The Patent Troll: Benign Middleman or Stick-Up Artist?*

David S. Abrams Ufuk Akcigit Gokhan Oz

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Abstract

How do non-practicing entities impact innovation and technological progress? The question has enormous importance to industrial policy, with virtually no direct evidence to inform it. This paper provides new evidence on the subject, both theoretically and empirically. In doing so we inform the debate that has portrayed 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. We make use of unprecedented access to NPE-derived patent and financial data as well as a novel model that guides our data analysis. We 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 or more likely to be litigated. We also find that downstream innovation drops in fields where patents have been acquired by an NPE. This evidence provides some support for both views of NPEs and suggests that a more nuanced perspective on NPEs as well as additional empirical work is necessary before informed policy decisions can be made.

Keywords: Non-practicing entity, NPE, PAE, patent troll, innovation, patent litigation.

JEL Classification: O31, O34.

*Author affiliations and contact information. Abrams: University of Pennsylvania Law School & Wharton email: dabrams@law.upenn.edu. Akcigit: University of Chicago Economics & NBER email: uakcigit@uchicago.edu Oz: University of Pennsylvania Economics email:gokhanoz@sas.upenn.edu. The authors would like to thank Ali Hortacsu, Casey Mulligan, Jeremy Pearce, Jill Popadak, Murat Alp Celik, Harun Alp, Francesco Lissoni, Ernest Miguelez, and Valerio Sterzi for very helpful comments and discussions.

1 Introduction

Are Non-Practicing Entities (NPEs)[1] 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 often self-interested) views. Concern about potential negative effects of NPEs has led to the introduction of legislation in both state legislatures and Congress aimed at curtailing their activity. This view of the NPE 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. Through the beginning of 2016 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 the NPE 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 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 our work is to help inform this important debate and to move closer to understanding whether NPEs facilitate to or harm innovation, or both.

This paper makes two major contributions in our understanding of NPEs. We develop a model of innovation that incorporates NPEs and makes testable predictions. We are then 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 we study, we 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, Celik, and Greenwood, 2015), which quantifies the technological similarity between patents or groups of patents.

We find a number of pieces of evidence, with some supporting the benign middleman perspective and others pointing towards the stick-up artist. We 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 mis-allocation 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

[1] We define an NPE broadly as a firm whose primary source of revenue is from patent licensing fees or patent litigation awards. In Section 2 we discuss the relationship with related terms such as patent assertion entities (PAEs) or patent trolls.

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 import to smaller innovating firms and in fact we find empirically that smaller inventors are more likely to sell to NPEs. We 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 we find the likelihood of sale to an NPE to be greater for more peripheral patents.

The next analysis explores 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, we find that the price paid for a patent is lower for smaller firms; this corroborates one of the predictions of our bargaining model between the NPE and innovating firm. We 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 the NPE business model is the licensing of patents to one or multiple firms. Here we find that licensees are willing to pay more for patents with higher litigation risk, holding everything else equal. Moreover, we 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, we seek to understand the impact of NPEs on subsequent or downstream innovation in fields with NPE activity. Specifically, we examine the impact of NPE patent acquisition on forward citations, comparing citation behavior before and after acquisition. We 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 paper 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 paper is organized as follows. Section 2 provides a brief summary of recent research as well as some institutional detail. In Section 3 we present our model of innovation with NPEs and in Section 4 we introduce the data analyzed. The main empirical results are presented in Section 5. Section 6 concludes.

2 Background

Since the terms patent troll, non-practicing entity (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 we study, as well as a sense of the history of these entities in the U.S. We 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 [2].

We will use the term NPE in this paper and focus on the final category of NPE - large firms that purchase patents and primarily license them or litigate when they cannot license. We focus on this category for several reasons. 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 for them (see below) and they are the most interesting case because there are plausible positive and negative attributes. 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.

2.1 Related Literature

Prior to this paper, 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 Meurer (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 Meurer (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

[2] See http://arstechnica.com/tech-policy/2013/01/patent-trolls-want-1000-for-using-scanners/

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, Mazzeo, and Zyontz (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, Gurun, and Kominers (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, Kesan, and Schwartz (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, Schankerman, and Serrano (2013) 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) and Tucker (2014b), 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 Institutional Setting

This section gives a bit more background on how the NPEs we study operate. As mentioned above, the source of the data we use cannot be representative of all NPEs because there are too many different business models. However, the data is likely typical of some of the larger and more professional NPEs.

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.

3 Model

In this section, we build a tractable model of production with innovation to help understand the decision to sell to or license from an NPE. 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 our empirical analysis.

Basic Environment Consider the following simple economy that is represented by a unit circle $\mathcal{C}$, as in Figure 1. There are many intermediate-good-producing firms that are located along that unit circle. A unique final good is produced from a combination of all these intermediate goods as follows:

$$Y = \frac{1}{1-\sigma} \int_{\mathcal{C}} q_i^{\sigma} k_i^{1-\sigma} di$$

where k_i denotes the quantity and q_i the productivity of intermediate good i used in final good production at time t.

A perfectly enforced patent for each leading-edge technology is held by a firm, which can produce it at constant marginal cost ψ in terms of the unique final good. Each monopolist firm chooses price and quantity to maximize profits on its product lines. In doing so, it faces an iso-elastic inverse

demand derived from the profit maximization of the final good sector, which can be written as:

$$P_i = q_i^{\sigma} k_i^{-\sigma}, \forall i \in \mathcal{C}.$$

The profit-maximization problem of the firm with leading-edge technology for intermediate good i can then be written as

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

The first-order condition of this maximization problem implies a constant markup over marginal cost, $P(q_i) = \psi/(1-\sigma)$, and thus

$$k(q_i) = \left[\frac{(1-\sigma)}{\psi} \right]^{\frac{1}{\sigma}} q_i. \tag{1}$$

Equilibrium profits for a product line with technology q_i are

$$\Pi(q_i) = \pi q_i, \tag{2}$$

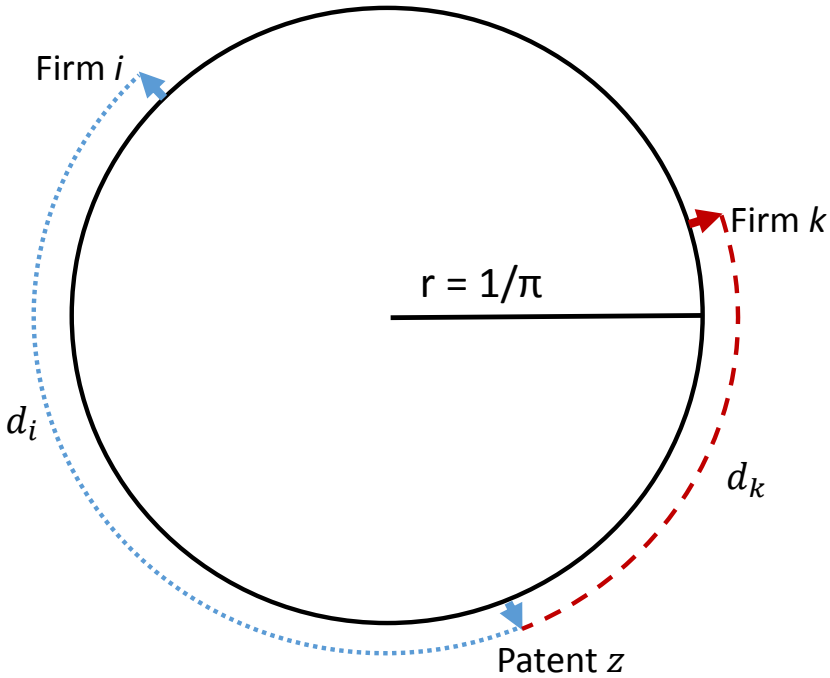
where $\pi \equiv \sigma \left[(1-\sigma)/\psi \right]^{\frac{1-\sigma}{\sigma}}$. Note the usual firm proxies, such as profits $\Pi(q_i) = \pi q_i$ and sales $P(q_i)\, k(q_i) = \left[(1-\sigma)/\psi \right]^{\frac{1-\sigma}{\sigma}} q_i$ both increase linearly in quality q_i. Therefore in what follows,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

3.1 Patents

Patent Distance and Firm Quality The radius of the circle $\mathcal{C}$ is normalized to $1/\pi$ such that the maximum distance between any two points along the circle is equal to 1. Similar to firms, ideas (patents) for production are also located along that circle.

Figure 1 illustrates this in an example. Firm i and firm 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 such that $d_k < d_i$.

Figure 1: Model Economy



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

$$q_i^{new} = q_i + \gamma x_i$$

where γ is some scale parameter and $x_i \in [0, 1]$ is the goodness of fit of the patent to the firm. Similarly, we 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), the incremental gain to firm j from licensing this patent is

$$\Delta\Pi_j = q_j\pi + \pi\gamma\left(1 - d_j\right) - q_j\pi = \pi\gamma\left(1 - d_j\right). \tag{3}$$

Given that π and γ will appear multiplicatively for the rest of the analysis, we normalize $\gamma = 1$ such that

$$\Delta\Pi_j = \pi\left(1 - d_j\right). \tag{4}$$

The NPE There are Non-practicing entities (NPEs) in this economy that act as middle men and also as stick-up artists. They have two key features: First, NPEs have a broad network of firms to

trade patents. Second, they have substantial financial and legal resources that gives them a higher chance of winning a case in the court. We detail these features now.

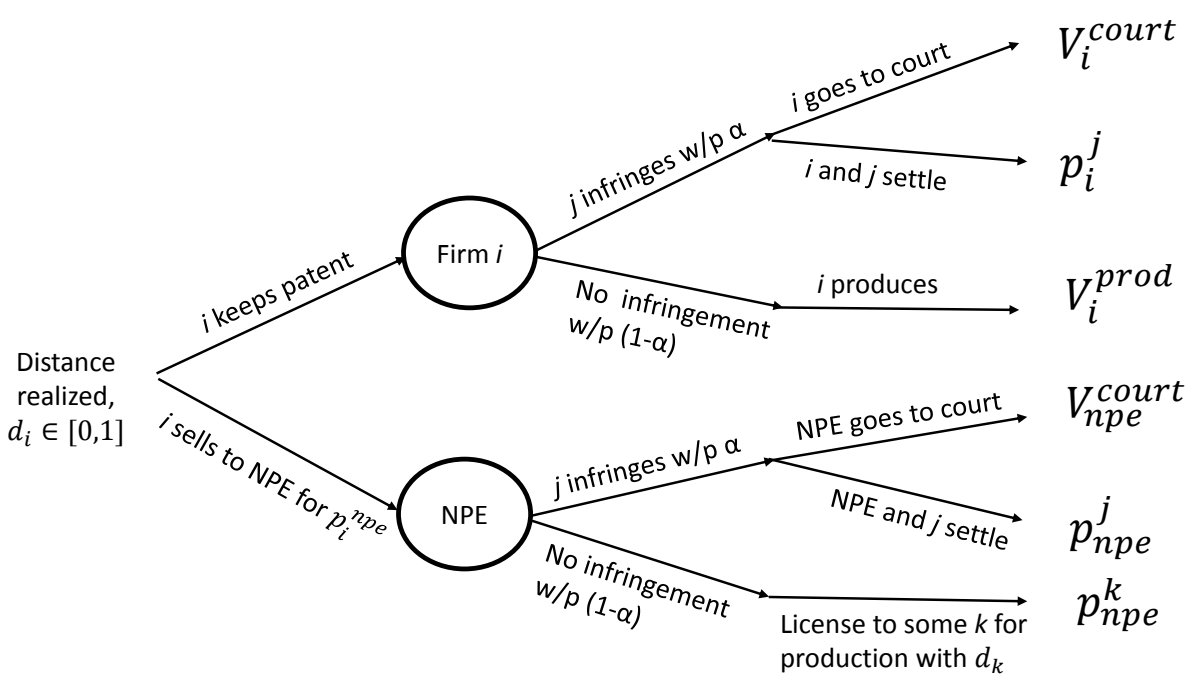
Any firm i that owns a patent can decide to keep its patent, or sell it to the NPE. The NPE, through its wide network in the market, can potentially find a user k that is a better fit for the patent with shorter distance $d_k < d_i$. Having access to a large network is the first strength of the NPE over a single innovating firm.

The second key ingredient of our model is that patents might get infringed by other firms. Let us 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 can win the lawsuit with probability β_i. Winning a court case depends on the resources and the size of the arsenal that the firm has to fight in the court. As a result, we make the following realistic assumption about β_i:

Assumption 1 *The probability of winning a court case, β_i, is increasing in firm size q_i. In other words, β_i is an increasing function of q_i such that $\beta_i = \beta(q_i)$ and $\beta'(q_i) > 0$.*

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

Figure 2: Game Tree



In the beginning of the game, firm i produces a patent with a random distance d_i. Next it decides to sell it to the NPE 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 α. 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 (the additional profit that the firm is making by using this new patent)

$$V_i^{prod} = \pi (1 - d_i).$$

If there is an infringement, which happens with probability α, then i tries to settle with j. If they cannot settle, i goes to court and wins with probability β_i. When i wins the case, it gets compensates for the lost profit

$$V_i^{court} = \beta_i \pi (1 - d_i).$$

Let Ω_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 gives up on Ω_j. Settlement generates a surplus that the two parties can split through Nash bargaining with equal bargaining powers for both sides. Let us denote the settlement fee that i will collect from j by p_i^j. Then the fee is simply the solution of the following problem

$$\max_{p_i^j} \left(p_i^j - \beta_i \pi (1 - d_i)\right)^{0.5} \left(\beta_i \pi (1 - d_i) + \beta_i \Omega_j - p_i^j\right)^{0.5}. \tag{5}$$

This problem delivers the following settlement fee

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

The fee is increasing in probability of winning the case β_i, and in the profit that firm j is making by infringing i's patent. As a result, the expected value of keeping the patent is simply

$$\begin{aligned} V_{keep} &= \alpha p_i^j + (1-\alpha) V_i^{prod} \\ &= \alpha \beta_i \left[\pi (1 - d_i) + \frac{\Omega_j}{2}\right] + (1-\alpha) \pi (1 - d_i). \end{aligned}$$

If i decides to sell it to the NPE, the game evolves according to the lower branch now. With probability α, there is a chance that j infringes the patent that now belongs to the NPE. In this case, the NPE can go to court or settle with j.[3] The main difference now, compared to (6), is that the NPE by definition does not produce and therefore does not have $\pi (1 - d_i)$ to ask. However, the NPE can block Ω_j and has a high probability of winning $\beta_{npe} \to 1$. Therefore the problem for the settlement can we written as

$$\max_{p_{npe}^j} \left(p_{npe}^j\right)^{0.5} \left(\beta_{npe} \Omega_j - p_{npe}^j\right)^{0.5}$$

[3]Note that in equilibrium, no party goes to court. Yet the possibility of going to court generates an threat that affects that bargaining through the outside option.

which delivers the following settlement fee

$$p_{npe}^{j} = \frac{\beta_{npe}\Omega_j}{2}.$$

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

$$\max_{p_{npe}^{k}} \left(p_{npe}^{k}\right)^{0.5} \left(\pi\left(1-d_k\right) - p_{npe}^{k}\right)^{0.5}.$$

Clearly, the price is simply

$$p_{npe}^{k} = \frac{\pi\left(1-d_k\right)}{2}.$$

Now we can compute the expected value for the NPE of owning the patent:

$$p_{npe} = \alpha\frac{\beta_{npe}\Omega_j}{2} + \left(1-\alpha\right)\frac{\pi\left(1-d_k\right)}{2}.$$

Next, we turn to the bargaining problem between i and the NPE. After the realization of the distance, firm i can sell the patent to the NPE through Nash bargaining. This problem can be written as

$$\max_{p_i^{npe}} \left(p_i^{npe} - V_{keep}\right)^{0.5} \left(p_{npe} - p_i^{npe}\right)^{0.5}$$

Hence

$$\begin{aligned} p_i^{npe} &= \frac{V_{keep} + p_{npe}}{2} \\ &= \frac{\alpha\beta_i\left[\pi\left(1-d_i\right) + \frac{\Omega_j}{2}\right] + \left(1-\alpha\right)\pi\left(1-d_i\right) + \alpha\frac{\beta_{npe}\Omega_j}{2} + \left(1-\alpha\right)\frac{\pi(1-d_k)}{2}}{2}. \end{aligned}$$

We assume that there is a cost of finding an NPE $\epsilon \sim U[0,\kappa]$. There will be a sale between i and the NPE if and only if, there is a potential surplus that is bigger than the cost, $p_i^{npe} - V_{keep} > \epsilon$. Therefore the probability of sale can be written as

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

3.2 Comparative Statics

In this section, we will generate a number of important comparative statics which we can later test using micro data. First, we focus on the determinants of the probability of a patent sale to the NPE. Our first result is that the probability of a sale is decreasing in firm size

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

In other words, *NPE is more likely to buy patents from small firms.*

Second, we look at the role of distance for a patent sale. Our model predicts that the *likelihood of a patent sale will increase in its distance to the initial innovating firm*

$$\frac{\partial}{\partial d_i}\Pr\left(sale\right)=\frac{\alpha\beta_i\pi+\left(1-\alpha\right)\pi}{\kappa}>0.$$

Note that *this effect if more pronounced for large firms*, i.e.,

$$\frac{\partial^2}{\partial d_i\partial q_i}\Pr\left(sale\right)=\frac{\beta'(q_i)\alpha\pi}{\kappa}>0.$$

Next, we focus on the relationship between patent sale and litigation risk α. Our model predicts that if the NPE is sufficiently more powerful in winning the lawsuits or if the infringing firm has sufficiently high stakes to lose in the case of a unfavorable court decision, i.e, if the following condition holds

$$\frac{\Omega_j}{\pi}\left[\beta_{npe}-\beta_i\right]>1$$

then *the likelihood of a patent being sold also increases in the litigation risk*

$$\begin{aligned}\frac{\partial}{\partial\alpha}\Pr\left(sale\right) &= \frac{1}{\kappa}\left[\frac{\Omega_j}{2}\left[\beta_{npe}-\beta_i\right]+\pi\left(1-d_i\right)\left(1-\beta_i\right)-\frac{\pi\left(1-d_k\right)}{2}\right]\\ &> 0.\end{aligned}$$

Note that under the same conditions, *this likelihood is more pronounced for small firms*,

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

Now, we can focus on the average licensing price. The *average price that any licensing firm will pay to the NPE is decreasing in the distance to the licensee*

$$\frac{\partial p_{npe}}{\partial d_k}=-\left(1-\alpha\right)\frac{\pi}{2}<0,$$

and *increasing in the litigation risk*:

$$\frac{\partial p_{npe}}{\partial\alpha}=\frac{\beta_{npe}\Omega_j}{2}-\frac{\pi\left(1-d_k\right)}{2}>0.$$

Finally, we focus on the price that the NPE is paying to buy the patent, p^i_{npe}. Note that *the acquisition price is decreasing in distance:*

$$\frac{\partial p_i^{npe}}{\partial d_i}=\frac{-\alpha\beta_i\pi-\left(1-\alpha\right)\pi}{2}<0$$

However, the acquisition price has an ambigous relationship with the litigation risk α :

$$\frac{\partial p_i^{npe}}{\partial \alpha} = \frac{(\beta_i - 1)\,\pi\,(1 - d_i) + \frac{(\beta_{npe}+\beta_i)\Omega_j}{2} - \frac{\pi(1-d_k)}{2}}{2}.$$

Note also that *the NPE pays more to large firm patents:*

$$\frac{\partial p_i^{npe}}{\partial q_i} = \frac{\beta'(q_i)\alpha\left[\pi\,(1 - d_i) + \frac{\Omega_j}{2}\right]}{2} > 0.$$

3.3 Entry into the Market

How does the existence of an NPE affect incentives to innovate? Here we consider the endogenous innovation decision of a downstream firm j. Our analysis proceeds in two steps. First, we consider a market without NPEs and then we examine the change in innovation rates when one enters the market.

The Case without an NPE Recall that the incremental profit of firm j from adding a new technology to its portfolio is simply $\pi\gamma x_j$. Products produced with this new technology may infringe an existing patent, and when there is no NPE in the market, there will be a side settlement between firm i and j at price $\tilde{p}_i$. Let us denote the probability of innovation by μ_j. Therefore the innovation decision is simply

$$\max_{\mu_j}\left\{\mu_j\left[\Omega_j - p_i^j\right] - \frac{\mu_j^{\xi}}{\xi}\right\}$$

where $\xi > 1$ governs the convexity of the cost function. This implies that when there is no threat of an NPE, the equilibrium innovation decision is

$$\mu_j = \left[\Omega_j - p_i^j\right]^{\frac{1}{\xi-1}}.$$

The Case with an NPE Consider now the case of an NPE in the market. In this case, the licensing fee is p_j. Therefore the maximization problem becomes

$$\max_{\mu_j^{NPE}}\left\{\mu_j^{npe}\left[\Omega_j - p_{npe}^j\right] - \frac{\left(\mu_j^{npe}\right)^{\xi}}{\xi}\right\}.$$

In equilibrium, the innovation rate is simply

$$\mu_j^{NPE} = \left[\Omega_j - p_{npe}^j\right]^{\frac{1}{\xi-1}}.$$

Now we can focus on the change in the innovation rate $\Delta\mu_j$ with and without an NPE in the market. The change innovation rate is simply

$$\Delta\mu_j \equiv \mu_j - \mu_j^{NPE} = \left[\Omega_j - p_i^j\right]^{\frac{1}{\xi-1}} - \left[\Omega_j - p_{npe}^j\right]^{\frac{1}{\xi-1}} > 0.$$

Note also that this effect is also more pronounced for more valuable innovations. Of course this ignores the ex-ante incentive effects on upstream firms.

$$\frac{\partial \Delta\mu}{\partial p_{npe}^j} > 0.$$

Summary of the Predictions Now we can summarize the predictions of the model.

1. Small firms are more likely to sell patents to an NPE.
2. Patents sold to an NPE are more likely to be distant from the innovating firms. The effect is more pronounced for patents sold by large firms.
3. High litigation risk patents are more likely to be sold to NPEs. The effect is more pronounced for patents acquired from small firms.
4. NPEs will pay more for patents acquired from larger firms.
5. The price paid for a patent by an NPE will decrease with distance to the innovating firm.
6. The price paid for a patent by an NPE will increase with entity size.
7. The patent licensing fee will decrease with distance to the licensee.
8. The patent licensing fee will increase with litigation risk.
9. When a patents is sold to an NPE, subsequent downstream invention declines. The effect is more pronounced for more valuable patents.

4 Data

This research is made possible by the use of confidential data obtained from NPEs on 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 we may disclose about the data, including the sources, exact number of patents, and non-normalized revenue figures. However, there are no restrictions on the types of analyses we may perform, nor pre-approval for any findings. Since there are a number of different data sources and a large amount of derived variables, we provide substantial further detail in the appendices.

In order to compare patents of different ages, both forward citations and revenue are estimated for the entire lifetime of the patent. We 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. We 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 1.

Table 1: Descriptive Stats for NPE VS USPTO Patents

	Panel 1:NPE Patents			Panel 2: Patent Universe		
Variables	**Mean**	**Median**	**Sd**	**Mean**	**Median**	**Sd**
Distance to Originating Entity	33.20	28.31	27.80	29.80	26.77	22.40
Originating Entity Size	2316.07	141	5011.73	8623.92	1858	14859.17
Log Originating Entity Size	4.99	4.95	2.81	6.95	7.53	2.81
Litigation Risk	11.82	10.31	8.74	9.00	7.85	7.42
Individual Inventor	0.06	0	0.23	0.01	0	0.10
Small Originating Entity	0.31	0	0.46	0.15	0	0.36
Medium Originating Entity	0.48	0	0.50	0.46	0	0.50
Large Originating Entity	0.15	0	0.35	0.38	0	0.49
Total Claims	19.19	17	14.87	18.47	17	13.02
Lifetime Forward Citations	22.63	7.34	44.91	12.75	3.00	32.24
Backward Citations	22.92	8	53.04	14.59	6	38.49
Hotness	31.39	25	29.76	26.67	17.5	29.48
Age	13.64	14	5.16	10.84	10	6.02
Age at Acquistion	8.23	8	5.16			
Lifetime Revenue	200	37.46	1953.093			

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 the NPE data. Individually Inventor is one if there is a single listed inventor and no assignee. USPTO data is weighted by NPE patent distribution across IPC3 classes. Please see the appendix for variable definitions.

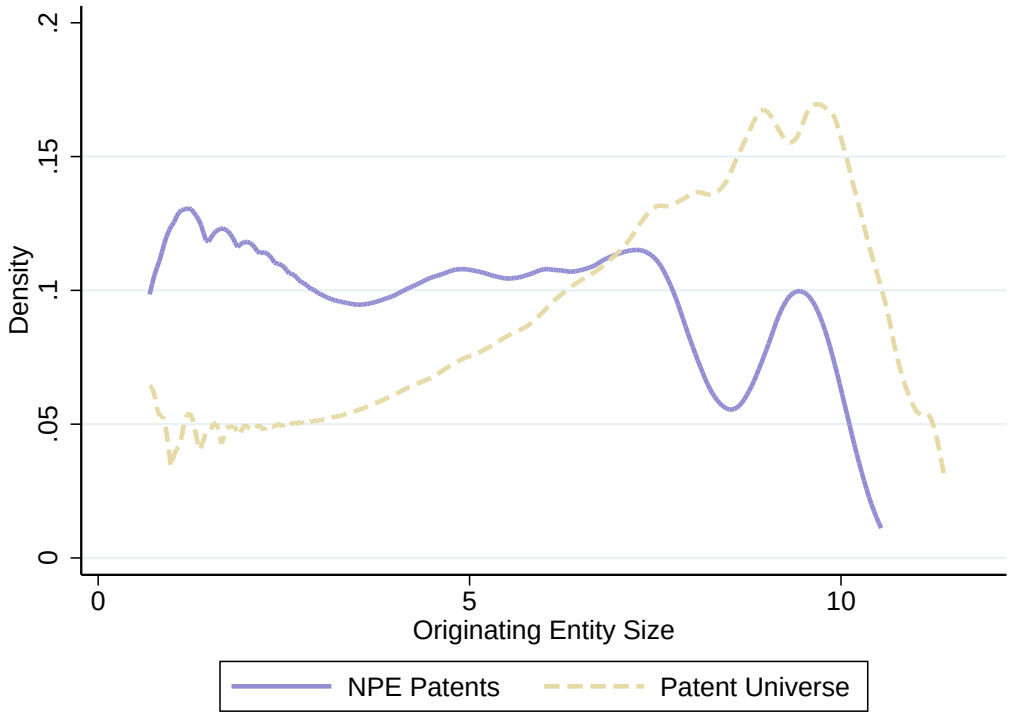
Table 1 reports patent-level summary statistics both for NPE-acquired patents and the comparable universe of patents applied for from the USPTO during the same years, 1987 - 2014. "Comparable universe" means the data in the second panel is weighted so that the distribution of IPC3 technology class is the same as for the NPE data in the first panel. [4] The table introduces several derived variables that we use extensively to help understand what impacts the decision to sell to NPEs or to license from them.

The first such variable is a patent distance metric, first introduced in Akcigit, Celik, and Greenwood (2015). The distance is a function of the overlap in technology classes of the backward citations of two patents.[5] We 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

[4] IPC3 refers to the 3-digit International Patent Classification code used to classify patents into technology categories.

[5] See Appendix 1 for the precise definition.

Figure 3: Originating Entity Size Distribution



assignee is missing. In both the NPE and PTO data, the distribution of the metric is slightly right-skewed, with a mean of 33.20 for NPE-held patents and 29.8 for all patents. Thus firms appear to be more likely to sell distant patents to NPEs, as our model in the previous section predicts.

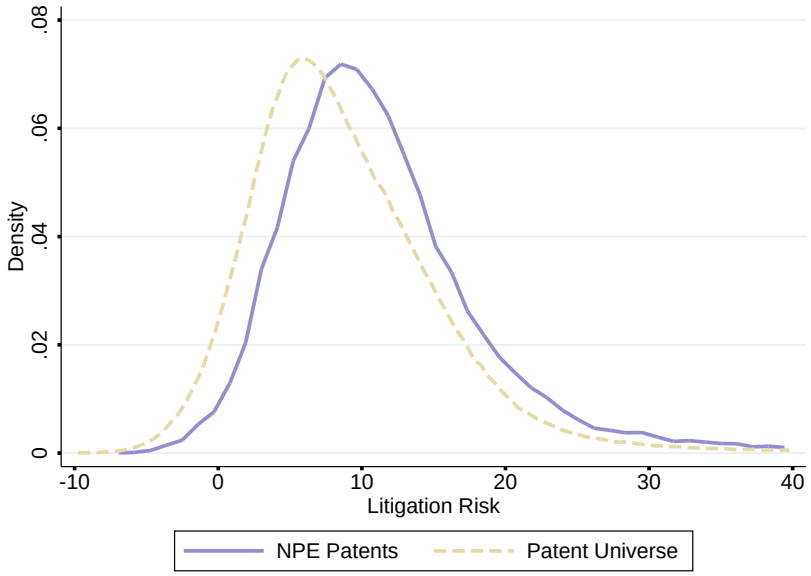
Litigation Risk is a measure of the likelihood that a patent will be litigated. We adopt the model in Lanjouw and Schankerman (2001) with small modifications to produce this index (see Appendix 1 for greater detail). Figure 4 plots the empirical litigation risk distribution. Mean litigation risk is substantially higher for patents held by NPEs, which is consistent with the predictions of our 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. This distribution is quite right-skewed (Figure 3), and the typical patent sold to an NPE comes from a much smaller patent portfolio than average. This is not surprising as we saw in Section 3 that smaller firms have more to gain from an NPE's larger network and bargaining power, relative to large firms. We report several other measures of size: small, medium and large originating entity as well as individual inventor.[6] A comparison of means for each of these measures reinforces the observation above: NPEs acquire patents from smaller entities.

NPE-held patents include slightly more claims than average, but there is a much larger disparity

[6]The definitions for these variables may be found in Appendix 1.

Figure 4: Litigation Risk Distribution



for forward and backward citations. The average patent sold to an NPE has over 50 percent more forward citations and 75 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 4.7 percentage point higher average hotness than the universe. They are also several years older than the comparison group, with an average age of 13.6 years (as of 2014, measured from application date) compared to 10.8 years for the universe and were acquired by NPEs at 8.2 years. Finally, as discussed above, lifetime licensing revenue is normalized to be 200.

Table 2 reports deal-level summary statistics on all deals through which the NPEs acquired patents from 2003 - 2014. Compared to Table 1, the average entity size is substantially smaller, indicating that the acquisitions from smaller firms are more numerous and with a smaller average deal size. In fact, deals from individual inventors represent 16% 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 4% of patent acquisition deals are struck with large originating firms.

The mean number of forward citations is substantially higher in Table 2 than Table 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,

Table 2: Patent Acquisition Deal Summary Statistics

Variables	Mean	p25	p50	p75	Sd
Distance to Originating Entity	31.70	0.01	28.64	54.31	28.15
Originating Entity Size	734.46	2	6.5	199.2	2732.84
Log Originating Entity Size	3.05	0.69	1.87	5.29	2.76
Litigation Risk	13.40	8.59	11.77	15.65	8.55
Individual Inventor	0.16	0	0	0	0.37
Small Originating Entity	0.51	0	1	1	0.50
Medium Originating Entity	0.28	0	0	1	0.45
Large Originating Entity	0.04	0	0	0	0.21
Total Claims	22.12	14.59	20	27	11.47
Lifetime Forward Citations	31.45	6	14.60	33.17	54.67
Backward Citations	20.29	6.43	10.67	20.75	31.25
Hotness	30.77	13.83	28.15	43.15	22.46
Deal Size	13.71	1	4	11	47.76
Age	7.10	4	7.18	10	4.24
Log Acquisition Price	6051.41	5149.64	5976.70	6849.79	1267.43

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.

and has a mean of just over 7 years. The deal acquisition price is normalized so that the mean is 200. The values reported are 1000 times the natural log of the normalized prices, used to make regression coefficients more legible.

Table 3 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 1 and 2). 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 5) 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 64.7, which shows that the NPE-licensed patents have substantially smaller distance from the licensees than average.

Returning to Table 3, we 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 3 is aggregated at the patent-licensee-year level, a direct comparison with Tables 1 and 2 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. The yearly per-patent licensing fee

Table 3: Licensing Transaction Summary Statistics

Variables	Mean	p25	p50	p75	Sd
Distance to Licensee	46.94	21.92	47.32	71.32	29.63
Licensee Size	5094.69	64	867	5347	9119.76
Log Licensee Size	6.19	4.16	6.77	8.58	3.01
Litigation Risk	12.02	6.93	10.48	14.92	8.71
Individual Inventor	0.06	0	0	0	0.25
Total Claims	19.32	10	17	24	15.24
Lifetime Forward Citations	22.93	2.06	8.00	24.03	45.21
Backward Citations	22.82	4	8	17	52.88
Hotness	32.08	2.56	25	50	29.97
Patent Age	11.98	8	12	15	5.14
Log Licensing Fee	1344.65	-623.11	1137.87	3426.99	2481.62

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.

distribution is displayed in Figure 6. The distribution is close to log normal. Note that the license fee is multiplied by 1000 for greater legibility of the regression tables. We have already seen some suggestive findings from the summary statistics; we now make use of regressions to further investigate the impact of NPEs on innovation markets.

5 Estimation and Results

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

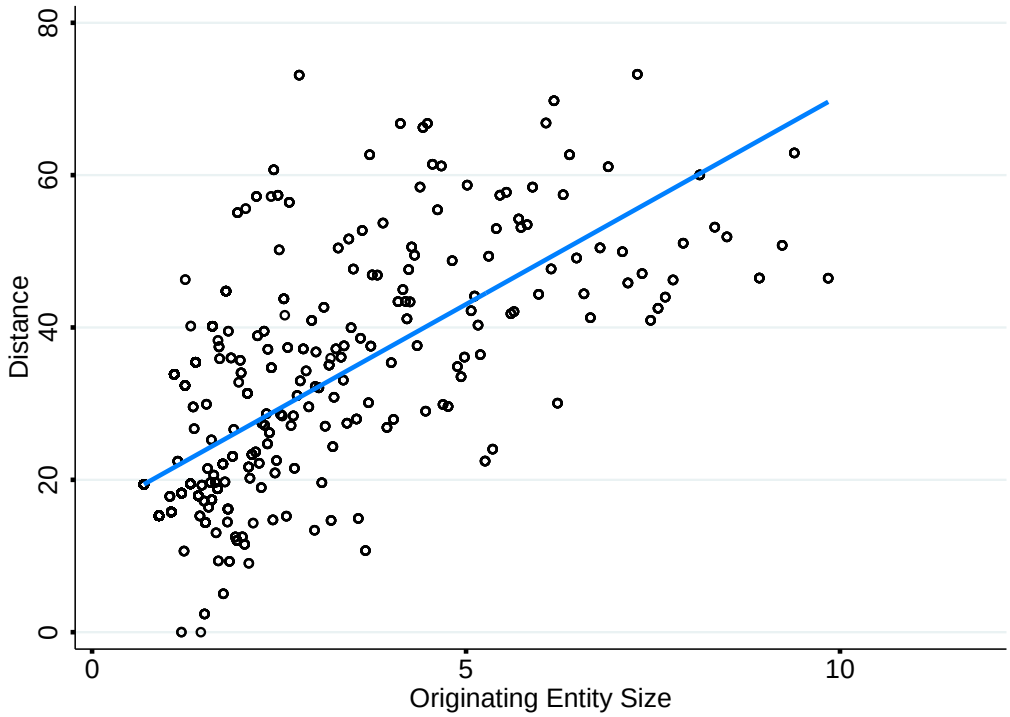
We first examine which factors impact likelihood of a patent sale using the following specification:

$$\textbf{Patent Sale}_{i,j,t} = \alpha + \beta \times X_{i,j,t} + \phi \times M_{i,j,t} + \psi \times Z_{i,j,t} + \gamma_j + \eta_t + \epsilon_{i,j,t} \tag{6}$$

where $\textbf{Patent Sale}_{i,j,t}$ is a dummy variable that is 1 if patent i in technology category j, with application year t is sold to an NPE and zero otherwise. $X_{i,j,t}$ is a vector consists of the main variables of interest, *Distance to innovating Entity*, *Log Entity Size*, *Individual Inventor Indicator*, and *Litigation Risk*. $M_{i,j,t}$ is a vector containing the interaction terms, which may be seen in Table 4. $Z_{i,j,t}$ are control variables: *Total Claims*, *Lifetime Forward Citations*, *Hotness Index*, *Backward Citations*, *Patent Age*, and $PatentAge^2$. γ_j is a set of technology category dummies, measured at three digit IPC level. η_t is a set of application year dummies(only for 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 4.

This table tests predictions 1, 2, and 3 of the model. It 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.

Figure 5: 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.

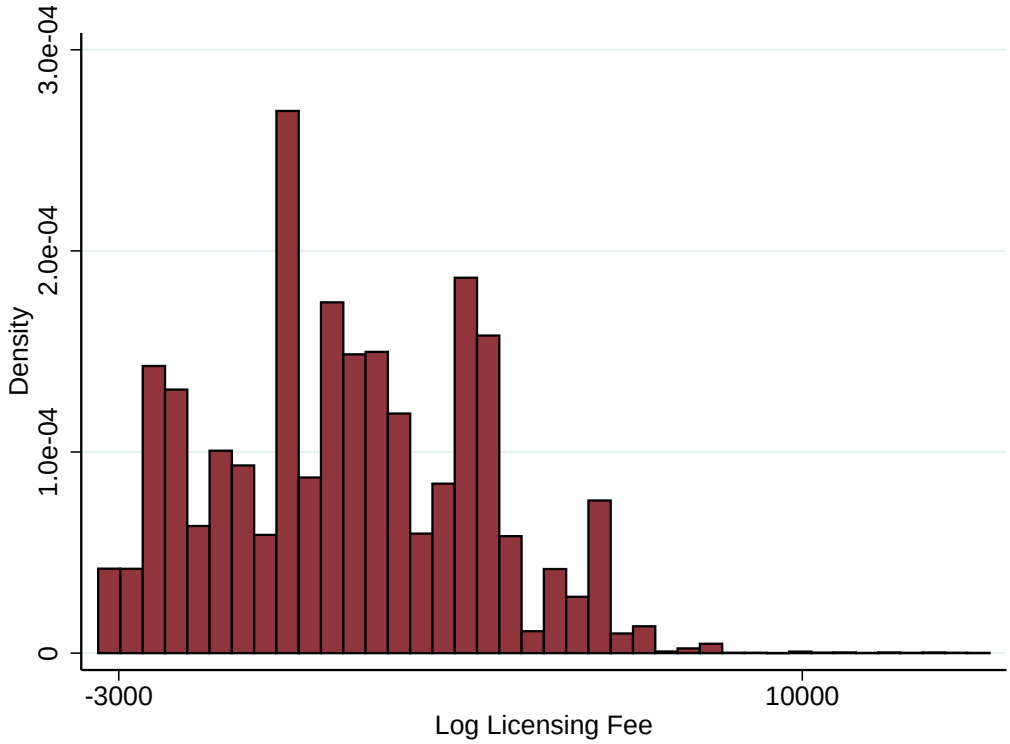
In the empirical application, we multiply dependent variable with 1000 to scale the coefficients. The estimated positive coefficient in front of distance variable indicates that patents that are more distant to the originating firm are more likely to be sold. The interaction with firm size delivers a positive coefficient indicating that distance becomes more pronounced as a reason for sale among large firms, which confirms prediction 2. The impact of litigation risk is strongly positive, which implies that patents that are more likely to be litigated are also more likely to be sold to the NPE. The interaction term is negative, which implies that litigation risk becomes a stronger factor among small firms for patent sale. This finding confirms prediction 3.

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

$$\textbf{Log Acquisition Price}_{i,t} = \alpha + \beta \times K_{i,t} + \phi \times M_{i,t} + \psi \times J_{i,t} + \eta_t + \epsilon_{i,t} \tag{7}$$

where $\textbf{Log Acquisition Price}_{i,t}$ 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 Originating Entity Size*. $M_{i,t}$ is a vector consisting of interaction variables that may be found in Table 5. $J_{i,t}$ is a vector

Figure 6: Log Licensing Fee Distribution



consisting of control variables: *Age*, Age^2, *Lifetime Forward Citations*, *Total Claims*, *Hotness*, *Deal Size*. η_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 5.

Table 5 documents that NPEs pay more to larger firms which confirms prediction 4 of the model. In addition, it shows that when a patent is more distant to the innovating firm, the NPEs pay less to buy it, which verifies prediction 5.

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

$$\textbf{Log Licensing Fee}_{i,j,t} = \alpha + \theta \times A_{i,j,t} + \rho \times B_{i,j,t} + \Gamma_i + \delta_t + \epsilon_{i,j,t} \tag{8}$$

where $\textbf{Log Licensing Fee}_{i,j,t}$ 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 $PatentAge^2$. Γ_i is a set if IPC3 technology class dummies and δ_t are year dummies. Robust standard errors are clustered at licensee level and results are reported in Table 6.

Table 6 reports regression results from the estimation of equation 8. Note that the license fee is multiplied by 1000 for greater legibility of the regression tables. We find that if a patent is distant

Table 4: Patent Sale Decision

Dependent Variable:	(1) Sale Indicator	(2) Sale Indicator	(3) Sale Indicator	(4) Sale Indicator	(5) Sale Indicator
Log Entity Size	-1.58**	-1.67***	-1.66***	-1.67***	-1.66***
	(0.196)	(0.189)	(0.189)	(0.189)	(0.190)
Distance	0.04**	0.08***	0.08***	0.08***	0.08***
	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
Log Entity Size x Distance		0.03***	0.03***	0.03***	0.03***
		(0.003)	(0.003)	(0.003)	(0.003)
Litigation Risk	0.18**	0.18***	0.18***	0.17***	0.13**
	(0.050)	(0.047)	(0.046)	(0.048)	(0.053)
Log Entity Size x Litigation Risk		-0.06***	-0.06***	-0.05**	-0.06***
		(0.019)	(0.020)	(0.021)	(0.019)
Individual Inventor	1.98	1.76*	1.77*	-0.43	1.72*
	(1.031)	(1.040)	(1.039)	(1.300)	(1.042)
Total Claims	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Lifetime Forward Citations	0.02	0.01	0.01	0.01	0.01
	(0.013)	(0.015)	(0.014)	(0.014)	(0.015)
Backward Citations	0.03*	0.03**	0.03**	0.03**	0.03**
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Hotness	0.03**	0.03***	0.03***	0.03***	0.02***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Distance x Litigation Risk			-0.00	-0.00	
			(0.001)	(0.001)	
Individual Inventor x Distance				-0.01	
				(0.014)	
Individual Inventor x Litigation Risk				0.32**	
				(0.143)	
Age	1.19**	1.22***	1.22***	1.23***	
	(0.214)	(0.204)	(0.204)	(0.206)	
Age^2	-0.04**	-0.04***	-0.04***	-0.04***	
	(0.007)	(0.007)	(0.007)	(0.007)	
Constant	4.29*	2.81	2.83	2.83	7.86***
	(1.956)	(1.855)	(1.858)	(1.859)	(1.276)
IPC-3 Controls	Yes	Yes	Yes	Yes	Yes
Application Year Control	No	No	No	No	Yes
R-squared	0.012	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.

from the licensee, the fee is lower. This is in line with prediction 7. The table also shows that the licensing fee is increasing in litigation risk, which confirms prediction 8.

Our fourth framework is designed to test the impact of an NPE patent acquisition on future research on the same subject as the acquired patent. Since forward citations are one measure of subsequent research on a topic, we examine the dynamics of forward citations before and after acquisition using an event study methodology. We use a balanced panel of NPE patents with at

Table 5: The Determinants of Patent Acquisition Price

	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price	(5) Log Price
Log Entity Size	111.60***	113.94***	113.21***	114.38***	110.59***
	(14.06)	(14.17)	(14.17)	(14.39)	(13.87)
Distance	-10.87***	-11.28***	-11.22***	-11.40***	-10.31***
	(1.10)	(1.14)	(1.13)	(1.29)	(1.14)
Distance x Log Entity Size		-2.02*	-2.14*	-1.83	-1.71
		(1.09)	(1.10)	(1.36)	(1.09)
Litigation Risk	-8.20	-8.05	-7.46	-8.60	1.16
	(8.77)	(9.25)	(9.50)	(10.06)	(9.26)
Litigation Risk x Log Entity Size		1.89	1.42	3.96	3.81
		(2.66)	(2.67)	(3.89)	(2.66)
Individual Inventor	-237.98***	-227.17***	-231.30***	-389.98*	-213.61**
	(87.73)	(86.99)	(87.16)	(212.41)	(86.41)
Total Claims	13.12***	13.19***	13.08***	13.16***	12.05***
	(4.18)	(4.19)	(4.19)	(4.21)	(3.78)
Lifetime Forward Citations	2.14	2.20	2.09	1.99	1.16
	(1.52)	(1.54)	(1.59)	(1.58)	(1.55)
Backward Citations	7.51***	7.42***	7.40***	7.41***	7.44***
	(1.02)	(1.02)	(1.02)	(1.03)	(1.01)
Hotness	-3.71	-3.67	-3.47	-3.61	-2.99
	(4.08)	(4.10)	(4.10)	(4.14)	(3.99)
Deal Size	8.49***	8.46***	8.46***	8.46***	8.55***
	(2.09)	(2.09)	(2.09)	(2.09)	(1.98)
Age	67.27***	67.19***	65.01***	66.87***	
	(19.47)	(19.60)	(19.85)	(20.18)	
Age2	-4.91***	-4.90***	-4.79***	-4.94***	
	(1.27)	(1.27)	(1.28)	(1.30)	
Distance x Litigation Risk			-0.09	-0.08	
			(0.14)	(0.14)	
Individual Inventor x Distance				0.99	
				(3.11)	
Individual Inventor x Litigation Risk				9.42	
				(12.38)	
Constant	5,557.32***	5,560.02***	5,564.72***	5,581.05***	5,329.60***
	(124.35)	(125.70)	(125.30)	(127.52)	(540.05)
IPC-3 Controls	Yes	Yes	Yes	Yes	Yes
Funding Year Control	No	No	No	No	Yes
R-squared	0.304	0.305	0.306	0.306	0.317

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.

least 9 years of observations available for each patent, 4 years before and 4 years after the acquisition by an NPE. This means that this analysis will exclude more recent NPE patent acquisitions. We estimate the following specification:

$$Y_{i,t} = \sum_{4 \geq j \geq -4} \beta_j \times D^j_{i,t} + \omega_i + \epsilon_{i,t} \tag{9}$$

Table 6: The Determinants of Patent Licensing Fee

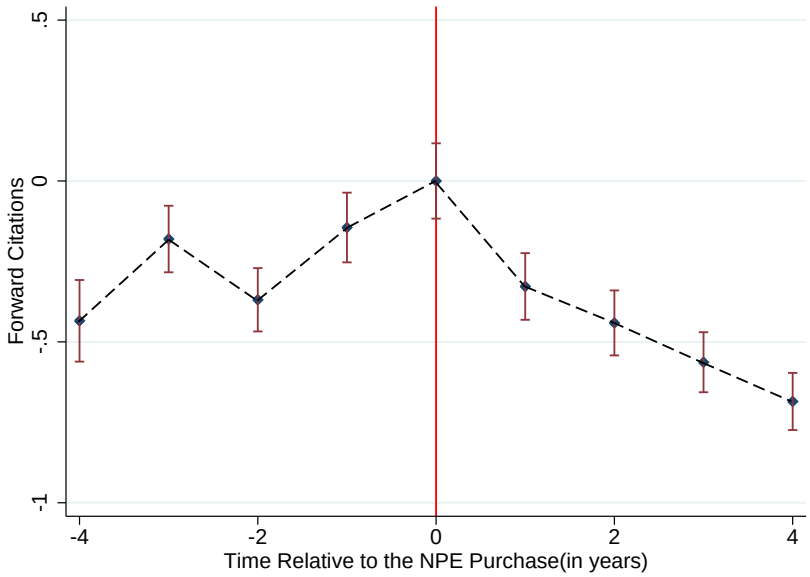
	(1) Log Licensing Fee	(2) Log Licensing Fee	(3) Log Licensing Fee	(4) Log Licensing Fee	(5) Log Licensing Fee
Distance to Licensee	-13.13**	-10.22***	-10.20***	-8.32**	-10.78**
	(5.26)	(3.72)	(3.73)	(3.27)	(4.90)
Log Licensee Size	451.70***	442.38***	442.05***	442.98***	456.49***
	(102.66)	(99.51)	(99.31)	(99.47)	(104.58)
Litigation Risk	5.17***	5.18***	4.93***	7.54***	6.20**
	(1.27)	(1.34)	(1.51)	(1.99)	(2.70)
Distance x Log Licensee Size		1.56	1.56	1.89	
		(1.50)	(1.50)	(1.41)	
Litigation Risk x Log Licensee Size		1.41**	0.84	1.47**	
		(0.65)	(0.73)	(0.64)	
Individual Inventor	19.37	20.17	21.26	37.18	32.59
	(27.78)	(27.69)	(27.72)	(30.89)	(32.22)
Total Claims	0.43	0.45	0.49	0.80*	0.81*
	(0.34)	(0.34)	(0.34)	(0.45)	(0.43)
Lifetime Forward Citations	0.54**	0.55**	0.52**	0.34	0.42
	(0.26)	(0.26)	(0.25)	(0.25)	(0.26)
Backward Citations	1.55***	1.55***	1.54***	1.57***	1.56***
	(0.40)	(0.40)	(0.40)	(0.41)	(0.41)
Hotness	0.38***	0.38***	0.39***	0.38**	0.26
	(0.12)	(0.12)	(0.12)	(0.17)	(0.22)
Age	2.67	2.48	2.31	0.22	4.19
	(9.84)	(9.88)	(9.91)	(10.81)	(10.63)
Age2	-0.51	-0.49	-0.48	-0.44	-0.56*
	(0.32)	(0.32)	(0.32)	(0.34)	(0.33)
Distance x Litigation Risk			-0.19***		
			(0.07)		
Constant	57.62	18.76	15.14	-76.13	-88.74
	(726.05)	(702.75)	(705.20)	(682.66)	(707.83)
IPC-3	yes	yes	yes	no	no
Transaction Year	yes	yes	yes	yes	yes
R-squared	0.546	0.548	0.549	0.546	0.541

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.

where $Y_{i,t}$ is the deviation of forward citations received by patent i in year t relative to the mean forward citations of the patents in the same technology category and with the same age in year t. The $D^j_{i,t}$ are dummy variables that are one for patent i if year t is exactly j years after the NPE acquisition of patent i, and zero otherwise. Thus the β_j denote the impact of the patent acquisition at various years relative to the acquisition year. ω_i captures time invariant patent level fixed characteristics such as IPC3 technology category dummies and period dummies (using a 3-year window).

Figure 7 graphically reports the β_j from an estimation of specification 9 for all NPE acquisitions. We see that there is a substantial and statistically significant decline in forward citations in the

Figure 7: Forward Citations Relative to NPE Acquisition



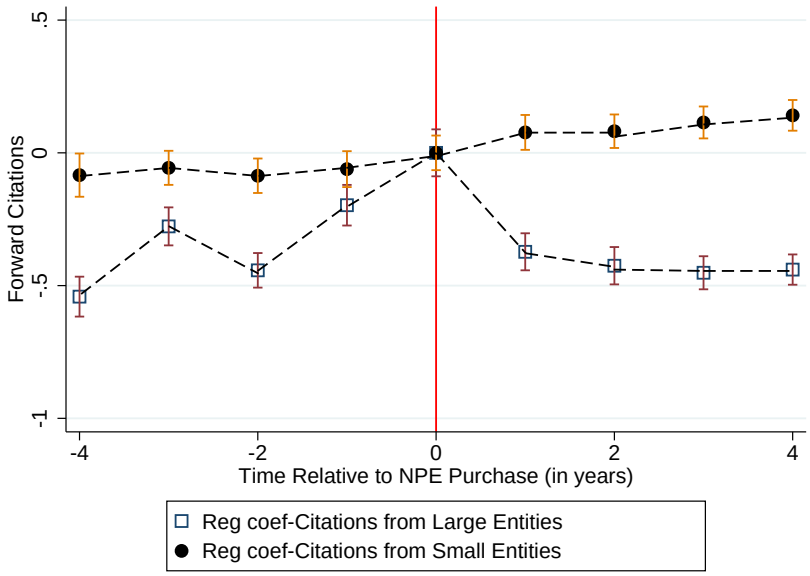
Notes: This figure reports results from a regression of annual forward citations on yearly time dummies relative to the year of acquisition of a patent by an NPE. The regression makes use of a balanced panel of patent-level data from 1987- 2010 for NPE-acquired patents and include controls for IPC3 technology class, year dummies in three year window. Robust standard errors are displayed as error bars.

years after a patent is acquired by an NPE. Since NPE-patent acquisitions are rarely reported or known publicly, this substantial decline requires some explanation. We propose that this finding likely results from the licensing of the patent, which is what actually leads to the decline in forward citations. This is due to the fact that the licensees may now stop research along similar avenues, since they have access to the original patent.

In addition to the overall impact of patent acquisition, we also estimate it separately for citations coming from large and small entities (Figure 8). [7] Here we see that almost all of the decline in citations comes from large citing entities. This is consistent with our expectations because our model predicts that large firms have more to lose from a legal dispute and therefore will be more reluctant to operate where NPEs are active and increase the likelihood of a loss in a court.

[7] See Figure 10 for the estimation for the top and bottom decile of patent value.

Figure 8: Forward Citations Relative to NPE Acquisition by Citing Entity Size



Notes: This figure reports results from two regressions of annual forward citations on yearly time dummies relative to the year of acquisition of a patent by an NPE. One of the regressions only counts citations from large entities and one from small entities. The regressions makes use of a balanced panel of patent-level data from 1987- 2010 for NPE-acquired patents and include controls for IPC3 technology class, year dummies in three year window.

6 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 paper, we 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. Our 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 incentivizes small firms 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 our model allowed us to come up with a number of important testable implications. The second part of the paper has utilized a first-hand data from the NPEs. Very importantly, we could see how litigation risk and goodness of fit of the patent affect patent sale decisions and pricing decisions. Our 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.

We believe that these new facts that are shown in this paper 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.

References

Akcigit, U., M. A. Celik, and J. Greenwood (2015): "Buy, Keep or Sell : Economic Growth and the Market for Ideas," *Econometrica*, *Forthcoming*.

Allison, J. R., M. A. Lemley, and J. Walker (2009): "Extreme Value or Trolls On Top?The Characteristics of the Most-Litigated Patents," *University of Pennsylvania Law Review*, 158.

——— (2011): "Patent Quality and Settlement Among Repeat Patent Litigants," *Georgetown Law Journal*, 99(6777), 12.

Ashtor, J. H., M. J. Mazzeo, and S. Zyontz (2014): "Patents at Issue: The Data Behind the Patent Troll Debate," *George Mason Law Review*, Forthcoming.

Bessen, J. E., and M. J. Meurer (2014): "The Direct Costs from NPE Disputes," *99 Cornell Law Review*, 387.

Chien, C. (2014): "Startups and Patent Trolls," *Stanford Technology Law Review*, 17:461.

Cohen, L., U. G. Gurun, and S. D. Kominers (2014): "Patent Trolls: Evidence from Targeted Firms," *Working Paper*.

Cotropia, C. A., J. P. Kesan, and D. L. Schwartz (2014): "Unpacking Patent Assertion Entities (PAEs)," *Minnesota Law Review*, 1571, 99.

Feldman, R., and M. A. Lemley (2015): "Do Patent Licensing Demands Mean Innovation?," *Iowa Law Review*, 101:137.

Fischer, T., and J. Henkel (2012): "Patent Trolls on Markets for Technology: An Empirical Analysis of NPEs Patent Acquisitions," *Research Policy*, 41, 9.

Galasso, A., M. Schankerman, and C. J. Serrano (2013): "Trading and Enforcing Patent Rights," *RAND Journal of Economics*, 44:2.

Hagiu, A., and D. B. Yoffie (2013): "The New Patent Intermediaries: Platforms, Defensive Aggregators, and Super-Aggregators," *Journal of Economic Perspectives*, 27, 1.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001): "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," *National Bureau of Economic Research Working Paper no:8498*.

Lamoreaux, N. R., and K. L. Sokoloff (2002): "Intermediaries in the U.S. Market for Technology,1870-1920," *NBER Working Papers*, 9017.

Lanjouw, J., and M. Schankerman (2001): "Characteristics of Patent Litigation: A Window on Competition," *RAND Journal of Economics*, 32, 1.

Lu, J. (2012): "The Myths and Facts of Patent Troll and Excessive Payment: Have Non-Practicing Entities (NPEs) Been Overcompensated?," *Business Economics*, 47:4.

Pènin, J. (2012): "Strategic Uses of Patents in Markets for Technology: A Story of Fabless Firms, Brokers and Trolls," *Journal of Economic Behavior and Organization*, 84(6334), 1.

Reitzig, M., J. Henkel, and F. Schneider (2010): "Collateral Damage for R&D Manufacturers: How Patent Sharks Operate in Markets for Technology," *Industrial and Corporate Change*, 19, 3.

Risch, M. (2012): "Patent Troll Myths," *Seton Hall Review*, 42:457.

Rivette, D., and K. Klein (2000): "Discovering New Value in Intellectual Property," *Harvard Business Review*.

Schwartz, D. L., and J. P. Kesan (2014): "Analyzing the Role of Non-Practicing Entities in the Patent System," *Cornell Law Review*, 99:2.

Serrano, C. J. (2010): "The Dynamics of the Transfer and Renewal of Patents," *RAND Journal of Economics*, 41, 4.

Shrestha, S. K. (2010): "Trolls or Market-Makers?," *An Empirical Analysis of Nonpractcing Entities. Columbia Law Review*, 110, 1.

Tucker, C. (2014a): "Patent Trolls and Technology Diffusion : The Case of Medical Imaging," Working Paper.

Tucker, C. E. (2014b): "The Effect of Patent Litigation and Patent Assertion Entities on Entrepreneurial Activity," Working Paper.

7 Appendix 1: Empirical Appendix

A. Data Description

We use the following data sources for this project: United States Patent and Trademark Office Patent Application Bibliographic Data (PAB), The NPE Data (ND), LexMachina (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.

1. 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 we 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.

2. NPE Data (ND)

This confidential data contains information on acquisition deals, licensing deals, and patent characteristics. The acquisition deal data includes the deal number, 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.

3. Lex Machina (LM)

From the Lex Machina database we 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.

4. 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. [8]

5. 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.'s (2009) 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.

B. Data Cleaning and Merging

Company Name Cleaning[9]

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 we discuss here. Our approach is similar to that used in the NBER Patent Database Project(PDP), but we extend past the 2006 end date of that data set.

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. *"MOSANTO TECHNOLOGY LLC", "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 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.

[8]We complement our 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.

[9]We would like to thank Murat Alp Celik for sharing his cleaning algorithm.

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. [10] We keep only utility patents and drop those with application dates before 1987.[11] We 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.

We keep only patents in technology categories (three-digit IPC) where the NPEs operate. We merge USPTO classes and IPC classes and use IPC classes in our analysis.[12] Each patent in PAB is matched with harmonized assignee identifiers.[13] The company name cleaning algorithm is used on assignee and licensee names from the ND data. We match licensees with PAB data and keep those for which there is patent data. We drop patents with missing distance to originating entity and litigation risk from the acquisition deals.

C. Variable Construction

1. Lifetime Citations

We 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. We 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 our 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, Jaffe, and Trajtenberg (2001). Note that in the final analysis we limit our attention to patents with application year after 1987.

2. Lifetime Revenue

As with citations, it is necessary to calculate a single revenue number so that we may compare patents of different ages. We 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

[10] We complement our data with recently announced citation and claim decomposition data. It can be found in the following link: http://www.patentsview.org/download.

[11] More than 99 percent of the NPE patents were applied for after 1987. This is the main reason that we focus on post-1987 patents.

[12] See http://www.uspto.gov/web/patents/classification for further information.

[13] These may be found at $http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/misc/data_cd.doc/assignee_harmonization/cy2$

cumulative revenue by the ratio of the mean lifetime revenue to the mean cumulative revenue for patents of the same age (by technology category). We 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) we 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 patents is classified as abandoned, acquired as inactive, lapsed, filed, or inactive is simply added to the normalized real revenue.

3. Distance

In order to quantify the distance between two technology classes, we define distance as in Akcigit, Celik, and Greenwood (2015), using the first 2 digit IPC to denote a technology class:

$$d(X,Y) \equiv 1 - \frac{\#(X \bigcap Y)}{\#(X \bigcup Y)}, \; with \; 0 \leq d(X,Y) \leq 1.$$

where #(X $\bigcap$Y) denotes the number of patents that cite technology classes X and Y together, and #(X $\bigcup$Y) denotes the number of patents which either cite X or Y or both.

Also following Akcigit, Celik, and Greenwood (2015), we 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.

$$d_\iota(p,f) \equiv \left[\frac{1}{||P_f||} \sum_{p' \in P_f} d(X_p, Y_{p'})^\iota \right]^{\frac{1}{\iota}}$$

where $0 < \iota < 1$, and where $0 \leq d_\iota(p,f) \leq 1$. 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'.

Our baseline results uses $\iota = \frac{2}{3}$. Using the measure above, we constructed two different distance measures. Distance to originating entity and distance to licensee. The resulting measure is multiplied by 100 to increase the readability.

4. Litigation Risk

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

$$\mathbf{I}_{Litigated_{i,j,t}} = \zeta + \eta_i + \delta_t + \phi \times CO_{i,j,t} + \epsilon_{i,j,t} \tag{10}$$

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. η_i is a firm fixed effect and δ_t the application year fixed effect. $CO_{i,j,t}$ is a vector

of covariates, and $\epsilon_{i,j,t}$ is the error.

Our model is motivated by Lanjouw and Schankerman (2001) but we 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.

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

5. 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.

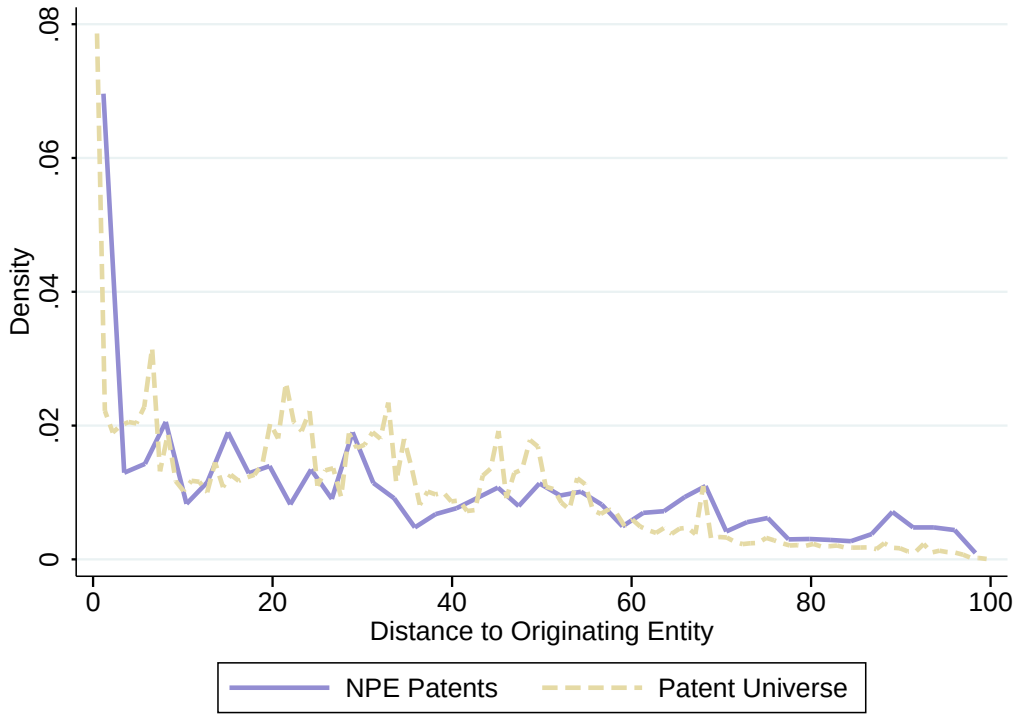
Medium Originating Entity: Medium Originating Entity is 1 if in the middle half of original entity size, 0 otherwise.

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. We define hotness as the percentage of backward citations to patents that are at most three years older than the citing patent.

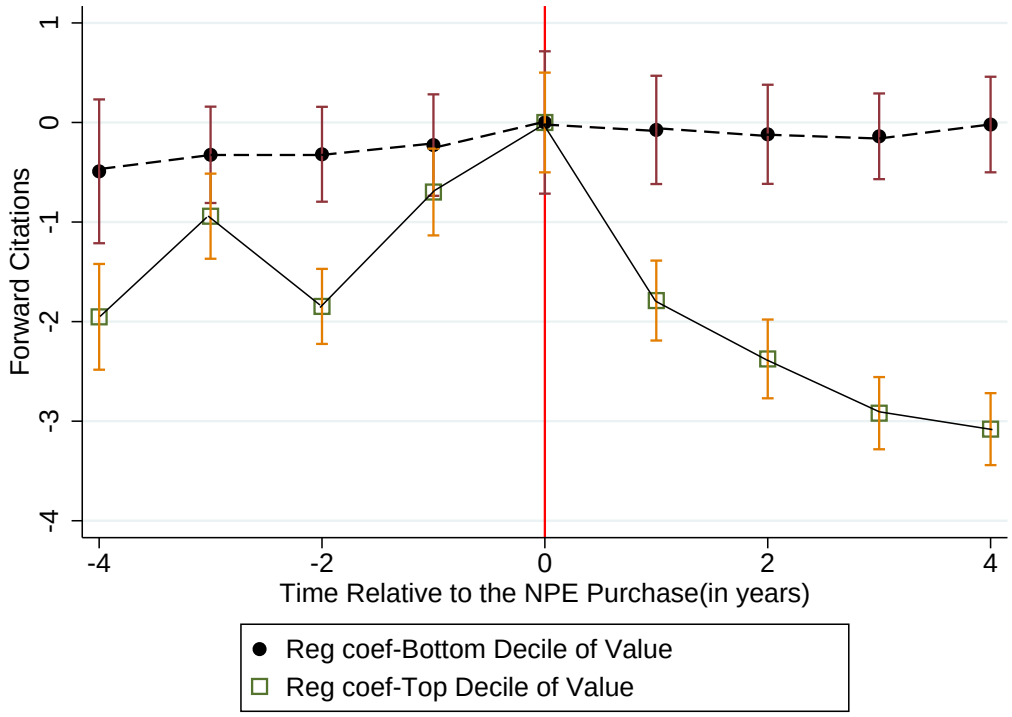
8 Appendix 2: Additional Tables and Figures

Figure 9: The Distribution of Distance



Notes:

Figure 10: The Citation Event Study for Top and Bottom Decile NPE Patents



Notes: See notes to Figure 7.