Does patent litigation reduce corporate R&D? An analysis of US public firms

Roger Smeets*
Rutgers University

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Abstract

This study investigates if firms' involvement in patent litigation as alleged infringers hinders their innovation. I develop a simple model that predicts a decrease in innovation following patent litigation. I investigate the model's implications in a sample of publicly listed US firms, using a combination of propensity score matching and difference-in-differences estimation. I find a negative impact of patent litigation on corporate R&D intensity – in the range of 2.6-4.7%-points – in small firms (with less than 500 employees), that are involved in extensive patent lawsuits (captured by the number of legal documents filed).

Keywords: Patent litigation, innovation, R&D

*Contact information: rsmeets@business.rutgers.edu, Tel:+1 957 353 1647 . Address: 1 Washington Park, Newark, NJ 07102. I am grateful to Alberto Galasso, Michelle Gittelman, Sarah Parker, Aviad Pe'er, Sabrina Safrin and Neha Shah for useful comments and discussions.

"*Mr. Phillips and [his company] Vlingo are among the thousands of executives and companies caught in a software patent system that federal judges, economists, policy makers and technology executives say is so flawed that if often stymies innovation.*"

"The patent, used as a sword" – *New York Times*, October 10 2012

1 Introduction

In 2011, Mr. Philips (from the opening quote) went to trial, as his company was accused of infringing patents on voice recognition software that were held by Nuance, a much larger voice recognition firm. Initially Mr. Philips was presented with an ultimatum: Sell Vlingo to Nuance, or be sued for patent infringement. Mr. Philips refused to sell, and the millions of dollars that he had set aside for R&D were redirected to lawyers and court fees. Eventually, a jury ruled in favor of Mr. Philips, concluding that Vlingo had not infringed on a broad voice recognition patent owned by Nuance. However, the lawsuit had cost Mr. Philips and his company over $3 million, which proved to be too much for this tiny start-up. In December of 2011, Mr. Philips agreed to sell his company to Nuance after all.

According to many observers, the story of Mr. Philips is symptomatic of the general functioning of the US patent system (Jaffe and Lerner, 2004; Bessen and Meurer, 2008*a*; Boldrin and Levine, 2013). It has been argued that rather than encouraging innovation, the patent system is increasingly hindering innovation by imposing costly patent litigation on firms. These costs include monitoring and detection, legal representation, claim construction, negotiation, settlement, and potential damages (Bessen and Meurer, 2008*b*). Taken together, they lower the expected net benefits of innovation and reduce the incentives to innovate. Additionally, in the actual event of a patent lawsuit, resource constrained firms will have to cover these costs at the expense of other activities, such as *ex-post* (i.e. after an actual patent lawsuit) innovation – like Mr. Philips and his company Vlingo.[1]

Despite these concerns, to date there is no systematic empirical evidence of the impact of patent litigation involvement on corporate innovation. The current paper is the first to assess the impact of patent litigation on the subsequent corporate R&D intensity of alleged infringers. I

[1] President Obama even referred to this problem in his 2014 State of the Union: "And let us pass a patent reform bill that allows our firms to stay focused on innovation, not costly, needless litigation." (http://www.cbsnews.com/news/obamas-2014-state-of-the-union-address-full-text/).

first develop a simple partial-equilibrium model of the relationship between corporate innovation and patent litigation. In the model, corporate innovation not only increases corporate revenue, but it also increases the likelihood of being involved in patent litigation as an alleged infringer. In equilibrium, the innovation rate is a negative function of past patent litigation. The reason is that patent litigation is costly. By reducing innovation, a firm not only brings current costs back in line with current revenue, it also reduces the future likelihood of innovation. The model further predicts that the innovation-reducing impact of patent litigation is stronger when firms are small, and when litigation costs are high and time-persistent.

These predictions are tested in a sample of 534 public US firms that were sued for patent infringment in the US during the period 2000-2012. The model suggests that patent litigation is endogenous. That is, litigated firms are inherently different from non-litigated firms, in particular in terms of their R&D intensity. Moreover, unobserved systematic differences between litigated and non-litigated firms further exacerbate this problem. In order to tackle these issues, this paper combines propensity score matching (PSM) techniques with differences-in-differences (DID) estimation. The PSM analysis tackles the endogeneity issue and accounts for observed differences between litigated and non-litigated firms. The subsequent DID analysis accounts for (time-invariant) unobserved heterogeneity.

The empirical results largely match the theoretical predictions. Corporate R&D intensity is reduced, generally during the first three years following patent litigation, but only in small firms (with less than 500 employees) that are involved in costly lawsuits (as proxied by the number of legal documents filed). The impact is substantial: The reduction in R&D intensity is between 2.6-4.7%-points. This result is robust to changes in sample composition, conceptual definitions, and various alternative explanations. There is no robust evidence that the impact is contingent on the length of the patent lawsuit, nor on the industry in which the firm operates, or the technology class of the patent(s) asserted in the lawsuit. However, the R&D-deterring impact of patent litigation is most pronounced when there is technological overlap between the patent(s) asserted in the lawsuit, and the patent portfolio of the defendant.

These findings contribute to the literature in a number of different ways. First, they add to the literature studying the efficacy of the US patent system. Jaffe and Lerner (2004) have argued that a number of institutional changes to the US patent system – notably the introduction of the Court of Appeals for the Federal Circuit (CAFC), as well as the patent examiner incentive system at the USPTO – have deteriorated the average quality of patents, while simultaneously strengthening the position of patent-holders in court. Bessen and Meurer (2008*a*) further argue that with the advent of patents in software and business methods, the boundaries between inventions protected in different patents have become fuzzy. They show that as a consequence, in many industries the costs of patents (throught litigation) have more than outweighted their benefits (with the drug and chemical industries as notable exceptions). This leads them to conclude that: "By almost every interpretation, the United States patent system could not be providing overall positive incentives [to innovation] to these US public firms by the end of the 1990s" (p.16). The findings of the current paper nuance this conclusion: Indeed, patent litigation reduces subsequent R&D intensity of alleged infringers, but only in small firms that are involved in extensive lawsuits.

Second, the results of the current paper identify litigation as a factor through which the patent system may hinder litigant innovation. That is, patent litigation reduces the innovation of the alleged infringers themselves. These results add to the literature on the impact of the patent system on cumulative innovation (Scotchmer, 1991, 2004; Bessen and Maskin, 2009). In this context, recent empirical studies have found that granting intellectual property rights in the form of patents has inhibited subsequent follow-on innovation (Murray and Stern, 2007; Huang and Murray, 2009; Williams, 2013; Galasso and Schankerman, 2013).

Third, the paper adds to a mounting stock of evidence regarding the role of firm size in patent litigation. In a study on the use of preliminary injuctions in patent litigation, Lanjouw and Lerner (2001) find that larger plaintiffs – in terms of sales and employment – are more likely to request such injunctive relief than smaller plaintiffs. Lanjouw and Schankerman (2004) find that *litigants* with small patent portfolios are at a disadvantage when protecting their intellectual property, because they are less likely to settle under the threat of patent litigation. Galasso and Schankerman (2013) analyze how patent rights impact cumulative innovation, by studying the impact of patent invalidation decisions on subsequent citation patterns. They show that these citations increase on average by 50%. However, this effect is entirely driven by invalidations of patents owned by large firms, and subsequent citations made by small firms. Taken together these results suggest that, in the context of patent litigation, being bigger is better. The findings in this paper reinforce that conclusion, by showing that only innovation in small firms is adversely affected when they are litigated in a patent lawsuit.

Finally, the results of this paper complement those reported in Tucker (2013). She studies the impact of patent litigation initiated by patent assertion entities (PAEs, or "patent trolls") on the sales of healthcare imaging software by a number of large vendors that were targeted as defendants. She finds that following litigation, sales drop by approximately one-third, due to a lack of incremental product innovations during the time of the trial. My results are consistent with these findings, and illustrate that the innovation-deterring impact of patent litigation extends beyond cases initiated by PAEs, and beyond health-care technologies.

The rest of this paper is structured as follows. Section 2 presents the model and derives a number of predictions regarding the impact of patent litigation on innovation. Section 3 discusses the data sources, variables, and empirical strategy. Section 4 presents some descriptive statistics. Section 5 gives the results to the baseline estimations and a number of robustness checks. Finally, Section 6 concludes. The Appendix provides details regarding the data matching procedure, and the classification of patents in different technological areas.

2 Theoretical model

2.1 Corporate innovation

Consider a firm i who's profits in period t are governed by the following profit function:

$$\Pi_{it} = (P_{it} - C_{it})Q_{it} - F_{it} - \sum_{t=0}^{t=T} \delta^{T-t} p^*_{it} L_{it} \tag{1}$$

P denotes the price, C denotes marginal production costs, Q denotes sold quantities, F is a per period fixed cost, p^* is the (latent) probability of being sued in a patent lawsuit as an alleged infringer, L are the ensuing litigation costs, and δ indicates the extent to which litigation costs of a particular lawsuit carry over into the future. Typically, litigation costs are not borne only in the year of litigation, but will be spread out over the length of the lawsuit which may take up several periods.[2]

[2] Since costs might either increase or decrease over time, or may be nonlinear (they could e.g. decrease exponentially), I make no further explicit assumptions on the range in which δ is allowed to vary, nor on its functional form.

I distinguish between *latent* patent litigation probability p^* and *realized* patent litigation probability p, such that $p^* \in [0, 1]$, whereas $p \in \{0, 1\}$. In particular, for some threshold probability $\hat{p} \in [0, 1]$, I assume:

$$\begin{aligned} p^*_{it} \leq \hat{p}_{it} \Rightarrow p_{it} = 0 \\ p^*_{it} > \hat{p}_{it} \Rightarrow p_{it} = 1 \end{aligned} \tag{2}$$

By distinguishing between latent and realized patent litigation probabilities, we can specify the former as a continuous function of its determinants below. This ensures the existence of the various derivatives, which we need for profit maximization as well as to guarantee the existence of an implicit innovation function later on.

The firm also engages in innovation I. Innovation enters the profit function in three distinct ways. First, by innovating firms can either increase the quality of their products (and hence their price P), or the efficiency of their production process (and hence reduce their marginal costs C). I also assume that there are decreasing returns from innovation on marginal revenue through either of these two channels:

$$\frac{\partial(P_{it} - C_{it})}{\partial I_{it}} > 0; \; \frac{\partial^2(P_{it} - C_{it})}{\partial I^2_{it}} < 0 \tag{3}$$

Second, innovation is costly. I assume that the costs of innovation arise only through the firm's per-period fixed costs. Indeed, extant empirical research confirms that the majority of R&D costs are typically of a fixed and recurrent nature, such as the salaries paid to R&D workers and the maintenance of research labs (Stiglitz, 1987; Manez et al., 2009). I further assume that there are non-decreasing costs of increased innovation:

$$\frac{\partial F_{it}}{\partial I_{it}} > 0; \; \frac{\partial^2 F_{it}}{\partial I^2_{it}} \geq 0 \tag{4}$$

Third, innovation increases the probability of patent litigation. In particular, more innovative firms are more likely to (inadvertently) infringe on existing patents (Lanjouw and Schankerman, 2001; Hall and Ziedonis, 2007). Whether this occurs at an increasing or decreasing rate as innovation increases is not clear *a priori*. On the one hand, an expansion of innovation efforts could imply that the risk of infringement accelerates as the number and variety of related patents increases. On the other hand, more innovation effort might be put into inventing around related patents. Because of these opposing mechanisms, I do not make any explicit assumptions on the second order condition. Summarizing:

$$\frac{\partial p_{it}^*}{\partial I_{it}} > 0; \; \frac{\partial^2 p_{it}^*}{\partial I_{it}^2} \gtreqless 0 \tag{5}$$

Patent litigation does not only occur in the event of actual patent infringement. Often, patent-holders will strategically litigate to pre-empt potential competitors, or establish reputations of toughness (Lanjouw and Schankerman, 2001; Lanjouw and Lerner, 2001; Somaya, 2003; Agarwal et al., 2009). Indeed, this strategic litigation behavior is one reason why many observers have argued that the (US) patent system has become increasingly dysfunctional. In order to capture this in the model, I assume that the impact of (current) innovation on the (current) latent litigation probability increases with the past realized litigation probability. The intuition for this assumption is that firms that were invoved in patent litigation in the past (i.e. $p_{i,t-1} = 1$) will be more visible to patent-holders in the future. That is, their involvement in patent litigation signals a potential (competitive) threat to patent-holders. Because patentees will try to strategically pre-empt innovative competitors, any subsequent innovation effort will have an increased impact on the latent litigation probability:[3]

$$\frac{\partial^2 p_{it}^*}{\Delta p_{i,t-1} \partial I_{it}} > 0 \tag{6}$$

The firm chooses its rate of innovation in such a way as to maximize profits:

$$\begin{aligned} \frac{\partial \Pi_{it}}{\partial I_{it}} &= \frac{\partial (P_{it} - C_{it})}{\partial I_{it}} Q_{it} - \frac{\partial F_{it}}{\partial I_{it}} - \sum_{t=0}^{t=T} \delta^{T-t} L_{it} \frac{\partial p_{it}^*}{\partial I_{it}} = 0 \\ \Leftrightarrow \frac{\partial (P_{it} - C_{it})}{\partial I_{it}} &= \frac{\partial F_{it}}{\partial I_{it}} \frac{1}{Q_{it}} + \sum_{t=0}^{t=T} \delta^{T-t} \frac{L_{it}}{Q_{it}} \frac{\partial p_{it}^*}{\partial I_{it}} \end{aligned} \tag{7}$$

That is, the marginal revenue of innovation equals its marginal costs. Notice that both current and past innovation enter the FOC via the final term on the RHS of (7).[4]

[3] A simple latent litigation probability function satisfying the conditions in (5) and (6) is $p_{it}^* = (\alpha + p_{i,t-1})\beta I_{it}$, with $\alpha, \beta > 0$ and $\beta \leq 1/[(\alpha + p_{i,t-1})I_{it}]$.

[4] Apart from this first-order impact of past innovation in the FOC, there are also multiple higher order impacts that I ignore here. To see this, note that past innovation affects the past latent probability of innovation (via (5)), which affects the past realized litigation probability (via (2)), which in turn affects the current latent

Under the assumptions above I can use the implicit function theorem to write the profit maximizing rate of innovation I^* as follows:

$$I^*_{it} = I(.,p_{i,t-\tau}) \quad \forall \ \tau = 1,..,t \tag{8}$$

Using the implicit function rule, and imposing some mild conditions, the partial derivative of optimal innovation with respect to the probability of patent litigation in periods $t-\tau$ is negative.[5] Figure 1 illustrates the model in the simplest scenario, i.e. when the second order conditions in (4) and (5) are zero and the marginal costs on the RHS of (7) are a linear function of the innovation rate. I^* depicts the equilibrium level of innovation in the baseline case (denoted by the solid revenue and litigation cost curves), where marginal revenue of innovation equals its marginal costs. The dotted litigation cost curve depicts an increase in latent litigation probability from p^* to p^*', induced by an increase in period $t-\tau$'s realized litigation probability (from 0 to 1). As a consequence, the optimal innovation rate drops to I^*'. The reason is that, by reducing innovation in period t, the firm will subsequently reduce period t's litigation probabiliy, and hence the impact of innovation on the litigation probability in period $t+1$. As a consequence, it will be able to bring (litigation) costs back in line with its revenues. Furthermore, it is clear that the innovation-reducing impact of $p_{i,t-\tau}$ is stronger when litigation costs per unit of output (L/Q) increase, or when the persistence of litigation costs (δ) increases.

<< INSERT FIGURE 1 ABOUT HERE >>

Despite the parsimonious nature of the theoretical model, the empirical analysis below should also acknowledge the impact of other determinants of optimal innovation rates, next to that of

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probability of innovation (since via (6), the latent litigation probability is a function of the past realized litigation probability). As shown in Appendix A, this implies that the total differential function of p^*_{it} is a direct function of the change in current innovation, as well as and indirect function of the change in all past innovation levels. Hence, so is the FOC. However, because these impacts are all of higher order, they get diluted rather strongly over time. Moreover, under the assumptions made above, they all reinforce the first-order marginal impact of innovation on the latent probability of patent litigation.

[5] $\partial I^*_{it}/\Delta p_{i,t-\tau} = -[(\partial^2\Pi_{it}/\Delta p_{i,t-\tau}\partial I_{it})/(\partial^2\Pi_{it}/\partial I^2_{it})]$. Given the assumptions above, it follows that the numerator is positive ($\partial^2\Pi_{it}/\Delta p_{i,t-\tau}\partial I_{it} = -\delta^{T-\tau+1}(L_{i,t-\tau+1}/Q_{i,t-\tau+1})(\partial p^*_{i,t-\tau+1}/\Delta p_{i,t-\tau}\partial I_{i,t-\tau+1}) < 0 \quad \forall \ \tau = 1,..,t$, so that -1×the numerator is positive). Hence, the sign of this derivative is determined by the sign of the denominator, which should be negative under profit maximization. From the conditions above it follows that $(\partial^2(P_{it}-C_{it})/\partial I^2_{it})Q_{it} - (\partial^2 F_{it}/\partial I^2_{it}) < \sum_{t=0}^{t=T}\delta^{T-t}L_{it}\partial^2 p^*_{it}/\partial I^2_{it}$ is a necessary condition for this to hold (note that $\partial^2 p^*_{it}/\partial I^2_{it} \geq 0$ is a sufficient condition). I assume that this condition is satisfied. Consequently, $\partial I^*_{it}/\Delta p_{i,t-\tau}$ is negative as well.

past patent litigation involvement:

$$I_{it}^{*} = I(x_{it}, p_{i,t-\tau}) + \eta_i + \nu_t \quad \forall \;\; \tau = 1, .., t \tag{9}$$

I thus assume that other determinants of the equilibrium innovation rate can be decomposed into an additive firm-specific component η_i and a period-specific component ν_t, as well as a vector of time-varying, firm-specific variables x_{it}.

2.2 Patent litigation

I assume that patent litigation – if it takes place – only takes place in period $t = 0$. In order to assess its impact, suppose that firm i is litigated and firm j is not. That is, $p_{i0} = 1$ and $p_{j0} = 0$. Accordingly, firm i's optimal innovation rates in periods 0 and 1 are written as:

$$\begin{aligned} I_{i0}^{*} &= \eta_i + \nu_0 + I(x_{i0}, 0) \\ I_{i1}^{*} &= \eta_i + \nu_1 + I(x_{i1}, 1) \end{aligned} \tag{10}$$

For firm j, equilibrium innovation rates are given by:

$$\begin{aligned} I_{j0}^{*} &= \eta_j + \nu_0 + I(x_{j0}, 0) \\ I_{j1}^{*} &= \eta_j + \nu_1 + I(x_{j1}, 0) \end{aligned} \tag{11}$$

The impact of patent litigation on firm i's innovation as then derived as follows:

$$\begin{aligned} I_{i1}^{*} - I_{i0}^{*} &= \eta_i + \nu_1 + I(x_{i1}, 1) - (\eta_i + \nu_0 + I(x_{i0}, 0)) \\ &= \nu_1 - \nu_0 + I(x_{i1}, 1) - I(x_{i0}, 0) \\ &= \nu_1 - \nu_0 + \frac{\partial I_{it}^{*}}{\partial x_{it}} \times \Delta x_{it} + \frac{\partial I_{it}^{*}}{\Delta p_{i,t-1}} \times \Delta p_{i,t-1} \\ &= \nu_1 - \nu_0 + \frac{\partial I_{it}^{*}}{\partial x_{it}} \times \Delta x_{it} + \frac{\partial I_{it}^{*}}{\Delta p_{i,t-1}} \end{aligned} \tag{12}$$

where the last equality follows from the fact that $\Delta p_{i,t-1} = 1$. There are two factors confounding the impact of patent litigation on innovation. First, the impact of the (unobserved) time trend, captured by the difference between ν_1 and ν_0. If the general trend in innovation is upward (downward), the expected negative impact of patent litigation on innovation would be underestimated (overestimated). Second, the impact of the (observed) change in other drivers of innovation x_{it}. To get rid of the time trend, consider the difference-in-differences impact, i.e. the difference between firm i and j in the change of their innovation rates:

$$\begin{aligned}(I_{i1}^* - I_{i0}^*) - (I_{j1}^* - I_{j0}^*) &= \frac{\partial I_{it}^*}{\partial x_{it}} \times \Delta x_{it} + \frac{\partial I_{it}^*}{\Delta p_{i,t-1}} - \frac{\partial I_{jt}^*}{\partial x_{jt}} \times \Delta x_{jt} - \frac{\partial I_{jt}^*}{\Delta p_{j,t-1}} \times \Delta p_{j,t-1} \\ &= \frac{\partial I_{it}^*}{\Delta p_{i,t-1}} + \frac{\partial I_t^*}{\partial x_t}(\Delta x_{it} - \Delta x_{jt})\end{aligned} \tag{13}$$

where the last equality follows from the fact that we assume identical functional forms across all firms, and that $\Delta p_{j,t-1} = 0$ by assumption. The difference-in-differences in impact in (13) is a function of observables only. Hence, controlling for Δx_{it} and Δx_{jt}, I am able to derive the impact of litigation on innovation through $\partial I_{it}^*/\Delta p_{i,t-1}$. In particular, note that $\Delta x_{it} - \Delta x_{jt} = (x_{i1} - x_{j1}) - (x_{i0} - x_{j0})$. Accordingly, matching firms i and j for which these differences are approximately zero should reduce the second term on the RHS in (13) to approximately zero. I will use propensity score matching (PSM) to accomplish this.

The DID impact of patent litigation in year $t - \tau$ on innovation in year τ can be written more generally as:

$$(I_{i\tau}^* - I_{i0}^*) - (I_{j\tau}^* - I_{j0}^*) = \frac{\partial I_{it}^*}{\Delta p_{i,t-\tau}} + \frac{\partial I_t^*}{\partial x_t}(\Delta x_{it} - \Delta x_{jt}) \tag{14}$$

It has already been estbalished that $\partial I_{it}^*/\Delta p_{i,t-\tau}$ is negative. Moreover (and as indicated above), using the first order profit condition in (7) it follows that this impact is conditional on δ^{T-t} as well as L_{it}/Q_{it} (also see footnote 5). More specifically, the innovation reducing impact of patent litigation is stronger (i) the smaller is the litigated firm (Q), (ii) the more persistent is the impact of litigation costs (δ), and (iii) the higher are litigation costs themselves (L).

The first theoretical implication has a straightforward empirical counterpart: Patent litigation reduces innovation more in small firms than in large firms *ceteris paribus*. Indeed, Lerner (1995) argues that the cost burden of patent litigation weights heavier on small firms, as they have to rely on outside legal counsel, whereas large firms often have an internal legal department. Similarly and in accordance with our model, Thomas (1990) and Jaffe and Lerner (2004) argue that it is not so much absolute litigation costs (L) that matter, but rather relative litigation costs (L/Q).

The second theoretical implication is more difficult to measure empirically, as information on how firms allocate their litigation costs over time is not readily available. Nonetheless, the length of the patent lawsuit might serve as a reasonably proxy. Earlier studies have used the time between patent lawsuit filing and termination as a proxy for the speed of technology diffusion through licensing (Galasso and Schankerman, 2010) and – more in line with the interpretation used here – as a proxy for patent litigation costs (Kesan and Ball, 2006). In particular, lawsuits that take longer to terminate should be expected to show a more extended and persistent impact of litigation on innovation.

The third theoretical construct – litigation costs – is difficult to capture, since such costs are virtually never made public.[6] Previous studies have suggested that the outcome of a case may signal the scope of litigation costs (Somaya, 2003; Lanjouw and Schankerman, 2004). In particular, cases that are adjudicated on the merits tend to involve more litigation activity and last longer, implying that litigation costs are higher as well. However, patent lawsuits that are decided in favor of the defendant should not be expected to reduce ex-post innovation, as the defendant can continue its activities (and will be rewarded damages as well). Moreover, Kesan and Ball (2006) and Bessen and Meurer (2008*b*) argue that non-adjudicated cases may also involve substantial legal activity, resulting in high litigation costs. Instead, Kesan and Ball (2006) propose to use the number of legal documents filed in a patent lawsuit as a proxy for litigation costs. Documents filed in a patent lawsuit may relate to a host of different topics such as magistrate orders, complaints by one of the litigants, motions to ammend or correct, and adjudications. As such, Kesan and Ball (2006) argue that the number of filed documents are relatively closely correlated with "billable hours" of attorney time. Accordingly, I expect that patent lawsuits with a high(er) number of filed legal documents will be more costly to the defendant, resulting in a more adverse impact on innovation.

Summarizing, I expect a negative impact of patent litigation on ex-post corporate innovation. In particular, such adverse impacts of litigation on innovation should be particularly salient in small firms, in patent lawsuits that take a long time to terminate, and in patent lawsuits in which many legal documents are filed.

[6]In some instances in which a patent lawsuit is adjudicated on the merits (i.e. either the plaintiff or the defendant wins the lawsuit), the damages paid by one party to the other are published. However, such transfers are also expected to occur when the litigating parties decide to license (cf. Scotchmer and Schankerman, 2001; Scotchmer, 2004). Instead,I am interested in the transaction costs incurred through the litigation process, such as the costs of legal representation.

3 Data & Methodology

3.1 Data

In order to assess the impact of patent litigation on corporate innovation, data are required on patent lawsuits, the firms that were involved (as defendants) in these lawsuits, and information on those firms. Data for patent lawsuits are taken from Lex Machina, a commercial data provider that tracks all US patent, trademark, copyright, and antitrust litigation since 2000. From the Lex Machina dataset, I collected data on all patent lawsuits. In particular, the following variables are obtained: The date the patent lawsuit was filed, the date of termination (if available – some patent lawsuits were not terminated yet at the time of data collection), the primary defendant, the patent(s) that was (were) asserted, the outcome of the patent lawsuit, and the number of legal documents filed in the lawsuit.[7]

The asserted patents in the Lex Machina dataset are matched to patent information provided in the 2012 (April) version of the European Patent Office's PATSTAT dataset. This is a dataset with detailed information on the application and examination process of individual patents for almost 80 patent offices, including the USPTO. It is used to identify the International Patent Classification (IPC) codes of the asserted patents.[8]

Firm-level data were obtained for US public firms from Compustat. The following variables were collected: the 4-digit SIC industry in which the company is active, the (US) state in which it is located, the number of employees, the total stock of fixed assets, total assets, net sales, R&D expenditures, total operating expenditures, and an indicator of whether the firm is domestically owned or foreign owned. Monetary variables are deflated using a 2-digit industry deflator from the Bureau of Labor Statistics. To match the companynames of the corporate defendants in Lex Machina to those in Compustat, I apply a matching procedure outlined in Thoma et al. (2010). Appendix A provides more details.

[7] I also checked whether district court's outcomes were appealed at the CAFC, and if so, what the eventual ruling of the CAFC was. In those cases, I use the eventual ruling of the CAFC as the outcome of the patent lawsuit. Moreover, Declatory Judgment cases are excluded from the analysis, as these are cases in which the patentee (rather than the alleged infringer) is the defendant.

[8] IPC codes comprise of a maximum of 8 alpha-numeric characters. I use the first four of these characters to identify a patent's technology class (also see note 17).

3.2 Propensity score matching

The objective of the empirical analysis is to determine if patent litigation affects ex-post corporate innovation. I use the filing year of the patent lawsuit as an indicator of treatment (i.e. of patent litigation involvement), and firms' R&D intensity (R&D expenditures as a share of total operating expenditures) to proxy innovation.[9] However, the model in Section 2 suggests that patent litigation involvement is endogenous, because innovation increases the litigation probability. Indeed, previous studies have demonstrated that R&D intensity increases the probability of being involved in patent litigation (Lanjouw and Schankerman, 2004; Hall and Ziedonis, 2007; Bessen and Meurer, 2008*a*). To tackle this issue, I construct a matched sample of litigated and non-litigated firms using a propensity score matching (PSM) model:

$$P(L_{it} = 1|X_{it}) = \Phi(X_{it}^k \beta_k) + \varepsilon_{it} \tag{15}$$

where i and t index firm and year respectively, L is a dummy indicating whether the firm was involved in a patent lawsuit (1) or not (0), X is a vector of explanatory variables, $\Phi(.)$ denotes the cumulative normal distribution function, and ε is an IID error term.[10]

The model and previous studies are used to guide the choice of explanatory variables. First and foremost, a measure of innovation (i.c. R&D intensity) should be included to account for the endogeneity of patent litigation. Following the model's assumptions, I also include its squared term to allow for potential nonlinearities. Second, previous research has demonstrated a relationship between litigation probability and firm size, which is captured by the number of employees. On the one hand, small firms might not represent a strong competitive threat to patentees given their lack of resources and small patent portfolios (Lanjouw and Schankerman, 2004). This implies that firm size positively affects patent litigation probability. On the other hand, large firms might be difficult targets in patent lawsuits, given their extensive resources and patent portfolios (Hall and Ziedonis, 2007; Lerner, 2010). This suggests a negative relationship between firm size and litigation likelihood. To capture the potential nonlinearity, I also include

[9] Other studies have used slightly different measures of R&D intensity, such as R&D expenditures as a share of sales or as a share of total assets. However, in the present sample this creates some exceptional outliers, in particular in the chemicals and pharmaceuticals industry (SIC 28). Expressing R&D expenditures as a share of total operating expenditures circumvents this problem.

[10] The error term is clusetered at the firm-level to account for within-firm over-time dependence of observations (this also applies to the error term in (16) below). As is well known, the incidental parameters problem prevents accounting for unobserved firm-level heterogeneity.

a squared term of firm size. Third, Bessen and Meurer (2008*a*) argue that the size of the fixed asset stock (relative to the total asset stock) may matter. The argument is that capital intensive firms are more willing to settle pre-filing, because litigation (and preliminary injunction) causes their capital stock to be idle, which may be very costly. Fourth, given that the focus is on US patent litigation, foreign (non-US) firms are expected to be less involved in litigation as their (relative) litigation costs will be higher than for US firms (Lanjouw and Schankerman, 2001). This implies that they are more likely to settle pre-filing. Furthermore, the model also includes full sets of state, industry (3 digit), and year dummies to capture any unobserved heterogeneity along any of these dimensions.

What is missing from this PSM model specification is a measure of patents. Arguably, firms with a lot of patents are also more likely to be sued for patent infringement.[11] Constructing a patent measure for the firm sample is problematic due to the fact that many of them are part of larger (multinational) companies. Therefore, the patents in the larger corporate network have to be accounted for as well. I use the NBER match between USPTO patents and Compustat firms to achieve this.[12] However, this match only runs until 2006, so that the extended analysis using patents is performed on a restricted sample. In addition to the variables discussed above, in this case the model also includes the (log of) patents, the (log of) knowledge stocks, and a no-patent dummy that takes the value 1 for firms that have no patents (and 0 otherwise).[13]

The PSM model is estimated for all litigated and non-litigated firms during the period 2000-2012. Based on the estimated coefficients, a propensity score – i.e. the conditional likelihood of being involved in patent litigation – is computed for each observation.[14] For each of the litigated firms in the sample, its nearest neighbor (without replacement) on the propensity score value is then determined, stratifying the matches according to year, 2-digit SIC industry, and country of origin.[15] The result is a pair of firms that are highly comparable on all observed characteristics (i.e. model variables), except for the fact that one is litigated whereas the other is not. A

[11]However, it is important to point out that patent infringement can (and does) occur without the alleged infringer applying for, or ever having applied for, any patents. Indeed, approximately 28% of the defendants in the sample do not own patents.

[12]See https://sites.google.com/site/patentdataproject/Home.

[13]Knowledge stocks were constructed applying the perpetual inventory method on patent counts, using a 15% depreciation rate (Hall and Mairesse, 1995). The year 1950 was chosen as the starting year.

[14]The propensity score is given by $P(L_{it} = 1|X = x_{it})$.

[15]Stratification implies that firm pairs are required to perfectly match on these dimensions. I use 2-digit SIC industries for stratification, because using a more granular industry definition typically results in too few firms per sector to ensure an appropriate match (as indicated by the balancing tests, see below).

number of balancing tests are further conducted to establish the successfulness of the match.

3.3 Difference-in-differences estimation

The PSM model outlined above not only tackles any potential endogeneity of patent litigation with respect to innovation, it also ensures that all firm pairs are highly similar on all the other observable model variables as well.[16] Nonetheless, there may still be other unobserved ways in which the firms in each pair differ. Moreover, other (unobserved) factors in addition to litigation might also affect innovation. In order to (partly) tackle these issues, I follow the approach in Section 2.2 and estimate a difference-in-differences (DID) model on all firm pairs to establish the impact of patent litigation on R&D intensity (cf. Arnold and Javorcik, 2009; Chang et al., 2013). In particular, the following model is estimated:

$$RDI_{it} = \gamma_0 + \gamma_1 L_i + \gamma_2 P_\tau + \gamma_3 L_i \times P_\tau + \varepsilon_{it} \tag{16}$$

where RDI is R&D intensity, L is involvement in patent litigation (1) or not (0), P is a dummy variable that takes the value 0 in the year of litigation (which is normalized to 0) and the value 1 in τ years after the year of litigation, and ε is an IID error term. As demonstrated in Cameron and Trivedi (2005), the coefficient of interest is γ_3 which captures the average treatment effect on the treated (ATT):

$$ATT = \frac{1}{N}\sum_{N}(RDI^{L=1}_{i,t=\tau} - RDI^{L=1}_{i,t=0}) - \frac{1}{M}\sum_{M}(RDI^{L=0}_{j,t=\tau} - RDI^{L=0}_{j,t=0}) \tag{17}$$

with N (M) denoting the total number of litigated (non-litigated) firms. This is the empirical counterpart of equation (14). Taking the difference in RDI between period τ and period 0 in both parts of (17) gets rid of any unobserved, time-invariant firm-level heterogeneity as in equations (10) and (11). Moreover, comparing the RDI change in litigated firms (the first term in (17)) with matched non-litigated firms (the second term in (17)) rules out any non-litigation related changes over time that could have an impact on RDI, as in equation (14).

Each time, the comparison is between R&D intensity in a year (τ) following patent-litigation and the year of litigation itself, with $\tau = 1, .., 4$. That is, I run separate models for each pairwise

[16] That is, in terms of equation (14) the matching should reduce the second term to zero by approximately reducing Δx to zero (on average).

comparison. By limiting the comparison each time between two years, I circumvent the problem of serially correlated errors that might bias the estimated standard errors of γ_3 (Bertrand et al., 2004).

4 Descriptives

The descriptive statistics presented here pertain to 534 litigated firms that could be matched to non-litigated firms in the PSM model (see below), and the patent lawsuits that they were involved in. More information on the original patent litigation sample is provided in Appendix A.

For the purposes of this study, only the first (observed) year of litigation for each firm in the sample period is considered. Originally, I was able to match 736 litigated firms from the Compustat dataset to the firms (i.e. defendants) in Lex Machina. However, since the focus is on the impact of patent litigation in year t on innovation in years $t + \tau$ for $\tau = 1, .., 4$ I further restrict the sample to fims that were not involved in patent litigation in any of the four years following their first (observed) patent lawsuit. This restriction ensures that I am not accidentally picking up the confouding impact of additional lawsuits in the years following the focal lawsuit. This leaves 534 firms for the eventual analysis. 486 of these firms were involved in one lawsuit during their first year of litigation, 40 firms in two lawsuits, five firms in three lawsuits, two firms in four lawsuits, and one firm in six lawsuits. Hence, the 534 sample firms account for 595 patent lawsuits.

Figure 2 shows the number of patent cases that were filed during each year of the sample period. The trend is downwards between 2004 and 2010, after which it increases substantially. The overall trend in patent litigation (i.e. in the original patent litigation file) is relatively constant up until 2010 (see Figure A.1). This deviation is mainly caused by the fact that I only consider the first year of patent litigation for each firm. Accordingly, subsequent patent cases (involving the same defendant) that were filed in later years are not included in the sample.

<< **INSERT FIGURE 2 ABOUT HERE** >>

Panel A of Table 1 shows the distribution of litigated firms across 2-digit SIC sectors. Firms active in business services (SIC 73) are most strongly represented, comprising 20% of the entire sample. They are followed by firms in electronics (SIC 36, 15%), instruments (SIC 38, 13.7%), chemicals and pharmaceuticals (SIC 28, 12.2%), and machinery (SIC 35, 10.1%). These top-5 industries together thus account for +/-71% of the total sample. Panel B shows the ranking in terms of asserted patent classifications in each patent lawsuit.[17] There is a strong representation of software-related patents (IPC codes G06F and G06Q), drugs and biotechnology (IPC codes A61K, G01N, and C12N), and telecommunication (IPC codes H04L and HO4N).[18] Overall, these patterns confirm previous findings regarding the prevalence of patent-litigation in these technologies (e.g. Lerner, 1995; Lanjouw and Schankerman, 2004; Bessen and Meurer, 2008*a*; Lerner, 2010).

<< INSERT TABLE 1 ABOUT HERE >>

Panel A of Table 2 presents a cross-tabulation of the top-5 2-digit SIC industries (as identified in Table 1) and a number of aggregated patent class categories pertaining to the asserted patents in the patent lawsuits (see Table A.2 in the Appendix for a definition of each category). The first column of the table demonstrates that in the majority of patent cases in which a software patent is asserted, the defendant is active in the business services sector. Software patent lawsuits are also prevalent in the electronics sector, as are patent lawsuits asserting telecommunication patents. Not surprisingly, firms in the chemicals & pharmaceuticals industry are mainly targeted in patent cases asserting drug and biotechnology patents.

<< INSERT TABLE 2 ABOUT HERE >>

Rather than looking at individual industries, we can also consider different industry *types*. A distinction that may be particularly relevant in the context of patent litigation is that between discrete and complex industries. Cohen et al. (2000) have shown that patents (on average) have rather different functions, depending on the industry type. In discrete industries, they serve the more "traditional" purpose of fencing off proprietary knowledge and inventions. In complex industries however, they are often used to build strategic patent portfolios that serve as assets in licensing or lawsuit negotiations. Panel B of Table 2 shows the distribution of the different

[17]The primary IPC code of each patent is used to establishing this ranking. When the primary IPC code is not known, I use the 4-digit IPC code that occurs most often in the different 8-digit IPC codes listed on a patent. In case of a draw, all IPC codes are considered. Hence, since one lawsuit can assert multiple patents, and since one patent can carry multiple (4-digit) IPC codes in this classificiation, the total number of IPC classifications in panel B of Table 1 (888) is higher than the total number of patent lawsuits (595) in the sample.

[18]See Table A.2 in Appendix A for a link between IPC codes and technological classifications.

types of litigated patents across discrete versus complex industries. I follow Arora et al. (2000) and define all (manufacturing) industries with SIC2≤35 as discrete and those with SIC2>35 as complex. The distribution of litigated patent types is rather intuitive and along the lines outlined by Cohen et al. (2000): The majority of drug and biotechnology patents belong to the discrete industries, consistent with the notion that they provide accurate notice (Bessen and Meurer, 2008*a*). Conversely, the majority of software, telecommunication, semiconductor, and instruments patents belong to complex industries.

In the sample of 534 firms, 187 (35%) are small firms (less than 500 employees), 63 (11.8%) are medium-sized firms (between 500 and 1,000 employees), and 284 (53.2%) are large firms (more than 1,000 employees). Panel A in Table 3 presents some summary statistics on the length of patent lawsuits (in days) across the three different firm types.[19] The average case length is shorter for small firms than for large firms (but the difference is not statistically significant (t=-0.69)), yet the median case length is slightly higher. Overall, the average (median) case length in our sample is 577 days (420 days). These numbers are higher than those reported in Kesan and Ball (2006) for the year 2000, in which case the average (median) case length was 443 days (295 days). A potential explanation for this difference is that we only consider cases that involve publicly listed firms, and hence disregard cases involving private firms, individual inventors, or non-profit organizations (e.g. universities). This may bias the length of patent lawsuits upwards, as public firms have comparatively more resources to finance patent lawsuits for a longer time.

<< **INSERT TABLE 3 ABOUT HERE** >>

Panel B in Table 3 depicts some summary statistics regarding the number of legal documents filed in patent lawsuits, again separated by firm type. In this case, there is little difference between small and large firms. The overall average (median) number of documents filed in our sample is 87 (40), which is again higher than the corresponding numbers reported by Kesan and Ball (2006) in the year 2000 (65 and 24 documents, respectively).

Finally, panel C in Table 3 shows the distribution of different case outcomes for the three different firm types. I distinguish between plaintiff wins (either through summary judgment or trial), defendant wins (either through summary judgment or trial), stipulated dismissals (i.e.

[19] In the case of multiple lawsuits, I use the length averaged across the different lawsuits. For cases that had not yet terminated when the data were collected, case length is recorded as missing.

settlements), plaintiff voluntary dismissals, and other outcomes (such as interdistrict transfers that could not be traced further, or procedural dismissals). Comparing small and large defendants, it is apparent that small defendants settle more often on average than large ones, whereas large defendants' patent lawsuits are more often terminated through plaintiff voluntary dismissals. These results are consistent with the notion that large firms are less resource constrained, and hence have less need to settle patent lawsuits and have greater leverage to move plaintiffs to voluntarily drop the lawsuit (cf. Lanjouw and Lerner, 2001).

5 Results

5.1 Propensity Score Matching

Table 4 presents the results of the PSM analysis for the full sample of public US firms in Compustat during the period 2000-2012. The dependent variable indicates whether a patent lawsuit was initiated in a particular year. Standard errors are clustered at the firm-level to account for dependence of observations within firms over time.

<< INSERT TABLE 4 ABOUT HERE >>

Column (1) presents the estimates of the PSM model in (15). This model thus only includes the first (observed) patent lawsuit in which each of our sample firms was involved. R&D intensity and its squared term both have a significant impact on litigation probability. As is well known, the marginal impact and statistical significance of squared variables in non-linear models is conditional on all model variables, and varies with different values of i.c. R&D intensity (Ai and Norton, 2003). The graphical results are reported in Figure A.2 in Appendix A. The inflection point lies around an R&D intensity of +/- 50%, after which the positive impact of R&D intensity on the litigation probability becomes negative. However, except for some observations at the very right tail of the R&D intensity distribution, this negative effect is not statistically significant.

Second, an increase in firm size (i.e. employment) has a positive impact on the litigation probability, but the negative coefficient on the squared value of firm size suggests a nonlinear relationship. Again, the marginal impact and statistical significance is computed for all values of the firm size distribution; results are reported in Figure A.3 Appendix A. Although there is a very slight indication of a non-linear relationship, for virtually all values of firm size, the marginal impact is positive.

Third, the fixed asset stock as a share of total assets is negative and statistically significant, as expected. Finally, there is no clear difference in litigation propensity between US and foreign firms, which is likely due to the small number of foreign (mostly Canadian) firms in the sample.

Column (2) in Table 4 presents the estimates of the extended model including several patent-related explanatory variables. As explained in Section 3.2, this model is estimated for a shorter time-period (2000-2006). The results discussed above generally carry over, with the exception of the two R&D intensity variables, which are no longer statistically significant. Instead, the (log of) patents now carries a positive and statistically significant coefficient. The (log of) knowledge stocks has a negative and marginally significant effect. Finally, the no-patent dummy indicates that firms without patents are less likely to be involved in patent litigation. In what follows, we use the estimates in column (1) as the baseline. The DID impacts of the estimates in column (2) are further explored in the robustness checks below.

Based on the estimates in column (1), a propensity score value is computed for all observations. In particular, I match litigated and non-litigated firms in the year in which the patent lawsuit is filed. As a result, I end up with 534 matched firm-pairs. Litigated firms all fall within the region of common support provided by the propensity scores of the non-litigated firms.

In order to assess the quality of the match, three test procedures are conducted as outlined in Caliendo and Kopeinig (2008). As a first test, the standardized bias (SB) is computed, which compares the means of each covariate included in the PSM model between litigated and non-litigated firms before and after matching, and expresses the difference as a percentage of the average variation of the covariates in both subsamples.[20] Although there is no official threshold criterion, Caliendo and Kopeinig (2008) indicate that an SB below 5% after matching indicates a qualitatively successful match.

Panel A of Table 5 shows the SBs before (column 1) and after the match (column 2). Matching reduces the standard bias on all variables to below 5% (in absolute value), in particular of employment, employment squared, and fixed assets (note that the SB on the foreign firm dummy is zero after matching due to stratification on this variable). This implies that the

[20] More precisely, $SB = 100 \times [(\overline{X}_L - \overline{X}_{NL}/\sqrt{0.5 \times (V_L(X) + V_{NL}(X))}]$ where subscripts L and NL denote litigated and non-litigated firms respectively, and $\overline{X}$ $(V(X))$ is the mean (variance) of the covariate X.

match is successful in substantially reducing the observed heterogeneity between litigated and matched non-litigated firms.

<< INSERT TABLE 5 ABOUT HERE >>

As a second test to assess the matching quality of the PSM model, Caliendo and Kopeinig (2008) suggest to perform t-tests on all the models covariates in order to assess whether the difference between the average values of the litigated versus the non-litigated subsamples is statistically significant. If matching is successful, no significant differences should arise. Panel B of Table 5 shows the results of the t-tests, i.e. the t-statistics of mean-comparisons and the relevant p-levels (within parentheses). Before matching, differences in employment, employment squared, fixed asset share, and the foreign firm dummy are large and statistically significant. Yet after matching, there remains no statistically significant difference between the litigated and matched non-litigated sample for any of the covariates. A Hotelling t-test on the differences between the joint vector of covariates also does not reject the null hypothesis of no statistically significant differences (p=0.998).

As a final test, I rerun the PSM model of Table 4 on the sample of matched firm-pairs only. If the matching is successful, none of the covariates should be a significant predictor of litigation probability. Panel C in Table 5 shows the results (all models again include a full set of year, industry, and state dummies). Column (1) repeats the results from column (1) in Table 4. As can be seen in column (2), in the matched firm-sample none of the explanatory variables has any predictive power. Also, the pseudo R-squared drops substantially in column (2), despite the strong decrease in the number of observations. All in all, these tests indicate that the match between litigated and non-litigated firms is successful in reducing the observed heterogeneity between the litigated and non-litigated firms.

5.2 Difference-in-differences

Table 6 presents the DID results. Panel A shows the ex-post impact of patent litigation for the full sample. The estimated ATT is consistently negative throughout the four years following patent litigation, but only (marginally) statistically significant in $\tau = 1$ The estimated reduction in R&D intensity is modest at 0.9%. Panel B shows the impact on small firms, defined as firms with less than 500 employees. Again, the ATT is consistently negative but never statistically significant. Panel C shows the impact of patent litigation on R&D intensity in patent cases with a duration above the median ($>$ 420 days). In this case there is a negative and statistically significant impact of patent litigation on R&D intensity in the first year following the filing of the lawsuit of approximately 1.3%-points. Finally, panel D considers the impact of extensive lawsuits, defined as those in which more than the median number of documents (i.e. 40) were filed. Againg, I find a statistically significant impact in the first year following the filing of the lawsuit (1.8%-ponts), as well as marginally significant impact in the third year after filing (1.4%-points).

<< **INSERT TABLE 6 ABOUT HERE** >>

As can be seen in the table, the number of observations drops as τ increases. In fact, already in the first year after patent litigation, the full sample estimates in panel A are only based on 375 firms (rather than 534 firms). There are three reasons for this. First, firms that experience their first lawsuit towards the end of the sample period – say in 2010, 2011, or 2012 – will drop out at some point since the firm-level data only run until 2012 (recall from Figure 2 that the number of patent cases increases substantially after 2010). Second, R&D expenditure data are missing for some firm-year combinations. Since firms are matched in the year of litigation, all firm-pairs have non-missing R&D expenditures in that year, implying that the sample is likely to get smaller in subsequent years. Third, firms might "exit" (or alternatively, stop doing R&D). That is, an alternative ex-post effect of patent litigation might be the disproportional push of litigated firms out the market (for innovation). I investigate this further below.

The results in Table 6 suggest that long and extensive patent lawsuits have a significantly negative – if only temporary – impact on ex-post firm-level R&D intensity. However, based on the model in Section 2, the impacts of firm-size, litigation costs, and duration reinforce each other. In other words, the moderating impacts of firm size, case length, and the number of legal documents on ex-post R&D migh have their strongest impact in-tandem. Table 7 explores this possibility.

<< **INSERT TABLE 7 ABOUT HERE** >>

Panel A shows the impact of long patent lawsuits in small firms. Compared to panel B in Table 6, the impact at $\tau = 1$ is now negative and statistically significant. Compared to panel

C in Table 6, the coefficient estimate of 3.2%-points is substantially larger. Nonetheless, there is no statistically significant impact in any of the subsequent periods.

Panel B shows the impact of relatively costly patent lawsuits in small firms. Compared to panel B in Table 6, the impacts at $\tau = 1, 2, 3$ are now negative and statistically significant. Compared to panel D in Table 6, the impact in $\tau = 2$ is now also statistically significant, and all the estimated impacts are substantially stronger, ranging between 2.6%-points and 4.7%-points.

Panel C shows the impact of long and costly patent lawsuits. As in panels C and D in Table 6, there is a negative and statistically significant impact at $\tau = 1$ only. The estimated coefficient is comparable to that of costly patent cases in panel D in Table 6.

Finally, panel D shows the impact of long and costly patent lawsuits in small firms. The results are highly similar to those in panel B (of the same table) considering the combination of costly patent lawsuits in small firms.

Taken together, these results suggest that small firms that are involved in extensive lawsuits (i.e. with many legal documents filed) are most adversely affected by patent litigation in terms of their ex-post R&D intensity. In what follows, I will use this result – from panel B in Table 7 – as the baseline and consider its robustness. Before doing that, panel E in Table 7 re-estimates the DID model for small firms and extensive lawsuits, now using a balanced sample of firms – i.e. for only the 34 firm-pairs that report R&D expenditures in each of the four years following patent litigation. As can be seen, the impact remains negative and statistically significant at $\tau = 1, 2, 3$. In this case, the effect becomes increasingly stronger as we move forward through time.

Figure 3 graphically shows the difference-in-differences impact of patent litigation on R&D intensity for this latter analysis (i.e. panel E in Table 7). Period 0 in the figure denotes the year of patent lawsuit filing. In addition to plotting the differences in R&D intensities in the four subsequent years, the graph also shows these differences in the four years preceding the year of patent litigation, in order to rule out that the ex-post estimates are picking up a long-term trend (also see the robustness tests below). The horizontal line in the figures depicts the difference in R&D intensities between litigated and non-litigated firms in the year of litigation (i.e. period 0).

<< INSERT FIGURE 3 ABOUT HERE >>

The graph demonstrates that there is a slightly downward trend in average R&D intensity in the four years preceding patent litigation. However, R&D intensity shows an explicit and sharp drop in the year directly following patent litigation, and its level further decreases in year two and three. Also note that that the upper-bound of the 95% confidence interval in the years following patent litigation virtually never exceeds the R&D intensity difference between litigation and non-litigated firms in period 0.

5.3 Robustness analysis

This section discusses a number of tests to establish the robustness of the results. To economize on space, the tables containing the results are relegated to Appendix B. Table B.1 uses the results in panel B of Table 7 as the baseline. Panel A considers the impact of patent litigation on R&D "exit". I create an *Exit* variable that takes the value of 1 if a firm has missing values on R&D intensity for at least two consecutive years. The analyses in panel B of Table 7are then repeated, now using *Exit* as the dependent variable instead of R&D intensity. The focus is now on comparing the exit rates of litigated and non-litigated firms following the year of patent litigation. The R&D exit rate of litigated firms is indeed substantially higher than that of non-litigated firms in all periods. However, the difference is never statistically significant.

As mentioned above, one potential concern with the results is that the decrease in R&D intensity in the litigated small firm sample was already taking place before the year of litigation, and what the estimates are picking up is just part of a longer trend. Figure 3 graphically rejects this possibility. In order to investigate this more formally, panel B in Table B.3 estimates the *ex-ante* impact of patent litigation. That is, it compares the change in R&D intensities of litigated versus non-litigated firms in the four years leading up to the year of patent lawsuit filing.[21] The results show no significant difference between litigated and non-litigated firms regarding R&D intensities in the pre-litigation period. If anything, litigated firms demonstrate a slightly smaller decrease in R&D intensities relative to non-litigated firms in the two years leading up to the patent lawsuit (consistent with the results in Figure 3).[22]

Panel C of Table B.1 investigates whether litigation costs (rather than firm size) are not

[21] The ATT to capture ex-ante effects is still denoted by the one in (17). However, a negative coefficient in this case implies that the reduction in R&D in litigated firms was less than that in non-litigated firms in the period before and at filing of the lawsuits (and vice versa for a positive coefficient).

[22] Restricting the ex-ante analysis to a balanced sample of firms does not change these results. Also, there is no indication of significant ex-ante differences in sample attrition between litigated and non-litigated firms.

just driving the results in Panel B of Table 7. Thus, it estimates the impact of extensive patent lawsuits on large firms ($>$ 1,000 employees). As can be seen, the litigation impact is actually positive at $\tau \geq 2$ but never statistically significant.

Panel D of Table B.1 considers whether firm size (rather than litigation costs) is not driving the original results, by investigating the impact of non-extensive lawsuits ($\leq$ 40 documents) on small firms. Again, the estimated impact is positive in all periods in this case, but never statistically significant.

Another potentially important consideration is the overlap between the technology of the asserted patent and the technology of the defendant's patent portfolio. We should expect that the R&D deterring impact of patent litigation is particularly salient when the technological overlap is high, implying that litigated technology is central to the defendant's own innovation. In order to test this, I create a top-5 of most frequent 4-character IPC codes as listed on the defendants' patent portfolios (for those defendants that own patents). I then create a simple "technology-match" dummy that takes the value 1 if the (4-character) IPC code of the asserted patent(s) matches at least one of those in the defendant's top-5. In 72% of the patent lawsuits in the sample, such a match exists. Table B.2 presents the DID estimates for the full sample of firms (panel A), small firms (panel B), and small firms in extensive lawsuits (panel C) while restricting the sample to those cases in which there is a technological match.[23] In all cases, the impact of patent litigation is stronger than before. For the total sample, the impact is now negative (+/- 1.6%-points) and statistically significant in $\tau = 1, 2$. For small firms, results are statistically significant in $\tau = 1, 3$, as well as economically significant: The impact varies between 3.2-6.1%-points. Finally, for small firms in extensive lawsuits, the impact is now statistically significant in all four years, with a peak of 8.3%-points in $\tau = 3$. Taken together, these results suggest that the R&D-reducing impact of patent litigation is most pronounced when the plaintiff and defendant are technologically similar.

Table B.3 continues the robustness checks by changing the document cutoff for extensive lawsuits. Panel A, B, and C consider cutoffs of 50, 100, and 150 documents respectively. As can be seen, the R&D-reducing impact of patent litigation is significant and in fact becomes somewhat stronger as the cutoff increases (in particular in the first year following patent lawsuit

[23] As it turns out, the balanced-panel results in panel E of Table 7 include only lawsuits in which there is a technological match.

filing), which is consistent with the notion that more extensive patent lawsuits are more costly.[24]

Panel D in Table B.3 estimates the DID model on matched firm pairs that are based on the extended PSM model in column (2) of Table 4.[25] The earlier negative impact of patent litigation on R&D in $\tau = 1$ now drops out, but it remains negative and statistically significant in $\tau = 2, 3$. In these latter two periods, the estimated effects are somewhat larger than in the baseline estimation.

As can be seen in panel B of Table 7, the R&D intensities in the year of patent lawsuit filing are rather different between litigated and non-litigated firms. This suggests that the propensity score matching may not have been fully successful in matching comparable firms. In particular, the differences in R&D intensities suggest that some small, R&D intensive (litigated) firms may be paired with larger, less R&D-intensive (non-litigated) firms (cf. Akcigit, 2011).

In order to account for this, I estimate the impact of extensive patent lawsuits on the R&D intensity of small firms while adding firm-level controls for (the log of) size (i.e. employees) and fixed asset share (i.e. two of the explanatory variables in the PSM model).[26] Table B.4 presents the results. As can be seen, both firm size and fixed asset share are negative and significant in most post-litigation periods, indicating that large(r), capital-intensive firms are less R&D-intensive than small(er) firms. This result is consistent with the findings by Akcigit (2011). More importantly, the impact of patent litigation remains statistically significant, and comparable to the estimated effects in panel B of Table 7.

As discussed in Section 2, previous studies have suggested that the type of adjudication following a lawsuit is indicative of litigation costs (Lanjouw and Schankerman, 2004; Kesan and Ball, 2006). In particular, it has been argued that cases decided on the merits (i.e. in which the outcome favors either the plaintiff or the defendant) are more costly because they typically take longer and involve more legal activity than cases that end in settlements.[27] Accordingly, the estimates may be picking up patent lawsuit adjudication rather than the extensiveness of

[24] We also re-estimated the models in Tables 6 and 7 using different cutoffs for the length of patent lawsuits (varying between 500, 1000, and 1,500 days), but the results remained qualitatively unchanged.

[25] Recall that this analysis is conducted only for the period 2000-2006. Matching litigated and non-litigated firms proceeds in a similar way as described before. In addition, firms are perfectly matched on whether or not they have any patents (i.e. on the "no patent-dummy"). The results of the balancing tests reported in Table 5 in this case also indicate that the matches are valid.

[26] The square of (log) size was never significant in any of the models, so that it is not included in Table B.4.

[27] Indeed, cases decided on the merits on average take 1,252 days to terminate, versus 498 days for cases not decided on the merits ($t = 4.54$). Similarly, on average 319 documents are filed in cases decided on the merits, versus 99 in other cases ($t = 4.87$).

the lawsuit. To account for this, panels A and B in Table B.5 re-estimate the DID model for the entire sample (panel A) and for small firms (panel B), considering only those lawsuits that were decided on the merits.[28]

The results demonstrate that the identified effects are not driven by patent lawsuits decided on the merits. Yet it should be noted that due to the small percentage of cases that are actually adjudicated (also see Table 3) there are relatively few observations in these models, in particular in panel B. Indeed, the standard errors of the estimated coefficients are relatively high.

Further, it has been argued that firms in so-called "complex technology" industries are more likely to be litigated due to the existing of patent thickets (Hall and Ziedonis, 2001, 2007; Bessen and Meurer, 2008*a*; Lerner, 2010). Therefore, it will be important for firms in such technologies to build-up a strong patent portfolio themselves in order to have a strong bargaining position in licensing negotations or court (Ziedonis, 2004). Accordingly, it might be expected that the largest impact of litigation on R&D intensity takes place in complex technologies, in particular for small firms. As such, not accounting for the type of technologies of the patents asserted in the lawsuit might confound the estimated effects.

Panels C and D of Table B.5 therefore only consider patent lawsuits that assert complex technology patents.[29] For the entire sample (panel C), the results correspond to the baseline estimates in Table 6. For small firms, there is a negative and statistically significant impact in the first year following patent litigation, but not subsequently. These results suggest that small firms' R&D intensity might indeed be somewhat more vulnerable in complex technologies. Yet the reinforcing impact of litigation costs (i.e. lawsuit extensiveness) is much more important.[30]

I furhter considered the impact of patent litigation on firms with multiple patent lawsuits in their first year of litigation (not reported). I did not find any significant R&D-intensity reducing impact in any of the years following the lawsuits, neither in the full sample nor in the small

[28]Following Kesan and Ball (2006) I include declatory judgments, adjudications following a (bench or jury) trial, as well as consent judgments. In terms of the adjudications in Table 3, I include plaintiff wins and defendant wins. In case of appeals at the CAFC, the CAFC's ruling (if available) is used as the final outcome.

[29]I consider patents in software, telecommunications, electronics, semiconductors, and (scientific) instruments to be complex technology patents, based on the results in Table 2. The reason for identifying complex technologies based on patents rather than industries, is that it allows for the inclusion of non-manufacturing industries (in particular business services – SIC 73). The specific assignment (based on IPC codes) of each patent to these categories is provided in Table A.2 in Appendix A.

[30]I also considered the mutually reinforcing impacts of extensive lawsuits ($\geq$ 40 documents) and complex technologies in small firms.This yields comparable results to those in the baseline estimates in panel B of Table 7. In particular, the effect in $\tau = 1$ is somewhat smaller, whereas the effects in $\tau = 2, 3$ are very similar. This suggests that adding the technology type to the model does not add real value, but only serves to reduce the sample size.

firm sample. Finally, I estimated the DID models for each of the top-5 2-digit SIC industries listed in Table 1 separately, in order to investigate whether the R&D-intensity reducing impact of patent litigation is concentrated in particular industries (estimating the DID model for the other industries typically yields too few observations). Again, this was done for both for the full sample as well as the sample of extensive lawsuits in small firms.

In the full sample, separating the models in this way does not matter. In the extensive-lawsuits-in-small-firms sample, there are two notable results (not reported): First, the impact in $\tau = 3, 4$ seems to be mainly concentrated in the drug and chemicals industry (SIC 28). The estimated effects are very large in this case (between 18.2-24.5%-point reduction in R&D intensity). Second, the impact in $\tau = 1, 2$ seems to be concentrated in the electronics industry (SIC 36), where the estimated impacts varies between 3.2-6.4%-points. However, in both cases the number of observations (and firm pairs) becomes very small, which undermines the reliability of these disaggregated results.

6 Conclusion

Is R&D reduced in firms that are litigated as alleged patent infringers? That is the question that this paper has set out to address. The answer is a qualified yes: Patent litigation involvement (as an alleged infringer) reduces subsequent R&D intensity, but only in small firms (with less than 500 employees), and only following extensive lawsuits (in which many legal documents are filed). These results are consistent with a simple theoretical model of innovation and patent litigation, in which innovation increases the likelihood of patent litigation, which in turn increases future innovation's impact on the litigation probability. In equilibrium, this results in an innovation-reducing effect of patent litigation,which is reinforced by a decrease in firm size and an increase in litigation costs. The estimated effects are substantial – ranging from 2.6-4.7%-point reductions in R&D intensity – and relatively persistent – occuring during up to three years following the initiation of a patent lawsuit. Moreover, the R&D-deterring impact of patent litigation is most pronounced when there is technological overlap between the patent(s) asserted in the lawsuit, and the patent portfolio of the defendant.

These results suggest that, in some cases, patent litigation creates social waste in terms of reduced innovation (R&D). The extent of this waste is difficult to gauge, as it depends on a number of parameters that are largely unobservable. For example, if litigated firms are indeed infringing on a valid patent, the reduction in ex-post R&D intensity may be considered as a correction of unwarranted or excessive ex-ante R&D. In those cases, social waste may be minimized (or even reduced to zero), depending on the net effect on R&D.

However, the empirical results are not consistent with such an interpretation. First, it is not clear that only relatively small firms are the ones that are actually infringing on valid patents, and hence should be affected in terms of their ex-post R&D. Second, the results hint that resources earmarked for R&D are instead redirected to finance the (transaction) costs of litigation. That is, regardless of the outcome of the patent lawsuit, it is the cost of the process itself that is halting innovation. Indeed, the robustness show no evidence that the actual outcome of the patent lawsuit matters for subsequent R&D.

For managers in small firms – such as the technology start-up described in the introduction – these results imply that in order to safeguard future innovation, it may be optimal to settle a lawsuit before a lot of legal costs are incurred. This introduces yet another source of social waste, as such settlements may turn out to be anti-competitive relative to a situation in which a patent lawsuit is litigated until an adjudication on the merits. It further implies that patent-holders can use patent litigation as a strategic instrument to deter or stifle small but innovative competitors.

A clear drawback of the current study is that it only considers the impact of patent litigation on publicly listed (US) firms. It has been argued that, due to more binding resource constraints, (small) privately owned firms, individual inventors, and non-profit organizations (such as universities) stand to be even more adversely affected in patent litigation (Jaffe and Lerner, 2004). Accordingly, one avenue of future research might replicate the analyses in this paper for such different sets of defendants in patent litigation.

Additionally, the current study only focuses on the impact of patent litigation on defendant innovation. However, by the same mechanism, innovation might be reduced after excessive litigation on the part of (small) litigants as well. There is one key difference: Litigants have the option to dismiss a lawsuit, which theoretically should enable them to optimize the extensiveness of a lawsuit when balancing a positive settlement outcome with a negative (ex-post) innovation outcome. Future research might investigate whether litigants in practice indeed optimize in such a way, or instead fall prey to their own litigation strategy.

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Appendix A

The profit maximization FOC

Under assumptions (5) and (6), the latent litigation probability p^*_{it} is a function of current innovation I_{it} and the past realized litigation probability $p_{i,t-1}$. This implies that the total differential function of the latent litigation probability can be written as:

$$dp^*_{it} = \frac{\partial p^*_{it}}{\partial I_{it}} dI_{it} + \frac{\partial p^*_{it}}{\partial p_{i,t-1}} dp_{i,t-1} \tag{A.1}$$

However, under assumption (2), $p_{i,t-1}$ is itself a function of past latent litigation probability $p^*_{i,t-1}$. Hence, a change in $p_{i,t-1}$ on the RHS of (A.1) is induced by a change in $p^*_{i,t-1}$. This implies that the differential function in (A.1) becomes recursive, so that the change in p^*_{it} is a function of all past changes in I_{it} and $p_{i,t-1}$ for $t = 0, .., t$.

In particular, the total derivative of p^*_{it} with respect to I_{it} is given by:

$$\frac{dp^*_{it}}{dI_{it}} = \frac{\partial p^*_{it}}{\partial I_{it}} + \frac{\partial p^*_{it}}{\partial p_{i,t-1}} \frac{\partial p_{i,t-1}}{\partial p^*_{i,t-1}} \left(\frac{\partial p^*_{i,t-1}}{\partial I_{i,t-1}} + \frac{\partial p^*_{i,t-1}}{\partial p_{i,t-2}} \frac{\partial p_{i,t-2}}{\partial p^*_{i,t-2}} \left(... \left(\frac{\partial p^*_{i0}}{\partial I_{i0}} \right) \right) \right) \tag{A.2}$$

In other words, the partial derivative of p^*_{it} with respect to I_{it} in the first order condition (FOC) for profit maximization in (7) should in fact be replaced by the total derivative in (A.2):

$$\begin{aligned}
\frac{\partial \Pi_{it}}{\partial I_{it}} &= \frac{\partial (P_{it} - C_{it})}{\partial I_{it}} Q_{it} - \frac{\partial F_{it}}{\partial I_{it}} - \sum_{t=0}^{t=T} \delta^{T-t} L_{it} \frac{dp^*_{it}}{dI_{it}} \\
&= \frac{\partial (P_{it} - C_{it})}{\partial I_{it}} Q_{it} - \frac{\partial F_{it}}{\partial I_{it}} \\
&\quad - \sum_{t=0}^{t=T} \delta^{T-t} L_{it} \underbrace{\left[\frac{\partial p^*_{it}}{\partial I_{it}} + \frac{\partial p^*_{it}}{\partial p_{i,t-1}} \frac{\partial p_{i,t-1}}{\partial p^*_{i,t-1}} \left(\frac{\partial p^*_{i,t-1}}{\partial I_{i,t-1}} + \frac{\partial p^*_{i,t-1}}{\partial p_{i,t-2}} \frac{\partial p_{i,t-2}}{\partial p^*_{i,t-2}} \left(... \left(\frac{\partial p^*_{i0}}{\partial I_{i0}} \right) \right) \right) \right]}_{= \Omega_{it}} = 0
\end{aligned} \tag{A.3}$$

Note that Ω_{it} enters the FOC in all periods $t = 0, .., T$. In other words, although current innovation only has a first-order impact on profits, past innovation has multiple order effects. The first order effects are captured by the first term in Ω_{it} in periods $t = 0, .., T-1$. All the higher order effects are captured by the lagged partial derivatives of $p^*_{i,t-1}$ with respect to $I_{i,t-1}$ in periods $t = 0, .., T$. From equation (A.3) it is clear that the higher order effects of past innovation get strongly diluted, both through δ^{T-t} as well as their recursive nature. This is why I only consider past innovation's direct (i.e. first-order) effects in the main analysis.

It should be noted that ignoring the higher order impacts is of little consequence for the model's main result, i.e. the fact that the first order derivative of the implicit innovation function in (8) with respect to past realized patent litigation is negative. To see this, recall from footnote 5 that $\partial^2\Pi_{it}/\Delta p_{i,t-\tau}\partial I_{it} > 0 \ \forall \ \tau = 1,..,t$ is a necessary condition for this result. In the FOC in (A.3), this translates into $\partial\Omega_{it}/\Delta p_{i,t-\tau} > 0$. If, in addition to assumptions (5) and (6), we further assume that $\partial p^*_{it}/\partial p_{i,t-1} > 0 \ \forall \ t = 1,..,T$ (which seems reasonable), this condition is satisfied.

The total number of lawsuits

I started out by retrieving all patent lawsuits as identified by Lex Machina as of March 19th 2013. The original dataset contains 37,051 unique patent cases. Figure A.1 below presents the number of patent cases per year between 2000 and 2012. To the extent that the studied periods overlap, the numbers in Figure A.1 roughly correspond to those reported in Jaffe and Lerner (2004, Figure I.2) and Bessen and Meurer (2008*a*, Figure 6.1). The substantial increase in patent litigation that these authors noted during the 1990s (from +/- 1,000 cases per year in 1990 to +/- 2,500 cases per year in 2000) has largely come to a halt afterwards. As of 2011 there is a huge jump again in the number of patent cases per year. This may be caused by the 2011 America Invents Act, under which the possibility to join multiple defendants in one lawsuit has been severely restricted.

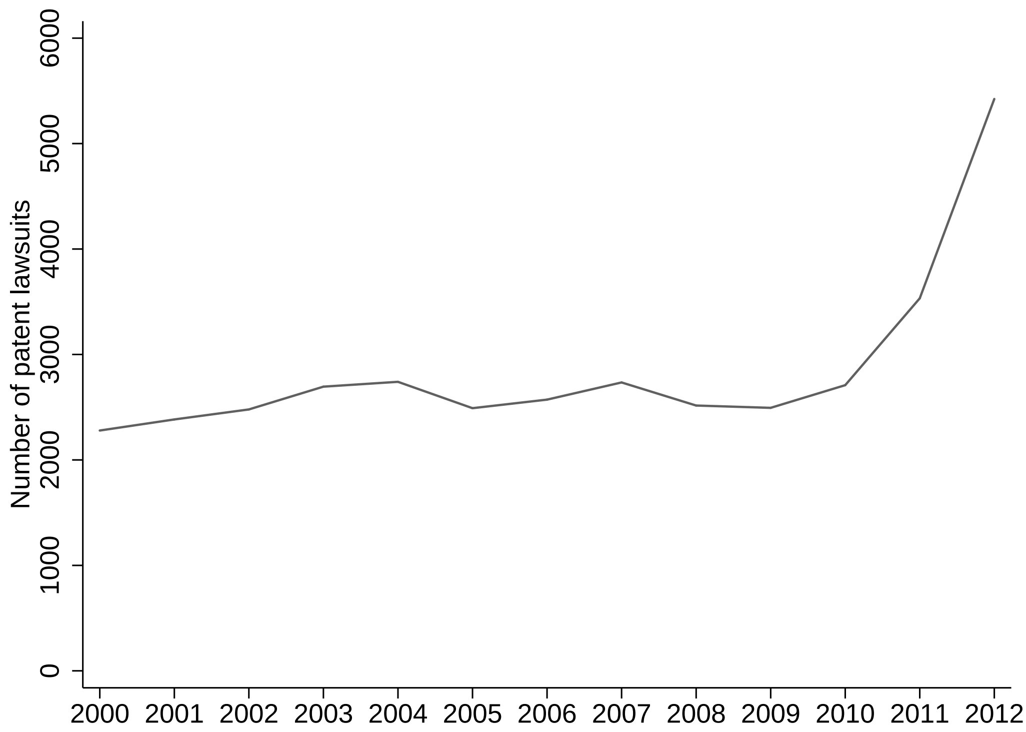

Figure A.1: Total number of patent litigation cases per year

Matching patent litigation data with Compustat

The next step in the data collection process is matching the patent data with firm-level data. I use the US Compustat database of listed firms as the source of firm-level information. The most obvious drawback of this dataset is that it only includes public firms, which biases our sample of firms mainly in terms of size. As argued by Bessen and Meurer (2008*a*) however, these firms are responsible for the majority of (US) R&D.

Each patent case lists the (primary) defendant by means of company (or person) name. I match these company names to the names in Compustat in a three-step process. First, I standardize the company names as they appear in the patent cases in order to make them comparable to the format used in Compustat. Second, I perform an exact match based on the full company names. Such a match is problematic even after extensive standardization of names, due to the string nature of the matched variables. That is, spelling mistakes or differences are not picked up by the standardization routine and result in a non-perfect match. Therefore, as a third step, for all the companies in the Lex Machina dataset that are not exactly matched with those in Compustat, I follow an approach recently forwarded by Thoma et al. (2010). These authors suggests the use of an index the so-called (weighted) J-distance index as a measure of similarity between different company names. The J-distance index is computed as follows:

$$J(X,Y) = 1 - 2\frac{\sum_{k|x_k \in X \cap Y} w_k}{\sum_{i|x_i \in X} w_i + \sum_{j|x_j \in X} w_j} \tag{A.4}$$

where X and Y are the two strings (i.c. company names) that are compared (i.e. one in the Lex Machina dataset – X – and the other in the Compustat dataset – Y). x and y denote individual tokens (i.c. individual words) that appear in X and Y respectively. $x_k \in X \cap Y$ denotes the k-th token that appears in both X and Y, whereas $x_i \in X$ ($y_j \in Y$) denotes the i-th (j-th) token that appears in X (Y) individually. The w's denote weights that each token receives. The purpose of these weights is to account for tokens that are very common in each of the two datasets. In particular, each token $l = i, j, k$ gets the following weight:

$$w_l = \frac{1}{log(n_l) + 1} \tag{A.5}$$

where n is the frequency of the token in the Compustat database. In other words, the more common a token is in the database the lower its weight, the reason being that the probability of finding a random (i.e. non-valid) match increases with the frequency of the token in the dataset.

In the case of a perfect match, the fraction in the second term of the J-index will be 0.5, and hence the J-index will be 0. Generally, the higher the J-index, the less perfect the match. The procedure I take is as follows: First, I compute the J-distance index for each unique Lex Machina-Compustat company pair (using only those Lex Machina companies that could not be perfectly matched to Compustat). For each Lex Machina company, I then select its Compustat match with the lowest J-distance value. After that, I manually check the resulting matching pairs for consistency and get rid of any non-valid matches. To keep this task manageable, I only consider matched pairs with a J-distance index below 0.2.[31] I execute this procedure for both claimants as well as defendants. Table A.1 shows the size of the sample at different stages in the sampling procedure.

In the original dataset, there are 16,323 unique defendants (i.e. alleged infringers). The

[31]This cutoff is rather arbitrary. Yet based on my experience while going through the dataset, valid matches become very scarce at J-distance levels above 0.15.

Table A.1: Lex Machina and Compustat matching

	Number	Share of original (%)	Share of total matched (%)
Original (Lex Machina)	16,323	100	–
Total matched	1,741	10.7	100
Perfect match	1,293	7.9	74.3
J-distance match	448	2.8	25.7
PSM match – all	736	4.5	42.3
PSM match – $p_\tau = 0$ for $\tau = 1, .., 4$	534	3.3	30.7

table shows that I am only able to match 10.7% of these with Compustat. The most important reason for this relatively low percentage is that I only consider public firms, implying that non-listed firms, individual inventors, an non-profit organizations fall outside the scope of the matching procedure. Additionally, I only consider US firms (or more accurately, firms listed on the US stock market), even though it often happens that parties in US patent litigation are foreign. However, note that the use of the J-distance index has real value added, as I am able to add another 448 corporate matches to the sample, on top of the 1,293 perfectly matched firms.

The table further shows a substantial drop in the sample of litigated firms that I am able to use in the propensity score matching (PSM) model. Eventually, I am left with only 3.3% of the firms in the original sample (or alternatively, 30.7% of firms from the complete matched sample). This additional drop in the sample is caused by (i) the restriction that to only include firms without any patent lawsuits in the four years following their first (observed) lawsuit, and (ii) missing data on one or more of the explanatory variables used in the PSM in the year of matching (i.e. the year of patent litigation).

Marginal impacts in the PSM model

Figure A.2 illustrates the marginal impact of R&D intensity in the PSM model estimates reported in column (1) of Table 4. At an R&D intensity below +/-50%, the marginal impact is negative. For higher values, the marginal impact turns negative. However, note that at high values of R&D intensity, the z-statistic is often not larger than —1.96—, indicating that the marginal effect is not statistically significant. In other words, the relationship between R&D

intensity and the probability of patent litigation is predominantly positive.

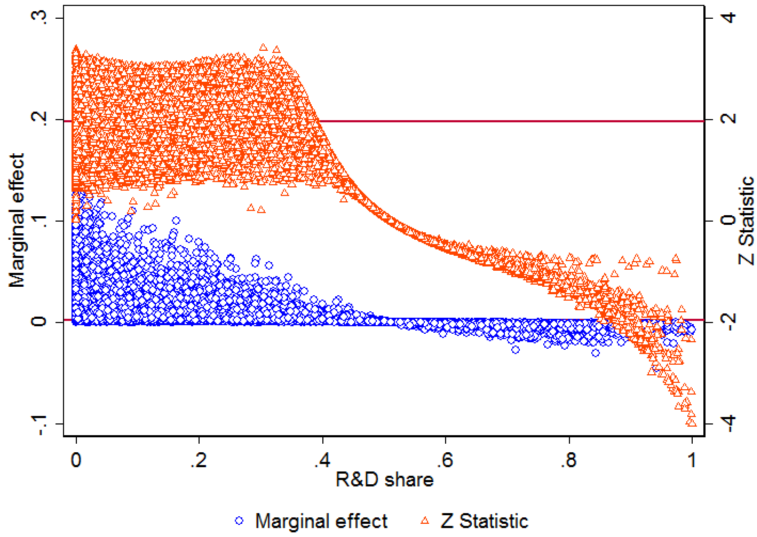

Figure A.2: Marginal impact of R&D intensity on probability of patent litigation

Figure A.3 illustrates the marginal impact of firm size (log of employees) in the PSM model estimates reported in column (1) of Table 4. There is a slight indication of a curvilinear relationship, as on average the marginal impact tends to be somewhat higher at low values of firm size than at high values. However, overall the relationship seems to be predominantly linear, with positive marginal impacts across the entire distribution of firm size.

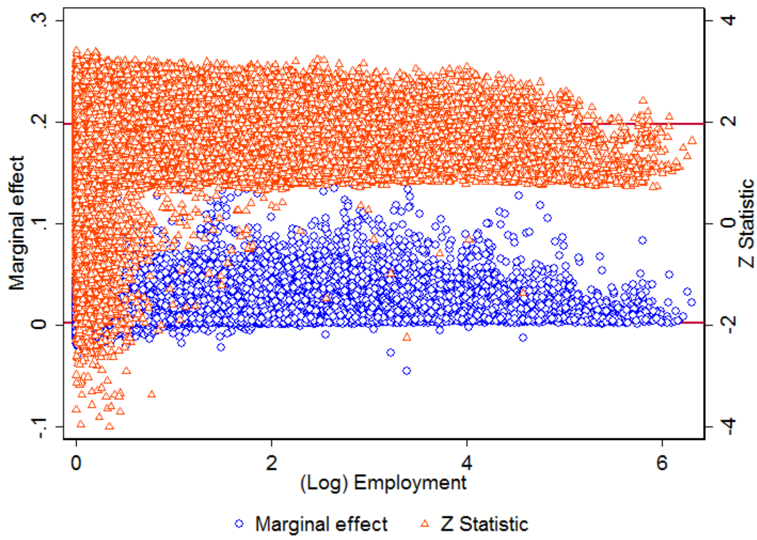

Figure A.3: Marginal impact of R&D intensity on probability of patent litigation

Table A.2: Technology types based on International Patent Classification (IPC) codes

Technology class	IPC codes	Source
Software	B04J, B41J, G06F, G06K, G06Q, G06T, G09G, G10L, H04B, H04L, H04	Allison and Mann (2007)
Telecommunications	G01S, G08C, G09C, H01P, H01Q, H01S, H15S, H03B, H03C, H03D H03H, H03M, H04B, H04J, H04K, H04L, H04M, H04N, H04Q	OECD
Drugs	A61K (excluding biotech subclasses)	Schmoch (2008)
Biotech	A01H1/00, A01H4/00, A61K38/00, A61K39/00, A61K48/00, C02F3/34, C07G11/00, C07G13/00 C07G15/00, C07K4/00, C07K14/00, C07K16/00, C07K19/00, C12M, C12N, C12Q, C12S G01N33/53, G01N33/54, G01N33/57, G01N33/68, G01N33/74, G01N33/76, G01N33/78 G01N33/88, G01N33/92	OECD (2005)
Semiconductors	H01L	Schmoch (2008)
Electronics	G11B, H03F, H03G, H03J, H04H, H04N, H04R, H04S	OECD
Instruments	A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61L, A61M, A61N, H05G	Schmoch (2008)

Appendix B

Table B.1: DID estimations - robustness tests

A. Sample attrition								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0	0.221	0	0.385	0	0.508	0	0.508
Non litigated	0	0.172	0	0.303	0	0.41	0	0.41
ATT		0.049		0.082		0.098		0.098
		(0.051)		(0.061)		(0.064)		(0.064)
Observations		488		488		488		488
Firm pairs		122		122		122		122

B. Ex-ante impacts								
	$\tau = -4$		$\tau = -3$		$\tau = -2$		$\tau = -1$	
	Pre	Filing	Pre	Filing	Pre	Filing	Pre	Filing
Litigated	0.255	0.2	0.236	0.207	0.225	0.199	0.205	0.201
Non litigated	0.154	0.124	0.163	0.137	0.166	0.134	0.152	0.139
ATT		0.025		0.003		-0.006		-0.009
		(0.031)		(0.017)		(0.017)		(0.01)
Observations		284		364		436		472
Firm pairs		71		91		109		118

C. Extensive patent lawsuits in large firms ($>$ 1,000 employees)								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.077	0.073	0.079	0.075	0.085	0.068	0.091	0.073
Non litigated	0.097	0.098	0.095	0.084	0.101	0.082	0.111	0.085
ATT		-0.005		0.007		0.002		0.008
		(0.005)		(0.007)		(0.008)		(0.012)
Observations		528		416		360		316
Firm pairs		132		104		90		79

D. Limited patent lawsuits ($\leq$ 40 documents) in small firms								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.198	0.189	0.221	0.204	0.216	0.182	0.234	0.191
Non litigated	0.192	0.169	0.221	0.188	0.211	0.169	0.212	0.16
ATT		0.014		0.016		0.008		0.009
		(0.019)		(0.028)		(0.044)		(0.055)
Observations		196		144		112		92
Firm pairs		49		36		28		23

Note: Dependent variable is R&D intensity in panels A, C, and D. Dependent variable is R&D exit in panel B. Standard errors clustered at the firm-level within parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.2: DID estimations - robustness tests (continued)

A.Technology match – All firms								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.167	0.145	0.163	0.139	0.163	0.126	0.170	0.126
Non litigated	0.144	0.138	0.151	0.143	0.142	0.122	0.141	0.117
ATT		-0.160^{**}		-0.160^{*}		-0.017		-0.020
		(0.007)		(0.009)		(0.012)		(0.015)
Observations		856		696		556		472
Firm pairs		214		174		139		118

B. Technology match – Small firms (< 500 employees)								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Pre	Filing	Pre	Filing	Pre	Filing	Pre	Filing
Litigated	0.234	0.193	0.238	0.190	0.267	0.187	0.273	0.194
Non litigated	0.166	0.157	0.182	0.164	0.168	0.149	0.152	0.129
ATT		-0.032^{**}		-0.030		-0.061^{*}		-0.056
		(0.016)		(0.019)		(0.033)		(0.041)
Observations		328		252		164		144
Firm pairs		82		63		41		36

C. Technology match – Extensive patent lawsuits (> 40 documents) in small firms								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.234	0.191	0.231	0.181	0.278	0.186	0.272	0.18
Non litigated	0.157	0.157	0.167	0.161	0.146	0.137	0.139	0.124
ATT		-0.043^{**}		-0.044^{**}		-0.083^{***}		-0.077^{*}
		(0.019)		(0.019)		(0.03)		(0.039)
Observations		212		164		96		88
Firm pairs		53		41		24		22

Note: Dependent variable is R&D intensity. Standard errors clustered at the firm-level within parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.3: DID estimations - robustness tests (continued)

A. Extensive patent lawsuits (> 50 documents) in small firms (< 500 employees)								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.2	0.168	0.218	0.177	0.235	0.169	0.231	0.167
Non litigated	0.15	0.161	0.148	0.133	0.121	0.107	0.116	0.102
ATT		-0.043^{**}		-0.026^{*}		-0.052^{**}		-0.050^{*}
		(0.021)		(0.014)		(0.021)		(0.029)
Observations		316		224		152		128
Firm pairs		79		56		38		32
B. Extensive patent cases (>100 documents) in small firms (< 500 employees)								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.208	0.17	0.222	0.177	0.24	0.167	0.236	0.154
Non litigated	0.152	0.166	0.138	0.124	0.127	0.112	0.122	0.105
ATT		-0.052^{*}		-0.031^{*}		-0.052^{**}		-0.065^{*}
		(0.027)		(0.017)		(0.026)		(0.036)
Observations		244		180		120		96
Firm pairs		61		45		30		24
C. Extensive patent cases (>150 documents) in small firms (< 500 employees)								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.22	0.177	0.224	0.177	0.241	0.167	0.236	0.154
Non litigated	0.146	0.165	0.137	0.125	0.127	0.112	0.122	0.105
ATT		-0.062^{**}		-0.037^{**}		-0.058^{**}		-0.065^{*}
		(0.031)		(0.018)		(0.026)		(0.036)
Observations		208		164		120		96
Firm pairs		52		41		30		24
D. DID estimates from the restricted PSM model								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.203	0.184	0.22	0.161	0.233	0.157	0.247	0.159
Non litigated	0.142	0.137	0.147	0.127	0.151	0.133	0.15	0.116
ATT		-0.014		-0.039^{*}		-0.058^{**}		-0.054
		(0.017)		(0.023)		(0.028)		(0.036)
Observations		244		204		148		116
Firm pairs		61		47		37		29

Note: Dependent variable is R&D intensity. Standard errors clustered at the firm-level within parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.4: DID estimations - firm-level controls

	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
ATT	-0.044^{**}	-0.034^{**}	-0.050^{**}	-0.050^{*}
	(0.02)	(0.015)	(0.02)	(0.029)
(Log) size	-0.039^{***}	-0.053^{***}	-0.027^{*}	-0.043^{***}
	(0.012)	(0.015)	(0.016)	(0.015)
Capital intensity	-0.045^{*}	-0.075^{*}	-0.067^{***}	-0.040
	(0.027)	(0.029)	(0.022)	(0.029)
Observations	336	240	164	136
Firm pairs	84	60	41	34

Note: Dependent variable is R&D intensity. Standard errors clustered at the firm-level within parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.5: DID estimations - robustness tests (continued)

A. Patent lawsuits decided on the merits - all firms

	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.136	0.131	0.131	0.12	0.13	0.105	0.132	0.116
Non litigated	0.102	0.099	0.1	0.091	0.1	0.085	0.096	0.079
ATT		-0.002		-0.002		-0.01		0.001
		(0.013)		(0.018)		(0.025)		(0.03)
Observations		212		200		180		160
Firm pairs		53		50		45		40

B. Patent lawsuits decided on the merits - small firms (< 500 employees)

	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.223	0.189	0.218	0.172	0.221	0.159	0.219	0.161
Non litigated	0.165	0.14	0.174	0.128	0.179	0.108	0.146	0.083
ATT		-0.009		0		0.009		0.005
		(0.04)		(0.051)		(0.084)		(0.112)
Observations		68		64		52		40
Firm pairs		17		16		13		10

C. Patent lawsuits in complex technologies - all firms

	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Pre	Filing	Pre	Filing	Pre	Filing	Pre	Filing
Litigated	0.153	0.143	0.156	0.142	0.161	0.134	0.16	0.134
Non litigated	0.141	0.14	0.146	0.138	0.151	0.127	0.157	0.128
ATT		-0.009^{*}		-0.006		-0.003		0.003
		(0.005)		(0.01)		(0.011)		(0.013)
Observations		712		516		420		360
Firm pairs		178		129		105		90

D. Patent lawsuits in complex technologies - small firms (< 500 employees)

	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.191	0.179	0.207	0.181	0.217	0.178	0.211	0.175
Non litigated	0.143	0.145	0.152	0.144	0.145	0.129	0.155	0.132
ATT		-0.014^{*}		-0.018		-0.021		-0.013
		(0.008)		(0.013)		(0.019)		(0.023)
Observations		300		204		156		128
Firm pairs		75		51		39		32

Note: Dependent variable is R&D intensity. Standard errors clustered at the firm-level within parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

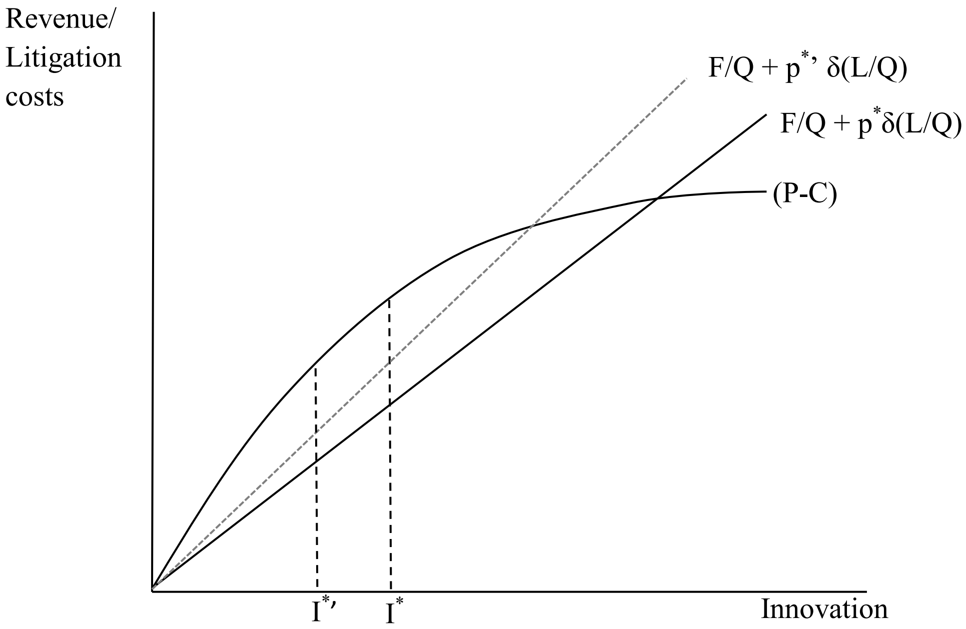

Figure 1: Optimal innovation rates and patent litigation

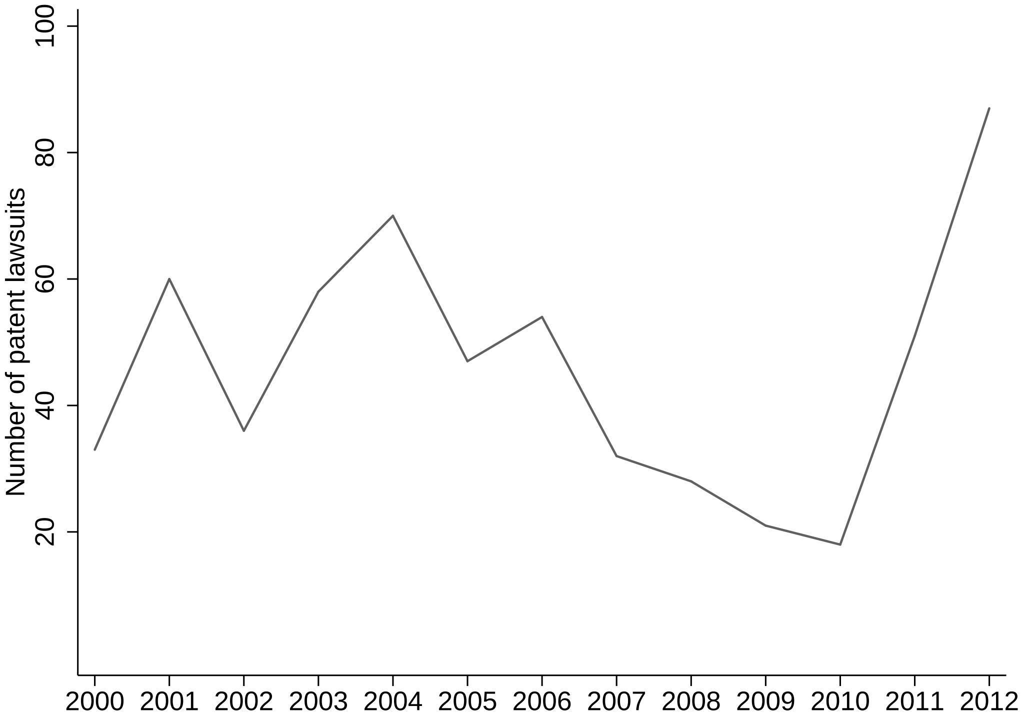

Figure 2: Number of patent litigation cases per year

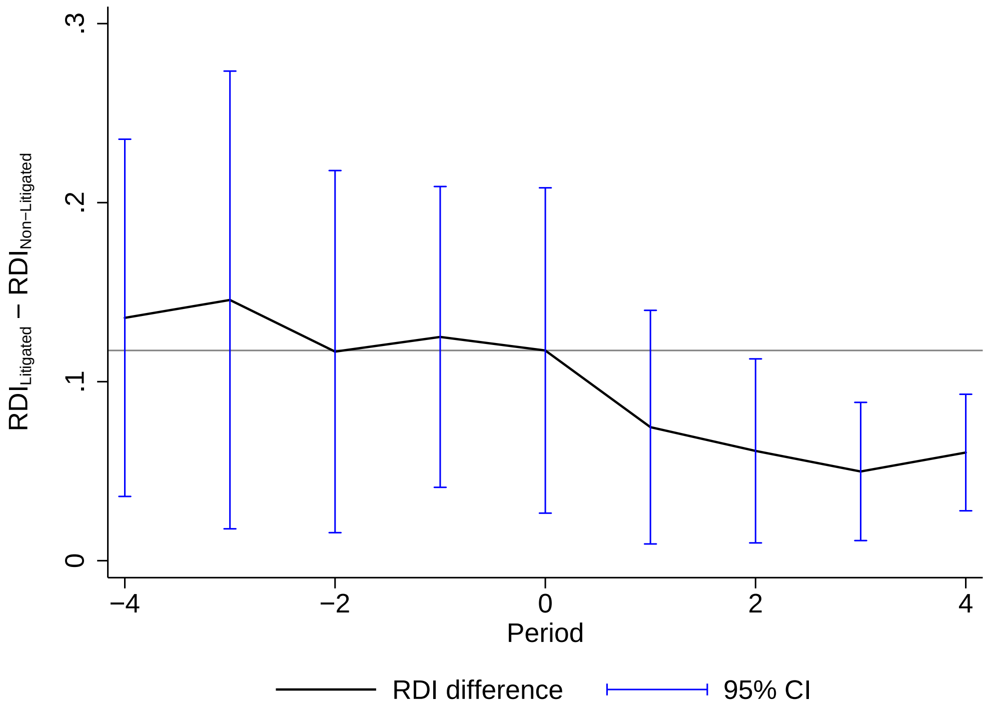

Figure 3: DID effects in small firms (< 500 employees) and extensive lawsuits (> 40 documents)

Table 1: Industry and IPC distribution of patent lawsuits

A. Industry distribution

SIC code	Description	Firms	Share (%)
73	Business services	107	20
36	Electronics	80	15
38	Instruments	73	13.7
28	Chemicals & pharmaceuticals	65	12.2
35	Machinery	54	10.1
37	Transport equipment	20	3.7
59	Miscellaneous retail	11	2.1
56	Apparel & accessory stores	10	1.9
50	Wholesale trade-durable goods	9	1.7
34	Fabricated metal products	8	1.5
–	Other	97	18.2

B. IPC distribution

IPC code	Description	Cases	Share (%)
G06F	Electrical digital data processing	99	11.1
G06Q	Data processing systems or methods	48	5.4
H04L	Transmission of digital information (e.g. telegraphic communication)	47	5.3
G07F	Coin-freed or like apparatus	34	3.8
A61B	Diagnosis, surgery, identification	28	3.2
A61K	Preparations for medical, dental, or toilet purposes	25	2.8
H04N	Pictorial communication	22	2.5
G01N	Investigating or analysing materials by determining their chemical or physical properties	20	2.3
C12N	Micro-organisms or enzymes	19	2.1
H01L	Semiconductor devices	19	2.1
–	Other	527	59.3

Table 2: Industry (type) and patent type correspondence

A. Industry-patent type correspondence

SIC	software	telecommunications	drugs	biotech	semiconductors	electronics	instruments
28	2	0	20	15	0	1	10
35	26	13	0	0	2	4	0
36	64	51	0	0	26	11	1
38	10	5	3	7	0	6	42
73	93	42	0	0	1	17	2

B. Industry type-patent type correspondence

Industry type	software	telecommunications	drugs	biotech	semiconductors	electronics	instruments
Complex	80	58	3	7	27	17	44
Discrete	31	17	20	15	2	5	16

Note: See Table A.2 for the patent type classification. Discrete industries in panel B are defined as manufacturing industries with SIC$\leq$35. Complex industries are defined as manufacturing industries with SIC>35 (Arora et al., 2000).

Table 3: Case length, documents, and outcome by firm size

	Small firms	Medium firms	Large firms
A. Length of lawsuit (in days)			
Mean	546.7	585.4	602.2
St Dev	488.5	839.7	571.2
Min	7	14.5	32.5
Median	454	266.5	421
Max	2956.5	3096.5	3234.5
B. Number of documents			
Mean	84.5	110.3	83.9
St Dev	139	139.3	128.7
Min	1	2	2
Median	40	52	37.5
Max	950	571	809
C. Case outcomes (% relative to total)			
Plaintiff wins	7.5	6.8	9.7
Defendant wins	8.8	4.6	7.9
Stipulated dismissal	58.5	70.5	43.4
Voluntary dismissal	9.5	9.1	18
Other	15.7	9	21

Note: Small firms $<$ 500 employees, medium firms $\geq$ 500 employees and $<$ 1,000 employees, large firms $\geq$ 1,000 employees.

Table 4: Propensity score matching model

	(1) Baseline model	(2) Extended model
R&D intensity	1.128***	0.648
	(0.412)	(0.473)
R&D intensity^2	−1.103*	−0.766
	(0.629)	(0.663)
(Log) Employment	0.291***	0.268***
	(0.04)	(0.062)
(Log) Employment^2	−0.038***	−0.051***
	(0.009)	(0.014)
Fixed asset share	−0.156***	−0.209***
	(0.045)	(0.067)
Foreign firm dummy	−0.349	0.397
	(0.318)	(0.271)
(Log) patents		0.150***
		(0.03)
(Log) knowledge stock		−0.056**
		(0.024)
No-patents dummy		−0.376***
		(0.067)
SIC dummies (3-digit)	Yes	Yes
State dummies	Yes	Yes
Year dummies	Yes	Yes
Pseudo R^2	0.067	0.080
Observations	40,943	22,751
Firms	6,276	4,931

Note: Dependent variable is litigation probability. Standard errors clustered at the firm-level within parentheses. ***; $p < 0.01$, **; $p < 0.05$, *; $p < 0.1$.

Table 5: PSM balancing tests

	(1) Before matching	(2) After matching
A. Standardized Bias Test		
R&D intensity	-5.48	1.47
R&D intensity^2	-4.11	2.3
(Log) Employment	25	-0.26
(Log) Employment^2	15.6	-0.64
Fixed asset share	-10.5	-2.66
Foreign firm dummy	-25.9	0
B. Standardized T-Tests		
R&D intensity	1.11	0.24
	(0.133)	(0.405)
R&D intensity^2	0.68	0.38
	(0.248)	(0.354)
(Log) Employment	-5.87	-0.04
	(0.000)	(0.517)
(Log) Employment^2	-3.78	-0.11
	(0.000)	(0.542)
Fixed asset share	1.81	-0.43
	(0.030)	(0.670)
Foreign firm dummy	5.26	0.00
	(0.000)	(1.000)
C. PSM models		
R&D intensity	1.128***	-0.170
	(0.412)	(0.705)
R&D intensity^2	-1.103^{*}	0.348
	(0.629)	(0.742)
(Log) Employment	0.291***	0.051
	(0.04)	(0.116)
(Log) Employment^2	-0.038^{***}	-0.006
	(0.009)	(0.024)
Fixed asset share	-0.156^{***}	-0.171
	(0.045)	(0.143)
Foreign firm dummy	-0.349	-0.106
	(0.318)	(0.999)
Pseudo R^2	0.067	0.029
Observations	40,943	1,068
Firms	6,276	534

Notes: Panel A presents the results of the standardized biased test expressed in % (see footnote 20). Panel B presents the results of a standardized t-test (p-values within parentheses). Panel C estimates the PSM (probit) model as in Table 4. The dependent variable is litigation probability. Standard errors clustered at the firm-level within parentheses. Both PSM models in panel C contain full sets of (3-digit) SIC industry dummies, state dummies, and year dummies. $^{***}; p < 0.01$, $^{**}; p < 0.05$, $^{*}; p < 0.1$.

Table 6: DID baseline estimations

A. All patent lawsuits	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.128	0.117	0.134	0.119	0.132	0.107	0.136	0.107
Non litigated	0.127	0.125	0.131	0.12	0.125	0.107	0.127	0.102
ATT		-0.009^{*}		-0.004		-0.007		-0.004
		(0.006)		(0.006)		(0.008)		(0.01)
Observations		1500		1136		924		784
Firm pairs		375		284		231		196

B. Small firms (< 500 employees)	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.195	0.174	0.215	0.185	0.221	0.171	0.228	0.175
Non litigated	0.163	0.162	0.173	0.153	0.155	0.13	0.154	0.124
ATT		-0.02		-0.01		-0.025		-0.023
		(0.014)		(0.014)		(0.021)		(0.027)
Observations		532		384		276		228
Firm pairs		133		96		69		57

C. Long patent lawsuits (> 420 days)	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.132	0.121	0.138	0.123	0.136	0.107	0.14	0.108
Non litigated	0.124	0.126	0.129	0.121	0.124	0.104	0.124	0.099
ATT		-0.013^{**}		-0.007		-0.009		-0.007
		(0.007)		(0.007)		(0.009)		(0.011)
Observations		1220		234		772		656
Firm pairs		305		936		193		164

D. Extensive patent lawsuits (> 40 documents)	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.132	0.117	0.122	0.111	0.139	0.105	0.143	0.108
Non litigated	0.121	0.124	0.137	0.118	0.114	0.094	0.119	0.093
ATT		-0.018^{**}		-0.008		-0.014^{*}		-0.008
		(0.007)		(0.007)		(0.008)		(0.011)
Observations		248		186		150		129
Firm pairs		992		744		600		516

Note: Dependent variable is R&D intensity. Standard errors clustered at the firm-level within parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: DID estimations - reinforcing impacts of firm size, case length, and case extensiveness

A. Long patent lawsuits (> 420 days) in small firms (< 500 employees)								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.205	0.18	0.219	0.184	0.225	0.168	0.234	0.174
Non litigated	0.154	0.161	0.159	0.147	0.143	0.121	0.134	0.112
ATT		-0.032^{*}		-0.023		-0.035		-0.038
		(0.017)		(0.015)		(0.024)		(0.031)
Observations		432		324		236		196
Firm pairs		108		81		59		49

B. Extensive patent lawsuits (> 40 documents) in small firms (< 500 employees)								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.195	0.165	0.21	0.173	0.224	0.163	0.224	0.165
Non litigated	0.147	0.158	0.144	0.133	0.117	0.103	0.114	0.1
ATT		-0.041^{**}		-0.026^{*}		-0.047^{**}		-0.045
		(0.02)		(0.014)		(0.02)		(0.027)
Observations		336		240		164		136
Firm pairs		84		60		41		34

C. Long (> 420 days) and extensive (> 40 documents) patent lawsuits								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.134	0.12	0.138	0.12	0.138	0.106	0.142	0.11
Non litigated	0.125	0.129	0.127	0.115	0.12	0.098	0.125	0.097
ATT		-0.018^{**}		-0.006		-0.01		-0.004
		(0.008)		(0.007)		(0.009)		(0.011)
Observations		872		676		552		480
Firm pairs		218		169		138		120

D. Long and extensive patent lawsuits in small firms								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.199	0.169	0.21	0.174	0.223	0.165	0.226	0.17
Non litigated	0.154	0.168	0.148	0.139	0.123	0.109	0.118	0.104
ATT		-0.044^{**}		-0.027^{*}		-0.044^{**}		-0.042
		(0.022)		(0.015)		(0.021)		(0.029)
Observations		300		220		152		128
Firm pairs		75		55		38		32

E. Extensive patent lawsuits in small firms - balanced sample								
	$\tau = 1$		$\tau = 2$		$\tau = 3$		$\tau = 4$	
	Filing	Post	Filing	Post	Filing	Post	Filing	Post
Litigated	0.223	0.187	0.223	0.170	0.223	0.164	0.223	0.165
Non litigated	0.114	0.114	0.114	0.107	0.114	0.107	0.114	0.100
ATT		-0.036^{**}		-0.046^{**}		-0.052^{**}		-0.044
		(0.015)		(0.018)		(0.023)		(0.027)
Observations		136		136		136		136
Firm pairs		34		34		34		34

Note: Dependent variable is R&D intensity. Standard errors clustered at the firm-level within parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.