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Abstract

How do non-practicing entities ("Patent Trolls") impact innovation and technological progress? We employ unprecedented access to NPE-derived patent and financial data and a novel model to answer this question. We find that NPEs tend to acquire litigation-prone patents from small firms and acquire patents less core to the seller's business. When NPEs license patents, those that generate higher fees are closer to the licensee's business and more litigation-prone. Moreover, downstream innovation drops when patents are acquired by NPEs. Quantitatively, the overall impact of NPEs depends on the share of infringements that come from non-innovating producers.

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

JEL Classification: O31, O34.

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> *"Having made a really meritorious invention, and having secured a patent thereupon, the battle of the inventor, who would sell his patent, is just begun. Heretofore he may have done some good skirmishing, but now he must face the music of solid battle."*
>
> William Edgar Simonds
> *Practical Suggestions on the Sale of Patents*, p.5, 1871

1 Introduction

Are Non-Practicing Entities (NPEs)[1], often referred to as "Patent Trolls", good or bad for technological progress? This longstanding question has gained renewed urgency with their recent proliferation. Concern about potential negative effects of NPEs has led to the introduction of legislation in state legislatures and Congress aimed at curtailing their activity. The view of the NPE as *stick-up artist* holds that they provide no benefits, but simply amass patents and hold up companies, using the threat of litigation to extract rents. At the same time, legislative efforts have been opposed 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*, the market for patents requires intermediation to facilitate inventors monetizing their ideas and overcoming the frictions noted in the opening quote. Thus, inventors who are not well-positioned to fully utilize their invention may sell or license them through an NPE's large network of industrial companies.

Despite the popularity and importance of the subject, the inner workings of NPEs have remained mysterious, and discussions about them have mostly been based on anecdotal evidence. This is largely because NPEs act in secrecy, making it harder for researchers to access micro data on their direct business transactions and paid prices. We seek to inform this important debate by analyzing extensive novel data obtained directly from large NPEs in order to understand their impact on innovation. We develop a new model that incorporates NPEs to frame our empirical analysis and calibrate it in order to understand whether NPEs facilitate or harm innovation.

This paper makes two major contributions to our understanding of NPEs. We first develop a model of innovation based on quality-ladder growth models that incorporates NPEs and makes testable predictions. We then test the model by using a proprietary dataset with detailed financial, transaction and technological information on tens of thousands of NPE-held patents (Abrams et al., 2018). We build on prior work that has developed important metrics for patents, such as litigation risk (Lanjouw and Schankerman, 2001) and patent distance (Akcigit et al., 2016), which quantifies the technological similarity between patents or groups of patents. While our dataset is quite large, it is far from the entire set of NPEs, and our empirical results should not be seen as universal or representative. They provide a new window into the impact of large professional NPEs.

[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.

Even though NPEs have received increased attention in recent years, middlemen in the market for ideas not a new phenomenon. In fact, the market for patents has been aided by intermediaries for about as long as patents have existed. This market, like most, suffers from informational and financial frictions that makes it harder to match the right buyers and sellers (Lamoreaux and Sokoloff, 1999). Intermediaries have the potential to serve an important function in this regard (Khan, 2014). People with meritorious inventions look for channels whereby they can be compensated if they cannot make the best use of their invention. According to Lamoreaux and Sokoloff (1999), 550 patent intermediaries were present in the 1880's across the United States, working to build a bridge between buyers and sellers of patents. There were even extensive guidebooks for interacting with patent intermediaries, such as Simonds (1871). Khan (2014, 2015) also show how constant NPEs have been throughout history.

Our analysis begins with a theoretical investigation which we use to guide our empirical analysis. Following in the tradition of quality-ladder growth models (Aghion and Howitt, 1992; Grossman and Helpman, 1991), we build a new model of innovation where patents can be infringed and sold in the secondary market with the help of an intermediary. The intermediary has two potential roles: as *benign middleman* and *stick-up artist*. In the model, patents are produced with multiple levels of uncertainty. First, as in classical models, the arrival rate of innovation is probabilistic. Second, unlike the traditional models, a patent can have differential fit (i.e. patent distance as in Akcigit et al. (2016)) to the original inventor. This creates an incentive for an inventor to sell a patent to another user if it does not fit the inventor's portfolio well. An NPE, with its more extensive network of buyers and sellers, facilitates this transaction and serves as a *benign middleman*.

In the model, there is also some probability other firms will infringe a particular patent. In this case, the patent-holders can sue and win the case with a probability determined by their legal and financial resources, which we capture by firm size. In their second role as *stick-up artist*, NPEs can buy patents from weak inventors and use their legal power and new status as the rightful owner of the patent to sue the infringing firm. This provides an incentive for smaller firms to sell their patents to an NPE. We use this framework to generate a number of predictions which we then test with our data as we detail below.

In addition to deal-level acquisition and licensing data received directly from NPEs, we also construct an index for how likely a patent is to be litigated (following Lanjouw and Schankerman (2001)), and compute a distance measure that denotes how well a patent fits to a firm's portfolio (following Akcigit et al. (2016)). These core measures allow us to examine several questions, which test predictions of the model: How do patent attributes, such as distance and likelihood of litigation, impact the price paid by NPEs in acquisition deals? How does the entity size of the original assignee affect likelihood of sale and price? When NPEs license patents, what patent characteristics impact licensing revenue? Finally, using patent citation data, we also investigate how the citation rate to patents varies around the time of acquisition by NPEs and whether there is heterogeneity by patent value.

In our empirical investigation, we find that patent distance contributes positively to the likelihood of a patent sale to an NPE, especially for large firms. Examining the source of NPE-held patents, we also find that they buy patents predominantly from smaller entities, and more so for litigation-prone patents. With another novel feature of our data, acquisition prices, we find that NPEs pay more for patents from large firms. We also find that NPEs pay less for patents that are a worse fit (greater distance) for the original inventor. Next, we focus on licensing transactions and find that NPEs receive higher fees from patents that have a lower distance (better fit) to the licensee's portfolio. All of these findings corroborate predictions made in the model. Finally, we find a decline in citations to NPE-acquired patents upon acquisition. This decline is driven primarily by high-value patents.

Our theoretical and empirical analysis is agnostic about the overall impact of NPEs on new technology creation since the existence of NPEs can have both positive and negative effects on innovation incentives. In order to understand the net effect of NPEs, we undertake a numerical exercise in which we bring the model closer to the data by matching a number of informative moments in our data using Simulated Method of Moments (SMM). We find mixed results depending on the quantitative magnitudes of the role of the benign middleman and stick-up artist mechanisms. The ultimate effect of NPEs on innovation depends on the source of patent infringement. If the majority of infringement comes from innovating producers, we find that the stick-up artist role dominates and NPEs reduce the overall innovation effort in the economy. If a significant majority of infringement is due to non-innovating producers, the benign middleman role dominates and NPEs increase the overall innovation effort.

Taken together, the evidence in this paper 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 aggregate innovation and some that may not. As debate continues both in academia and the policy world, it will be helpful to keep these benefits and costs in mind. The rest of the paper is organized as follows. Section 2 provides some institutional details and a summary of the literature. In Section 3 we present our model of innovation with NPEs, stressing the multiple roles NPEs can play. In Section 4 we introduce the data with the main empirical results presented in Section 5. Section 6 presents the numerical analysis and calibration exercise. Section 7 concludes.

2 Background and Related Literature

Since the terms patent troll, NPE, and patent assertion entity (PAE) are frequently used to denote similar or overlapping entities, it is useful to have a clear definition of what we study in this paper. 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). We here also exclude a related group of legal entities that issued demand letters to hundreds of businesses alleging patent infringement for the use of networked scanners to email documents.[2]

We will use the term NPE in this paper and focus on large firms that purchase patents and primarily license them or litigate when they cannot license. We 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. They are also arguably the most interesting case because there are plausible positive and negative attributes. In addition, university licensing is unlikely to become a hot policy issue. Finally, not only is their effect on innovation more contentious and uncertain, these large firms are most likely making the biggest impact of the set of middlemen in markets for innovation.

Related Literature This paper contributes to an extensive literature that links the role of patents to growth in the aggregate economy. In particular, Eaton and Kortum (1996) estimate a model to explain international patterns of productivity and patenting while Jaffe and Trajtenberg (1999) show how international knowledge flows occur through patents. Akcigit et al. (2017) show that economies that produce more patents also grow faster in the long-run. Kortum (1997) emphasizes the role of searching for ideas in linking patents to productivity growth. As Ahmadpoor and Jones (2017) and Henderson et al. (1998) show, patents can contribute to aggregate productivity through channeling basic academic research to products. Caballero and Jaffe (1993) estimate a quality-ladder model using patent data to quantify the role of creative destruction on economic growth. At a more micro level, Bloom and Van Reenen (2002) show that patents have a significant impact on firm-level productivity and market value. Blundell et al. (1999) find a strong and robust effect of the headcounts of innovations and patents on market share.

In the theoretical model, we build on endogenous growth theory where ideas are the fundamental building blocks of long-run growth. Our framework applies quality ladder models following in the tradition of Aghion and Howitt (1992), Grossman and Helpman (1991), Klette and Kortum (2004), Lentz and Mortensen (2008), Acemoglu et al. (2018) and Akcigit and Kerr (2018). Other papers in this space, i.e. Benhabib et al. (2014), Konig et al. (2016), and Perla and Tonetti (2014) focus on how growth emerges initially from innovation but also from imitation as technologies ripple through the economy. Patents here can serve as a channel for incentivizing idea creation, making information available to the public, as well as increasing the value of a firm.

For the most part, idea transfer and middlemen in the market for ideas has not been central to the theory of growth–but as Serrano (2010) and Akcigit et al. (2016) note, the transfer of ideas can be key for a firm building its portfolio. Within the quality ladder framework, Akcigit et al. (2016) address the misallocation and reallocation of ideas being a key contributor to economic

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

growth. In another theoretical exploration, Chatterjee and Rossi-Hansberg (2012) discuss how idea "spinoffs" can be fundamental to growth and address problems of information asymmetry in marketing new ideas. Although the role of NPEs is not addressed in this literature, these investigations leave a large space for a middleman that can reduce informational frictions.

Serrano (2010, 2018) finds that patent renewal and transfer is an important component of innovation. As such, there seems to be a role for the NPE in serving as a important player in this market. Indeed, Akcigit et al. (2016) find that the secondary market in patents is mostly governed by middlemen. Griffith et al. (2003, 2004) find that R&D investment also allows firms to generate "absorptive capacity," as firms may spend more on R&D with the expectation that they can engage in technology transfer through middlemen. This absorptive capacity may also make firms more likely to be linked to networks of patent middlemen–with capabilities to move on ideas the firm itself does not create.

This paper also contributes to a rich literature on industrial policy, knowledge spillovers (Bloom et al., 2013), and firm size e.g. (Garicano et al., 2016). In particular, we focus on issues related to patent and innovation policy. Galasso and Schankerman (2015) use exogenous variation from patent examination and invalidation and find a heterogeneous effect of changes in patent rights on downstream innovation, significantly depending on industry. We may expect the NPE to reflect this underlying reality, as areas with high litigation may induce the NPE to fulfill their role through their legal resources. In areas where downstream innovation is unaffected, the NPE may indeed be a benign middleman simply serving the role of improving idea allocation. Galasso et al. (2013) use exogenous changes in tax rates and find that taxes strongly affect the market for innovation. In addition, they find the reallocation of patent rights reduces litigation risk, indicating that patents are moving to more highly valued owners.

We unite this mostly theoretical growth literature with a burgeoning empirical literature on the role of NPEs in the market for innovation that has primarily focused on the role of NPE as stick-up artist. The biggest challenge of this set of papers has been data limitations. As discussed earlier, NPEs often operate in private and it is very hard to get at both the transactions and the underlying prices of these transactions. However, some creative papers have tried to measure this NPE impact through various methods.

Some studies attempt to measure the impact of NPE assertions outside of the courtroom, drawing from data beyond 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. RPX invited 250 (nonrandomly selected) firms to participate in the survey, of which 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 of patent cases, curated by RPX, to conclude that most defendants in NPE suits are smaller companies. Through polling in-house attorneys across an array of industries, Feldman and Lemley (2015) find that when an NPE expressed an interest in licensing from firms, it did not induce further innovation. Lu (2012) finds the royalty rates paid to NPEs are similar to those paid to practicing entities, using information from vendors that aggregate royalty rates primarily drawn from companies' public SEC filings.

Tucker (2014) focuses on the heathcare technology industry and finds a large reduction in sales of defendants' software projects that were allegedly infringed by a selected NPE's patents, while surrounding products and firms did not see the same effect. A limitation of this study is the single focus on defendants. When Kiebzak et al. (2016) look across industry by district pairs, they find that venture capital investment and patent litigation follows an inverted-U relationship. This could indicate how litigation to protect patents both holds back investment and induces new innovators.

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. Risch (2012) attempted to defend the decision to only include 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. Cohen et al. (2016, 2017, 2018) used proprietary data from PatentFreedom, another company that aggregates litigation data, in arguing that NPEs are more likely to target cash-rich firms. However, Ashtor et al. (2013) 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. 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.

Some scholars, including Schwartz and Kesan (2014), have questioned the generality of conclusions based on data that is potentially unrepresentative and unreliable. They suggest that there may be an overemphasis on technology firms, and express concerns about varying definitions of what constitutes an NPE. In terms of using litigation data, the aggregate economic effect of NPEs may be underestimated, since many assertions may 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.

Fischer and Henkel (2012) may not be subject to this problem as the classify NPEs using public searches, newspapers, blogs, and websites. With these identified NPEs, they then search the patent assignment databases to arrive at a sample of patent acquisitions by NPEs. Using proxy indicators for various characteristics of the acquired patents, they conclude that NPE-acquired patents are likely to be higher-quality and of broader scope and application than non-NPE patents.

Czarnitzki and Toole (2011) explore the role of patent protection in mitigating uncertainty, something which a reliable intermediary can improve. Toole and Turvey (2009) find that reducing risk, in turn, can lead to increases in follow-on funding. This would be especially valuable for liquidity-constrained small firms–the types of firms we find most commonly selling to NPEs.

This complements Haber and Werfel (2015, 2016) who present experimental evidence that NPEs provide insurance and liquidity to firms by committing resources to protecting inventors' property rights.

Lemley and Feldman (2016) argue that NPEs are more prominent in litigation than in facilitating intellectual property transfers. They discuss the expanding importance of NPEs in the market for patents, indicating that NPEs account for the majority of patent lawsuits filed. However, Cotropia et al. (2014) note that when we focus on the number of alleged infringers as opposed to cases, as in Lemley and Feldman (2016), there is little increase in NPE share of litigation. While Lemley and Feldman (2016) suggest the idea of the middleman is not convincing, they caution that the evidence is from small sample survey data.

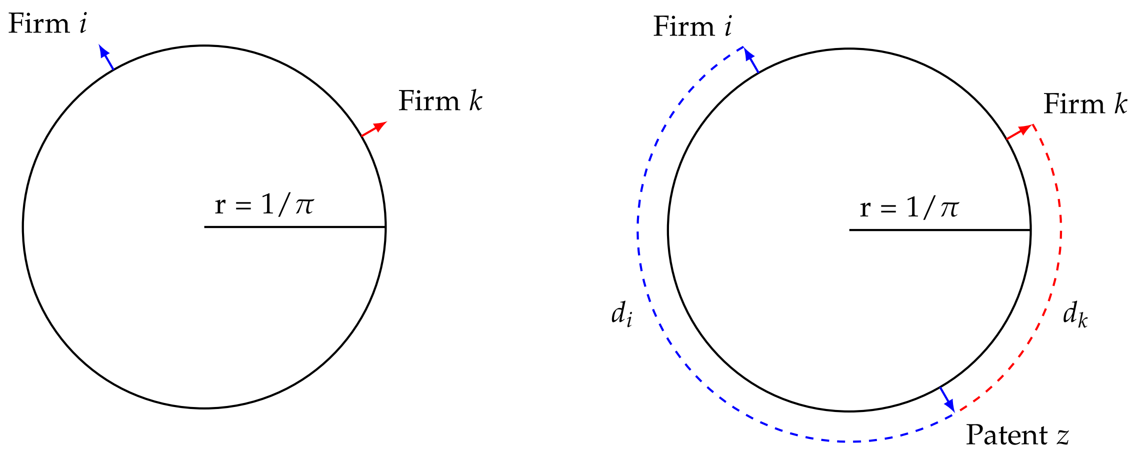
When it comes to NPEs, the underlying legal institutions will be a relevant concern. Feng and Jaravel (2017) find that heterogeneity in patent outcomes is often based on how the rights are crafted in the examination process. They find that NPEs are active in targeting patents with "lenient" examiners–backing up the story that NPEs can act as stick-up artists. As Marco and Miller (2017) and Graham et al. (2015) note, problems in the examination process can lead to patents having a higher risk of litigation. There are cases where patent thickets and aggregation, in particular from NPEs, can reduce innovation. If this is prominent, we can see how problems in the underlying property institution can induce NPEs to act more as stick-up artist than middleman, which could be linked to the "destructive" role of patents, which Nicholas (2013) addresses in general. Our paper allows for both channels discussed in this section. We start with the model to frame our empirical analysis.

3 Model

In this section, we build a tractable model of production with innovation to address the role NPEs play in the market for innovation. By examining a firm's decision to sell to an NPE or license from one, our goal is to find theoretical implications for the stick-up artist and benign middleman views of NPEs, which we then test with data. The model generates a number of predictions about how patent and firm characteristics, such as *patent fit (distance)*, *litigation risk*, and *firm size*, impact the decision to sell or license; in addition, the model generates predictions on how these characteristics affect the prices at which NPEs buy and license. This provides the framework that will guide our empirical analysis in Section 5 and inform our calibration in Section 6.

Basic Environment Consider a simple economy represented by a unit circle $\mathcal{C}$, as in Figure 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: $Y = \frac{1}{1-\sigma} \int_{\mathcal{C}} q_i^{\sigma} k_i^{1-\sigma} di$, where k_i denotes the quantity and q_i the quality of intermediate good i used in final good production. The final-good sector

Figure 1: Model Economy, Unit Circle $\mathcal{C}$



(a) Example of Two Firms i and k

(b) Two Firms and a Patent z

operates with perfect competition, and we normalize the price of the final good to 1 without any loss of generality. Therefore, the objective function in the final-good sector is simply:

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

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

$$P_i = q_i^{\sigma} k_i^{-\sigma}. \tag{1}$$

Each intermediate good i is produced by a monopolist who owns a patent for their cutting edge technology. The monopolist can produce k_i at a constant marginal cost ψ in terms of the unique final good. Each monopolist firm chooses a price and quantity to maximize profits on its product line, taking the demand in (1) into account. The profit-maximization problem of the monopolist with a cutting edge technology for intermediate good i can then be written as

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

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

$$\Pi_i = \pi q_i, \tag{2}$$

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

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

3.1 Patents

Patent Distance and Firm Quality The circumference of the circle $\mathcal{C}$ in Figure 1 is normalized to 2 such that the maximum distance between any two points along the circle is equal to 1. Like firms, innovations (patents) in production are located along the circle. Figure 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

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

where γ is some scale parameter and $x_i \in [0, 1]$ is the goodness of fit of the patent to the firm, which is the inverse of *patent distance* $d_i \in [0, 1]$:

$$d_i = 1 - x_i.$$

Low values of d_i (i.e., high x_i) indicate that a patent is a good fit to the firm i. Given the linearity of the profit function in (2), the incremental gain to monopolist i from using this patent is

$$\begin{aligned} \Delta\Pi_i &= \pi\left[q_i + \gamma\left(1 - d_i\right)\right] - \pi q_i \\ &= \pi\gamma\left(1 - d_i\right). \end{aligned} \tag{3}$$

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

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

3.2 Non-practicing Entities

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

The Middleman 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 $d_k < d_i$ or larger profit scale, Ω_k (discussed below). Having access to a large network is the first advantage of the NPE over a single innovating firm. To keep things tractable and allow for focus on other dimensions, we use this as a reduced form treatment, which is microfounded in Akcigit et al. (2016).

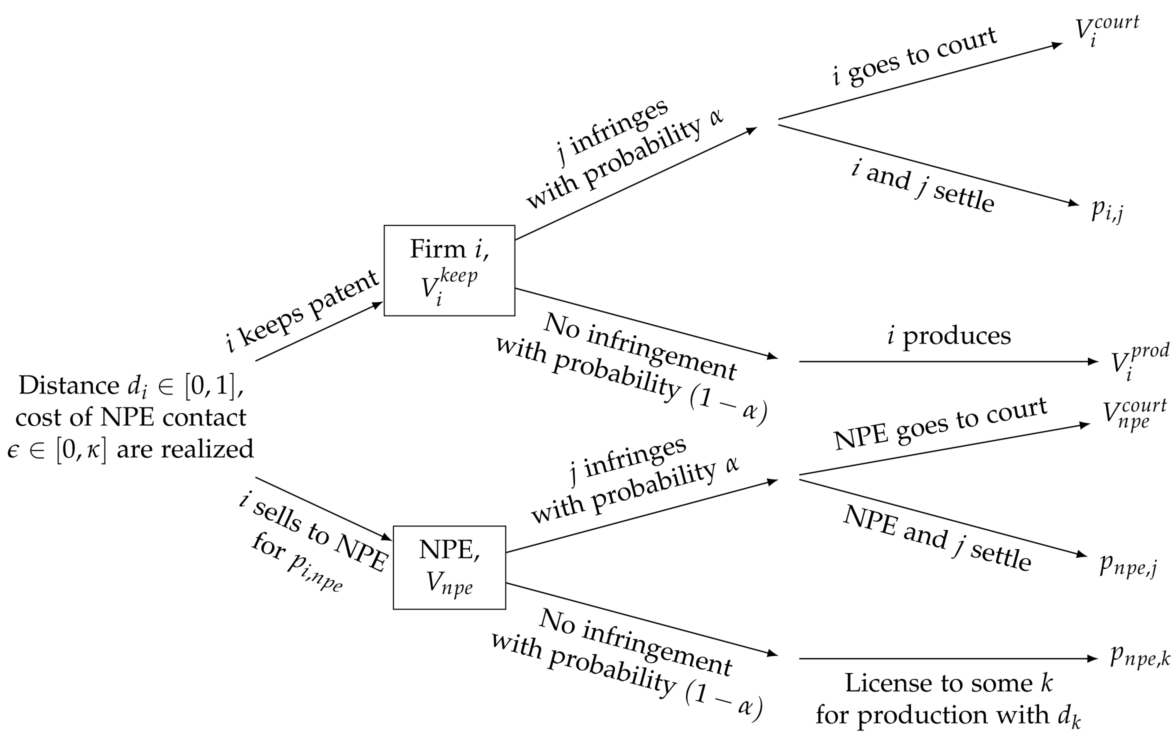
The Stick-up Artist The second key ingredient of our model is that patents may be infringed upon by other firms. Let us denote the firm that infringes on firm i's patent by j. When j infringes on i's patent, firm i can go to court and sue j. Winning a court case depends on resources that a firm has to fight in the court, as has been empirically shown in Haber and Werfel (2015, 2016). We capture this by assuming that a firm i wins the lawsuit with probability β_i where β_i increases in firm size such that:[3]

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

The second strength of the NPE is that it has greater experience and resources to fight in court, i.e., it has a high probability of winning in court, β_{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.

We describe the rest of the dynamics of the model with the help of the game tree shown in Figure 2.

Figure 2: Game Tree



[3]Our 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, we will 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 $d_i \in [0,1]$ with mean ν_i. In addition, firm i realizes an idiosyncratic cost of finding an NPE, ϵ. Next, it decides whether 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.[4] Before production takes place, the patent is infringed with probability α. While α is assumed to be exogenous in this section, it will be endogenized in Section 6. If there is no infringement, which has 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 makes by using its new patent)

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

If there is infringement, which happens with probability α, then i can no longer procure the incremental profits without patent enforcement; thus i will try 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 compensated for lost profits $\pi (1 - d_i)$. Hence, the expected value of going to court is:

$$V_i^{court} = \beta_i \pi (1 - d_i). \tag{5}$$

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 loses Ω_j. Settlement generates a surplus that the two parties split through Nash bargaining with equal bargaining power for both sides. Let us 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

$$p_{i,j} = \arg\max \left(p_{i,j} - V_i^{court}\right)^{0.5} \left(V_i^{court} + \beta_i \Omega_j - p_{i,j}\right)^{0.5}. \tag{6}$$

Note that player i could receive V_i^{court} if there is no agreement and therefore her net surplus from bargaining is $p_{i,j} - V_i^{court}$. Likewise, player j will need to pay V_i^{court} and also give up his Ω_j additional profit if the case goes to court and the court decides in favor of i with probability β_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 (5). The settlement fee that j pays i is increasing in i's probability of winning the case β_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, we can calculate the expected value

[4] Since our focus on this paper is the role of an NPE, we 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. (2016).

to i of keeping the patent as

$$\begin{aligned} V_i^{keep} &= \alpha p_{i,j} + (1-\alpha) V_i^{prod} \\ &= \alpha \beta_i \left[\pi (1-d_i) + \frac{\Omega_j}{2} \right] + (1-\alpha) \pi (1-d_i). \end{aligned} \tag{7}$$

Next, consider what happens if i decides to sell the patent to the NPE, as illustrated by the lower branch. 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.[5] There are two differences from (6): one is that the NPE by definition does not produce and therefore does not have $\pi (1-d_i)$ as a bargaining chip. However, the NPE can block j from gaining Ω_j and has potentially a higher probability of winning, β_{npe}. Therefore, the problem for the settlement can be written as

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

which delivers the following settlement fee that the NPE 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 $d_k \sim D_k$, which is taken from a uniform distribution on the unit circle. and profit equal to Ω_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

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

With these prices, we can compute the expected value to the NPE of owning the patent:

$$V_{npe} = \alpha p_{npe,j} + (1-\alpha) p_{npe,k}. \tag{8}$$

At this point, we have solved for the end-game values in each state of the world. Knowing the continuation values in each branch of Figure 2, how much would the inventor i charge the NPE for a patent sale? We are now ready to solve for 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. If $V_{npe} > V_i^{keep}$, this problem can be written as

$$p_{i,npe} = \arg\max \left(p_{i,npe} - V_i^{keep}\right)^{0.5} \left(V_{npe} - p_{i,npe}\right)^{0.5}. \tag{9}$$

[5]Note how, 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.

Hence, the equilibrium price that firm i charges the NPE is:

$$p_{i,npe} = \frac{V_i^{keep} + V_{npe}}{2}, \tag{10}$$

where V_i^{keep} is expressed in (7) and V_{npe} in (25). We assume that there is a cost of contracting with an NPE, ϵ, that comes from a uniform distribution as $\epsilon \sim U[0,\kappa]$. 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, $p_{i,npe} - V_i^{keep} > \epsilon$. Therefore, the probability of sale can be written as

$$\Pr(sale) = \frac{p_{i,npe} - V_i^{keep}}{\kappa} \tag{11}$$

3.3 Model Predictions

In this section, we generate a number of important comparative statistics that we later test using micro data.[6] First, we focus on the determinants of the probability of a patent sale to the NPE in (11). Our first result relates to the NPE's role as a stick-up artist, and describes how patent sale relates to litigation risk and firm size.

Prediction 1 *The NPE is more likely to buy patents from small firms*:

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

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

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

This follows from the fact that small firms have a harder time defending themselves in court (i.e., small β_i). As a result, the NPE purchases patents from small firms in order to enforce their patent rights in the case of infringement. Thus, the NPE purchases more often from smaller firms, and at even more so for litigation-prone patents.

Next, we focus on the NPE as a middleman, which reallocates innovations to reduce the distance to the owning firm.

[6] We write out the math for the proofs more complete in Appendix D

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

$$\begin{aligned}\frac{\partial}{\partial d_i}\Pr(sale) &= \frac{\alpha\beta_i\pi + (1-\alpha)\pi}{2\kappa} \\ &> 0.\end{aligned}$$

Moreover, this effect is more pronounced for large firms, i.e.,

$$\begin{aligned}\frac{\partial^2}{\partial d_i \partial q_i}\Pr(sale) &= \frac{\beta'(q_i)\alpha\pi}{2\kappa} \\ &> 0.\end{aligned}$$

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 consider selling it in the secondary market through the NPE. This is especially true for large firms. Because large firms have greater court capability, they are more likely to use the NPE to reduce distance. Thus, the impact of distance on probability of sale is more pronounced for large firms.

Our model has clear predictions on the sale price of a patent that was expressed in (10). We now turn to these predictions.

Prediction 3 *The NPE pays more for large firms' patents:*

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

The equilibrium price of a patent is determined through Nash bargaining as described in (9). Since legal strength and resources are increasing in firm size, the outside option of a patent is higher for large firms. Hence, large firms receive a higher price for their patents.

Next, we focus on the link between sale price and patent distance.

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

$$\begin{aligned}\frac{\partial p_{i,npe}}{\partial d_i} &= -\frac{[\alpha\beta_i + 1 - \alpha]\pi}{2} \\ &< 0\end{aligned}$$

The intuition for this result is similar to its counterpart on 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.

We now turn to the licensing side.

Prediction 5 *The average price that a licensing firm pays to the NPE decreases as distance to the licensee increases.*

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

The intuition here is straightforward. More distant patents are worth less to licensees, so they have a lower willingness to pay.

3.4 The NPE and Overall Innovation

How does the existence of an NPE affect incentives to innovate? The NPE influences both downstream (firm j) and upstream innovation (firm i). While the overall effect is not obvious, in this section we study each of these in turn.

3.4.1 Downstream Entry into the Market

Here we consider the endogenous innovation decision of a downstream firm j and endogenize infringement probability, α, which we took as exogenous in the previous section. Our analysis proceeds in two steps. First, we consider a market without an NPE; then, we examine the change in innovation rates when an NPE enters the market.

The Case without an NPE In the above model, parameter α 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 ϕ, or (ii) because the downstream firm made an attempt to innovate a brand-new product with endogenous probability μ_j but fell short of being sufficiently non-obvious and ended up infringing i's patent with probability τ. Therefore α has two components:

$$\alpha = \underbrace{\phi}_{non-innovator} + \underbrace{\tau \mu_j}_{innovator}$$

where ϕ captures the probability that a non-innovating and $\tau\mu_j$ an innovating downstream j infringes i.[7]

We focus now on the endogenous innovation decision μ_j. Recall that the incremental profit of firm j from adding a new technology to its portfolio is simply Ω_j. Products produced with this new technology may infringe an existing patent with probability τ, and when there is no NPE in the market, there will be a side settlement between firm i and j with expected price $\mathbb{E}(p_{i,j})$. There

[7]In Section 6, we will make the necessary assumptions to ensure that $\alpha \in [0, 1]$.

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

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

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

$$\mu_j^{no-npe} = \left[\eta(\Omega_j - \tau\mathbb{E}[p_{i,j}]) \right]^{\frac{1}{\xi-1}}.$$

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 the NPE in the market. Thus, the expected price j will pay is equal to:

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

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

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

In equilibrium, the innovation rate is simply

$$\mu_j^{npe} = \left[\eta(\Omega_j - \tau\mathbb{E}(p_{\cdot,j})) \right]^{\frac{1}{\xi-1}}.$$

Now, we can focus on the change in the innovation rate $\Delta\mu_j \equiv \mu_j^{npe} - \mu_j^{no-npe}$ with and without an NPE in the market. The change in innovation rate is simply

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

When $\mathbb{E}(p_{\cdot,j}) > \mathbb{E}(p_{i,j})$ the NPE decreases *downstream* innovation. We do indeed find this to be the case in almost all specifications of our calibration exercise in Section 6.

3.4.2 Upstream Innovation

We have already shown how NPEs can decrease innovation incentives of downstream firms. We now look at the innovation incentives of upstream firms. Firm i's innovation decision problem will look similar to j's problem. We start in the case without the NPE:

$$\max_{\mu_i} \left\{ \mu_i V_{keep} - \frac{\mu_i^{\xi}}{\eta\xi} \right\}$$

which implies

$$\mu_i = \left(\eta V_{keep}\right)^{\frac{1}{\xi-1}}$$

When there is an NPE, the maximization problem becomes

$$\max_{\mu_i^{npe}} \left\{ \mu_i \eta \left[\max\left(\mathbb{E}[p_{i,npe} - \epsilon], \mathbb{E}[V_{keep}]\right)\right] - \frac{(\mu_i^{npe})^{\xi}}{\eta \xi} \right\},$$

yielding

$$\mu_i^{npe} = \left(\eta \left[\max\left(\mathbb{E}[p_{i,npe} - \epsilon], \mathbb{E}[V_{keep}]\right)\right]\right)^{\frac{1}{\xi-1}}.$$

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

$$\begin{aligned}\Delta\mu_i &= \left[\eta[\max(\mathbb{E}[p_{i,npe} - \epsilon], \mathbb{E}[V_{keep}])]\right]^{\frac{1}{\xi-1}} - \left[\eta \mathbb{E}[V_{keep}]\right]^{\frac{1}{\xi-1}} \\ &\geq 0,\end{aligned}$$

which follows from the fact that (by i's revealed preference)

$$\max[\mathbb{E}[p_{i,npe} - \epsilon], \mathbb{E}[V_{keep}]] \geq \left[\mathbb{E}[V_{keep}]\right]$$

3.4.3 Overall Innovation

The paramount policy question is how NPEs impact overall innovation in the market. While the existence of an NPE in the market provides additional innovation incentives to the upstream firm i, it may induce enough of a reduction in downstream innovation by firm j to be a net negative force on innovation on the whole. Consider i and j's innovations, both with and without the NPE. Note that with an active NPE i's innovation rate increases while j's downstream innovation is generally negative though uncertain.[8] The change innovation rate to adding the NPE is

$$\Delta\mu \equiv \underbrace{(\mu_j^{npe} - \mu_j^{no-npe})}_{(-/+)} + \underbrace{(\mu_i^{npe} - \mu_i^{no-npe})}_{(+)} \lesseqgtr 0.$$

We note here the ambiguous effect on overall innovation. Therefore, we approach this question in two ways. First, in Section 5, we look at follow-on innovation for patents that go to the NPE. Then, in order to characterize the general equilibrium effects and understand the numerical properties of this result and our model in general, we do a calibration exercise in Section 6.

[8] This is detailed further in Appendix D.6

3.5 Final Remarks on the Theory

In the model above, we focused on various predictions of impacts on patent sales and pricing. Given the extensive discussion on NPE's and patent litigation, we explore how patent litigation risk affects patent sale probability and prices. Through the lens of our model, litigation risk affects the likelihood of a sale as follows:

$$\begin{aligned}\frac{\partial \Pr(sale)}{\partial \alpha} &= \left[\underbrace{\frac{[\beta_{npe}-\beta_i]\,\Omega_j}{2}+[1-\beta_i]\,\pi\,(1-d_i)}_{Stick-up\ \ Artist}-\underbrace{\frac{\Omega_k\,(1-d_k)}{2}}_{Middleman}\right]/2\kappa \\ &\lesseqgtr 0.\end{aligned} \tag{12}$$

Note that the impact of litigation has both positive and negative impacts on the likelihood of a sale. The overall sign depends on the specific role of the NPE. If the dominant role of the NPE is to defend a firm's patent rights in 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 or higher Ω_k), then higher litigation risk has a negative impact on sales. This is because the higher litigation risk mitigates the NPE's ability 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 the NPE would charge or the price that the NPE would pay to purchase the patent depends on the magnitude of the two roles of the NPE. For instance, the expected licensing fee is $\mathbb{E}(p_{npe,.}) = \alpha p_{npe,j} + (1-\alpha)p_{npe,k}$. Then the impact of the increased litigation risk on licensing fee is

$$\begin{aligned}\frac{\partial \mathbb{E}(p_{npe,.})}{\partial \alpha} &= \left[\beta_{npe}\Omega_j-(1-d_k)\Omega_k\right]/2 \\ &\lesseqgtr 0.\end{aligned} \tag{13}$$

The impact of litigation risk on the acquisition price is

$$\begin{aligned}\frac{\partial p_{i,npe}}{\partial \alpha} &= \frac{[\beta_i+\beta_{npe}]\,\Omega_j-2\,[1-\beta_i]\,\pi\,(1-d_i)-\Omega_k\,(1-d_k)}{4}. \\ &\lesseqgtr 0.\end{aligned} \tag{14}$$

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

Summary of Predictions We summarize the predictions of the model as follows:

Prediction 1 *The NPE is more likely to buy patents from small firms. Moreover, this likelihood is more pronounced for litigation-prone patents.*

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

Prediction 3 *The NPE pays more for large firms' patents.*

Prediction 4 *The acquisition price decreases as patent distance to the seller increases.*

Prediction 5 *The average price that any licensing firm will pay to the NPE decreases as distance to the licensee increases.*

Summary of Ambiguous Results Multiple features of the model were agnostic regarding the effect of the NPE. These will be further explored in the empirical analysis in Section 5 and the calibration in Section 6.

1. The NPE has an ambiguous effect on overall innovation.

2. Increases in litigation risk have an ambiguous effect on the probability of sale.

3. Increases in litigation risk have an ambiguous effect on the NPE licensing fee.

4. Increases in litigation risk have an ambiguous effect on the price the upstream firm sells to the NPE.

4 Data and Variables

This research is made possible by the use of confidential data obtained from large NPEs covering tens of thousands of patents. This includes several unique measures on NPE business activities: 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 sources, exact number of patents, and non-normalized revenue figures. However, there are no restrictions on the types of analyses we may perform, nor is pre-approval needed 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 Appendix A.

The NPEs usually acquire patents in small groups from individuals or firms who are almost always the original assignees. The patents are generally 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.

4.1 Data Sources

We rely on five data sources for our analysis as follows:

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. We use the following variables from this dataset:

- **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/name:** An assignee number (with associated name) assigned to each patent granted by USPTO. Where the assignee is an individual this field is blank, 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, Appendix A.1.1 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 patent acquisitions, patent licensing, and patent characteristics. The acquisition data includes unique identifiers for each acquired portfolio, patent acquisition date, and amount paid. The licensing data includes the licensee name, licensing date, and primacy of patent. 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 due to the fact that citations to sources other than U.S. utility patents are often reported haphazardly. [9]

[9] We complement our citation data with the citation data located at `http://www.patentsview.org/web/`. The main

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. (2009)'s updated dataset. These authors use inventor names and addresses as well as patent characteristics to generate unique inventor identifiers, so we use this to complement the PAB. 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.

4.2 Variables and Summary Statistics

Table 1: Descriptive Statistics for NPE and Comparable USPTO Patents

	Panel 1: NPE Patents			**Panel 2: USPTO Patents**		
Variables	**Mean**	**Median**	**Sd**	**Mean**	**Median**	**Sd**
	—Original Variables —					
Log Originating Entity Size	5.01	4.97	2.82	6.96	7.53	2.82
Individual Inventor	0.06	0	0.23	0.01	0	0.10
Forward Citations	31.1	11.3	60.0	18.1	5.4	41.2
Backward Citations	22.7	8.0	52.6	14.5	6.0	38.2
Age	13.6	14.0	5.2	10.8	10.0	6.0
Claims	19.2	17.0	14.9	18.5	17.0	1300
Sale Indicator	100	100	0	1.4	0	11.6
	—Derived Variables —					
Litigation Risk	1.17	1.03	0.86	0.88	0.77	0.73
Distance to Originating Entity	0.33	0.27	0.27	0.30	0.27	0.22
Hotness	31.4	25.0	29.8	26.5	16.7	29.5
Lifetime Revenue	200	37.5	1950	n/a	n/a	n/a

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. 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 A.2 for detail on variable construction.

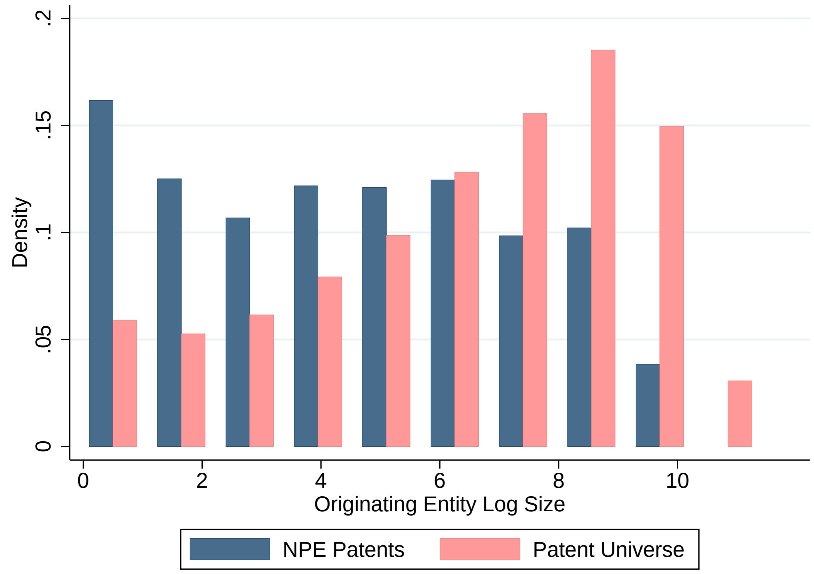
Table 1 reports patent-level summary statistics both for NPE-acquired patents and the comparable universe of patents applied for from the USPTO during the same years, 1987 - 2014. "Comparable universe" means the data in the second panel is weighted so that the distribution of IPC3 technology classes is the same as for the NPE data in the first panel.[10] The table introduces various variables that we use in order to understand what impacts the decision to sell to NPEs, license from NPEs, and the prices at which patents are sold and licensed. As the NPEs

reason is to identify the citing entity characteristics for the event study.

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

buy multiple patents in deals, the normalized mean and standard deviation of acquisition price[11] at the deal level are $1.54 million and $3.54 million, respectively.

FIGURE 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.

We define log originating entity size as the log of the number of patents (including subsequently granted applications) in the entity's portfolio at the time of the patent's grant. Individual inventor indicates that the patent was registered to a single inventor not at a firm. A comparison of means for NPE-owned and all USPTO patents shows that NPE patents come from smaller entities than average. Figure 3, which shows the distribution of originating entity size for NPE and all patents, provides more details on this comparison. We note in Figure 3 that the typical patent sold to NPEs comes from a much smaller patent portfolio than average. This should not be surprising as we saw in Section 3 that smaller firms have more to gain from the NPEs' larger network and legal resources relative to large firms. We also see that individual inventors are much more heavily represented in patents that are sold to NPEs. This illustrates clearly the role of NPEs in buying patents from small firms and independent inventors.

Backward citations are the number of patent references in the patent application and forward citations are the number of times a patent is cited in subsequent applications. 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

[11] These values are normalized for confidentiality purposes, per our data use agreement.

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 can be found in Appendix A.2.

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 NPEs 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 (although see Abrams and Sampat (2019) and Abrams et al. (2018) for evidence that citations may be a poor proxy for value, especially in this context). The average age of the patent is 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.

We construct a patent distance metric, first introduced in Akcigit et al. (2016) and described in more detail in Appendix A.2.4, as a measure of technological similarity of two patents. Using this metric, we calculate the average distance between a patent and the patent portfolio of its originating firm. In both the NPE and USPTO data, the distribution of distance is slightly right-skewed and somewhat higher for NPE-held patents, with a mean of 0.33, compared to 0.30 for all patents.

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 A.2.5 for greater detail). Patents acquired by NPEs have a higher probability of being litigated. 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 18.3% higher average hotness than the universe. Lastly, the lifetime revenue is normalized to 200 following a similar procedure to citations, discussed in greater detail in Appendix A.2.3.

In the appendix, we report additional summary statistics. In particular, B.1 reports acquisition-level summary statistics on all acquisitions through which the NPEs acquired patents for over a decade beginning in the 2000s and B.2 reports patent-licensee level summary statistics.

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.

5.1 Patent Sale (Predictions 1 and 2)

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

$$\textbf{Patent Sale}_{i,j,t} = \alpha + \beta \times X_{i,j,t} + \psi \times Z_{i,j,t} + \gamma_j + \eta_t + \epsilon_{i,j,t} \tag{15}$$

Patent Sale$_{i,j,t}$ is a dummy variable that is "1" if patent i in technology category j, with application year t is ever sold to an NPE and "0" otherwise.[12] $X_{i,j,t}$ is a vector consists of the main variables of interest: *Log Entity Size*, *Distance to Innovating Entity*, *Litigation Risk*, *Firm Size × Litigation Risk*, *Firm Size × Distance*. In addition, $Z_{i,j,t}$ contains control variables: *Total Claims*, *Lifetime Forward Citations*, *Backward Citations*, and *Hotness Index*. In the same specification, γ_j is a set of technology category dummies, measured at three-digit IPC level; η_t is a set of application year dummies 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 which effectively tests predictions 1 and 2 of the model.

Table 2: The Determinants of the Patent Sale Decision

	(1)	(2)	(3)	(4)
Dependent Variable:	**Sale Indicator**	**Sale Indicator**	**Sale Indicator**	**Sale Indicator**
Originating Entity Size	-0.145**	-0.146**	-0.157**	-0.164**
	(0.020)	(0.020)	(0.020)	(0.019)
Litigation Risk		0.034	0.048	0.054
		(0.045)	(0.044)	(0.043)
Entity Size × Litigation Risk		-0.066**	-0.066**	-0.055**
		(0.018)	(0.018)	(0.019)
Distance to Originating Entity			0.426**	0.794**
			(0.087)	(0.110)
Entity Size × Distance				0.283**
				(0.025)
IPC-3 Controls	Yes	Yes	Yes	Yes
Application Year Control	Yes	Yes	Yes	Yes
R-squared	0.011	0.012	0.012	0.013

**, **. Significant at 5% and 1% level respectively.*

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. Note that probability of sale is multiplied by 100 for greater legibility. In addition to application year and class controls, we also control for the individual inventor indicator, total claims, lifetime forward citations, backward citations, and hotness. Please see the text and Appendix A.2 for variable definitions and normalization.

[12] Here we use a linear probability model but find similar results with a probit and logit.

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 addition to being statistically significant, the magnitude is economically important as well. A one standard deviation increase in log firm size decreases the probability of sale by 0.409 percentage points, which is 30% of the mean. Moreover, column 2 shows litigation risk as insignificant, a result that is compatible with the ambiguous effect of litigation risk on patent sale in the model in Equation 12. The interaction term (*Firm Size* $\times$ *Litigation Risk*) is negative, which implies that litigation risk becomes a relatively more important factor among small firms for patent sale. The findings of the effect of firm size on probability of sale and the interaction term on litigation risk confirm prediction 1.

In column 3, we 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 to be sold. In column 4, we introduce the interaction of distance with firm size. The positive coefficient indicates that changes in distance have a larger effect on probability of sale for large firms. The two coefficients discussed in columns 3 and 4 confirm prediction 2. Note that a standard deviation increase in distance (0.224) increases the probability of sale by .18 percentage points, which is 13.1% ($= 0.224 \times 0.794/1.36$). Then, considering the interaction term (*Firm Size* $\times$ *Distance*), we see for larger firms this effect is even more pronounced.

5.2 Acquisition Price (Predictions 3 and 4)

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.

Our specification is similar to Equation 15, with dependent variable **Log Acquisition Price**$_{i,j,t}$, which is the log normalized acquisition price for deal i in year t. $X_{i,j,t}$ is a vector consisting of the main variables of interest, taken as means at the deal level, *Distance*, *Firm Size*, *Litigation Risk*, *Firm Size* $\times$ *Litigation Risk*, and *Firm Size* $\times$ *Distance*. $Z_{i,j,t}$ is a vector consisting of control variables, again taken as means at the deal-level: *Total Claims*, *Lifetime Forward Citations*, *Backward Citations*, *Hotness*, and *Deal Size*. Similar to Table 2, γ_j is a set of technology category dummies, taken as the mode of the deal at the three-digit IPC level; η_t is a set of transaction year dummies, and $\epsilon_{i,t}$ is the error term, where we use robust standard errors.

Columns 1-3 in Table 3 document that NPEs pay more to larger firms which confirms prediction 3 of the model. In columns 2 and 3, we find that NPEs pay less the more distant a patent is to the innovating firm, verifying prediction 4. The magnitudes are economically important as well. In column 3, we see a 1% increase in the size of an inventing firm increases the acquisition price by 0.103%. A standard deviation increase in distance (0.27) decreases acquisition price by 33.3% ($= -123.18 \times 0.27$). Litigation risk on its own is insignificant. This is consistent with Equation 14, which predicted an ambiguous effect of litigation risk on price. However, litigation risk has a more negative effect on price for larger firms, who may be more likely to use NPEs for distance

Table 3: The Determinants of Patent Acquisition Price

Dependent Variable:	(1) Log Price	(2) Log Price	(3) Log Price
Originating Entity Size	4.419**	8.518**	10.333**
	(1.407)	(1.480)	(1.617)
Distance to Originating Firm		-104.582**	-123.180**
		(11.531)	(12.798)
Litigation Risk			-5.955
			(7.810)
Firm Size × Litigation Risk			-3.331*
			(1.683)
Firm Size × Distance			-17.306**
			(4.598)
IPC-3 Controls	Yes	Yes	Yes
Transaction Year Control	Yes	Yes	Yes
Application Year Control	Yes	Yes	Yes
R-squared	0.266	0.305	0.313

**, **. Significant at 5% and 1% level respectively.*

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 modal IPC3 in parentheses. Note that acquisition price is multiplied by 100 for greater legibility. In addition to year and class controls, we also control for total claims, lifetime forward citations, backward citations, hotness, and deal size. Please see the text and Appendix A.2 for variable definitions and normalization.

reduction purposes.

5.3 Licensing Fee (Prediction 5)

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

$$\textbf{Log Licensing Fee}_{i,l,j,t} = \alpha + \beta \times X_{i,j,t} + \psi \times Z_{i,j,t} + \Gamma \times W_{i,l,j,t} + \gamma_j + \eta_t + \epsilon_{i,l,j,t} \qquad (16)$$

Our dependent variable **Log Licensing Fee**$_{i,l,j,t}$ is the log normalized licensing fee received for patent i, from licensee j, in year t. Since this specification concerns prices paid at the licensing level, we have an additional index l and variables of interest $W_{i,l,j,t}$ that were not present in Sections 5.1 and 5.2. The variable of interest in vector $X_{i,j,t}$ is *Litigation Risk*. $Z_{i,j,t}$ is a vector including entity-level and patent-level controls, which are *Total Claims*, *Backward Citations*, *Hotness*, *Lifetime Forward Citation*, and *Application Year*. γ_j is a set of IPC3 technology class dummies and η_t are transaction year dummies. $W_{i,l,j,t}$ contains variables of interest related to licensee l for patent i such as *Distance to Licensee* , *Licensee Size*, *Licensee Size* × *Distance*, and *Licensee Size* × *Litigation Risk*. Robust standard errors are clustered at licensee level and results are reported in Table 4.

Table 4, column 1 shows that distance has a negative relationship with the log licensing fee, though only significant at the 10% level. This effect becomes more significant when we control

Table 4: The Determinants of Patent Licensing Fee

Dependent Variable:	(1) Log Licensing Fee	(2) Log Licensing Fee	(3) Log Licensing Fee
Distance to Licensee	-117.491	-101.587*	-101.525*
	(62.124)	(39.375)	(39.327)
Licensee Size		32.672**	32.680**
		(8.806)	(8.801)
Licensee Size $\times$ Distance		3.027	3.074
		(10.009)	(10.001)
Litigation Risk			4.946**
			(1.283)
Licensee Size $\times$ Litigation Risk			0.480
			(1.183)
IPC-3 Controls	Yes	Yes	Yes
Transaction Year Control	Yes	Yes	Yes
Application Year Control	Yes	Yes	Yes
R-squared	0.064	0.211	0.211

*, **. *Significant at 5% and 1% level respectively.*

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. Note that licensing fee is multiplied by 100 for greater legibility. In addition to year and class controls, we also control for total claims, lifetime forward citations, backward citations, hotness, and deal size. Please see Appendix A.2 for variable definitions and normalization.

for firm size in column 2 and further controls in column 3. This is in line with prediction 5 of the model. We also see that the licensing fee is increasing in litigation risk and firm size.

The magnitude is economically important too. Using column 3 as our reference, we find a standard deviation increase in distance (0.33) decreases the fee by 33.5% $(= 101.5 \times 0.33)$. We also see that an increase of 1% in licensee firm size increases licensing fee by 0.327%. Litigation risk also plays an important role quantitatively. A standard deviation increase in litigation risk (0.86) increases the licensing fee by 4.25 % $(= 0.86 \times 4.946\%)$. In the model, we found an ambiguous effect of litigation risk on the licensing fee as in Equation 13. A positive, but modest effect of litigation risk on log licensing fee is compatible with legal resources being an important feature of the NPEs' business model.

5.4 Downstream Innovation

We use forward (subsequent) citations received by the focal patent to proxy for downstream innovation. In order to understand the effect of NPE patent acquisitions on patent citations, we want to build a matching set of patents that were not acquired by NPEs and follow their citation patterns. As a first step in our research design, we match NPE patents with those in the USPTO universe by exactly matching on their application year and number of forward citations prior to NPE-acquisition period and the technology category (IPC at three digit level) via coarsened exact matching algorithm (CEM).[13] These matched pairs of patents constitute the main sample for the event study.

To probe the validity of our design, we test whether there is any effect of NPE acquisition before the event occurs. Our strategy is similar to Jaravel et al. (2018), in terms of testing for event pre-trends by looking at a full set of leads and lags ($k = -5, ..., 5$, excluding -1) for matched and treated patents (L_{ik}). Our dependent variable is the number of forward citations received by patent i at time t. The dynamic effects associated with lags are denoted as $\{\beta(k)\}_{k=-5}^{5}$. Second, we include a period event dummy *After* that is equal to 1 post event and is common to real and placebo acquired patents (after). The predicted effect is denoted by β^{All}. Lastly, we add three distinct sets of fixed effects: age fixed effects (a_{it}), transaction year fixed effects (η_t) and patent fixed effects (α_i).

We estimate the following specification with OLS:[14]

$$\mathbf{Y}_{i,t} = \sum_{k=-5}^{5} \beta_k 1_{\{L_{it}=k\}} + \beta^{All} \times After + \sum_{j=1}^{20} \lambda_j 1_{\{age_{it}=j\}} + \sum_{m=1998}^{2014} \eta_m 1_{\{t=m\}} + \alpha_i + \epsilon_{i,t} \qquad (17)$$

We combine all NPE patents together with placebo patents and estimate the model using specification 17. Figure 4a plots the β's which indicate the number of forward citations relative to year of NPE acquisition. We see a relative decline over time in the number of citations after acquisition.

In order to further understand the fall in citations, we split the NPE sample into top and bottom value decile and combine them with the placebo patents in Figure 4b.

F-test for Pretrends We can formally test the hypothesis that point estimates are the same before and after NPE acquisition. The null hypothesis is:

$$H_o^{before}: \ \beta_{-5} = \beta_{-4} = \beta_{-3} = \beta_{-2} \qquad\qquad H_o^{after}: \ \beta_5 = \beta_4 = \beta_3 = \beta_2 = \beta_1$$

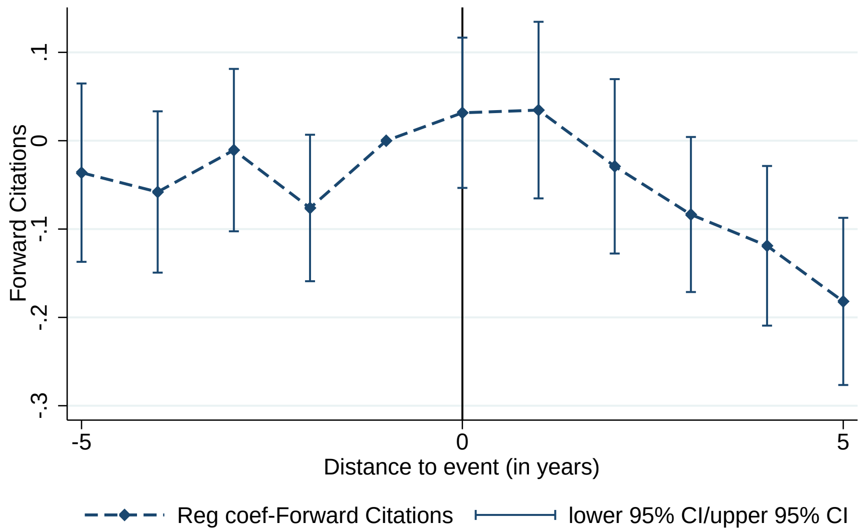
Our results indicate that we cannot reject the hypothesis that the point estimates are all the same before NPE acquisition, but we can after NPE acquisition. Briefly, Table 5 indicates that there are no pretrends but an effect after NPE acquisition.

The interesting finding in Figure 4a is the decline in follow-on innovation after the patent is acquired by an NPE. We next examine the temporal pattern of citations for the top and bottom decile of value, with the results reported in Figure 4b. The decline in citations is most pronounced for high value patents but not at all apparent for low value patents. The magnitude of the decline is 1.05 over five years, which is sizable, given the mean number of citations for high value patents

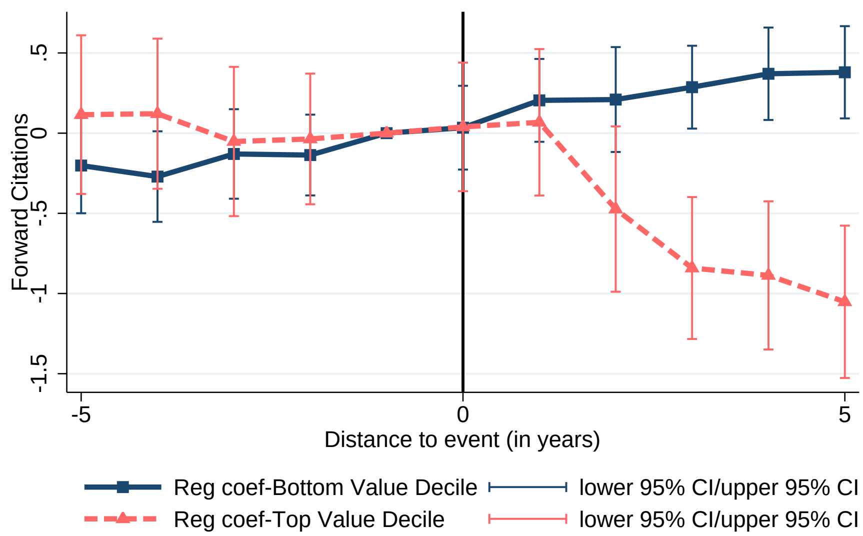
[13]The details regarding matching algorithm can be found at `http://gking.harvard.edu/files/gking/files/cem-stata.pdf`.

[14]Adding the fixed effects above generates a collinearity problem. We follow the literature and drop the first age dummy as well as the coefficient on the -1 period with (which shows up as 0).

Figure 4: Event Studies



(a) Forward Citations Relative to NPE Acquisition



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

Notes: Figure (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 includes controls for patent, age, and year fixed effects. Robust standard errors are clustered at NPE acquired patent level as error bars. Figure (4b): This figure reports a similar analysis for NPE-acquired patents located at top and bottom value decile, placebo patents, and includes controls for patent, age, and year fixed effects. Robust standard errors are clustered at NPE acquired patent level as error bars.

Table 5: Testing For Dynamic Effects, P values from F-test

	Panel A(β)	Panel B(β^{top})
For H_0^{Before}	0.43	0.83
For H_0^{After}	0.00001	0.00001

Notes: This panel reports the p-values of F-tests for equality of the β Real k coefficients from specification 17, before and after NPE acquisition, as specified by the hypotheses H_0^{Before} and H_0^{After}.

over five years is 9.61. This suggests that downstream innovative activity slows down with the acquisition of a patent by NPEs. Given our study design, it seems likely that the effect of NPE acquisition on downstream citations is causal. A pure selection effect would predict an increase in forward cites among the most valuable patents after NPE acquisition. The decline of downstream innovation and the impact of NPEs on overall innovation is something we explore further in the next section.

6 Numerical Analysis

So far, we have seen that the empirical results lend support for the model introduced in Section 3 and the model's predictions on prices and likelihood of sale. An important question remains: what is the overall effect of NPEs on innovation in the economy? To answer this question, we calibrate our model as described in this section.

In order to ensure that probability of infringement remains between 0 and 1, we consider the following form for the probability j infringes i: $\tau = (1 - \phi)\lambda$, where ϕ is the probability of non-innovator infringement and $\lambda \in [0, 1]$. Since our data does not contain direct information on the balance sheet of downstream firms j and k, we identify their financial returns by setting $\Omega_k = \Omega_j = \Omega$ and target some informative moments using the prices at which NPEs buy and license patents (see Section 6.1). Moreover, we target the mean $\beta = \mathbb{E}[\beta_i]$ legal strength/legal resources of firm i. This leaves our model with the following 10 parameters to be calibrated:

$$\Theta \equiv [\eta, \kappa, \nu_i, \Omega, \pi, \phi, \lambda, \beta, \beta_{npe}, \xi]$$

We calibrate our parameters in two steps. For three of the parameters, we do an external calibration without simulating the model. For the rest of the parameters, we 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 Θ, using a simulated annealing algorithm, as follows:

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

6.1 Identification

Here we describe the identification of each parameter. The externally calibrated parameters (η, ξ, ν_i) are chosen as follows:

1,2. *R&D cost parameter and convexity of cost function, η and ξ:* These parameters are taken from (i) the external innovation parameter calibrated in Akcigit and Kerr (2018) and (ii) a large literature summarized in Akcigit and Kerr (2018) that estimates the innovation production function to be a quadratic.

3. *Mean distance to innovating entities, ν_i:* This parameter is the mean distance of patents within firms that sell to the NPE. Note that distance is measured as distance to innovating entity. It is calculated from NPE data, using the universe of upstream firms.

The internally calibrated parameters are:

1. *Profit of licensing entity, Ω:* This parameter is a proxy for the value of a patent to the potential licensee before distance adjustment.

2. *Profit of innovating entity, π:* This parameter is a proxy for the value of a patent to the inventing entity before distance adjustment.

3. *Probability of winning in court (innovating entity), β:* This parameter captures the strength of the 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 $\sim U[0, \kappa]$ and κ is the maximum value.

6,7. *Probability producer infringement and downstream infringement probability, ϕ, τ:* This determines the probability of an infringement by a non-innovating producer or downstream innovator.

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

M_1. *Price upstream producer sells to NPE:* This comes from NPE acquisition cost data. This price, together with the next moment M_2, informs us about the legal strength of the upstream producer β and NPE β_{npe}.

M_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. The two prices (M_1 and M_2) together inform us about the legal strength (β and β_{npe}) of upstream producer and NPE.

M_3. *Correlation between the distance of upstream to NPE and price:* This moment informs us about the profit size π of the upstream producer.

M_4. *Correlation between the price sold and bought from NPE:* For this moment, we compute the correlation between the acquisition cost and the lifetime revenue. This informs us about the profit size of the downstream producer Ω.

M_5. *Innovation intensity of the downstream innovator:* This is taken as the percentage of patents in the NPE set that are cited by downstream innovators. This informs us about the probability of innovator infringement τ.

M_6. *Probability of sale to NPE:* The probability of a sale is taken as the average probability of reassignment in the patent class (IPC4) where NPEs are most active. This informs us on the maximum search cost of producer to finding NPE κ.

M_7. *Proportion of infringement from non-innovators:* Since this informative moment is not readily available in the data, we try three alternative values for this target. In our benchmark estimation in Section 6.2.1, we assume that 50% of all infringements come from non-innovators, i.e., we set $\phi/\alpha = 0.5$. In sections 6.2.2 and 6.2.3, we try two other extremes by setting $\phi/\alpha = 0$ and 1, respectively, and re-estimate all other parameters in each case.

6.2 Calibration

The next three sub-sections evaluate the three conditions on the source of infringement ($\phi/\alpha \in \{0, 0.5, 1\}$). Because we do not know the proportion of infringement that comes from firms innovating versus firms not innovating, we examine the conditions of the model under three different scenarios discussed in our targeting moments. First, we set $\phi/\alpha = 0.5$ as our benchmark. There is some evidence for this in the literature. Kempf and Spalt (2018) find that in class-action SEC filings they define as meritorious, about half of these filings target highly innovative firms. We then check for two extremes in order to explore the sensitivity of the results. In particular, the second value we take is $\phi/\alpha = 0$ (no infringement from non-innovators) and the third is $\phi/\alpha = 1$ (all infringement from non-innovators). For any given set of calibrated values $\phi/\alpha \in \{0, 0.5, 1\}$, we further explore the behavior of the model by changing ϕ and β_{npe} while keeping all other parameters at their calibrated values in Figures 5, 6, and 7.

6.2.1 Case 1: Innovators contribute to half of the infringement, $\phi/\alpha = 0.5$

This section is our benchmark section for thinking about infringement. We assume half of the infringement comes from innovators, i.e. $\phi/\alpha = 0.5$. We thus target this value in our calibration. The matched moments are described in Table 6, and the estimated parameters together with their descriptions are provided in Table 7.

Table 6: Moments

Moment	Data	Model
1. Price upstream producer sells to NPE	1	1
2. Average price NPE sells to downstream	1.54	1.52
3. Correlation between distance of upstream to NPE and price	-0.07	-0.07
4. Correlation between price sold and bought from NPE	0.37	0.31
5. Innovation intensity of downstream innovator	0.74	0.76
6. Probability of sale to NPE (reassignment rate in NPE's top class)	0.23	0.22
7. Proportion of infringement from non-innovators	0.50	0.50

Table 7: Parameter Values

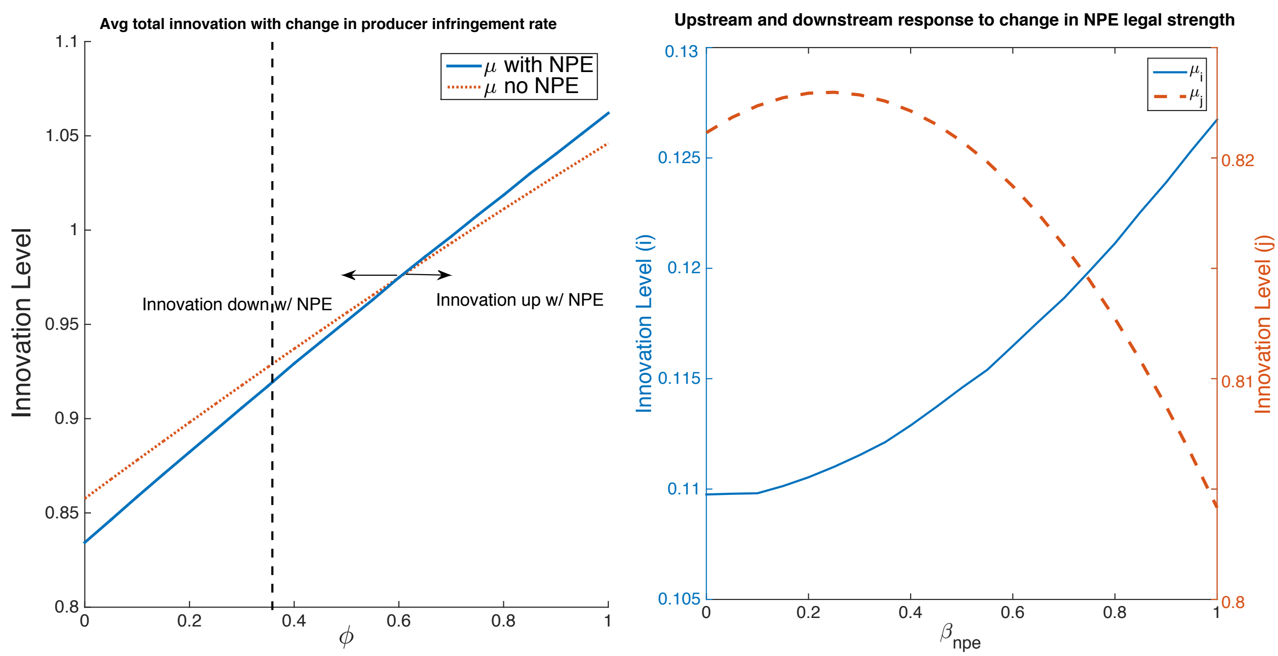
Parameter	Description	Value	Main Identification
	— Panel A. External Calibration —		
ξ	Curvature of R&D cost	2	Akcigit and Kerr (2018)
η	R&D cost scale	0.25	Akcigit and Kerr (2018)
ν_i	Mean distance of upstream to NPE	0.30	NPE Distribution
	— Panel B. Internal Calibration —		
Ω	Return of licensing entity	3.50	Correlation of prices
π	Return of innovating entity	0.11	Correlation between p_i and d_i
ϕ	Probability non-innovator infringement	0.36	Share of infringers
τ	Downstream infringement risk	0.47	R&D intensity of j and share of infringers
β	Probability of upstream firm winning	0.36	Correlations, Prices
β_{npe}	Probability of NPE winning in court	0.99	Prices
κ	Max. Search Cost	2.35	Pr(sale)

Notes: All parameters are estimated jointly.

Table 6 shows that the model replicates the empirical moments very well. Note the negative correlation between distance and price, indicating the role of NPEs in buying (and paying less for) more distant patents to the innovating firm. When it comes to parameter values, of particular interest is the difference between β and β_{npe}; we see that the likelihood of winning in court is almost three times larger for NPEs than the average firm, which highlights the *stick-up artist* role of NPEs. The second role of NPEs as *benign middleman* is evident from the sizable value of Ω, which captures the greater returns from allocating patents to a better user k.

In Figures 5a and 5b, we take the estimated values (from targeting $\phi/\alpha = 0.5$) and shift the parameter values of proportion of infringement from non-innovators (ϕ in Figure 5a), and the legal strength of the NPEs (β_{npe} in Figure 5b). In Figure 5a, the y-axis contains the total innovation effort in the economy, i.e., $\mu = \mu_i + \mu_j$. The dotted red line plots the total innovation effort when there is no NPE, and the solid blue line shows the same total innovation effort for the case where the economy features an active NPE. When the solid line is above the dotted line this indicates that, for the corresponding value of ϕ, the economy with NPEs produces more innovation compared to an economy without any NPEs, and vice versa. In Figure 5b, we track innovation of i (solid line) and downstream innovation of j (red dotted line) as legal strength of the NPEs changes.

FIGURE 5: UPSTREAM AND DOWNSTREAM INNOVATION WITH AND WITHOUT NPE, TARGET $\phi/\alpha = 0.5$



(A) CHANGE IN INNOVATION WITH CHANGE IN ϕ (B) CHANGE IN INNOVATION WITH CHANGE IN β_{npe}

Notes: These figures report changes of innovation in response to the listed parameters, at values calibrated for $\phi/\alpha = 0.5$ Figure (5a): This figure illustrates the response of overall innovation to changes in the rate of non-innovator infringement, ϕ. There is a vertical dashed line at the estimated value of ϕ. Figure (5b): This figure illustrates the upstream and downstream innovation rate response to a change in the legal strength of the NPE, β_{npe}.

These exercises allow us to evaluate the different worlds under which the NPEs' role can be more or less productive. Figure 5a shows that at the estimated parameter values ($\phi = 0.36$, noted by the vertical dashed line), we see a small decline in the aggregate rate of innovation, 1 percentage point with NPEs. Even though the average number is informative, decomposition of the effect shows that upstream innovators benefit from NPEs in comparison to downstream innovators. More specifically, at the estimated parameter value, there is a 1.8 percentage point (13.6%) increase in the innovation rate of upstream firms while there is a 2.8 percentage point (3.6%) decline in the innovation rate of downstream firms.

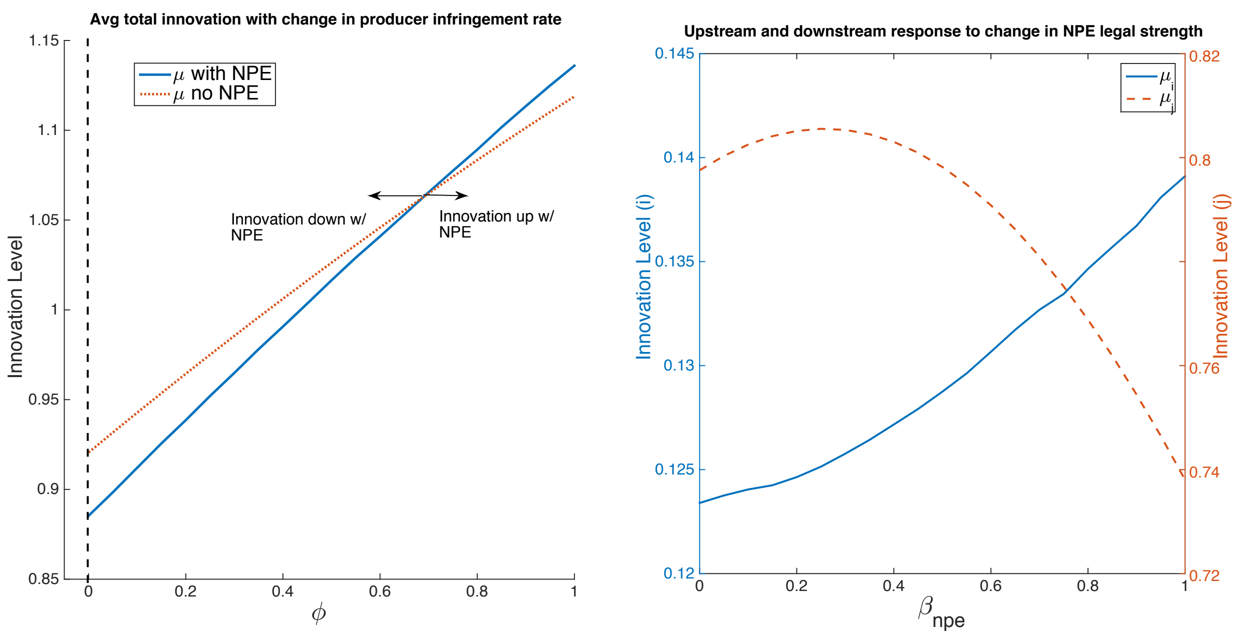
In Figure 5b, we can clearly see the heterogeneous impact of NPEs on i and j when we plot the changes in the innovation rate as a function of the legal strength of the NPE, β_{npe}, for the specified value of $\phi/\alpha = 0.5$. Here we note that as the legal capacity of NPEs increase j's innovation will briefly go up when $\beta_{npe} < \beta$, as j is more likely to face a weaker legal adversary, but overall we see i and j's innovation move in the expected direction. This speaks to a very basic conclusion that serves as the foundation for the rest of our analysis. The NPEs' legal strength will have a positive impact on i's innovation, since it increases the return to a patent if there is any infringement, and a negative impact on j's, since j has to pay more in case it infringes an existing patent which might be defended by an NPE.

6.2.2 Case 2: All infringements come from innovators, $\phi/\alpha = 0$

In this section, we target a moment in our calibration assuming all infringement comes from innovators, i.e. $\phi/\alpha = 0$. In order to save some space, the estimated parameters together with their descriptions and the calibrated moments are provided in Appendix C.

In the following figures, we again shift the parameter values of probability of infringement from non-innovators ϕ and the legal strength of the NPE, β_{npe}.

FIGURE 6: UPSTREAM AND DOWNSTREAM INNOVATION WITH AND WITHOUT , TARGET $\phi/\alpha = 0$



(A) CHANGE IN INNOVATION WITH CHANGE IN ϕ (B) CHANGE IN INNOVATION WITH CHANGE IN β_{npe}

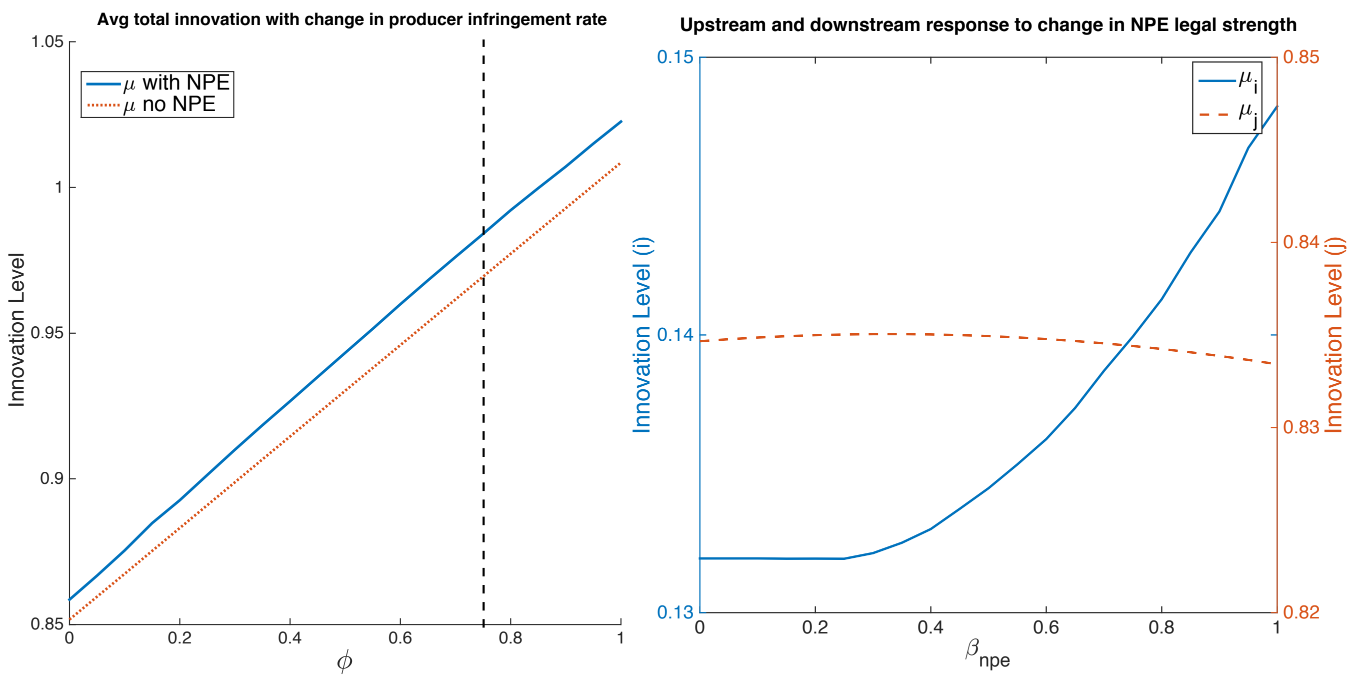
Notes: These figures report changes of innovation in response to the listed parameters, at values calibrated for $\phi/\alpha = 0$. Figure (6a): This figure illustrates the response of overall innovation to changes in the rate of non-innovator infringement, ϕ. There is a vertical dashed line at the estimated value of ϕ. Figure (6b): This figure illustrates the upstream and downstream innovation rate response to a change in the legal strength of the NPE, β_{npe}.

The overall changes in innovation efforts in response to the underlying changes in ϕ and β_{npe} look very similar to Figures 5a and 5b. Just like in Case 1, the overall innovation effort declines when there are NPEs in the market. The effect when there are no non-innovating infringers is more pronounced, as innovation drops by 4 percentage points. This is again due to the fact that NPEs discourage follow-on innovations when there is an associated risk of infringement.

6.2.3 Case 3: Innovators contribute to none of the infringement, $\phi/\alpha = 1$

In this section, we target values such that all of the infringement comes from non-innovators, i.e. $\phi/\alpha = 1$. The estimated parameters together with their descriptions are provided in Appendix Table B3 and the matched moments are described in Appendix Table B4.

FIGURE 7: UPSTREAM AND DOWNSTREAM INNOVATION WITH AND WITHOUT NPE, TARGET $\phi/\alpha = 1$



(A) CHANGE IN INNOVATION WITH CHANGE IN ϕ

(B) CHANGE IN INNOVATION WITH CHANGE IN β_{npe}

Notes: These figures report changes of innovation in response to the listed parameters, at values calibrated for $\phi/\alpha = 1$. Figure (7a): This figure illustrates the response of overall innovation to changes in the rate of non-innovator infringement, ϕ. There is a vertical dashed line at the estimated value of ϕ for this targeted value. Figure (7b): This figure illustrates the upstream and downstream innovation rate response to a change in the legal strength of the NPE, β_{npe}.

We see from Figures 5a, 6a, and 7a that when most infringement comes from non-innovating firms, i.e. $\phi \approx 1$, NPEs have an overall positive impact on innovation. This makes intuitive sense because here NPEs increase ex-ante incentives of upstream firms but doesn't reduce downstream innovation. However, as we can see from Figures 5a and 6a, if most infringement is due to innovators ($\phi \approx 0$), then NPEs have an overall negative impact on innovation. Further research on the proportion of infringement due to firms in the process of innovating versus copycats could help us clarify which world we are in.[15]

Our results from these three exercises indicate that the implications of the effect of NPEs on overall innovation boil down to the following question: how prevalent are non-innovating firms in infringement? If most of the infringement is due to non-innovators, the NPEs' role is that of protecting innovators and will tend to increase innovation. If most of the infringement comes from innovators, the NPEs could slow overall innovation, although not by a great deal according to our calibration. Our results provide preliminary evidence on these distinguishing factors in a general equilibrium setup. Further research should focus on the degree to which infringers are solely producers or in fact innovators themselves.

7 Conclusion

What do non-practicing entities do, and how do they impact innovation and technological progress? Despite the heated debates on this issue in both academic and policy circles, the direct evidence on their business models is quite limited. In this paper, we attempt to answer these questions both empirically and theoretically.

On the theoretical side, the model provides new insights into how NPEs operate. In line with standard approaches, the model allows for NPEs to purchase patents and license them to other firms without using those patents for production. Our model highlights two crucial roles for the NPEs: First, they can purchase patents that are more litigation-prone and use them to threaten other firms to extract more licensing revenue. While this is commonly associated with "trolling," there is a positive contribution of this role: NPEs create value by defending the intellectual property of small firms who do not have sufficient means to defend their patents. While this protection incentivizes small firms to innovate more, the same action discourages large firms who might be infringing on small firm patents. The second role of the NPEs have been as 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.

The elements in our model allow us to come up with a number of relevant and testable implications. We are able to evaluate these predictions by examining transaction-level data from large NPEs for the first time. We find that NPEs buy non-core patents from smaller originating entities, and especially litigation-prone patents. They pay more for patents that come from large

[15] Also note that the innovation from j, μ_j, is very unresponsive to changes in β_{npe}. This is because in targeting $\phi/\alpha = 1$ (and matching $\phi/\alpha = 0.97$) we get only a very small probability that j will infringe i as the targeted value for $\tau = 0.03$.

firms and for those that are more core to the seller's business. On the licensing side, NPEs attain higher fees for those patents that have smaller distance to the licensee. We also find that citations to NPE-held patents decline around the time of acquisition. This effect is not significant for low value patents, but is most pronounced for those with higher value.

In our final exercise, we calibrate the model to attempt to estimate a net effect of NPEs on innovation. A crucial component of the model is the amount of patent infringement due to innovators and that due to producers who do not innovate. If a large amount of infringement comes from non-innovating producers, NPEs have a positive effect on innovation. If most infringement comes from downstream producers, NPEs generate a net negative effect.

We believe that both the framework and new facts put forth in this paper can shed light on the debate of the role of NPEs for overall innovation. The welfare and innovation consequences of NPEs is a policy issue that continues to be relevant and much additional work is needed on this crucial topic. Our paper suggests further exploration is warranted. For instance, one important aspect noted in this paper is the degree to which infringement comes from producing entities as opposed to those who both produce and innovate. Another area is the degree to which infringement truly hampers the capability of small firms to protect their technology. We hope this paper can help provide a foundation for further research on these topics as intellectual property and its secondary market remain central to discussions of innovation.

References

Abrams, D. S., U. Akcigit, and J. Grennan: 2018, 'Patent Value and Citations: Creative Destruction or Strategic Disruption?'. Working Paper.

Abrams, D. S. and B. Sampat: 2019, 'Drug Patent Citations and Value'. Working Paper.

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr: 2018, 'Innovation, Reallocation, and Growth'. *American Economic Review* **108**(11), 3450–91.

Aghion, P. and P. Howitt: 1992, 'A Model of Growth Through Creative Destruction'. *Econometrica* **60**(3), 323–351.

Ahmadpoor, M. and B. Jones: 2017, 'The Dual Frontier: Patentable Inventions and Prior Scientific Advance'. *Science* **357**(6351), 583—587.

Akcigit, U., M. A. Celik, and J. Greenwood: 2016, 'Buy, Keep, or Sell: Economic Growth and the Market for Ideas'. *Econometrica* **84**(3), 943–984.

Akcigit, U., J. Grigsby, and T. Nicholas: 2017, 'The Rise of American Ingenuity: Innovation and Inventors of the Golden Age'. Technical report. National Bureau of Economic Research WP23047.

Akcigit, U. and W. R. Kerr: 2018, 'Growth through Heterogeneous Innovations'. *Journal of Political Economy* **126**(4), 1374–1443.

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**.

Allison, J. R., M. A. Lemley, and J. Walker: 2011, 'Patent Quality and Settlement Among Repeat Patent Litigants'. *Georgetown Law Journal* **99**(6777), 12.

Ashtor, J. H., M. J. Mazzeo, and S. Zyontz: 2013, 'Patents at Issue: The Data behind the Patent Troll Debate'. *George Mason Law Review* **21**, 957.

Benhabib, J., J. Perla, and C. Tonetti: 2014, 'Catch-up and Fall-back through Innovation and Imitation'. *Journal of Economic Growth* **19**(1), 1–35.

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

Bloom, N., M. Schankerman, and V. R. John: 2013, 'Identifying Technology Spillovers and Product Market Rivalry'. *Econometrica* **81**(4), 1347–1393.

Bloom, N. and J. Van Reenen: 2002, 'Patents, Real Options and Firm Performance'. *The Economic Journal* **112**(478), C97–C116.

Blundell, R., R. Griffith, and J. Van Reenen: 1999, 'Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms'. *Review of Economic Studies* **66**(3), 529–554.

Caballero, R. and A. Jaffe: 1993, 'How High are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth'. *NBER Macroeconomics Annual* **8**(1), 15–86.

Chatterjee, S. and E. Rossi-Hansberg: 2012, 'Spinoffs and the Market for Ideas'. *International Economic Review* **53**(1), 53–93.

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

Cohen, L., J. M. Golden, U. G. Gurun, and S. D. Kominers: 2017, 'Troll Check: A Proposal for Administrative Review of Patent Litigation'. *Boston University Law Review* **97**, 1775.

Cohen, L., U. G. Gurun, and S. D. Kominers: 2016, 'The Growing Problem of Patent Trolling'. *Science* **352**(6285), 521–522.

Cohen, L., U. G. Gurun, and S. D. Kominers: 2018, 'Patent Trolls: Evidence from Targeted Firms'. *Management Science*. forthcoming.

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

Czarnitzki, D. and A. A. Toole: 2011, 'Patent protection, Market Uncertainty, and R&D Investment'. *The Review of Economics and Statistics* **93**(1), 147–159.

Eaton, J. and S. Kortum: 1996, 'Trade in Ideas: Patenting and Productivity in the OECD'. *Journal of International Economics* **40**(3), 251—278.

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

Feng, J. and X. Jaravel: 2017, 'Crafting Intellectual Property Rights: Implications for Patent Assertion Entities, Litigation, and Innovation'. LSE Working Paper.

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. and M. Schankerman: 2015, 'Patents and Cumulative Innovation: Causal Evidence from the Courts'. *Quarterly Journal of Economics* **130**(2), 317–369.

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

Garicano, L., C. Lelarge, and J. Van Reenen: 2016, 'Firm Size Distortions and the Productivity Distribution: Evidence from France'. *American Economic Review* **106**(11), 3439—3479.

Graham, S., A. Marco, and R. Miller: 2015, 'The USPTO patent examination research dataset: A window on the process of patent examination'.

Griffith, R., S. Redding, and J. Van Reenen: 2003, 'R&D and Absorptive Capacity: Theory and Empirical Evidence'. *Scandinavian Journal of Economics* **105**(1), 99–118.

Griffith, R., S. Redding, and J. Van Reenen: 2004, 'Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries'. *Review of Economics and Statistics* **86**(4), 883–895.

Grossman, G. M. and E. Helpman: 1991, 'Quality Ladders in the Theory of Growth'. *Review of Economic Studies* **29**(4), 43–61.

Haber, S. H. and S. H. Werfel: 2015, 'Why Do Inventors Sell to Patent Trolls? Experimental Evidence for the Asymmetry Hypothesis'. Stanford University Working Paper.

Haber, S. H. and S. H. Werfel: 2016, 'Patent Trolls as Financial Intermediaries? Experimental Evidence'. *Economics Letters* **149**, 64–66.

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*.

Henderson, R., A. Jaffe, and M. Trajtenberg: 1998, 'Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965Ð1988'. *Review of Economics and Statistics* **80**(1), 119–127.

Jaffe, A. and M. Trajtenberg: 1999, 'International Knowledge Flows: Evidence From Patent Citations'. *Economics of Innovation and New Technology* **8**(1-2), 105–136.

Jaravel, X., N. Petkova, and A. Bell: 2018, 'Team-Specific Capital and Innovation'. *American Economic Review* **108**, 1034–1073.

Kempf, E. and O. Spalt: 2018, 'Litigating Innovation: Evidence from Securities Class Action Lawsuits'. University of Chicago, Booth School of Business Working Paper.

Khan, B. Z.: 2014, 'Trolls and Other Patent Inventions: Economic History and the Patent Controversy in the Twenty-first Century'. *George Mason Law Review* **21**, 825.

Khan, B. Z.: 2015, 'Inventing Prizes: A Historical Perspective on Innovation Awards and Technology Policy'. *Business History Review* **89**(4), 631–660.

Kiebzak, S., G. Rafert, and C. E. Tucker: 2016, 'The Effect of Patent Litigation and Patent Assertion Entities on Entrepreneurial Activity'. *Research Policy* **45**(1), 218–231.

Klette, T. and S. Kortum: 2004, 'Innovating Firms and Aggregate Innovation'. *Journal of Political Economy* **112**(5), 986–1018.

Konig, M., J. Lorenz, and F. Zilibotti: 2016, 'Catch-up and Fall-back through Innovation and Imitation'. *Theoretical Economics* **11**(3), 1053–1102.

Kortum, S.: 1997, 'Research, Patenting, and Technological Change'. *Econometrica* **65**(6), 1389—1419.

Lai, R., A. D'Amour, and L. Fleming: 2009, 'The Careers and Co-authorship Networks of US Patent-holders, since 1975'. *Unpublished Working Paper, Harvard University*.

Lamoreaux, N. R. and K. L. Sokoloff: 1999, 'Inventors, Firms, and the Market for Technology in the Late Nineteenth and Early Twentieth Centuries'. *Learning by Doing in Markets, Firms, and Countries*. ed. by N. R. Lamoreaux, D. M. G. Raff, and P. Temin, pp. 19–60. University of Chicago Press.

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

Lemley, M. A. and R. Feldman: 2016, 'Patent Licensing, Technology Transfer, and Innovation'. *American Economic Review, Papers and Proceedings* **106**(5), 188–92.

Lentz, R. and D. T. Mortensen: 2008, 'An Empirical Model of Growth through Product Innovation'. *Econometrica* **76**(6), 1317–1373.

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

Marco, A. C. and R. Miller: 2017, 'Patent Examination Quality and Litigation: Is There a Link?'.

Nicholas, T.: 2013, 'Are Patents Creative or Destructive?'. *Antitrust Law Journal* **79**, 405–421.

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.

Perla, J. and C. Tonetti: 2014, 'Equilibrium Imitation and Growth'. *Journal of Political Economy* **122**(1), 52—76.

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.: 2010, 'The Dynamics of Transfer and the Renewal of Patents'. *RAND Journal of Economics* **41**(4), 686—708.

Serrano, C.: 2018, 'Estimating the Gains from Trade in the Market for Patent Rights'. *International Economic Review* **41**(4), 686—708. forthcoming.

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

Simonds, W. E.: 1871, *Practical Suggestions on the Sale of Patents*. Connecticut: Self-Published.

Toole, A. A. and C. Turvey: 2009, 'How Does Initial Public Financing Influence Private Incentives for Follow-on Investment in Early-stage Technologies?'. *Journal of Technology Transfer* **34**, 43–58.

Tucker, C.: 2014, 'Patent Trolls and Technology Diffusion : The Case of Medical Imaging'. Working Paper.

A Data and Variable Descriptions

A.1 Data Cleaning and Merging

A.1.1 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 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.[16]

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 whenever there is a change to their legal status (e.g. *"MONSANTO TECHNOLOGY LLC"*, *"MONSANTO TECHNOLOGY LLP"*).

In order to tackle the flaws generated by USPTO identifiers, we employ a conservative company name cleaning algorithm, 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.

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"*)

A.1.2 Data Merging

The PAB, LM, INV, and ND datasets are merged on patent number.[17] We keep only utility patents and drop those with application dates before 1987.[18] We keep patents assigned to individuals if the number of listed inventors is one. This is due to the difficulty in calculating portfolios for

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

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

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

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.[19] Each patent in PAB is matched with harmonized assignee identifiers.[20] 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.

A.2 Variable Construction

A.2.1 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 et al. (2001). Note that we limit our attention to patents with application year after 1987 in the final analysis.

A.2.2 Acquisition Price

The patents are purchased in bundles of firms at a given cost. We deflate this cost to real 2010 dollars. For our deal-level analysis, e.g. Table 3, some patent bundles combine patents that are not part of our analysis with those that are (e.g. we do not use international patents). In this case, we adjust the acquisition cost by the revenue weights representative of the overall outside and inside sample. For instance, if international patents are on average worth 1/5 of a US patent in the sample, we assign in the deal 5/6 of the cost to the patent in the sample for every 1/6 assigned to international patent.

A.2.3 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

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

[20] Found at http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/misc/data_cd.doc/assignee_harmonization/cy2014

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). We then normalize all revenue amounts so that total lifetime revenue is 200 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. If a patent realizes revenue while classified as abandoned, lapsed, or inactive, it is simply added to the normalized real revenue.

A.2.4 Distance

In order to quantify the distance between two technology classes, we define distance as in Akcigit et al. (2016), 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 cite X or Y or both.

Also following Akcigit et al. (2016), we construct a patent-to-entity distance metric. The distance of a patent p to an entity f's patent portfolio is calculated by averaging the 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'.

We set $\iota = \frac{2}{3}$ for our baseline results. Using the measure above, we constructed two different distance measures: distance to originating entity and distance to licensee.

A.2.5 Litigation Risk

To estimate the likelihood a patent may be involved in litigation, we use the linear probability model developed in Lanjouw and Schankerman (2001):

$$\mathbf{I}_{Litigated_{i,j,t}} = \zeta + \eta_i + \delta_t + \phi \times CO_{i,j,t} + \epsilon_{i,j,t} \tag{18}$$

Where the dependent variable is a dummy variable equaling 1 if the patent is ever litigated or a complaint is ever 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 following additional variables: examiner backward and forward citation percent, growth of technology categories, and entity fixed effects. We omit indicator variables for entity types (such as individual inventors, foreign firms operating in the U.S., and 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.

B Additional Tables and Figures

B.1 Deal-level Summary Statistics

Table A1 reports deal-level summary statistics on all deals through which the NPEs acquired patents from 2003 - 2014. Compared to Table 1, which reported patent level statistics, 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. Deals with individual inventors and small firms accounts combined accounts for fully two-thirds of the total acquisition deals. Only 5% of patent acquisition deals are struck with large originating firms.

The mean number of forward citations is substantially higher in Table A1 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, and has a mean of just over 7 years. The deal acquisition price is normalized so that the mean is 200. We first divide the acquisition prices of the deals by the number of patents involved. Then, we normalize this value so that mean is 200. Finally, we multiply the normalized values per deal with the number of patents involved to construct normalized acquisition prices for each deal.

B.2 Patent-level Summary Statistics

Table A2 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

Table A1: Patent Acquisition Deal Summary Statistics

Variables	Mean	p25	p50	p75	Sd
Distance to Originating Entity	0.32	0	0.29	0.53	0.28
Originating Patent Portfolio Size	762.56	2.31	6.54	200.40	2896.74
Log Originating Patent Portfolio Size	3.07	0.84	1.88	5.30	2.76
Litigation Risk	13.22	8.57	11.61	15.43	8.73
Individual Inventor	0.17	0	0	0	0.37
Total Claims	22.09	14.72	20	27	11.44
Lifetime Forward Citations	42.68	10.13	21.28	46.31	66.74
Backward Citations	20.11	6.34	10.57	20.67	30.98
Hotness	30.68	13.46	27.94	42.90	22.59
Deal Size	23.10	2	4	13	98.84
Age	7.09	4	7.11	10	4.27
Log Acquisition Price	5.91	4.99	5.85	6.74	1.27

Notes: Acquisition deal-level data from 2003 - 2014 includes all NPE patent acquisition deals in the U.S.

about 50% larger than the mean distance to originating entity (Table 1 and A1). This may lead one to believe that the reallocation of patents from originator to licensee via NPEs is inefficient, insofar as 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 B1), and the mean licensee size is several times larger than originating entity size. The correct comparison would be the mean empirical distance to licensee (0.47) versus the mean distance for a randomly chosen set of patents in the licensee's portfolio. The mean distance for the randomly chosen patents to the licensee portfolios is 0.64, which shows that the NPE-licensed patents have substantially smaller distances from the licensees than average.

Returning to Table A2, 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 A2 is aggregated at the patent-licensee-year level, a direct comparison with Tables 1 and A1 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. We have seen some suggestive findings from the summary statistics; we now make use of regressions to further investigate the impact of NPEs on innovation markets.

B.3 Additional Figures

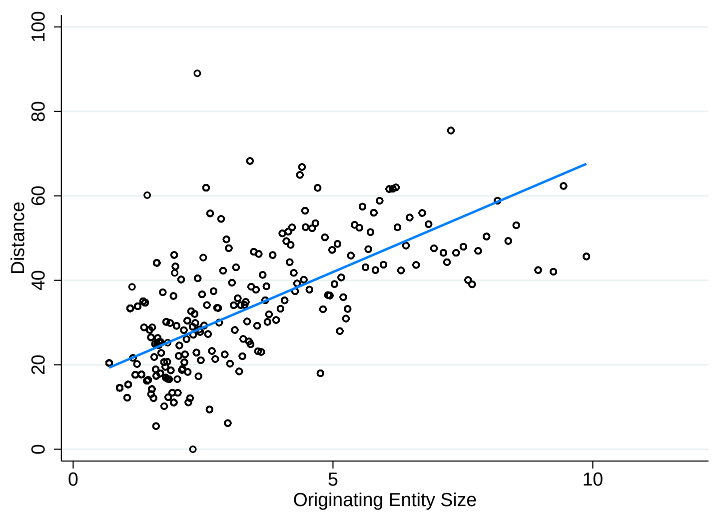
We noted in the discussion of Table A2 how the distance measure is correlated with firm size. Here we plot a scatter of the relationship to illustrate it is indeed the case.

Table A2: Licensing Transaction Summary Statistics

Variables	**Mean**	**p25**	**p50**	**p75**	**Sd**
Distance to Licensee	0.47	0.23	0.45	0.71	0.30
Distance of Random Patent to Licensee	64.35	33.38	76.77	93.49	33.34
Licensee Patent Portfolio Size	5095.57	64	867	5347	9120.51
Log Licensee Patent Portfolio Size	6.19	4.16	6.77	8.58	3.01
Litigation Risk	11.85	6.93	10.40	14.62	8.61
Individual Inventor	0.06	0	0	0	0.25
Total Claims	19.30	10	17	24	15.22
Lifetime Forward Citations	31.34	3.46	11.34	32.86	60.32
Backward Citations	22.64	4	8	17	52.40
Hotness	32.07	2.56	25	50	29.97
Age	11.98	8	12	15	5.15
Log Licensing Fee***	8.25	6.28	8.04	10.33	2.48

Notes: Patent-Licensee-Year level data includes all NPE licensing transactions from 2008 - 2014. Please see the text and Appendix A.2 for variable definitions and normalization.

Figure B1: Distance and Originating Entity Size



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

C Calibration

Here we report the calibrated values for when we targeted $\phi/\alpha = 0$ and $\phi/\alpha = 1$. The figures from our selected exercises can be found in Section 6, Figures 6 and 7.

Table B1: Parameter Values, target $\phi/\alpha = 0$

Parameter	Description	Value	Main Identification
	— Panel A. External Calibration —		
η	R&D cost scaling for external innovation	0.25	Akcigit and Kerr (2018)
ξ	Convexity of R&D cost	2	Akcigit and Kerr (2018)
$\mathbb{E}[d_i]$	Expected distance of upstream to NPE	0.30	NPE Distribution
$\mathbb{E}[d_k]$	Expected distance of downstream to NPE	0.50	Taken in uniform[0,1]
	— Panel B. Internal Calibration —		
Ω	Profit of Licensing Entity	3.80	Correlation of prices
π	Profit of Innovating Entity	0.11	Correlation between p_i and d_i
ϕ	Probability producer infringement	0	Pr producer infringement
τ	Probability innovator infringement	0.88	Pr producer infringement
β	Probability of Winning (Upstream)	0.34	Correlations, Prices
β_{npe}	Probability of Winning in Court (NPE)	0.94	Prices
κ	Max. Search Cost	2.25	Pr(sale)

Notes: All parameters are estimated jointly.

Table B2: Moments, target $\phi/\alpha = 0$

Moment	Data	Model
Price upstream producer sells to NPE	1	1
Average Price NPE sells to downstream	1.54	1.54
Correlation between distance of upstream to NPE and price	-0.07	-0.07
Correlation between price sold and bought from NPE	0.37	0.37
Innovation intensity of downstream innovator	0.74	0.74
Probability of sale to NPE	0.23	0.23
Proportion of infringement from non-innovators	0	0.01

Table B3: Parameter Values, target $\phi/\alpha = 1$

Parameter	Description	Value	Main Identification
	— Panel A. External Calibration —		
η	inverse *external* R&D cost scaling	0.25	Akcigit and Kerr (2018)
ξ	Convexity of R&D cost	2	Akcigit and Kerr (2018)
$\mathbb{E}[d_i]$	Expected distance of upstream to NPE	0.30	NPE Distribution
$\mathbb{E}[d_k]$	Expected distance of downstream to NPE	0.50	Taken in uniform[0,1]
	— Panel B. Internal Calibration —		
Ω	Profit of Licensing Entity	3.36	Correlation of prices
π	Profit of Innovating Entity	0.09	Correlation between p_i and d_i
ϕ	Probability producer infringement	0.75	Pr producer infringement
τ	Probability innovator infringement	0.03	Pr producer infringement
β	Probability of Winning (Upstream)	0.38	Correlations, Prices
β_{npe}	Probability of Winning in Court (NPE)	1	Prices
κ	Max. Search Cost	2.28	Pr(sale)

Notes: All parameters are estimated jointly.

Table B4: Moments, target $\phi/\alpha = 1$

Moment	Data	Model
Price upstream producer sells to NPE	1	1.02
Average Price NPE sells to downstream	1.54	1.50
Correlation between distance of upstream to NPE and price	-0.07	-0.07
Correlation between price sold and bought from NPE	0.37	0.28
Innovation intensity of downstream innovator	0.74	0.82
Probability of sale to NPE	0.23	0.21
Proportion of infringement from non-innovators	1	0.97

D Theoretical Appendix

This section more explicitly derives the predictions of the model. We first write out some objects and prices in the economy that we will reference in our derivations.

$$\Pr(sale) = \frac{p_{i,npe} - V_i^{keep}}{\kappa} \tag{19}$$

$$p_{i,npe} = \frac{V_i^{keep} + V_{npe}}{2} \tag{20}$$

$$p_{npe,j} = \frac{\beta_{npe}\Omega_j}{2} \tag{21}$$

$$p_{npe,k} = \frac{\Omega_k (1 - d_k)}{2} \tag{22}$$

$$p_{i,j} = \beta_i \pi (1 - d_i) + \frac{\beta_i \Omega_j}{2} \tag{23}$$

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

$$\begin{aligned} V_i^{keep} &= \alpha p_{i,j} + (1 - \alpha) V_i^{prod} \\ &= \alpha \beta_i \left[\pi (1 - d_i) + \frac{\Omega_j}{2} \right] + (1 - \alpha) \pi (1 - d_i). \end{aligned} \tag{24}$$

$$V_{npe} = \alpha p_{npe,j} + (1 - \alpha) p_{npe,k} \tag{25}$$

D.1 Derivation of Prediction 1

The NPE is more likely to buy patents from small firms. Moreover, this effect is more pronounced for litigation-prone patents

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

With probability of sale given in Equation 19, we plug in Equation 20. In order to fully characterize, we then use Equations 24 and 25:

$$\Pr(sale) = \frac{V_{npe} - V_i^{keep}}{2\kappa} = \frac{\alpha p_{npe,j} + (1 - \alpha) p_{npe,k} - \alpha p_{i,j} - (1 - \alpha) \pi (1 - d_i).}{2\kappa}$$

Plug in Equations 21, 22, and 23 to get the probability of sale as a function of exogenous variables with respect to i.

$$\Pr(sale) = \frac{\alpha \frac{\beta_{npe}\Omega_j}{2} + (1-\alpha)\frac{\Omega_k(1-d_k)}{2} - \alpha\left(\beta_i \pi (1-d_i) + \frac{\beta_i \Omega_j}{2}\right) - (1-\alpha)\pi(1-d_i)}{2\kappa} \tag{26}$$

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

We then take the derivative with respect to litigation risk:

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

D.2 Derivation of Prediction 2

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

$$\frac{\partial}{\partial d_i}\Pr(sale) = \frac{\alpha\beta_i\pi + (1-\alpha)\pi}{2\kappa} > 0.$$

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

Both of these follow from derivatives of Equation 26 with respect to distance and firm size.

D.3 Derivation of Prediction 3

The NPE pays more for large firms' patents:

Here we write out the acquisition price from Equation 20 which plugs in Equations 21, 22, 24 and 25, which are the values that determine the price:

$$p_{i,npe} = \frac{\alpha\beta_i\left[\pi(1-d_i) + \frac{\Omega_j}{2}\right] + (1-\alpha)\pi(1-d_i) + \alpha\frac{\beta_{npe}\Omega_j}{2} + (1-\alpha)\frac{\Omega_k(1-d_k)}{2}}{2} \tag{27}$$

Now we simply take derivative with respect to q_i which shows up through β_i

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

D.4 Derivation of Prediction 4

The acquisition price decreases as patent distance to the seller increases:

See Equation 27 and take the derivative with respect to distance for i, d_i–

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

D.5 Derivation of Prediction 5

The average price that a licensing firm pays to NPEs decreases as the distance to the licensee increases

Recall Equation 22:

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

The prediction immediately follows from differentiation with respect to d_k.

D.6 Ambiguous effect on firm j's innovation

Here we show how the NPE has an ambiguous effect on firm j's innovation. Recall:

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

$$\Delta\mu_i = \eta^{\frac{1}{\xi-1}}\left[\mathbb{E}[p_{i,npe} - \epsilon]\right]^{\frac{1}{\xi-1}} - \eta^{\frac{1}{\xi-1}}\left[\mathbb{E}[V_{keep}]\right]^{\frac{1}{\xi-1}}$$

To show the ambiguous effect on μ_j, it is sufficient to show that for some parameters $p_{npe,j} > p_{i,j}$ and for other parameters $p_{npe,j} < p_{i,j}$ and show that even in these cases i visits the NPE with positive probability. Recall $\mathbb{E}(p_{.,j}) = \Pr(i \text{ uses NPE}) \times p_{npe,j} + [1 - \Pr(i \text{ uses NPE})] \times \mathbb{E}[p_{i,j}]$

Plugging in the values for $p_{npe,j}$ and $p_{i,j}$, we want to show uncertainty over the relationship between:

$$\beta_i\pi(1 - \mathbb{E}[d_i]) + \frac{\beta_i\Omega_j}{2} \lesseqgtr \frac{\beta_{npe}\Omega_j}{2}$$

We see that for $\beta_i = 0$ and $\beta_{npe} > 0$ one side of the inequality is confirmed (j will innovate less with the NPE). For $\beta_{npe} < \beta_i$, the other side of the inequality is confirmed (j will innovate more with the NPE).

We lastly verify there are cases where i goes to the NPE with positively probability even if $\beta_{npe} < \beta_i$. This can occur when $V_{npe} > V_i^{keep}$ rewritten as:

$$\alpha\frac{\beta_{npe}\Omega_j}{2} + (1-\alpha)\,\frac{\Omega_k\,(1-d_k)}{2} > \alpha\beta_i\left[\pi\,(1-d_i) + \frac{\Omega_j}{2}\right] + (1-\alpha)\,\pi\,(1-d_i)$$

Assume $\beta_{npe} = 0$ and $\beta_i > 0$. Note that for certain values of $\Omega_k (1 - d_k)$ the inequality of the above equation will still hold:

$$(1-\alpha)\frac{\Omega_k (1-d_k)}{2} > \alpha\beta_i \left[\pi (1-d_i) + \frac{\Omega_j}{2}\right] + (1-\alpha)\,\pi (1-d_i)$$

When $d_i \to 0$ and $d_k > 0$ we see the result holds for small α. The intuition for this is that i may choose to visit the NPE due to its distance reduction role even if the NPE is worse in court capability. Thus j will observe less potential interference. This will only hold for low values of β_{npe}, which we do not find in our calibration.