. First, it leads to a decline in settlement fees that intermediary charges to the licensees, which is translated into lower profits for intermediaries. Second, lower profits for intermediaries lead to a decrease in acquisition price that intermediary offers to the inventors. Thus, inventors on the margin choose to litigate by themselves instead of transferring their assets to intermediaries. It decreases the income that inventors are able to generate out of their assets. Please note that there is no binding liquidity constraints for the inventors in the model in any regimes. The existence of such constraints can have a direct impact on revenue generated by enforcement. For example, even if enforcement has positive return on
expectation for inventors, inventors may not be able to finance litigation costs and sell their assets. Thus, the lack of such constraints in my model can overestimate litigation fees paid by inventors and underestimate the benefits of NPEs on inventors. Key take away from the mechanism is the following: Policies that increase the litigation costs for the intermediaries decrease the outside option of the inventors and may lead to an increase in litigation by inventors.

1.8 Conclusion

This chapter provides new insights on the role of alternative patent enforcement regimes on inventors’ outside options. I establish a strong link between patent trade and enforcement costs. Specifically, I show that the increase in enforcement costs push small firms and inventors to sell their assets to intermediaries at a lower price. Intermediaries target higher quality assets after an increase in enforcement costs. This chapter provides a new structural model of patent enforcement and trade in the presence of intermediaries to evaluate the impact of alternative patent enforcement regimes. The key feature of the model is that it connects enforcement activity of intermediaries and patent trade to evaluate the potential effects of alternative patent enforcement regimes on inventors.

Empirical results show that intermediaries have a comparative advantage in enforcement and reduce transaction costs in the market. My research demonstrates that intermediaries share the surplus with the inventors. The quantitative experi-
ment suggests that in the no-intermediary world, average transaction costs increase by 7.46 percent and average revenue generated by inventors decreases by 15.23 percent. The key takeaway from the results is that application of different costs for each agent in the market yields dramatic results. A policy change where enforcement costs decrease for inventors and increase for the intermediaries leads to excessive enforcement by less capable entities. Furthermore, the policy change leads to higher litigation fees paid in equilibrium and lowers the inventors’ gains.
2 Chapter 2: Patent Trolls: Benign Middleman or Stick-Up Artists?\textsuperscript{16}

2.1 Introduction

Are Non-Practicing Entities (NPEs)\textsuperscript{17} good or bad for technological progress? This longstanding question has gained renewed urgency with their recent proliferation. Advocates and opponents are often vehement, with strongly-held (and sometimes self-interested) views. Concern about potential negative effects of NPEs has led to the introduction of legislation in state legislatures and Congress aimed at curtailing their activity. This view of NPEs as “stick-up artist” holds that they provide no benefits, but simply amass patents and literally hold up companies using the threat of litigation to extract rents. In the meantime, legislative efforts have been repelled by advocates who hold that NPEs can provide positive benefits akin to market intermediaries found in a range of industries. According to this view of NPEs as “benign middleman,” these firms facilitate innovation by buying patents from inventors who are not well-positioned to fully utilize their invention and selling or

\textsuperscript{16}This chapter is based on research that I conducted with David S. Abrams, Ufuk Akcigit.

\textsuperscript{17}I define an NPE broadly as a firm whose primary source of revenue is from patent licensing fees or patent litigation awards. In Section 2.2 I discuss the relationship with related terms such as patent assertion entities (PAEs) or patent trolls.
licensing them through their large network of industrial companies.

Despite the popularity and importance of the subject, the inner workings of NPEs has remained a mystery and discussions about them have, with few exceptions, been based on anecdotal evidence. This is largely due to the fact that NPEs act in secrecy, making it harder for researchers to access micro data on their direct business transactions and paid prices. The goal of my work is to help inform this important debate and to move closer to understanding whether NPEs facilitate to or harm innovation, or both.

This chapter makes two major contributions in the understanding of NPEs. I develop a model of innovation that incorporates NPEs and makes testable predictions. I am able to test the model by use of a proprietary and previously unstudied dataset with detailed financial, transaction and technological information on tens of thousands of NPE-held patents. Like the innovating firms I study, I do so by building on prior work that has developed important metrics for patents, such as litigation risk [Lanjouw and Schankerman, 2001] and patent distance [Akcigit et al., 2015], which quantifies the technological similarity between patents or groups of patents.

I find a number of pieces of evidence, with some supporting the benign middleman perspective and others pointing towards the stick-up artist. I first consider what motivates inventors to sell to NPEs. Innovating firms can capitalize on their patents in a few primary ways: by producing a product, by selling to a better-
situated producer, or by suing an infringer. As with all markets, secondary markets for innovations may suffer from informational problems: since the inventor has limited information about potential users, they often cannot license or sell their patents even if they wish to do so. This informational problem can lead to a misallocation of innovation. One way to address the problem is to use patent intermediaries or NPEs. As Lamoreaux and Sokoloff [2002] describe, trade is facilitated by these intermediaries due to their ability to reduce search costs from years of accumulated information about market participants on both sides. Another important way NPEs can increase returns to inventors is by capitalizing on their substantial financial and legal resources to enforce infringed patents.

Both of these features will be of greater importance to smaller innovating firms and in fact I find empirically that small inventors are more likely to sell to NPEs. I also find a significantly greater share of patents that are likely to be litigated are sold to NPEs. Since firms are more likely to produce a product based on a patent that is closer to the core business, it is also not surprising that I find the likelihood of sale to an NPE to be greater for more peripheral patents.

I also explore the business model of the profit-maximizing NPE by attempting to understand the determinants of the price NPEs pay for patents. Unlike the likelihood of sale, I find that the smaller firms are paid less than larger firms that sell their patents to the NPEs; this corroborates one of the predictions of my bargaining model between NPEs and innovating firm. I also find that patents that are
more distant from innovating firm portfolios command a lower price, which also corresponds to the model prediction.

The other half of a NPE business model is the licensing of patents to one or multiple firms. Here I find that licensees are willing to pay more for patents with higher litigation risk, holding everything else equal. Moreover, I find that licensing fees increase in the goodness of fit to the licensee: the less distant the patent is, the more the licensee is willing to pay. This supports the benign middleman theory that NPEs are providing greater value when they facilitate the reallocation of patents where they can be more useful.

Finally, I seek to understand the impact of NPEs on subsequent or downstream innovation in fields with NPE activity. Specifically, I examine the impact of NPE patent acquisition on forward citations, comparing citation behavior before and after acquisition. I find a statistically significant decline in forward citations after NPEs acquire patents, which provides some evidence for the stick-up artist theory.

Taken together, the evidence in this chapter is mixed and does not solely support the benign middleman or the stick-up artist theory. Rather it suggests that there are some aspects of NPEs that may increase innovation and some that may not. The rest of the chapter is organized as follows. Section 2.2 provides a brief summary of recent research as well as some institutional detail. In Section 2.3 I present my model of innovation with NPEs and in Section 2.4 I introduce the data analyzed. The main empirical results are presented in Section 2.5. Section 2.6 presents a
calibration exercise. Section 2.8 concludes.

2.2 Background

Since the terms patent troll, NPE, and patent assertion entity (PAE) are frequently used to denote similar or overlapping things, it is useful to have a clear definition of what I study, as well as a sense of the history of these entities in the U.S. I define an NPE broadly as a firm whose primary source of revenue is from patent licensing fees or patent litigation awards. This can include a large array of entities, from individual inventors who do not practice their inventions, to shell companies that file hundreds of lawsuits, to universities, to patent aggregators whose primary revenues come from licensing fees. Some use the term PAE almost synonymously to NPE, but excluding entities that perform research, such as universities (and potential inventors who still invent). “Patent Troll” seems to be used to refer to any type of entity the user of the term doesn’t like. Certainly included in this would be the related group of legal entities that issued demand letters to hundreds of businesses using networked scanners to email documents.\(^\text{18}\)

I will use the term NPE in this chapter and focus on the final category of NPE - large firms that purchase patents and primarily license them or litigate when they cannot license. I focus on this category for several reasons. First, these are the types of NPEs receiving the most attention from the media and legislatures in recent years. The attention is for a reason - there is less historical precedent

\(^{18}\)See http://arstechnica.com/tech-policy/2013/01/patent-trolls-want-1000-for-using-scanners/
for them (see below) and they are the most interesting case because there are plausible positive and negative attributes. Second, university licensing is unlikely to be outlawed and almost all can agree that suing small businesses for scanning documents is unproductive. But the impact on innovation of large entities that generate substantial revenues from licensing fees and litigation is less clear. Finally, these firms are likely making the biggest impact on markets for innovation.

2.2.1 Related Literature

Several others have made empirical investigations of NPEs, all subject to various data limitations, since direct data was unavailable. On the theoretical side, much of the work has been policy-focused and descriptive, and not relying on formal models.

Some studies attempt to measure the impact of NPE assertions outside of the courtroom, drawing data not just from claims litigated to finality. In a well-known study, Bessen and Meuer [2014] utilized survey data gathered by RPX, a risk-management company helping firms deal with patent litigation. There was no random sampling; RPX invited 250 firms to participate in the survey, of which only 82 provided information on lawsuits, and 46 provided information on non-litigation assertions (such as demand letters). Bessen and Meuer [2014] concluded from this limited sample that NPE assertions resulted in $29 billion in direct costs, disproportionately burdening smaller and medium-sized companies. Similarly, Chien [2014] relied on nonrandom survey responses and a database, curated by RPX, of patent
cases to conclude that most defendants in NPE suits are smaller companies. Feldman and Lemley [2015] polled in-house attorneys at companies that produced products in various industries, concluding that NPE demands did not lead to more innovation. And Lu [2012] studied royalty rates paid in 46 transactions involving NPEs using information from vendors that aggregate royalty rates primarily drawn from companies’ public SEC filings. Lu [2012] found the royalty rates paid to NPEs as similar to those paid to practicing entities.

Some scholars, including Schwartz and Kesan [2014], have questioned the validity of such sweeping conclusions based on data that is potentially unrepresentative and unreliable. There may be an overemphasis on technology firms, and there are also varying definitions of what constitutes an NPE.

Another strain of research focuses solely on litigated cases, deriving information on NPE activity from awarded damages or whether an asserted patent is found invalid. Ashtor et al. [2014] rejected the notion NPE litigation activity differs significantly from practicing entity patent assertions. They examined over 1,750 patent cases litigated to a verdict, and found little difference in outcomes between NPEs and practicing entities. Cohen et al. [2014] used proprietary data from PatentFreedom, another company that aggregates litigation data, in arguing that NPEs are more likely to target cash-rich firms. And Cotropia et al. [2014] hand-coded information about the litigants in all patent infringement lawsuits filed in 2010 and 2012, concluding that the hype about the dangers posed by NPE litigation is overblown.
But assessing the aggregate economic effect of NPEs by only analyzing litigation may underestimate their impact, since many assertions are theorized to take place outside the scope of publicly accessible records; instead, NPEs may rely on extracting licensing royalties, much of which is contractual and not subject to public disclosure. Risch [2012] attempted to defend the decision not to include non-litigation data in a study of the 10 most litigious NPEs by asserting that it is more likely that litigious NPEs’ activities incur greater social costs. Though it is true that litigation is itself an additional potential cost, that is not proof of anything relating to the relative costs of litigation versus non-litigation NPE assertions.

Fischer and Henkel [2012] adopted a wholly different tack, analyzing NPE patent acquisitions by first identifying NPEs are using public searches and newspapers, blogs, websites, then searching patent assignment databases for arrive at a sample of patent acquisitions by NPEs. Using proxy indicators for various characteristics of the acquired patents, Fischer and Henkel [2012] conclude that NPE-acquired patents are likely to be higher-quality and of broader scope and application than non-NPE patents. But the study is handicapped by the quality of the proxy variables; for instance, the authors use international patent classification (IPC) classes, a highly subjective taxonomical exercise to identify potential applications of the patent ex ante, as a proxy for patent scope. In a clever study, Galasso and Schankerman [2014] instead used patent assignment, litigation, and tax data for the period spanning 1983-2001, finding that NPEs play an insubstantial role in buying or litigating
patents owned by individuals.

Previous papers that discuss the impact of NPEs on subsets of the economy include Tucker [2014a,b], which cross-reference the names of frequent plaintiffs in patent cases using the PatentFreedom database of known NPEs; this is the same database Hagiu and Yoffie [2013] use. Tucker [2014b] explores the effects on the healthcare information technology sector by measuring the impact of litigation by one purported NPE, Acacia, who had acquired two patents that would make patient data electronically available for remote access by physicians. Tucker [2014b] found a large supply-side reduction in sales of the defendants software products that were allegedly infringed by Acacia’s patents when compared to the defendants’ other products that did not fall under the scope of the asserted patents. Similarly, firms not targeted by Acacia that sold similar software products to the Acacia defendants’ allegedly infringed software did not see a drop in sales. Additionally, Tucker [2014a] finds that patent litigation and venture capital investment follow an inverted U-shaped relationship. Tracking the effects of litigation of PatentFreedom identified NPEs on entire capital funding, The author found that high levels of patent litigation was correlated with decreased total venture capital in the region the litigation was filed. The author of both papers acknowledges potential robustness issues with her methodology that reduce the ability to draw conclusions from either study.
2.2.2 Institutional Setting

This section gives more background on how the NPEs I study operate. As mentioned above, the source of the data I use cannot be representative of all NPEs because there are too many different business models.

Patents are acquired, usually in small groups from individuals or firms; these are almost always the original assignees. The patents are almost always purchased outright, although in rare occasions there can be subsequent compensation or rights to future revenue. Almost all of the NPEs revenues derive from subsequent licensing of patents. Patents are usually licensed for multiple years in large portfolios. Patent-specific revenues are determined from licensing deals based on the prominence that each patent played in the licensing negotiation. Occasionally the NPEs litigate over infringement claims, although this leads to a small share of overall revenues.

2.3 Model

In this section, I build a tractable model of production with innovation to help understand the role NPEs play in the market for innovation. By examining the decision to sell to or license from an NPE I hope to find evidence that can test the stick-up artist and benign middleman views of NPEs. The model generates a number of predictions about how patent and firm characteristics, such as patent fit (distance), litigation risk, and firm size impact these decisions. This provides the framework that will guide my empirical analysis.
**Basic Environment**  Consider the following simple economy represented by a unit circle $C$, as in Figure 2.1a. There are many intermediate-good-producing firms that are located along that unit circle, each of which produces a differentiated good $i$. A unique final good is produced from a combination of all these intermediate goods as follows: $Y = \frac{1}{1-\sigma} \int_{C} q_i^\sigma k_i^{1-\sigma} di$, where $k_i$ denotes the quantity and $q_i$ the quality of intermediate good $i$ used in final good production. The final-good sector operates with perfect competition and I normalize the price of the final good to 1 without loss of any generality. Therefore the objective function in the final-good sector is simply:

$$\max_{k_i} \left\{ \frac{1}{1-\sigma} \int_{C} q_i^\sigma k_i^{1-\sigma} di - \int_{C} P_i k_i di \right\}, \quad \forall i \in C.$$  

where $P_i$ is the price of variety $i$. This maximization problem delivers the following demand function for each intermediate good $i$:

$$P_i = q_i^\sigma k_i^{-\sigma}. \quad (2.3.1)$$

A single perfectly enforceable patent for each leading-edge technology is held by a firm, which can produce it at constant marginal cost $\psi$ in terms of the unique final good. Each monopolist firm chooses price and quantity to maximize profits on its product line taking the demand in (2.3.1) into account. The profit-maximization problem of the firm with leading-edge technology for intermediate good $i$ can then
be written as

$$\Pi (q_i) = \max_{k_i \geq 0} \left\{ q_i^{\sigma} k_i^{1-\sigma} - \psi k_i \right\}.$$  

The first-order condition of this maximization problem implies a constant markup over marginal cost, $P(q_i) = \psi/(1 - \sigma)$, and thus $k(q_i) = \left[\frac{1-\sigma}{\psi}\right]^{\frac{1}{\sigma}} q_i$. Equilibrium profits for a product line with technology $q_i$ are

$$\Pi (q_i) = \pi q_i,$$  

(2.3.2)

where $\pi \equiv \sigma \left[ (1 - \sigma) / \psi \right]^{\frac{1-\sigma}{\sigma}}$.

The usual firm size proxies, such as profits $\Pi (q_i) = \pi q_i$ and sales $P(q_i) k(q_i) = \left[ (1 - \sigma) / \psi \right]^{\frac{1-\sigma}{\sigma}} q_i$ both increase linearly in quality $q_i$. Therefore in what follows, I proxy for firm size using $q_i$. 

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2.3.1 Patents

Patent Distance and Firm Quality  The radius of the circle $C$ is normalized to $1/\pi$ such that the maximum distance between any two points along the circle is equal to 1. Similar to firms, innovations (patents) in production are also located along the circle. Figure 2.1b illustrates this in an example. Firms $i$ and $k$ are located in different parts of the circle. There is a patent $z$ that has a distance $d_i$ to firm $i$ and $d_k$ to firm $k$.

Firm quality improves upon the invention or acquisition of new, patented innovations. Consider an innovating firm $i$. Its quality improves according to the following law of motion

$$q_{i}^{\text{new}} = q_i + \gamma x_i$$

where $\gamma$ is some scale parameter and $x_i \in [0, 1]$ is the goodness of fit of the patent to the firm. Similarly, I can define patent distance $d_i \in [0, 1]$ as the inverse of goodness of fit:

$$d_i = 1 - x_i.$$ 

Low values of $d_i$ indicate that a patent is a good fit to firm $i$. Given the linearity of the profit function in (2.3.2), the incremental gain to monopolist $i$ from licensing
this patent is

\[
\Delta \Pi_i = \pi [q_i + \gamma (1 - d_i)] - \pi q_i = \pi \gamma (1 - d_i).
\]

(2.3.3)

Given that \( \pi \) and \( \gamma \) will appear multiplicative for the rest of the analysis, I normalize \( \gamma = 1 \) such that

\[
\Delta \Pi_i = \pi (1 - d_i).
\]

(2.3.4)

2.3.2 Non-practicing Entities

There are NPEs in this economy that may act as (i) middle men or as (ii) stick-up artists. They have two key features: First, they have a broad network of firms to whom they may license patents as middle men. Second, they have substantial financial and legal resources that increases their likelihood of winning a case in court when they act as a stick-up artist. I detail these features now.

The Middle Man Any firm \( i \) that owns a patent can decide to keep its patent, or sell it to NPEs. NPEs, through its wide network in the market, can potentially find a user \( k \) that is a better fit for the patent with shorter distance \( d_k < d_i \). Having access to a large network is the first advantage of the NPE over a single innovating firm.
The Stick-up Artist  The second key ingredient of my model is that patents may be infringed by other firms. Let me denote the firm that infringes on firm i’s patent by j. When j infringes on i’s patent, firm i can go to court and sue j. Firm i wins the lawsuit with probability $\beta_i$. Winning a court case depends on resources that a firm has to fight in the court. As a result, I assume that probability of winning the court case is a function increasing in firm size such that:  

$$\beta_i = \beta(q_i) \quad \text{and} \quad \beta'(q_i) > 0.$$ 

The second strength of NPEs is that it has greater experience and resources to fight in the court, i.e., it has a high $\beta_{npe}$. Therefore, when a firm does not have enough resources and faces a risk of infringement, it might be desirable for the firm to sell the patent to an NPE.

I describe the rest of the dynamics of the model with the help of the following game tree:

---

My analysis relies on the fact that an NPE and a patent producer have differential bargaining and/or negotiating power on the market. To keep the math tractable, I assume symmetric bargaining power throughout yet differential negotiating power across firms and NPEs. Alternatively, one can model the bargaining power (instead of the winning probability) as a function of the firm size. The results would go through the same way, yet the expressions would be less tractable.
In the beginning of the game, firm $i$ produces a patent with a random distance $d_i$. In addition, firm $i$ realizes an idiosyncratic cost of finding an NPE, $\epsilon$. Next it decides to sell it to NPEs or keep it within the firm.

If it decides to keep the patent, then the game evolves according to the upper branch. Before production takes place, the patent is infringed with probability $\alpha$. If there is no infringement with probability $(1 - \alpha)$, then the firm produces and collects the end-of-period return $V_i^{prod}$ which is simply equal to the marginal profit.

---

$^{20}$Since my focus on this chapter is the role of an NPE, I do not model the possibility of a patent owner selling her patent to the end user. This structure is imposed without apology since patents are sold mainly through intermediaries due to their larger networks, as described in Akcigit et al. [2015].
(the additional profit that the firm makes by using its new patent)

\[ V_{i}^{\text{prod}} = \pi (1 - d_i). \]

If there is an infringement, which happens with probability \( \alpha \), then \( i \) tries to settle with \( j \). If they cannot settle, \( i \) goes to court and wins with probability \( \beta_i \). When \( i \) wins the case, it gets compensated for lost profits \( \pi (1 - d_i) \). Hence the expected value of going to court is:

\[ V_{i}^{\text{court}} = \beta_i \pi (1 - d_i). \]  \hfill (2.3.5)

Let \( \Omega_j \) denote the profit that \( j \) is making by infringing \( i \)'s patent. When the court decides in favor of \( i \), then firm \( j \) also loses \( \Omega_j \). Settlement generates a surplus that the two parties split through Nash bargaining with equal bargaining power for both sides. Let me denote the settlement (licensing) fee that \( i \) will collect from \( j \) by \( p_{i,j} \). Then the fee is simply the solution to the following problem

\[ p_{i,j} = \arg \max \left( p_{i,j} - V_{i}^{\text{court}} \right)^{0.5} \left( V_{i}^{\text{court}} + \beta_i \Omega_j - p_{i,j} \right)^{0.5}. \]  \hfill (2.3.6)

Note that player \( i \) could receive \( V_{i}^{\text{court}} \) if there is no agreement and therefore her net surplus from bargaining is \( p_{i,j} - V_{i}^{\text{court}} \). Likewise, player \( j \) will need to pay \( V_{i}^{\text{court}} \) and also give up his \( \Omega_j \) additional profit if the case goes to court and the court decides in favor of \( i \) with probability \( \beta_i \). Therefore \( j \)'s surplus from bargaining is
$V_i^{court} + \beta_i \Omega_j$. This problem delivers the following settlement amount

$$p_{i,j} = V_i^{court} + \frac{\beta_i \Omega_j}{2},$$

where $V_i^{court}$ is expressed in (2.3.5). The settlement fee that $j$ pays $i$ is increasing in $i$’s probability of winning the case $\beta_i$, and in the profit that firm $j$ is making by infringing $i$’s patent. Now, going back one step in the game tree in Figure 2.2, I can calculate the expected value to $i$ of keeping the patent as

$$V_i^{keep} = \alpha p_{i,j} + (1 - \alpha) V_i^{prod}$$

$$= \alpha \beta_i \left[ \pi (1 - d_i) + \frac{\Omega_j}{2} \right] + (1 - \alpha) \pi (1 - d_i).$$

(2.3.7)

Now consider what happens if $i$ decides to sell the patent to NPEs, as illustrated by the lower branch. With probability $\alpha$, there is a chance that $j$ infringes the patent that now belongs to NPEs. In this case, NPEs can go to court or settle with $j$.\textsuperscript{21}

The main difference now, compared to (2.3.6), is that NPEs by definition does not produce and therefore does not have $\pi (1 - d_i)$ to ask. However, NPEs can block $j$ from gaining $\Omega_j$ and has potentially a higher probability of winning $\beta_{npe}$. Therefore the problem for the settlement can be written as

$$p_{npe,j} = \arg \max \left( p_{npe,j} \right)^{0.5} \left( \beta_{npe} \Omega_j - p_{npe,j} \right)^{0.5}$$

\textsuperscript{21}Note that in equilibrium, no party goes to court. Yet the possibility of going to court generates a threat that affects that bargaining through the outside option.
which delivers the following settlement fee that NPEs will charge \( j \): 

\[
p_{npe,j} = \frac{\beta_{npe} \Omega_j}{2}.
\]

If there is no infringement with probability \((1 - \alpha)\), the NPE licenses the patent to some firm \( k \) with a distance equal to \( d_k \) and profit equal to \( \Omega_k \). The price again is determined through Nash bargaining as follows:

\[
p_{npe,k} = \arg \max \left\{ p_{npe,k} \right\}^{0.5} \left[ \Omega_k (1 - d_k) - p_{npe,k} \right]^{0.5}.
\]

The price is simply

\[
p_{npe,k} = \frac{\Omega_k (1 - d_k)}{2}.
\]

Now I can compute the expected value to NPEs of owning the patent:

\[
V_{npe} = \alpha p_{npe,j} + (1 - \alpha) p_{npe,k}.
\] (2.3.8)

Next, I turn to the bargaining problem between \( i \) and NPEs. After the realization of the distance, firm \( i \) can sell the patent to NPEs through Nash bargaining. As long as \( V_{npe} > V_i^{keep} \), this problem can be written as

\[
p_{i,npe} = \arg \max \left( p_{i,npe} - V_i^{keep} \right)^{0.5} \left( V_{npe} - p_{i,npe} \right)^{0.5}.
\] (2.3.9)
Hence the equilibrium price that firm $i$ charges NPEs is,

$$p_{i,npe} = \frac{V_i^{\text{keep}} + V_{npe}}{2},$$

(2.3.10)

where $V_i^{\text{keep}}$ is expressed in (2.3.7) and $V_{npe}$ in (2.3.8). I assume that there is a cost of contracting with an NPE, $\epsilon$, that comes from a uniform distribution as $\epsilon \sim U[0, \kappa]$.

There will be a sale between $i$ and NPEs if and only if, there is a potential surplus that is bigger than the cost, $p_{i,npe} - V_i^{\text{keep}} > \epsilon$. Therefore the probability of sale can be written as

$$\Pr(\text{sale}) = \begin{cases} 
0 & \text{if } p_{i,npe} - V_i^{\text{keep}} < 0, \\
1 & \text{if } p_{i,npe} - V_i^{\text{keep}} > \kappa, \\
\frac{p_{i,npe} - V_i^{\text{keep}}}{\kappa} & \text{otherwise.}
\end{cases}$$

(2.3.11)

### 2.3.3 Model Predictions

In this section, I generate a number of important comparative statics which I later test using micro data.

First, I focus on the determinants of the probability of a patent sale to NPEs in (2.3.11). My first result relates the probability of a sale to the size of the innovating firm.
Prediction 1  An NPE is more likely to buy patents from small firms:

\[
\frac{\partial}{\partial q_i} \Pr (\text{sale}) = -\frac{\beta'(q_i)\alpha}{2\kappa} \left[ \pi (1 - d_i) + \frac{\Omega_j}{2} \right] < 0.
\]

Moreover, this effect is more pronounced for litigation-prone patents:

\[
\frac{\partial^2}{\partial \alpha \partial q_i} \Pr (\text{sale}) = -\frac{\beta'(q_i)}{2\kappa} \left( \frac{\Omega_j}{2} + \pi (1 - d_i) \right) < 0.
\]

This result follows from the fact that small firms have a harder time defending themselves in court. Hence, NPEs purchase patents from small firms in order to enforce their patent rights in the case of infringement. That is the reason why NPEs purchase patents from small firms, especially more litigation-prone patents.

Next, I focus on the second role of NPEs, which is reallocating innovations to reduce the distance to the owning firm.

Prediction 2  The likelihood of a patent sale increases with distance of the patent from the initial innovating firm:

\[
\frac{\partial}{\partial d_i} \Pr (\text{sale}) = \frac{\alpha \beta_i \pi + (1 - \alpha) \pi}{2\kappa} > 0.
\]
Moreover, this effect is more pronounced for large firms, i.e.,

\[
\frac{\partial^2}{\partial d_i \partial q_i} \Pr(\text{sale}) = \frac{\beta'(q_i) \alpha \pi}{2\kappa} > 0.
\]

The intuition for this result is that patents that are a poor fit with the inventing firm will not be well-utilized. The inventing firm will therefore considers selling it in the secondary market through NPEs. Note that a technologically close patent is more valuable for a large firm than a small one. When distance increases it lowers the value of a patent more for large firm. Hence, high patent distance is more costly for large firms and increases the probability of a sale faster for large firms than for small ones.

My model has important predictions on the sale price of a patent that was expressed in (2.3.10). I now turn to these predictions.

**Prediction 3** NPEs pay more for large firms’ patents:

\[
\frac{\partial p_{i,npe}}{\partial q_i} = \frac{\beta'(q_i) \alpha}{2} \left[ \pi (1 - d_i) + \frac{\Omega_i}{2} \right] > 0.
\]

The equilibrium price of a patent is determined through a bargaining that was described in (2.3.9). The outside option of a patent is higher for large firms since they can defend the patent better. Hence, large firms receive a higher price for their
Next I focus on the link between sale price and patent distance.

**Prediction 4** The acquisition price decreases with patent distance to the seller:

\[
\frac{\partial p_{i,npe}}{\partial d_i} = - \left[ \alpha \beta_i + 1 - \alpha \right] \pi \frac{\Omega_i}{2} < 0
\]

The intuition for this result is similar to its counterpart on the patent sale probability. Distant patents are less valuable to the original inventor, which lowers the outside value of the patent. This reduces the price that is asked by the seller.

I now turn to the licensing side.

**Prediction 5** The average price that a licensing firm pays to NPEs is decreasing in the distance to the licensee

\[
\frac{\partial p_{npe,k}}{\partial d_k} = - \frac{\Omega_k}{2} < 0,
\]

The intuition here is straightforward: More distant patents are worth less to licensees, so they have a lower willingness to pay.
2.3.4 Downstream Entry into the Market

How does the existence of an NPE affect incentives to innovate? In this section, I consider the endogenous innovation decision of a downstream firm \( j \). My analysis proceeds in two steps. First, I consider a market without an NPE and then I examine the change in innovation rates when an NPE enters the market.

The Case without an NPE In the above model, parameter \( \alpha \) captured the probability that a downstream firm \( j \) infringes firm \( i \)'s patent. In reality, this can happen because (i) the downstream firm is a non-innovator and simply produces a "me-too" product with probability \( \phi \), or (ii) because the downstream firm made an attempt to innovate a brand-new product with endogenous probability \( \mu_j \) but fell short of being sufficiently non-obvious and ended up infringing \( i \)'s patent with probability \( \tau \). Therefore \( \alpha \) has two components:

\[
\alpha = \phi_{\text{non-innovator}} + \tau \mu_{\text{innovator}}
\]

where \( \phi \) captures the probability that a non-innovating and \( \tau \mu_j \) an innovating downstream \( j \) infringes \( i \).\(^{22}\)

I focus now on the endogenous innovation decision \( \mu_j \). Recall that the incremental profit of firm \( j \) from adding a new technology to its portfolio is simply \( \Omega_j \). Products produced with this new technology may infringe an existing patent with

\(^{22}\)In Section 2.6, I will make the necessary assumptions to ensure that \( \alpha \in [0, 1] \).
probability $\tau$, and when there is no NPE in the market, there will be a side settlement between firm $i$ and $j$ at price $p_{i,j}$. There is a convex cost to innovation $c(\mu_j) = \frac{\mu_j^\xi}{\eta^\xi}$ where $\xi > 1$ governs the convexity of the cost function. Therefore the innovation decision is simply

$$\max_{\mu_j} \left\{ \mu_j \left[ \tau (\Omega_j - p_{i,j}) + (1 - \tau) \Omega_j \right] - \frac{\mu_j^\xi}{\eta^\xi} \right\}.$$ 

This implies that when there is no threat of an NPE, the equilibrium innovation decision is

$$\mu_{j}^{\text{no-npe}} = [\eta(\Omega_j - \tau p_{i,j})]^{\frac{1}{\xi-1}}.$$ 

**The Case with an Active NPE** Consider now the case of an NPE in the market. This time, inventor $i$ has the option of using NPEs in the market. Since I have already shown that $p_{\text{npe},j} \geq p_{i,j}$, this increases the expected price

$$\mathbb{E}(p_{-.j}) \equiv \Pr(i \text{ uses NPE}) \times p_{\text{npe},j} + [1 - \Pr(i \text{ uses NPE})] \times p_{i,j}$$

paid by $j$ in the case of a conflict. Therefore the maximization problem becomes

$$\max_{\mu_{j}^{\text{npe}}} \left\{ \mu_{j}^{\text{npe}} \left[ \tau (\Omega_j - \mathbb{E}(p_{-.j})) + (1 - \tau) \Omega_j \right] - \left( \frac{\mu_{j}^{\text{npe}}}{\eta^\xi} \right) \right\}.$$ 

---

23 Even though $p_{\text{npe},j} \geq p_{i,j}$, $i$ will not always sell to an NPE even when one is in the market because of the cost $\epsilon$ of contracting with NPEs.
In equilibrium, the innovation rate is simply

\[ \mu_{jnpe} = [\eta(\Omega_j - \tau E(p_{n,j}))]^{\frac{1}{\xi}}. \]

Now I can focus on the change in the innovation rate \( \Delta \mu_j \equiv \mu_{jnpe} - \mu_{jno-npe} \) with and without an NPE in the market. The change in innovation rate is simply

\[ \Delta \mu_j = \eta^{\frac{1}{\xi}}\left[[\Omega_j - \tau E(p_{n,j})]^{\frac{1}{\xi}} - [\Omega_j - \tau p_{i,j}]^{\frac{1}{\xi}}\right] \]

< 0.

since \( p_{npe,j} > p_{i,j} \). Note also that this effect is more pronounced for more valuable innovations.

**Prediction 6** The introduction of NPEs reduces downstream innovation, \( \mu_j \).

### 2.3.5 Final Remarks on the Theory

In the above model, I focused on various predictions of impacts on patent sales and pricing. An additional question of interest is, how does patent litigation risk affect patent sale probability and price? Through the lens of my model, litigation risk
affects the likelihood of a sale as follows:

\[
\frac{\partial \Pr(sale)}{\partial \alpha} = \left[ \frac{[\beta_{npe} - \beta_i] \Omega_j}{2} + [1 - \beta_i] \pi (1 - d_i) - \frac{\Omega_k (1 - d_k)}{2} \right] / 2 \kappa
\]

\[\leq 0.\]

Note that the impact of litigation has both positive and negative impact on the likelihood of a sale. The sign depends on the specific role of NPEs. If the dominant role of NPEs is to defend a firm’s patent rights in the court, then increased litigation risk increases the likelihood of a sale. However, if the dominant role of an NPE is to allocate innovations more efficiently in the market (through lower \(d_k\)), then higher litigation risk has a negative impact on sales. This is because the higher litigation risk mitigates the ability of NPEs to allocate innovations to a better user for production. The net effect depends on the exact magnitudes of these two forces, therefore the link between litigation risk and patent sale is ambiguous.

Likewise, the link between litigation risk and the expected licensing fee that NPEs would charge or the price that NPEs pays to purchase the patent depends on the magnitude of the two roles of NPEs. For instance the expected licensing fee is

\[\mathbb{E}(p_{npe,\cdot}) = \alpha p_{npe,j} + (1 - \alpha)p_{npe,k}.\]

Then the impact of the increased litigation risk
on licensing fee is

$$\frac{\partial E(p_{npe,.})}{\partial \alpha} = [\beta_{npe}\Omega_j - (1 - d_k)\Omega_k]/2$$

$$\leq 0.$$  

The impact of litigation risk on the purchase price is

$$\frac{\partial p_{i,npe}}{\partial \alpha} = \frac{[\beta_i + \beta_{npe}]\Omega_j - 2[1 - \beta_i] \pi (1 - d_i) - \Omega_k (1 - d_k)}{4}$$

$$\leq 0.$$  

As these expressions indicate, my model predicts that the direct impact of litigation risk on patent sale and price is ambiguous and depends on the exact magnitudes of the two roles of NPEs.

**Active NPE and the Overall Innovation**  
Ultimately, the paramount policy question is how do NPEs impact overall innovation in the market? To answer this question, I first look at the innovation incentives of upstream firms.

The existence of an NPE in a market increases the outside option for the original producer of the patent. Hence, if I denote the change in innovation effort of firm $i$ as $\Delta \mu_i \equiv \mu_{i,npe} - \mu_{i,\text{no-npe}}$, then I can show that

$$\Delta \mu_i = \eta [E[p_{i,npe} - \epsilon]]^{\frac{1}{\tau - r}} - \eta [E[V_{keep}]]^{\frac{1}{\tau - r}}$$

$$\geq 0.$$
Hence, the existence an NPE in the market provides additional innovation incentive to the upstream firm $i$. Consider now both $i$ and $j$’s innovation, with and without NPEs. I note that $i$’s innovation rate increases when NPEs shows up while $j$’s downstream innovation decreases. The change innovation rate to adding NPEs is

$$
\Delta \mu \equiv (\mu_{i}^{npe} - \mu_{i}^{no-npe}) + (\mu_{j}^{npe} - \mu_{j}^{no-npe}) \leq 0.
$$

I note here the ambiguous effect, which depends on the parameter values. I calibrate the model and discuss further in Section 2.6 and the appendix.

**Summary of Predictions** I summarize the predictions of the model as follows:

1. NPEs are more likely to buy patents from small firms. Moreover, this likelihood is more pronounced for litigation-prone patents.

2. The likelihood of a patent sale increases with distance to the initial innovating firm. Moreover, this effect is more pronounced for large firms.

3. NPEs pay more for large firms’ patents.

4. The acquisition price decreases with patent distance to the seller.

5. The average price that any licensing firm will pay to NPEs decreases with distance to the licensee.

6. The introduction of NPEs reduces downstream innovation.
2.4 Data and Variables

This research is made possible by the use of confidential data obtained from a collection of NPEs covering tens of thousands of patents. This includes several unique measures of NPEs: individual patent-level licensing revenue, licensing agreements, characteristics of assignees that sell to NPEs, and characteristics of firms that license from NPEs. A data use agreement places some mild restrictions on what I may disclose about the data, including the source, exact number of patents, and non-normalized revenue figures. However, there are no restrictions on the types of analyses I may perform, nor pre-approval for any findings. Since there are a number of different data sources and a large amount of derived variables, I provide substantial further detail in the appendices.

2.4.1 Data Sources

I use the following data sources for this project: United States Patent and Trademark Office Patent Application Bibliographic Data (PAB), NPE Data (ND), Lex-Machina (LM), U.S. Patent Citation Data (USCIT), The Careers and Co-Authorship Networks of U.S. Patent Inventors (INV). The first source contains basic front page data for patents and patent fixed characteristics. The second source helps us to retrieve yearly licensing costs for each patent, the name of the licensee, the amount of money paid to obtain the patents from originating entities, the date of licensing for each transaction and the date of acquisition for each patent. The third source is
used to retrieve information on litigated patents. The fourth source is used to construct certain variables related to citations for patents recorded in the first source. The fifth source is used to retrieve information about individually owned patents. Further detail on the data follows.

**Patent Application Bibliographic Data (PAB)**  This database contains basic ‘front page’ data for patents issued from 1963 to 2014. It comes from a custom extract DVD generated by Electronic Information Products Division of USPTO. The following variables are used from this database:

- **Patent number**: The unique patent number is assigned to each patent granted by USPTO.

- **Application date**: Date of application for each patent.

- **Grant date**: Date of grant for each patent.

- **Assignee number**: The assignee number assigned to each patent granted by USPTO. Where the assignee is an individual this field is blank, so I merge the data with INV using unique patent numbers to obtain the inventor/assignee. Since PAB identifiers do not account for subsidiaries, mergers or acquisitions, Part B describes an algorithm to minimize problems this may cause.

- **Patent technology class**: The technology class assigned to the patent by USPTO according to its internal classification system as of 12/31/2014.
NPE Data (ND)  This confidential data contains information on acquisition deals, licensing deals, and patent characteristics. The acquisition deal data includes the unique identifier for acquired portfolio, patent acquisition date and amount paid. The licensing data includes the licensee name, licensing date, primacy of patent in the deal. The patent characteristics include citations, claims, expiration date, and technology category.

Lex Machina (LM)  From the Lex Machina database I use number of times that a patent is asserted in court, number of infringements found in each case, findings of invalidity, total damages awarded, and case beginning and end dates. The database includes only USPTO granted patents and covers cases filed after 1999.

U.S. Patent Citation Data (USCIT)  U.S. Patent Citation Data includes U.S. patent citations for utility patents issued from 1975-2014. Each observation is a citing-cited pair. The database is based on information from a custom extract DVD generated by the Electronic Information Products Division of the USPTO.

Non-utility patents were eliminated from the cited patent list. Citing patents include all types of patents. In addition, cited U.S. patent applications were removed from the file. These patents were removed as citations to sources other than U.S. utility patents are reported haphazardly.  

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24I complement the citation data with the citation data located at http://www.patentsview.org/web/. The main reason is to identify the citing entity characteristics for the event study.
The Careers and Co-Authorship Networks of U.S. Patent Inventors (INV)

Extensive information on the inventors of patents granted in the United States is obtained from Lai et al. [2009]’s updated dataset. These authors use inventor names and addresses as well as patent characteristics to generate unique inventor identifiers. This data set is mainly used to retrieve assignee identifiers for individually owned patents as the PAB does not specify any assignee number for individually owned patents.

2.4.2 Variables and Summary Statistics

In order to compare patents of different ages, both forward citations and revenue are estimated for the entire lifetime of the patent. I calculate lifetime citations by inflating the total citations already received by the ratio of the total mean citations of the same technology class divided by the mean for the average patent of the same age and technology class. I employ an analogous approach for the lifetime revenue calculation, based on current realized revenue, with the addition that revenues are normalized so that the annual mean is 10. Further detail on the normalization procedures may be found in Appendix B.1.

Table 2.1 reports patent-level summary statistics both for NPE-acquired patents and the comparable universe of patents applied for from the USPTO during the same years, 1987 - 2014. “Comparable universe” means the data in the second panel is weighted so that the distribution of IPC3 technology classes is the same
Table 2.1: Descriptive Statistics for NPE and Comparable USPTO Patents

<table>
<thead>
<tr>
<th>Variables</th>
<th>Panel 1: NPE Patents</th>
<th>Panel 2: PTO Patents</th>
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<td>10.3</td>
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</tr>
<tr>
<td>Sale Indicator</td>
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<td>100</td>
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</tbody>
</table>

Notes: Panel 1: Patent-level data from 1987 - 2014 includes all patents in NPE dataset. Panel 2: Patent-level data from 1987 - 2014 includes all patents granted by USPTO in IPC3 categories with at least one patent in NPEs data. USPTO data is weighted by NPE patent distribution across IPC3 classes. Individual Inventor is one if there is a single listed inventor and no assignee. Please see text and appendix for variable definitions.

The first such variable is a patent distance metric, first introduced in Akcigit et al. [2015] and described in more detail in Appendix B.1.1. The distance is a function of the overlap in technology classes of the backward citations of two patents. I calculate the average distance between a patent and the patent portfolio...
of its originating firm as a measure of whether the patent is relatively central or peripheral to the firm. The originating entity refers to the original assignee or original inventor if the original assignee is missing. In both NPEs and PTO data, the distribution of the metric is slightly right-skewed, with a mean of 32.95 for NPE-held patents and 29.74 for all patents. Thus firms appear to be more likely to sell distant patents to NPEs, as my model in the previous section predicts.

Litigation Risk is a measure of the likelihood that a patent will be litigated. I adopt the model in Lanjouw and Schankerman [2001] with small modifications to produce this index (see Appendix B.1.1 for greater detail). Mean litigation risk is substantially higher for patents held by NPEs, which is consistent with the prediction of my model.

The next variable is more straightforward: Originating entity size is the number of patents (including subsequently granted applications) in the entity’s portfolio at the time of the patent’s grant. The distribution for NPE-held patents is quite right-skewed (Figure 2.3), and the typical patent sold to an NPE comes from a much smaller patent portfolio than average. This is not surprising as I saw in Section 2.3 that smaller firms have more to gain from an NPEs larger network and bargaining power, relative to large firms. I report several other measures of size: small, medium and large originating entity as well as individual inventor.26 A comparison of means for each of these measures reinforces the observation above: NPEs acquire patents from smaller entities.

26 The definitions for these variables may be found in Appendix B.1.1.
Figure 2.3: Originating Entity Size Distribution

Notes: Originating entity size is defined as the log patent portfolio size of the originating firm at the time of NPE patent acquisition.

NPE-held patents include slightly more claims than average, but there is a much larger disparity for forward and backward citations. The average patent sold to an NPE has over 70 percent more lifetime forward citations and 57 percent more backward citations than average. Since forward citations and backward citations are among the most commonly-used proxies for patent value, and NPEs presumably target high-value patents, these findings should not be surprising. NPE-held patents also cite more recent patents, which is captured by the hotness variable. Hotness is defined as the share of backward citations to patents that are at most three years older than the patent itself. NPE-held patents have a 4.85 percentage point higher average hotness than the universe. They are also several years older than
the comparison group, with an average age of 13.64 years (as of 2014, measured from application date) compared to 10.84 years for the universe and were acquired by NPEs at 8.24 years. Finally, as discussed above, lifetime licensing revenue is normalized to be 200.

In the appendix I report additional summary statistics. In particular, B.1.2 reports deal-level summary statistics on all deals through which the NPEs acquired patents from 2003-2014 and B.1.2 reports patent-licensee level summary statistics.

2.5 Estimation and Results

My model has many implications that can be tested with the data. In this section, I report the results from several different empirical analyses aimed at doing so.

2.5.1 Patent Sale (Predictions 1 and 2)

I first examine which factors relate to the likelihood of a patent sale using the following specification:

\[
\text{Patent Sale}_{i,j,t} = \alpha + \beta \times X_{i,j,t} + \phi \times M_{i,j,t} + \psi \times Z_{i,j,t} + \gamma_j + \eta_t + \epsilon_{i,j,t}
\]  

(2.5.1)

where \text{Patent Sale}_{i,j,t} is a dummy variable that is “1” if patent \(i\) in technology category \(j\), with application year \(t\) is sold to an NPE and “0” otherwise. \(X_{i,j,t}\) is a vector consists of the main variables of interest: \text{Log Entity Size}, \text{Distance to innovating Entity}, \text{Litigation Risk} and \text{Individual Inventor Indicator}. \(M_{i,j,t}\) is
a vector containing interaction terms, which may be seen in Table 2.2. \( Z_{i,j,t} \) are control variables: \textit{Total Claims}, \textit{Lifetime Forward Citations}, \textit{Backward Citations}, \textit{Hotness Index}, \textit{Patent Age}, and \textit{PatentAge}^2. \( \gamma_j \) is a set of technology category dummies, measured at three-digit IPC level. \( \eta_t \) is a set of application year dummies (only in column 5) and \( \epsilon_{i,j,t} \) is the error term. Robust standard errors are clustered at innovating entity level. The results are reported in Table 2.2.

This table tests predictions 1 and 2 of the model. Column 1 shows that the probability of a patent sale to an NPE is decreasing in firm size and the effect is statistically significant across all specifications. In the empirical application, I multiply dependent variable with 1000 to scale the coefficients. In addition to being statistically significant, the magnitude is economically important as well.\(^{27}\) Holding all other variables at the mean level, a one percent increase in log entity size increases the probability of sale by 1.57 \%. Moreover, the impact of litigation risk is strongly positive, which implies that patents that are more likely to be litigated are more likely to be sold to NPEs. The interaction term is negative, which implies that litigation risk becomes more important factor among small firms for patent sale. This finding confirms prediction 1.

Next, I introduce focus on the relationship between patent distance and probability of a patent sale. The estimated positive coefficient on the distance variable indicates that patents that are more distant to the originating firm are more likely

\(^{27}\)Small Entities were those at least 2 standard deviation below the mean size and individual inventors. I use specification 4 for magnitude analysis.
Table 2.2: Patent Sale Decision

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<th>(4) Sale Indicator</th>
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IPC-3 Controls: Yes Yes Yes Yes Yes
Application Year Control: No No No No Yes
R-squared: 0.011 0.013 0.013 0.013 0.013
R-squared: 0.011 0.013 0.013 0.013 0.013

Notes: Linear probability model with patent sale to NPE as binary dependent variable. Sample contains all U.S. patents granted 1987 - 2014. Distance measure is calculated with respect to innovating entity. Robust standard errors clustered by originating entity in parentheses. Please see the text and appendix for variable definitions and normalization.

to be sold. The positive coefficient on interaction with the firm size indicates that distance becomes more pronounced as a reason for sale for large firms, which confirms prediction 2. Note that a standard deviation increase in distance (22.35)
increases the probability of sale by 13 % (= (0.08 × 22.35)/13.64) while one standard deviation increase in litigation risk (7.27) increases sale probability by 5% (= (7.27 × 0.10)/13.64). Litigation risk is more important for small entities and individual inventors. A standard deviation increase in litigation risk increases sale probability by 24 % for small entities.

2.5.2 Acquisition Price (Predictions 3 and 4)

I perform a second set of regressions designed to test the implications of my theory regarding patent acquisition prices. I estimate the OLS model specified below using NPE deal-level data from 2003-2014.

\[
\text{Log Acquisition Price}_{i,t} = \alpha + \beta \times K_{i,t} + \phi \times M_{i,t} + \psi \times J_{i,t} + \eta_t + \epsilon_{i,t} \tag{2.5.2}
\]

where \(\text{Log Acquisition Price}_{i,t}\) is the log normalized acquisition price for deal \(i\) in year \(t\). \(K_{i,t}\) is a vector consisting of the main variables of interest, \(Distance\) and \(Log Entity Size\). \(M_{i,t}\) is a vector consisting of interaction variables that may be found in Table 2.3. \(J_{i,t}\) is a vector consisting of control variables: \(Total Claims, Lifetime Forward Citations, Backward Citations, Hotness, Deal Size, Age, Age^2\). \(\eta_t\) is a set of year dummies (included in column 5) and \(\epsilon_{i,t}\) is the error term. Robust standard errors are clustered at the deal level. The results are reported in Table 2.3.

Table 2.3 documents that NPEs pay more to larger firms which confirms predic-
Table 2.3: The Determinants of Patent Acquisition Price

<table>
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<tr>
<th>Dependent Variable:</th>
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<th>(4)</th>
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</tr>
</thead>
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<td>(1.23)</td>
<td>(1.36)</td>
<td>(1.24)</td>
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Notes: OLS regressions with Log Price as dependent variable. Acquisition deal-level data includes all NPE patent acquisition deals in U.S. Distance measure is calculated with respect to innovating entity. Robust standard errors clustered by acquisition deals in parentheses. Please see the text and appendix for variable definitions and normalization.

In addition, it shows that when a patent is more distant to the innovating firm, NPEs pay less to buy it, which verifies prediction 4. Magnitudes are economically important as well. A 100% increase in licensee size increases the
fee by 13%. While a standard deviation increase in distance (28.01) decreases it by 37% \((28.01 \times 13.33)/1000\).  

2.5.3 Licensing Fee (Prediction 5)

I next examine the determinants of the licensing fee paid to NPEs:

\[
\text{Log Licensing Fee}_{i,j,t} = \alpha + \theta \times A_{i,j,t} + \rho \times B_{i,j,t} + \Gamma_i + \delta_t + \epsilon_{i,j,t} \quad (2.5.3)
\]

where \(\text{Log Licensing Fee}_{i,j,t}\) is log normalized licensing fee received for patent \(i\), from licensee \(j\) in year \(t\). The main variables of interests are included in vector \(A_{i,j,t}\) which consists of Distance to Licensee, Litigation Risk and interactions. \(B_{i,j,t}\) is a vector includes entity-level and patent-level controls, which are Log Licensee Size, Total Claims, Backward Citations, Hotness, Lifetime Forward Citation, Patent Age, and PatentAge\(^2\). \(\Gamma_i\) is a set if IPC3 technology class dummies and \(\delta_t\) are year dummies. Robust standard errors are clustered at licensee level and results are reported in Table 2.4.

I find that the more distant a patent from the licensee, the lower the fee is (Table 2.4). This is in line with prediction 5 of the model. I also see that the licensing fee is increasing in litigation risk and firm size. \(^{29}\)

The magnitudes are economically important as well. A 100% increase the licens-

\(^{28}\)I use specification 5 for this analysis.

\(^{29}\)Note that the license fee is multiplied by 1000 for greater legibility of the regression tables.
### Table 2.4: The Determinants of Patent Licensing Fee

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1) Log Licensing Fee</th>
<th>(2) Log Licensing Fee</th>
<th>(3) Log Licensing Fee</th>
<th>(4) Log Licensing Fee</th>
<th>(5) Log Licensing Fee</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Licensee Size</td>
<td>318.83*** 317.07***</td>
<td>317.00*** 316.68***</td>
<td>318.66***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(75.75) (73.98)</td>
<td>(73.96) (73.98)</td>
<td>(76.43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to Licensee</td>
<td>-5.72** -5.23**</td>
<td>-5.24** -4.45**</td>
<td>-4.62**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.74) (2.47)</td>
<td>(2.48) (2.03)</td>
<td>(2.27)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Licensee Size x Distance</td>
<td>0.92 (0.90)</td>
<td>0.92 (0.90)</td>
<td>1.05 (0.90)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Litigation Risk</td>
<td>5.77*** 5.38***</td>
<td>5.05*** 9.28***</td>
<td>9.39**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.54) (1.56)</td>
<td>(1.72) (1.92)</td>
<td>(2.07)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Licensee Size x Litigation Risk</td>
<td>0.60 (1.13)</td>
<td>0.58 (1.11)</td>
<td>0.63 (1.13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual Inventor</td>
<td>27.26 27.78</td>
<td>28.08 43.84</td>
<td>42.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(36.30) (36.35)</td>
<td>(36.35) (37.98)</td>
<td>(37.94)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Claims</td>
<td>0.43 (0.43)</td>
<td>0.44 (0.43)</td>
<td>0.83* (0.49)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lifetime Forward Citations</td>
<td>0.76*** (0.28)</td>
<td>0.75*** (0.28)</td>
<td>0.56* (0.27)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Backward Citations</td>
<td>1.89*** 1.88***</td>
<td>1.88*** 1.93***</td>
<td>1.93***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.42) (0.43)</td>
<td>(0.43) (0.44)</td>
<td>(0.44)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hotness</td>
<td>0.02 (0.18)</td>
<td>0.04 (0.18)</td>
<td>0.23 (0.20)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance x Litigation Risk</td>
<td>-0.05 (0.07)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>58.47*** 58.03***</td>
<td>58.05*** 52.30***</td>
<td>53.73***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15.17) (15.17)</td>
<td>(15.18) (15.46)</td>
<td>(15.50)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age2</td>
<td>-2.03*** -2.02***</td>
<td>-2.02*** -1.90***</td>
<td>-1.94***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.50) (0.50)</td>
<td>(0.50) (0.49)</td>
<td>(0.50)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPC-3 Controls</td>
<td>Yes Yes Yes Yes No</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transaction Year Control</td>
<td>Yes Yes Yes Yes Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.552 0.554 0.555 0.552 0.549</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table reports results of OLS regressions with Log Licensing Fee as dependent variable. Patent-Licensee-Year level data includes all NPE licensing transactions. Distance measure is calculated with respect to licensee. Robust standard errors clustered by licensee in parentheses. Please see the text and appendix for variable definitions and normalization.

The log licensing fee increases by 31.7% while a standard deviation increase in distance (29.73) decreases it by 13.3% (= \((4.45 \times 29.73)/1000\)). Litigation risk also plays an important role quantitatively. A standard deviation increase in litigation risk (8.61) increases the log licensing fee by 8% (= \((8.61 \times 9.28)/1343.19\)).

---

30I use specification 4 for magnitude analysis.
2.5.4 Downstream Innovation (Prediction 6)

In order to understand the effect of NPE patent acquisitions on patent citations, I want to build the counterfactual of patent citations to NPE-held patents, had they not acquired by NPEs. There are two main challenges to identify this effect. First, the patents acquired by NPEs may have a different citation arrival trajectory than the full population of patents. To address this challenge, I construct control a group of placebo acquired patents in a difference-in-differences research design. Second, the acquisition behavior of NPEs may not be exogenous to citation arrival. I show that estimated effects of NPE-acquisition are significant only after the year of acquisition, which alleviates potential concerns.

As a first step in my research design, I pair NPE patents with the patents in population by exactly matching on their application year and number of forward citations prior to acquisition period and the technology category (IPC at three digit level) via coarsened exact matching algorithm (CEM).\textsuperscript{31} These matched pairs constitute the main sample for the event study.

In order to understand the dynamics of the effect, while probing the validity of my design by testing whether there is any effect of NPE acquisition before the event occurs, I use a panel data model. The dependent variable is $Y_{i,t}$ which denotes the number of forward citations received by patent $i$ at time $t$. I include full set of leads and lags around NPE acquisition for real acquired patents ($L_{it}^{Real}$). The dynamic

\textsuperscript{31}The details regarding matching algorithm can be found at http://gking.harvard.edu/files/gking/files/cem-stata.pdf.
effects are associated with lags are denoted as \( \{\beta^\text{Real}(k)\}_{k=-5}^5 \). Second, I include a two period event dummy after around NPE acquisition that is both common to real and placebo acquired patents (after). The predicted effect is denoted by \( \beta^\text{All} \).

Lastly, I add three distinct set of fixed effects: age fixed effects \((a_{it})\), year fixed effects \((\eta_t)\) and patent fixed effects \((\alpha_i)\).

I estimate the following specification with OLS:\(^{32}\)

\[
Y_{i,t} = \sum_{k=-5}^{5} \beta_k^\text{real} 1_{\{L_{\text{Real}}=k\}} + \beta^\text{All} \times \text{After} + \sum_{j=1}^{20} \lambda_j 1_{\{\text{age}_{it}=j\}} + \sum_{m=1998}^{2014} \eta_m 1_{\{t=m\}} + \alpha_i + \epsilon_{i,t}
\]

(2.5.4)

I combine all NPE patents together with placebo patents and estimate the model using specification 2.5.4. I plot \( \{\beta^\text{Real}(k)\}_{k=-5}^5 \) in Figure 2.4a.

In order to alleviate concerns for selection effects, I set patents that are acquired by NPEs but located at the bottom decile of the value distribution as additional control group and add set of leads and lags around NPEs acquisition. I split NPEs sample as top and bottom value decile and combine them with the placebo patents. Then, I estimate the following model:

\[
Y_{i,t} = \left\{ \begin{array}{l}
\sum_{k=-5}^{5} \beta_k^\text{real,top} 1_{\{L_{\text{Real,top}}=k\}} + \sum_{k=-5}^{5} \beta_k^\text{real,bottom} 1_{\{L_{\text{Real,bottom}}=k\}} + \beta^\text{All} \times \text{After} + \\
\sum_{j=1}^{20} \lambda_j 1_{\{\text{age}_{it}=j\}} + \sum_{m=1998}^{2014} \eta_m 1_{\{t=m\}} + \alpha_i + \epsilon_{i,t}
\end{array} \right\}
\]

(2.5.5)

\(^{32}\)Adding the fixed effects above generates a collinearity problem. I follow the literature and drop first two age and year dummies. I also normalize the coefficient of the -1 period with 0 as in line with the literature.
I plot \( \{\beta^{\text{Real, top}}(k)\}_{k=-5}^{5}, \{\beta^{\text{Real, bottom}}(k)\}_{k=-5}^{5} \) in Figure 2.4b.

**Figure 2.4: Event Studies**

(a) Forward Citations Relative to NPE Acquisition

(b) Forward Citations Relative to NPE Acquisition by Value Decile

Notes: Figure (2.4a): This figure reports results from a regression of the annual forward citations on event dummies relative to the year of acquisition of a patent by an NPE. The regression makes use of a balanced panel of patent-level data (5 years before and after acquisition year) from 1998-2014 for NPE-acquired patents, placebo patents and include controls for patent, age and year fixed effects. Robust standard errors are clustered at NPE acquired patent level as error bars. Figure (2.4b): This figure reports a similar analysis for NPE-acquired patents located at top and bottom value decile, placebo patents and include controls for patent, age and year fixed effects. Robust standard errors are clustered at NPE acquired patent level as error bars.

**F test for Pretrends** I can formally test the hypothesis that point estimates are the same before NPE acquisition and after NPEs acquisition. I cannot reject the hypothesis that the point estimates are all the same before NPEs acquisition, but I can after NPEs acquisition. Briefly, Table 2.5 indicates that there is no pre-trending but an effect after NPE acquisition.
\[ H_{0}^{before} : \beta_{5}^{real} = \beta_{4}^{real} = \beta_{3}^{real} = \beta_{2}^{real} = \beta_{1}^{real} \]

\[ H_{0}^{after} : \beta_{5}^{real} = \beta_{4}^{real} = \beta_{3}^{real} = \beta_{2}^{real} = \beta_{1}^{real} \]

Table 2.5: Testing For Dynamic Effects, P values from F-test

<table>
<thead>
<tr>
<th></th>
<th>Panel A((\beta^{real}))</th>
<th>Panel B((\beta^{real,top}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>For (H_{0}^{Before})</td>
<td>0.43</td>
<td>0.83</td>
</tr>
<tr>
<td>For (H_{0}^{After})</td>
<td>0.00001</td>
<td>0.00001</td>
</tr>
</tbody>
</table>

Notes: This panel reports the p-values of F-tests for equality of the \(\beta\) Real k coefficients from specification 2.5.4 and 2.5.5, before and after acquisition, as specified by the hypotheses \(H_{0}^{Before}\) and \(H_{0}^{After}\).

The magnitude of the effect is modest. The decline in citations after acquisition (at one significant digits) amounts to 2.6% (.05/1.9) for specification 2.5.4. (The average differential decline in all NPE patents in comparison to placebo patents.)

**Explaining why the effect appears gradually** I find that the nature of licensing business and the nature of innovation as a stochastic process explain why the effect of NPE acquisition manifests itself gradually, as shown by the changes in the slopes in Figure 2.4a, and 2.4b. My data shows that NPE acquisitions do not directly translated into licensing deals right away. It takes time to find the right licensing entity. Mean duration is around 4.09 years in the data. The longer the duration, the more likely that more potential licensing entities are contacted. As
more entities are contacted and license patents over time, the identity of the patents are more likely to be revealed to the current and potential licensees. This may lead entities to stay away from innovating over NPE-patents to prevent future contact with them. The fact that high citation and high value patents receive less citation after NPE acquisition over time is consistent with this explanation.

2.6 Calibration

I have now seen empirical results that have corroborated a number of predictions of the model. In this section, I would like to see the numerical properties of my model for a reasonable set of parameter values. For this purpose, I now calibrate the structural model.

In order to ensure that probability of infringement remains between 0 and 1, I consider the following form for $\tau = (1 - \phi)\lambda$. Hence, my model has the following 11 parameters to be calibrated:

$$\Theta \equiv [\eta, \kappa, \mathbb{E}[d_i], \mathbb{E}[d_k], \Omega, \pi, \phi, \lambda, \beta_i, \beta_{\text{npe}}, \xi]$$

I calibrate the parameters in two steps. For four of the parameters, I rely on the existing literature and use the commonly accepted values (external calibration). For the rest of the parameters, I pick seven informative empirical moments $M^E$ and minimize the distance between model-simulated moments $M(\Theta)$ and their empirical
counterparts by searching over the parameter space \( \Theta \) as follows,

\[
\min_{\Theta} \sum_{i=1}^{7} (M_i^E - M_i(\Theta))^2.
\]

In the next section, I describe the identification of each parameter.

2.6.1 Identification

The externally calibrated parameters \((\eta, E[d_i], E[d_k], \xi)\) are chosen as follows:

1. **R&amp;D Cost Parameter, \(\eta\):** This parameter is calculated as the ratio of R&amp;D expenditures to firm sales for all licensing and innovating entities (who sell their patents to NPEs) who have a record in Compustat.

2. **Expected Distance to Innovating Entities, \(E[d_i]\):** This parameter is the mean distance of patents that are sold to NPEs. Note that distance is measured as distance to innovating entity. It is calculated from NPE data, using the universe of upstream firms.

3. **Expected Distance to Licensing Entities, \(E[d_k]\):** This parameter is the mean distance of patents that are licensed from NPEs. Please note that distance is measured as distance to licensing entity. It is assumed to take a uniform distribution on the unit circle.

4. **Convexity of Cost Function, \(\xi\):** The innovation production function has been estimated to be a quadratic by a large literature as it is summarized in Akcigit.
and Kerr [2017].

Next, I describe the moments that I use to identify the internally calibrated parameters. The reader should note that all these moments are jointly targeted.

1. *Price upstream producer sells to NPE*: This is set to 1 and is noted in relation to the price NPEs sell to downstream producer. From NPE acquisition cost data.

2. *Price NPE sells to downstream producer or outside producer* This comes from NPE revenue data and is solved in terms of its ratio to acquisition cost.

3. *Correlation between distance of upstream to NPE and price* Correlation between the distance of $i$ and the price.

4. *Correlation between price sold and bought from NPE* Correlation between the acquisition cost and the lifetime revenue.

5. *Innovation intensity of upstream innovator* This is taken as the percentage of patents in NPE set that are cited by downstream innovators.

6. *Probability of sale to NPE* The probability of sale is taken as the average probability of reassignment in the patent class (IPC4) where NPEs are most active.

7. *Proportion of infringement from non-innovators* I set this benchmark value
to 0.50 as the to denote the probability that an NPE will go after a non-innovating producer if infringed.

Next, I describe the parameters.

1. *Profit of Licensing Entity, Ω:* This parameter is a proxy for the value of patent to the potential licensee.

2. *Profit of Innovating Entity, π:* This parameter is a proxy for the value of patent to the inventing entity.

3. *Probability of Winning in Court (Innovating Entity), βᵢ:* This parameter captures the strength of innovating entity in court. In particular, it captures the probability that the innovating entity wins an infringement case.

4. *Probability of Winning in Court (NPE), β_{npe}:* This parameter captures the strength of NPE in court. In particular, it captures the probability that NPE wins an infringement case.

5. *Max. Search cost, κ:* i will pull a search cost ∼ U[0, κ] and κ is the maximum value.

6.7. *Probability producer infringement and downstream Infringement Probability, φ, τ:* This determines the probability of whether an infringement comes from a non-innovating producer or downstream innovator.
2.6.2 Calibration Results

An important moment in my quantitative analysis is the proportion of infringement coming from innovating versus non-innovating firms. Since I do not have a direct moment to discipline this ratio, in the benchmark estimation, I will assume that 50% of the infringement is coming from non-inventors, i.e., $\phi/\alpha = 0.5$. Later in my analysis, I will check the robustness of my results to alternative values, such as $\phi/\alpha \in \{0, 0.25, 0.75, 1\}$. The estimated parameters together with the descriptions are provided in Table 2.7 and the matched moments are described in Table 2.9.

Table 2.6: Parameter Values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Main Identification</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta$</td>
<td>R&amp;D cost scaling</td>
<td>0.13</td>
<td>R&amp;D/Sales</td>
</tr>
<tr>
<td>$\xi$</td>
<td>Convexity of R&amp;D cost</td>
<td>2</td>
<td>Akcigit and Kerr [2017]</td>
</tr>
<tr>
<td>$E[d_i]$</td>
<td>Expected distance of upstream to NPE</td>
<td>0.30</td>
<td>NPE Distribution</td>
</tr>
<tr>
<td>$E[d_{ik}]$</td>
<td>Expected distance of downstream to NPE</td>
<td>0.50</td>
<td>Taken in uniform[0,1]</td>
</tr>
<tr>
<td>$\Omega$</td>
<td>Profit of Licensing Entity</td>
<td>4.03</td>
<td>Correlation of prices</td>
</tr>
<tr>
<td>$\pi$</td>
<td>Profit of Innovating Entity</td>
<td>0.17</td>
<td>Correlation between $p_i$ and $d_i$</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Probability producer infringement</td>
<td>0.34</td>
<td>Pr producer infringement</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Probability innovator infringement</td>
<td>0.66</td>
<td>Pr producer infringement</td>
</tr>
<tr>
<td>$\beta_i$</td>
<td>Probability of Winning (Upstream)</td>
<td>0.22</td>
<td>Correlations, Prices</td>
</tr>
<tr>
<td>$\beta_{npe}$</td>
<td>Probability of Winning in Court (NPE)</td>
<td>0.96</td>
<td>Prices</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Max. Search Cost</td>
<td>3.08</td>
<td>Pr(sale)</td>
</tr>
</tbody>
</table>

Notes: All parameters are estimated jointly.
Table 2.7: Parameter Values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Main Identification</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\eta$</td>
<td>R&amp;D cost scaling</td>
<td>0.13</td>
<td>R&amp;D/Sales</td>
</tr>
<tr>
<td>$\xi$</td>
<td>Convexity of R&amp;D cost</td>
<td>2</td>
<td>Akcigit and Kerr [2017]</td>
</tr>
<tr>
<td>$E[d_i]$</td>
<td>Expected distance of upstream to NPE</td>
<td>0.30</td>
<td>NPE Distribution</td>
</tr>
<tr>
<td>$E[d_k]$</td>
<td>Expected distance of downstream to NPE</td>
<td>0.50</td>
<td>Taken in uniform[0,1]</td>
</tr>
</tbody>
</table>

— Panel B. Internal Calibration —

| $\Omega$  | Profit of Licensing Entity | 4.03  | Correlation of prices |
| $\pi$     | Profit of Innovating Entity | 0.21  | Correlation between $p_i$ and $d_i$ |
| $\phi$    | Probability producer infringement | 0.33  | Pr producer infringement |
| $\tau$    | Probability innovator infringement | 0.67  | Pr producer infringement |
| $\beta_i$ | Probability of Winning (Upstream) | 0.26  | Correlations, Prices |
| $\beta_{npe}$ | Probability of Winning in Court (NPE) | 0.90  | Prices |
| $\kappa$  | Max. Search Cost | 2.62  | Pr(sale) |

Notes: All parameters are estimated jointly.

Table 2.8: Moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price upstream producer sells to NPE</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>Average Price NPE sells to downstream</td>
<td>1.63</td>
<td>1.65</td>
</tr>
<tr>
<td>Correlation between distance of upstream to NPE and price</td>
<td>-0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>Correlation between price sold and bought from NPE</td>
<td>0.32</td>
<td>0.35</td>
</tr>
<tr>
<td>Innovation intensity of upstream innovator</td>
<td>0.47</td>
<td>0.46</td>
</tr>
<tr>
<td>Probability of sale to NPE</td>
<td>0.23</td>
<td>0.21</td>
</tr>
<tr>
<td>Proportion of infringement from non-innovators</td>
<td>0.50</td>
<td>0.53</td>
</tr>
</tbody>
</table>

Table 2.9: Moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price upstream producer sells to NPE</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>Average Price NPE sells to downstream</td>
<td>1.55</td>
<td>1.57</td>
</tr>
<tr>
<td>Correlation between distance of upstream to NPE and price</td>
<td>-0.08</td>
<td>-0.10</td>
</tr>
<tr>
<td>Correlation between price sold and bought from NPE</td>
<td>0.38</td>
<td>0.41</td>
</tr>
<tr>
<td>Innovation intensity of upstream innovator</td>
<td>0.47</td>
<td>0.45</td>
</tr>
<tr>
<td>Probability of sale to NPE</td>
<td>0.23</td>
<td>0.21</td>
</tr>
<tr>
<td>Proportion of infringement from non-innovators</td>
<td>0.50</td>
<td>0.51</td>
</tr>
</tbody>
</table>
2.7 Comparative statics

In this section, using the estimated parameter values, several quantitative experiments are conducted to better understand the activity of NPEs in the market for ideas.

My quantitative analysis tries to explore the conditions and the market structure under which NPEs can increase or decrease the innovation rate. Briefly, I would like to answer the following questions: First off, given the structural parameters of the model, what would happen to overall innovation level if there is no NPE in the market in comparison to the case when there is one? Second, what happens to innovation as the legal strength of NPEs increases? My answers to the questions above regarding the market micro structure help me to propose potential policies which may have a concrete impact on how NPEs operate and affect the innovation.

However, as I know this will depend on the degree of infringement that comes from producers versus innovators. Hence I will vary \( \phi \) (probability of another producer infringing) and put a vertical line in the places of the corresponding calibrated values. As I see with the following exercises, the NPEs effect on innovation depends on \( \phi \). I now look at changing values of \( \phi \) on innovation level in Figure 2.5.

Before delving into any type of conclusion, I would like to clarify the term middleman. As discussed in earlier sections, I ascribe two main roles to NPEs as middleman. First, as I see the examples in other industries, the NPEs can be experts at finding a better user for the patents. By transferring the assets where they can
be used more productively, the NPEs can serve as a middleman. Second, the NPEs can help small entities to enforce their property rights. In my analysis, I do not automatically assume that all type of litigation or enforcement activity is harmful to the economy. The innovation literature shows that the effect of enforcement can go both ways. New entrants can benefit from enforcement as it increases the return on their assets by discouraging potential infringers. On the other hand, incumbents may stop innovating as the expected loss can be very large in case of infringement even if the probability of infringement is very low. My approach here is to quantify
the effect of an NPE licensing on innovation. If the welfare cost of enforcement is too large, then I would take it as an evidence for stick up artist theory.

Figure 2.5 shows that at the estimated parameter values I see a decline in the aggregate rate of innovation. The decline amounts to 2.6%. Even though average number is informative, decomposition of the effect shows that entrants benefit from NPEs in comparison to the incumbents. More specifically, at the estimated parameter value, there is 8.4% increase in the innovation rate of new entrants while 11% decline in the innovation rate of incumbents.

The welfare implications of my results boil down to the question of how soci-
enty values innovation by entrants and incumbents. Those who put more value on incumbent innovation may take the evidence as an indicator of Stick-Up Artist Theory while others may think the NPEs are middleman helping small inventors and entrants. Another way to interpret the results is within the lens of innovation literature. The main question is who find better ideas? Incumbents or new entrants? Young firms or old firms? Akcigit [2009] and Akcigit and Kerr [2017] suggest that young firms are likely to find ground breaking ideas. In that sense, small increase in new entrant innovation rate can bring about bigger changes even if it happens at expense of incumbents.

In the following analysis, I would like to understand the effect of NPEs on innovation for various values of enforcement capacity of new entrants. The analysis is important in the sense that industries with higher rate of new entrants exhibit different response to the NPEs in comparison to the industries dominated by the incumbents. Thus, this analysis help me to understand whether one size fits all type of policies are preferable in this setting. Results show that NPEs have comparative advantage in enforcing property rights ($\beta_i < \beta_{npe}$). The results are quantitatively important as well. Figure 2.6 shows that any policy change which increases the enforcement capacity of new entrants by 1 percent increases their innovation rate by 0.15 percent holding all other estimated parameter values constant. On the other hand, the same increase in the enforcement capacity of new entrants lead to no change in innovation for incumbents.
To sum up, my quantitative results show that NPEs can be taken as a middleman or stick-up artists depending on how society values innovation by entrants and incumbents.

2.8 Conclusion

What do non-practicing entities do and how do they impact innovation and technological progress? Despite the heated debates on this issue both in academic and policy circles, the direct evidence on their business models is quite limited. In this chapter, I attempt to answer these questions both theoretically and empirically. On the theoretical side, the model gave new insights on how NPEs operate. Following the common arguments, the model allowed for NPEs to purchase patents and license them to other firms without using those patents for production. My model highlighted two crucial roles for the NPEs: First, they could purchase patents that are more litigation-prone and use them to threaten other firms to extract more licensing revenue. Even though this argument sounds negative, on the positive side it creates value for the intellectual properties for the small firms who do not have the sufficient means to defend their patents. While this give small firms incentives to innovate more by restoring their patent values, the same action discourages large firms who might be infringing on small firm patents. The second role of the NPEs have been the middleman in the market for patents, which suffer deeply from informational asymmetry. By having access to the full broker network around the
country, NPEs can allocate patents to better users.

These elements in my model allowed me to come up with a number of important testable implications. The second part of the chapter has utilized a first-hand data from the NPEs. Very importantly, I could see how litigation risk and goodness of fit of the patent affect patent sale decisions and pricing decisions. My empirical analysis has shown that NPEs on average buy litigation-prone patents from small firms and bad-fit patents from large firms. Both the distance and goodness of fit reflect on the prices that the NPEs pay when they purchase and charge when they license out.

I believe that these new facts that are shown in this chapter can shed light in this important debate. Understanding the welfare consequences of the NPEs is one of the most important policy issues that awaits further research.
Bibliography


Jonathan H. Ashtor, Michael J. Mazzeo, and Samantha Zyontz. Patents at issue:


S. Kiebzak, G. Rafert, and Tucker. The effect of patent litigation and patent


Appendices
A Appendix: Chapter 1

A.0.1 Data Cleaning and Merging

Company Name Cleaning

In order to aggregate patents produced by or sold to the same entities properly, it is critical to have a way to clean company names, which I discuss here. My approach is similar to that used in the NBER Patent Database Project (PDP), but I extend past the 2006 end date of that data set.\textsuperscript{33}

Company identifiers used by the USPTO are known to contain serious flaws. The most recent efforts to harmonize the company names do not take many issues into account. In particular, the same firms are assigned to different identifiers because of a change in their legal status (e.g. \textit{“MOSANTO TECHNOLOGY LLC”}, \textit{“MOSANTO TECHNOLOGY LLP”}).

In order to tackle the flaws generated by USPTO identifiers, a conservative company name cleaning algorithm is employed, so that assignee identifier flaws are

\textsuperscript{33}I would like to thank Murat Alp Celik for sharing his cleaning algorithm.
minimized. The main idea behind the cleaning algorithm is to clean all unnecessary company indicators, and company type abbreviations. If the resulting string variables are the same, the algorithm assigns the same assignee identifier to each modified string. The same algorithm is used to clean licensee names in ND.

The algorithm can be summarized as follows:

1. All letters of the string are made upper case.
2. Any part of the string coming after a first comma is deleted.
3. All non-alphanumeric characters are deleted.
4. The first 3 characters of the string are deleted if it starts with “THE”.
5. The company indicators such as CO, CORP, LLC, etc are removed.
6. If the resulting string has zero length, the original string is used. (e.g. “ABCO, INC”, “COCO, INC”)

Data Merging

The PAB, LM, INV, ND datasets are merged on patent number. 34 I keep only utility patents and drop those with application dates before 1987. 35 I keep patents assigned to individuals if the number of listed inventors is one. This is due to the difficulty in calculating portfolios for ever-changing assignee groups of multiple inventors. Thus, small, unincorporated groups are omitted from the analysis.

34 I complement the data with recently announced citation and claim decomposition data. It can be found in the following link: http://www.patentsview.org/download.
35 More than 99 percent of the NPE patents were applied for after 1987. This is the main reason that I focus on post-1987 patents.
I keep only patents in technology categories (three-digit IPC) where the NPEs operate. I merge USPTO classes and IPC classes and use IPC classes in my analysis.\textsuperscript{36} Each patent in PAB is matched with harmonized assignee identifiers. The company name cleaning algorithm is used on assignee and licensee names from the ND data. I match licensees with PAB data and keep those for which there is patent data. I drop patents with missing distance to originating entity and litigation risk from the acquisition deals.

\section*{A.0.2 Variable Construction}

\textbf{Exposure} The first measure is exposure measure, which purports to identify the sectors and firms that are more likely to be affected by the policy change. The measure is widely used in literature.\textsuperscript{37}

\begin{equation}
\text{exposure}_j = \frac{\sum_i k_i \sigma_i}{N}
\end{equation} \hspace{1cm} (A.0.1)

The construction of the measure can be summarized in two steps. First, I calculate litigation intensity measure, $\sigma$, for each four-digit IPC (International Patent Classification) technology categories. Litigation intensity is the fraction of litigated patents at four-digit IPC level before Supreme Court Decision (2003-2006). The exposure index is constructed both at the firm level and industry level. Exposure measure

\textsuperscript{36}See http://www.uspto.gov/web/patents/classification for further information.

\textsuperscript{37}Please check Mezzanotti [2016].
at the industry level is identical to litigation intensity.

Constructing firm-level exposure variable requires a little more effort. Using the patent portfolio information of each inventing entity, and 4-digit IPC classification of the patents, I constructed a weighted average of litigation intensity for each portfolio. The resulting measure is exposure at the firm level. Equation A.0.1 illustrates the measure at the entity level, where $j$ denotes the entity, $i$ denotes the technology category of the patents in firm $j$ portfolio, $k_i$ denotes the number of entity $j$ patents in technology category $i$, and $N$ is the portfolio size of the inventing entity.

The main reasoning behind my measure is as follows: Entities operating in high litigation intensity sectors are more likely to be affected by the policy change.

### A.0.3 Additional Tables

Table A.1: Deal Level Descriptive Statistics

<table>
<thead>
<tr>
<th>stats</th>
<th>Mean</th>
<th>p50</th>
<th>sd</th>
</tr>
</thead>
<tbody>
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<td>Log Acquisition Fee</td>
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</tr>
<tr>
<td>Deal Quality</td>
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<td>Exposure</td>
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<td>0.046</td>
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<td>Deal Size</td>
<td>10.38</td>
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<tr>
<td>Age</td>
<td>7.53</td>
<td>7.30</td>
<td>3.55</td>
</tr>
<tr>
<td>Backward Citations</td>
<td>18.54</td>
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<td>26.93</td>
</tr>
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<td>Entity Size</td>
<td>21.30</td>
<td>2</td>
<td>64.99</td>
</tr>
<tr>
<td>Funding Year</td>
<td>2007.19</td>
<td>2008</td>
<td>1.45</td>
</tr>
</tbody>
</table>

*Notes:* NPE patent-level data from 2003 - 2009. Please see the appendix for variable definitions.
A.0.4 Simplified Version of the Model

This section illustrates the model using simplified version of the main model.

**Licensing Negotiations** ($\beta_1$) Consider a one-period enforcement game between licensee(l) and intermediaries with the following parameters: $r = 100$, $C_p = 20$, $\beta_1 = -0.5$, $P_I = 0.1$, $\rho = 0.1$, $\beta_2 = 0$, $\beta_3 = 0$ and the choice specific errors. An increase in $\beta_1$ from $-0.3$ to $-0.2$ makes the settlement more attractive option for the licensee. Intermediaries reoptimize the settlement offers. The optimization leads to an increase in the settlement offer from 19 to 30 and a decrease in the probability that the offer being taken from 0.90 to 0.88. The intuition is very simple. An increase in $\beta_1$ means that the licensee is willing to pay more for settlement over going to the court. Intermediaries prices the licensee preference for the settlement by considering the trade-off between the increase in settlement offer and the reduction in choice probability. The different levels of $\beta_1$ exhibit different patterns in response to an increase in enforcement costs. In response to an increase in the costs of enforcement, everything else equal, intermediaries decrease settlement offer. Licensees with lower $\beta_1$ are more likely to take the offer relative to the ones with high $\beta_1$. Figure A.1 shows a clear picture for various parameter values.

($P_N$) Consider a one-period version of the enforcement game between the licensee and intermediaries with the following parameters: $r = 100$, $C_p = 20$, $\beta_1 = -0.5$, $P_I = 0.1$, $\rho = 0.1$, $\beta_2 = 0$, $\beta_3 = 0$ and the choice specific errors. An increase in $P_N$ from 0.1 to 0.2 leads to an increase in the expected cost of resolving the
Figure A.1: Acceptance Probability, Settlement Offers and $\beta_1$
case at the court from -28.1 to -36.2.\textsuperscript{38} As the option to go to the court is more expensive than not going to the court, intermediaries can re-optimize by increasing the settlement offer from 11.5 to 27. The licensee’s utility of settling the case outside the court decreases from -5.75 to -13.5 respectively. The corresponding increase in the choice probabilities (from 0.91 to 0.94) shows that the settlement offer is more likely to get accepted after the increase in $P_N$. An increase in $P_N$ leads to increase both in the settlement offer and the probability of reaching a deal. The different levels of $P_N$ exhibit different patterns in response to an increase in enforcement costs. In response to an increase in the costs of enforcement, everything else equal, intermediaries slightly decrease the settlement offer. The licensee with lower $P_N$ gains a lot more regarding the increase in choice probability (offer being taken) conditional on the decrease in settlement offers. Figure A.2 illustrates it for various parameter values.

**Heterogeneity & Dynamics** Two primary heterogeneities generate interesting cross-sectional variation and dynamics in the model. The first is the intrinsic value ($r$). Consider two patents with $(r_1, r_2)$ with ($r_1 > r_2$). As the option to go to court is more expensive with the high intrinsic value $r_1$, intermediaries can re-optimize by increasing the settlement offer and taking its effect on the choice probability into account. The higher the intrinsic value, the higher the settlement offer and the probability of offer being taken by the licensee. Differences in intrinsic values among different patents generate a reasonable cross-sectional variation in the

\textsuperscript{38}Using the formula $(P_N \times r \times (1 - P_I) \times (1 - \rho) - C_p)$.  

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Figure A.2: Acceptance Probability, Settlement Offers and $P^N$
settlement offers and probabilities. The evolution of the intrinsic value \( r \) over time is also an important heterogeneity rationalizing the intermediaries’ optimal choice of enforcement across periods. The movement of \( r \) over time mainly comes from the trade-off between the depreciation of knowledge versus finding new ways to utilize the same idea. The Markov distribution specified in the previous section captures it. The second source of heterogeneity is the product market revenues of the licensees. The following example clarifies the role of the product market revenues in generating dynamics in the model.

**Example** Consider a two-period version of the enforcement game with the following parameters in each period \( C_p = 20, \ C_d = 0, \ \beta_1 = -0.5, \ P_I = 0.1, \ \rho = 0.1, \ \beta_2 = 0.1, \ \beta_3 = 0, \ r = 100, \ \beta = 1. \) I assume that \( \beta_2 > 0. \) The assumption implies that the firms with higher revenue have a preference towards settlement. Assume further that licensee makes no revenue in product markets in the first period and makes 100 in the second period. The optimal settlement offer for each period is 73 and 93 with choice probabilities 0.96 and 0.97. The expected intermediary-profit
from enforcement is 71 and 91 respectively. The optimal strategy for intermediaries is to wait in the first period and enforce the patent in the second period. The simple example underlines the crucial fact that product market revenues can have an impact on the dynamics of the enforcement decision.
B Appendix: Chapter 2

B.1 Data and Variable Descriptions

B.1.1 Variable Construction

Lifetime Citations

I construct a lifetime forward citation variable for each patent to account for the fact that patents are different ages, and therefore have differing amounts of time to accumulate citation.

In order to construct this measure, the mean forward citations-patent age relationship is constructed for each technological category. I calculate lifetime citations by inflating the total citations already received by the ratio of the total mean citations of the same technology class divided by the mean for the average patent of the same age and technology class. While this procedure will understate the number of lifetime citations for any patent that has zero in the data set, the mean number of lifetime cites should still be correct.

The procedure is applied to all patents granted after 1976 using technology categories in Hall et al. [2001]. Note that in the final analysis I limit my attention
to patents with application year after 1987.

**Acquisition Price**

The patents are purchased in bundles of firms at a given cost. I deflate this cost to real 2010 dollars. For deal-level analysis, e.g. 2.3, some patent bundles combine patents that are not part of the analysis with those that are (e.g. I do not use international patents). In this case, I adjust the acquisition cost by the revenue weights at the broadest level–i.e. whether the patent is in my sample or not. For instance, if a patent outside my sample on average is worth 20% of a patent in the sample, I assign in the deal 5/6 of the cost to the patent in the sample for every 1/6 assigned to international patent.

**Lifetime Revenue**

As with citations, it is necessary to calculate a single revenue number so that I may compare patents of different ages. I begin with per-patent annual nominal revenue numbers and use the CPI to deflate them to real 2010 dollars. For each technology category, a mean revenue-patent age relationship is constructed. The lifetime revenue of a patent is estimated by inflating the observed cumulative revenue by the ratio of the mean lifetime revenue to the mean cumulative revenue for patents of the same age (by technology category). I then normalize all revenue amounts so that mean annual revenue is 10 in order to maintain the confidentiality.

Occasionally patents generate licensing revenue after expiration (since they may
still generate income from prior infringement). In this case no normalization procedure is used and the observed real revenue is simply summed. Since patents may also generate revenue prior to grant (in anticipation of grant) I begin observing revenue at the first filing date (which is the same as application date for 90 percent of patents). That is, patent age is defined as the difference between revenue generation year and first filing year. Revenue realized while a patent is classified as abandoned, acquired as inactive, lapsed, filed, or inactive is simply added to the normalized real revenue.

**Distance**

In order to quantify the distance between two technology classes, I define distance as in Akcigit et al. [2015], using the first 2 digit IPC to denote a technology class:

\[
d(X,Y) \equiv 1 - \frac{(X \cap Y)}{(X \cup Y)}, \text{ with } 0 \leq d(X,Y) \leq 1.
\]

where \( (X \cap Y) \) denotes the number of patents that cite technology classes X and Y together, and \( (X \cup Y) \) denotes the number of patents which either cite X or Y or both.

Also following Akcigit et al. [2015], I construct a patent-to-entity distance metric. The distance of a patent p to an entity f’s patent portfolio is calculated by calculating the average distance of p to each patent in entity f’s patent portfolio as follows.
\[ d_i(p, f) \equiv \left[ \frac{1}{||P_f||} \sum_{p' \in P_f} d(X_p, Y_{p'})^\epsilon \right]^{\frac{1}{\epsilon}} \]

where \(0 < \epsilon < 1\), and where \(0 \leq d_i(p, f) \leq 1\). Note that \(P_f\) represents the set of all patents that were invented by entity \(f\) prior to patent \(p\), \(||P_f||\) denotes the cardinality of the set, and \(d(X_p, Y_{p'})\) measures the distance between technology classes of patents \(p\) and \(p'\).

My baseline results use \(\epsilon = \frac{2}{3}\). Using the measure above, I constructed two different distance measures. Distance to originating entity and distance to licensee. The resulting measure is multiplied by 100 to increase the readability.

**Litigation Risk**

In order to estimate the likelihood a patent may be involved in litigation I make use of the linear probability model model developed in Lanjouw and Schankerman [2001]:

\[ I_{Litigated_{i,j,t}} = \zeta + \eta_i + \delta_t + \phi \times CO_{i,j,t} + \epsilon_{i,j,t} \quad (B.1.1) \]

where the dependent variable is a dummy variable that is 1 if the patent is ever litigated or a complaint filed and 0 otherwise and \((i,j,t)\) represent patent, technology category and application year, respectively. \(\eta_i\) is a firm fixed effect and \(\delta_t\) the application year fixed effect. \(CO_{i,j,t}\) is a vector of covariates, and \(\epsilon_{i,j,t}\) is the error.
My model is motivated by Lanjouw and Schankerman [2001] but I include the additional variables Examiner Backward and Forward Citation Percent, growth of technology categories and entity fixed effects and omit indicator variables for entity types, such as individual inventors, foreign firms operating in the U.S., firms operating in the U.S. which were in the original model.

I estimate the model on the full dataset and then predict litigation risk for each patent. Robust standard errors are clustered at originating entity level.

Other Variables

**Individual Inventor:** 1 if the patent is assigned to one inventor, and there is no corporate assignee of the patent, 0 otherwise.

**Small Originating Entity:** Small Originating Entity is 1 if in the bottom quartile of original entity size, 0 otherwise.

**Medium Originating Entity:** Medium Originating Entity is 1 if in the middle half of original entity size, 0 otherwise.

**Large Originating Entity:** Large Originating Entity is 1 if in the top quartile of original entity size, 0 otherwise.

**Hotness:** The hotness index captures the recent growth in a field by measuring the share of backward citations that are recent. I define hotness as the percentage of backward citations to patents that are at most three years older than the citing patent.
B.1.2 Additional Summary Statistics

Deal-level Summary Statistics

Table B.1 reports deal-level summary statistics on all deals through which the NPEs acquired patents from 2003 - 2014. Compared to Table 2.1, the average entity size is substantially smaller, indicating that the acquisitions from smaller firms are more numerous and have a smaller average deal size. In fact, deals from individual inventors represent 17% of total deals, over an order of magnitude higher than the share of individual inventors in the patent universe. Combining deals with individual inventors and small firms accounts for fully two-thirds of the acquisition deals. Only 5% of patent acquisition deals are struck with large originating firms.

Table B.1: Patent Acquisition Deal Summary Statistics

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<th>Variables</th>
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<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>Sd</th>
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<tr>
<td>Distance to Originating Entity</td>
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<tr>
<td>Log Originating Patent Portfolio Size</td>
<td>3.07</td>
<td>0.84</td>
<td>1.88</td>
<td>5.30</td>
<td>2.76</td>
</tr>
<tr>
<td>Litigation Risk</td>
<td>13.22</td>
<td>8.57</td>
<td>11.61</td>
<td>15.43</td>
<td>8.73</td>
</tr>
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<td>0.17</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.37</td>
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<td>Small Originating Entity</td>
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<td>1</td>
<td>1</td>
<td>0.50</td>
</tr>
<tr>
<td>Medium Originating Entity</td>
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<td>0</td>
<td>0</td>
<td>1</td>
<td>0.45</td>
</tr>
<tr>
<td>Large Originating Entity</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.21</td>
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<td>66.74</td>
</tr>
<tr>
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<td>20.67</td>
<td>30.98</td>
</tr>
<tr>
<td>Hotness</td>
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<td>27.94</td>
<td>42.90</td>
<td>22.59</td>
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<td>98.84</td>
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<td>4.27</td>
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<td>Log Acquisition Price</td>
<td>5.91</td>
<td>4.99</td>
<td>5.85</td>
<td>6.74</td>
<td>1.27</td>
</tr>
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</table>

Notes: Acquisition deal-level data from 2003 - 2014 includes all NPE patent acquisition deals in the U.S. Please see the text and appendix for variable definitions and normalization.
The mean number of forward citations is substantially higher in Table B.1 than Table 2.1, while age is lower, indicating that smaller firms are likely selling newer, more highly cited patents. Larger firms are most likely selling NPEs larger numbers of older, less-cited patents. Deal size is right-skewed with a small number of very large deals driving the mean up substantially; the median acquisition deal involves only 4 patents. Age here is defined as the acquisition date minus application date, and has a mean of just over 7 years. The deal acquisition price is normalized so that the mean is 200. I first divide the acquisition prices of the deals by the number of patents involved. Then, I normalize this value so that mean is 200. Finally, I multiply the normalized values per deal with the number of patents involved to construct normalized acquisition prices for each deal. The values reported are 1000 times the natural log of the normalized prices, used to make regression coefficients more legible.

**Deal-level Summary Statistics**

Table B.2 reports patent-licensee-year level summary statistics derived from NPE licensing deal data from 2008 to 2014. The licensee is the ultimate end-user of the patent; most patents in the dataset have multiple licensees. It is immediately apparent that the mean distance to licensee is about 50% larger than the mean distance to originating entity (Table 2.1 and B.1). This may lead one to believe that the reallocation of patents from originator to licensee via the NPE is inefficient, in that
it increases the mean patent distance and thus usefulness of a patent to a firm. This conclusion would be unjustified, as the distance metric is an increasing function of firm size (Figure B.1) and the mean licensee size is several times larger than originating entity size. The correct comparison would be the mean empirical distance to licensee (46.9) versus the mean distance for a randomly chosen set of patents in the licensees portfolio. The mean distance for the randomly chosen patents to the licensee portfolios is 64.35, which shows that the NPE-licensed patents have substantially smaller distance from the licensees than average.

Table B.2: Licensing Transaction Summary Statistics

<table>
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<th>Variables</th>
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<th>p50</th>
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<th>Sd</th>
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<tr>
<td>Distance to Licensee</td>
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<td>71.21</td>
<td>29.73</td>
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<td>Distance of Random Patent to Licensee</td>
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<td>33.38</td>
<td>76.77</td>
<td>93.49</td>
<td>33.34</td>
</tr>
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<td>Licensee Patent Portfolio Size</td>
<td>5095.57</td>
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<td>5347</td>
<td>9120.51</td>
</tr>
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<td>Log Licensee Patent Portfolio Size</td>
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<td>8.58</td>
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<td>0</td>
<td>0</td>
<td>0.06</td>
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<td>Lifetime Forward Citations</td>
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<td>Backward Citations</td>
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<tr>
<td>Hotness</td>
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<td>25</td>
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<tr>
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<tr>
<td>Log Licensing Fee***</td>
<td>8.25</td>
<td>6.28</td>
<td>8.04</td>
<td>10.33</td>
<td>2.48</td>
</tr>
</tbody>
</table>

Notes: Patent-Licensee-Year level data includes all NPE licensing transactions from 2008 - 2014. Please see the text and appendix for variable definitions and normalization.

Returning to Table B.2, I see that as with originating entity size, the licensee size is also right-skewed. Licensee size is the number of patents (including subsequently granted applications) in the licensee’s portfolio at the time of the licensing deal. Because data in Table B.2 is aggregated at the patent-licensee-year level, a direct
comparison with Tables 2.1 and B.1 is complicated, but most of the variable means are similar. Patent age, with a mean and median of around 12, is defined as the duration between application date and licensing date. Note that the license fee is multiplied by 1000 for greater legibility of the regression tables. I have seen some suggestive findings from the summary statistics; I now make use of regressions to further investigate the impact of NPEs on innovation markets.

Figure B.1: Distance versus Originating Firm Size

Notes: This figure shows the relationship between firm size and mean patent distance for patents sold to NPEs. Larger firms sell more distant patents on average.
B.2 Additional Tables and Figures

Figure B.2: The Distribution of Distance

Notes: See the notes for Figure 2.6.