Patent Thickets, Defensive Patenting, and Induced R&D: An Empirical Analysis of the Costs and Unintended Potential Benefits of Fragmentation in Patent Ownership*

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01 February 2011

Job Market Paper

Abstract

Patent thickets are sets of overlapping intellectual property rights that occur in fragmented technology markets, and increase the costs of commercializing innovations due to transaction costs, double marginalization, complement problem, and the possibility of hold-up and prolonged litigation. These costs of patent thickets have become an increasing concern in recent years. In this paper, I estimate the direct and indirect effects of patent thickets on market value of firms, using panel data on 1,272 publicly traded US manufacturing firms from 1979 to 1996. I find that patent thickets decrease the market value of firms, holding R&D and patenting activities of firms constant. I also find that while firms do not change their R&D activities in response to patent thickets, through defensive patenting firms are able to reduce, but not eliminate the negative impact that patent thickets have on market value.

Keywords: Innovation, Patent Thicket, Spillovers, Market Value, Fragmentation
JEL classification numbers: L43, O31, O33, O32, O34, O38

*I thank Mikko Packalen, Lutz Busch and Anindya Sen for encouragement and advice. I thank participants at the 2009 International Industrial Organization Conference and participants at the 2009 Canadian Economics Association meetings for comments. All errors and omissions are mine.

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1 Introduction

The establishment of the United States Court of Appeals for the Federal Circuit (CAFC) in 1982 and the subsequent pro-patent shifts in the United States Patent and Trademark Office (USPTO) reduced costs, and increased benefits and ease of obtaining patents.[1] These changes caused a proliferation of patents and a higher fragmentation of patent ownership in the technology market (Jaffe and Lerner, 2007, p. 10).

Highly fragmented technology markets result in dense "patent thickets "for subsequent (cumulative) innovators. A subsequent innovator builds innovation upon a set of complementary patents, owned by previous innovators. Shapiro (2001) refers to the set of complementary patents a patent thicket. Patent thickets require subsequent innovators to obtain permission from all the right holders in their thicket, before they can commercialize their own innovation. In patent systems that lead to highly fragmented technology markets, subsequent innovators are faced with dense patent thickest, which means they have to deal with a large number of external patent holders in their patent thicket. The large number of patent holders in dense patent thickets leads to high costs, which are discussed below, and can act as a disincentive to innovation.

The costs imposed on subsequent innovators by dense patent thickets arise from the high licensing fees associated with the complement problem and double marginalization, the transaction costs, and the possibility of hold-up and prolonged litigation, all explained below. The origin of the complement problem goes back to Cournot (1838); he analyzed a

[1] In the 1970s, there was a concern that the United States had fallen behind other industrialized countries in terms of its technology (Meador, 1992). Thus, according to Gallini (2002), the CAFC was established to efficiently deal with patent disputes. Prior to 1982, patent disputes were solved in the appellate courts of various circuits that differed in their interpretation of patent law (Jaffe and Lerner, 2007, p. 9). The CAFC helped unify standards across circuits and granted stronger patent rights to patent holders in infringement lawsuits (Gallini, 2002). Therefore, the CAFC increased the benefits of obtaining patents by strengthening patent rights.

According to Jaffe and Lerner (2007, p. 11), the USPTO adopted a pro-patent attitude following the decision of Congress in the early 1990s that changed the USPTO from an agency funded by tax revenues to an agency funded by fees that the USPTO collects. Thus, the USPTO started to grant patents extensively.

manufacturer of brass who needed two inputs: zinc and copper. He showed that the price of brass is lower when the inputs are controlled by a single monopolist than when each input is controlled by a separate monopolist. Shapiro (2001) illustrates the negative impacts of fragmentation in patent ownership by applying the complement analysis of Cournot (1838) to the case of intellectual property rights. Shapiro (2001) shows subsequent innovators in fragmented technology markets have to pay a considerable licensing fee due to the presence of multiple right holders in their thicket. In other words, these innovators pay higher licensing fees when the complementary patents in their thicket are owned by two or more licensors than when the complementary patents are owned by only one licensor. Consequently, the existence of separate licensors for complementary patents leads to higher prices of final goods. Fragmentation in patent ownership therefore lowers both the licensors' profits and consumers' welfare.

Dense patent thickets are also costly due to increased double marginalization in fragmented technology markets. The double marginalization problem refers to a vertical sequence of monopolists in which a markup is charged on a markup (e.g., Varian, 2010, p. 492). In the case of intellectual property rights, a subsequent innovator is a downstream monopolist who needs to obtain licenses from a stream of upstream monopolists (the owners of existing patents upon which the subsequent innovator's own innovation builds upon or relies on). This implies a double markup and increases the licensing fee for the subsequent innovator.

Another cost of dense patent thickets is the transaction costs for identifying and negotiating licenses for complementary patents (Shapiro, 2001). The identification of all of the related existing patents in a patent thicket is not always easy.[2] Firms often become aware of the related patents only after making large sunk investments in their own innovation process.

[2]The difficulty in identification makes the use of ex-ante solutions costly or even impossible.An example of an ex-ante solution is the formation of a patent pool. According to Shapiro (2001), in a patent pool, one entity, who can be one of the patent holders, licenses patents of two or more entities to third parties.

The associated potential for hold-up and litigation further discourages firms from investing in manufacturing facilities and innovation.

Dense patent thickets and their costs might lead to underinvestment in subsequent innovation. This aspect is emphasized by Heller and Eisenberg (1998), who discuss the potential impacts of patent thickets on innovative activities in the biomedical sector and compare the problem to the tragedy of commons, that is, the overuse of resources.[3] They argue that the large number of intellectual property rights in the biomedical sector leads to underuse of resources, because subsequent innovators should obtain permission from patent holders in their thicket if they want to use the complementary patents. Heller and Eisenberg (1998) call this phenomenon "the tragedy of anti-commons."

Dense patent thickets and their costs have led to several proposals for amendments and legislations in the US patent system (e.g., the 2007, 2009, and 2010 Patent Reform Acts). These amendments have created considerable debate. The reform supporters, represented by the Coalition for Patent Fairness, argue that the resources used to cover the costs of patent thickets would be better spent on job creation and innovation.[4] Innovation Alliance, in contrast, argues that the reform would weaken patent rights, which would decrease innovation and have a negative impact on the US technology leadership at the global level.[5] Both sides of this debate are represented in economic analyses on patent thickets. As discussed above, Heller and Eisenberg (1998) and Shapiro (2001) argue that patent thickets deter innovation. In contrast, Merges (2001) argues that firms largely avoid potential problems induced by patent thickets via establishing institutions such as patent pools in which to conduct their transactions with other right holders. The presence and the extent of damaging impacts

[3]Fishing grounds and clean water are examples of commons.

[4]DiMartino, David. Coalition for Patent Fairness "Members of Senate High-Tech Task Force Ask Senate Judiciary Leadership Not to Weaken the Patent Reform Act of 2009" (http://www.patentfairness.org/media/press/; last accessed 27 Jan. 2011).

[5]Metz,Cade. The Register "Techies oppose US Patent reform bill" (http://www.theregister.co.uk/2007/10/25/techies_send_letter_to_senate_against_patent_reform_bill/; last accessed 27 Jan. 2011).

from dense patent thickets is therefore an empirical question.

In this paper, I assess the economic impacts of patent thickets by estimating their effect on the market value of firms. I argue that dense patent thickets in highly fragmented technology markets could have two types of impacts: direct and indirect. The direct impact is the effect of patent thickets on firms' market value, while I hold the all firms' patenting and R&D behavior constant. The potential costs of patent thickets, as discussed above, lower the expected earnings of firms and thereby lower their market value. Estimating the direct impact of patent thickets is not sufficient to determine the effects of patent thickets, because patent thickets might also change the behavior of firms. Hence, I estimate the indirect impacts of patent thickets as well.

Specifically, I estimate the indirect potential impacts that patent thickets have on market value through the likely effects that patent thickets have on patenting and R&D activities of firms. Patent thickets may encourage firms to patent defensively (the increase in patenting attributed to avoiding thicket costs) in order to increase bargaining power in negotiations with other right holders (Ziedonis, 2004). Firms may also reduce their reliance on other firms' innovation by increasing their R&D expenditures. The R&D activities and defensive patenting behavior of firms may increase their market value, and therefore reduce or even eliminate the negative direct impact that patent thickets have on the market value of firms.

In addition, this study captures the potential direct and indirect impacts that firms' patent thickets might have on one another (patent thicket spillovers). Assuming a given firm, the rationale behind the direct impact of other firms' patent thickets on the market value of the given firm is that other firms charge higher licensing fees from the given firm for using their complementary patents. They do so because other firms are also faced with their own patent thicket, and they want to cover the potential costs of obtaining licenses for the complementary patents in their own patent thicket. Therefore, higher licensing fees that other firms charge the given firm due to the costs of their own patent thicket lower expected profits and stock market valuation of the given firm. I also measure the potential indirect impacts of others' patent thickets on the market value of the given firm through the effects of others' patent thickets on the given firm's patenting and R&D activities. Other firms' patent thickets could make them raise their R&D and defensive patenting. It is often asserted that the R&D and patenting activities of firms have positive spillover effects on one another. The changes in R&D and patenting activities of the given firm due to positive spillovers from other firms will be reflected in higher expected profits and the market value of the given firm.

In my analysis, I use panel data on 1,272 publicly traded US manufacturing firms from 1979 to 1996. The analysis builds on the methodologies developed in Griliches (1981) and Hall et al. (2005).[6] My analysis also allows for the presence of R&D spillovers and patent thicket spillovers (other firms' patent thickets) among firms, and to measure spillovers I employ the methodologies developed in Bernstein and Nadiri (1989), Jaffe (1986), and Bloom et al. (2006), all of whom examine R&D spillovers.

My results suggest that patent thickets, both firms' own as well as other firms', have a negative direct impact on the market value of firms. I also find that both firms' own and other firms' patent thickets increase defensive patenting, but do not have a statistically significant effect on firms' R&D activities. While defensive patenting alleviates the direct negative impact that patent thickets have on market value, the total impact of patent thickets on the market value of firms is still negative. This finding implies that the concerns over the negative impacts of patent thickets are valid.

The prior empirical evidence on the effects of patent thickets is mixed. Hall and Ziedonis (2001) and Ziedonis (2004) examine the semiconductor industry and find that firms patent

[6] Griliches (1981) examines the impact of patenting and R&D on the market value of firms using a sample of 157 large US firms from Compustat data for the period from 1968 to 1974. Hall et al. (2005) analyze the driving factors of the market value of firms by examining the impact of patenting and patent citations on the market value of firms. This study employs a non-linear model in a sample of 1982 patenting manufacturing US firms from 1979 to 1988.

aggressively in more fragmented technology markets, and that this effect is more pronounced for capital-intensive firms.[7] Graevenitz at al. (2010) also find fragmentation has a positive impact on patenting activities of firms in very complex technology areas in Europe.[8] Noel and Schankerman (2006) focus on the software industry and find that patent thickets have a negative impact on firms' market value. Entezarkheir (2010) finds that patent thickets have negative impacts on market value of manufacturing firms in general, while she holds R&D and patenting activities constant. Walsh et al. (2003) perform 70 interviews with personnel in universities, the biotechnology sector, and pharmaceutical firms. According to their interviews, the anti-commons problem is manageable. Walsh et al. (2005) perform a survey on 414 biomedical researchers in universities, government, and non-profit institutions. They find that limited access to intellectual property does not restrict biomedical research. Murray and Stern (2007) find only a modest anti-commons effect in biomedical patenting.

This paper makes three contributions to the literature. First, to calculate the direct and indirect impacts of patent thickets on the market value of firms, I estimate the effects that patent thickets have on patenting and R&D as well as on market value, using three separate estimating equations. To my knowledge, only Noel and Schankerman (2006), who focus on the software industry, have previously examined the impacts of patent thickets on these three outcome variables. I instead examine the impacts of patent thickets on these three outcome variables in the manufacturing sector. Second, I use the estimates of the three empirical equations to determine the direct, indirect, and total impacts of patent thickets on firms' market value. To my knowledge, no prior study has quantified the indirect and total impacts of patent thickets on the market value of firms. Third, my estimating equations allows for the possibility that other firms' patent thickets also have direct and indirect impacts on the market value of a given firm. As far as I am aware, no prior study has considered the impact

[7]The Hall and Ziedonis' (2001) sample includes 95 US semiconductor firms from 1979 to 1995. The Ziedonis' (2004) sample consists of 67 US semiconductor firms from 1980 to 1994.

[8]The Graevenitz at al. (2010) employ a panel data on 2074 firms in 30 technology areas over 15 years in Europe. This sample is based on PATSTAT data base.

that other firms' patent thickets may have on a firm's market value or behavior.

2 Empirical Framework

In this section, I first present the functional relationships that determine the total impact of patent thickets on the market value of firms. In the second subsection, I present three estimating equations, one for each functional relationship. In the third subsection, I discuss how the parameter estimates can be used to calculate the direct, indirect, and total impacts of patent thickets on the market value of firms. In the fourth subsection, I discuss measuring the patent thicket variables used in the analysis.

2.1 Three Functional Relationships

The empirical framework is based on three functional relationships that enable me to calculate patent thickets' direct and indirect impacts on market value. The first functional relationship is the impact of a firm's own patent thicket (F) and other firms' patent thickets ($spillF$) on the firm's market value:

$$Market\ Value = f(F, spillF, R\&D, Patents, ...). \tag{1}$$

As is depicted in this relationship, R&D and patenting activities of a firm also impact its market value. Since patent thickets may influence R&D expenditures and the patenting behavior of firms, measuring the total impact of patent thickets on market value requires that I estimate the impact of patent thickets on R&D and patenting as well. As a result, the second functional relationship is the impact of a firm's own and other firms' patent thickets on the firm's R&D expenditures:

$$R\&D = g(F, spillF, ...), \tag{2}$$

and the third functional relationship is the impact of a firm's own and other firms' patent thickets on the firms' patenting behavior:

$$Patent = h(F, spillF, R\&D, ...). \tag{3}$$

As is illustrated in relationship (3), patenting activity by a firm is also influenced by its R&D expenditures.[9]

The estimating equations for the relationships (1) through (3) are presented below. After estimating the impacts of the right-hand side variables in the three relationships, I calculate the direct impact of patent thickets on market value as

$$DIRECT = \frac{\partial Market\ Value}{\partial F} + \frac{\partial Market\ Value}{\partial spillF} \times \frac{\partial spillF}{\partial F}, \tag{4}$$

the indirect impact of patent thickets on market value through R&D as

$$\begin{aligned} INDIRECT(R\&D) \quad = \quad & \frac{\partial Market\ Value}{\partial R\&D} \times \frac{\partial R\&D}{\partial F} \\ & + \frac{\partial Market\ Value}{\partial R\&D} \times \frac{\partial R\&D}{\partial spillF} \times \frac{\partial spillF}{\partial F}, \end{aligned} \tag{5}$$

and the indirect impact of patent thickets on market value through patenting as

$$\begin{aligned} INDIRECT(PATENTING) \quad = \quad & \frac{\partial Market\ Value}{\partial Patents} \times \frac{\partial Patents}{\partial F} \\ & + \frac{\partial Market\ Value}{\partial Patents} \times \frac{\partial Patents}{\partial spillF} \times \frac{\partial spillF}{\partial F}. \end{aligned} \tag{6}$$

The total impact of patent thickets on market value is calculated as the sum of direct impact (4) and the two indirect impacts (5-6).

[9]The R&D expenditures of a firm impact its patenting, as successful R&D leads to innovation, and the firm can obtain patents for innovation (Griliches and Pakes, 1980).

2.2 Three Estimating Equations

2.2.1 Market Value Equation

To estimate the relationship (1) depicting the direct impacts of patent thickets on the market value of a firm, I use

$$\begin{aligned} logq_{it} = {} & \delta_1 logF_{it-1} + \delta_2 logspillF_{it-1} + \delta_3 logspillR\&D_{it-1} \\ & +\gamma_1\Psi(log(\frac{R\&Dstock}{TA})_{it-1}) + \gamma_2\Omega(log(\frac{PATstock}{R\&Dstock})_{it-1}) \\ & +\gamma_3\Gamma(log(\frac{CITEstock}{PATstock})_{it-1}) + \delta_4 logsale_{it-1} + \delta_5 logsale_{it-2} \\ & +\delta_6 logHHI_{it-1} + \alpha_i^{MV} + m_t + \epsilon_{it}^{MV}. \end{aligned} \tag{7}$$

For a detailed derivation of equation (7) see Appendix A. The dependent variable $logq_{it}$ is the logarithm of Tobin's q.[10] The variables $logF_{it-1}$ and $logspillF_{it-1}$ measure the firm's own patent thicket and the other firms' patent thickets, respectively. The construction of these variables is explained in section 2.4. The variables $(\frac{R\&Dstock}{TA})_{it-1}$, $(\frac{PATstock}{R\&Dstock})_{it-1}$, and $(\frac{CITEstock}{PATstock})_{it-1}$ are $R\&D$, patent, and citation intensities, respectively. These variables measure the intangible assets of the firm. The construction of these variables is discussed in Appendix A. The parameters Ψ, Ω, and Γ denote the polynomials of the measures of intangible assets. The variable $logspillR\&D_{it-1}$ captures potential (positive) spillovers from other firms' R&D expenditures on the firm's market value.[11] The construction of this variable is discussed in Appendix C. The variable $logHHI_{it-1}$ controls for market structure impacts.[12] The parameters α_i^{MV} and m_t represent firm and time fixed effects, respectively.[13] The

[10] This variable is explained in Appendix A.

[11] The R&D activities of other firms raise the available research effort in the economy, which could help the firm to achieve more innovation and consequently, higher future net cash flows and market value.

[12] To control for market structure, I use a Herfindahl index (HHI) that utilizes firm-level sales in four-digit SIC codes.

[13] I assume that α_i^{MV} is additive, time-invariant and not correlated across firms.

variable ϵ_{it}^{MV} is the error term.

The lag structure in the right-hand side variables of equation (7) is designed to alleviate the reflection problem (Manski, 1993), which could make the estimates of the market value equation inconsistent.[14] This problem points to the fact that it is difficult to distinguish whether the coefficients on the spillover variables ($logspillR\&D_{it-1}$, $logspillF_{it-1}$) reflect actual spillover effects or (technological opportunity) shocks that are correlated across related firms. The distributed lag structure in the firm-level sales ($logsale_{it-1}$ and $logsale_{it-2}$) decrease the potential inconsistency from demand shocks.[15] To avoid the omitted variable bias due to unobserved firm heterogeneities, I estimate equation (7), using a within estimator for panel data.[16]

2.2.2 R&D Equation

To estimate the relationship (2), I apply the equation

$$
\begin{aligned}
logR\&D_{it} = {} & \theta_1 logR\&D_{it-1} + \theta_2 logF_{it-1} + \theta_3 logspillF_{it-1} \\
& + \theta_4 logspillR\&D_{it-1} + \theta_5 logsale_{it-1} \\
& + \theta_6 logsale_{it-2} + \theta_7 logHHI_{it-1} \\
& + m_t + \alpha_i^{R\&D} + \epsilon_{it}^{R\&D}.
\end{aligned} \tag{8}
$$

The parameters $\alpha_i^{R\&D}$ and m_t represent firm and time fixed effects, respectively. The variable $\epsilon_{it}^{R\&D}$ is an idiosyncratic error term.[17]

The lag structure on the right hand side is designed to lessen the impact of the reflection

[14] I assume that the lagged values of the right-hand side variables are not correlated with ϵ_{it}^{MV}. An alternative solution would be to use more distant lags as instruments.

[15] Higher order lags of the firm-level sales were not statistically significant.

[16] Estimates of equation (7) imply that the fifth order polynomial is satisfactory. I do not consider the multiplicative terms of the measures of INA_{it-1} in equation (7) because including them does not change the results.

[17] The fixed effects $\alpha_i^{R\&D}$ are assumed to be additive, time-invariant and not correlated across firms.

problem. The reflection problem could make the estimates of the R&D equation inconsistent. Any shock that has an impact on the R&D expenditures of the firm is likely to have impacts on other firms' R&D expenditures in the same technology field. Thus, a correlation between the R&D of other firms and their patent thickets with the given firm's R&D expenditures could be related to actual spillover effects or to technological opportunity shocks that all the firms are experiencing.

The distributed lag structure in the firm-level sales decreases the inconsistency from possible demand shocks.[18] In order to capture the dynamics of the firm's R&D expenditures, I include one lag of the dependent variable as an explanatory variable in this equation.[19] Based on the argument in Nickell (1981), the long time dimension in the panel data used in this study prevents inconsistent estimates due to the lagged dependent variable in equation (8).[20] To avoid the omitted variable bias due to unobserved firm heterogeneities, I estimate equation (8) using a within estimator for panel data.

2.2.3 Patenting Equation

As the patent data is inherently a count data, I adapt the approach in Hausman et al. (1984) by estimating the relationship (3) using

$$\begin{aligned} E(Patent_{it}|X_{it}^{RHS}) \quad = \quad & \exp(\beta_1 logF_{it-1} + \beta_2 logspillF_{it-1} + \beta_3 logspillR\&D_{it-1} \\ & +\beta_4 logR\&Dstock_{it-1} + \beta_5 logsale_{it-1} + \beta_6 logsale_{it-2} \\ & +\beta_7 logHHI_{it-1} + \beta_8 log\ pre - sample\ patents_i \\ & +m_t). \end{aligned} \tag{9}$$

[18]Higher order lags of the firm-level sales were not statistically significant.

[19]According to Pakes (1985), previous values of R&D expenditures have impact on the current firms' R&D expenditures. I only consider one lag of the dependent variable in the right-hand side of equation (8) because, according to Griliches (1979), the R&D expenditures are highly correlated over the years, and estimating the separate contribution from each lag with precision is hard.

[20]An alternative approach would be to use the panel generalized method of moments estimator of Arellano and Bond (1991) for dynamic panels. This approach uses the panel GMM estimator, where the instruments are lags of the dependent variable, and they are assumed to be weakly exogenous.

The dependent variable is the number of successful patent applications made by a firm in a given year. A Poisson estimator is the appropriate estimator for equation (9).[21]

One lag of the right hand side variables is included to mitigate the reflection problem.[22] The distributed lags of firm-level sales are included to capture demand shocks. The parameter m_t represents time fixed effects.

Firms' unobserved heterogeneities could make estimates of patent thicket impacts on patenting inconsistent. Firms might differ because of their pre-sample stock of innovations, or their abilities to absorb external technologies for reasons that are not explained by independent variables. Blundell et al. (1999) use a mean-scaling approach to control for firms' unobserved heterogenities. They argue that one reason behind the heterogenities among firms is the diffrences in firms' entry level of innovation, and this innovation is uncorrelated with subsequent shocks to innovation. Therefore, Blundell et al. (1999) use the pre-sample

[21]The Poisson estimator requires the satisfaction of the equi-dispersion assumption (equality of the conditional mean and variance of the dependent variable) for efficiency of estimates. Cameron and Trivedi (2006, p. 670), assuming y_{it} as a dependent variable with a count data nature and X_{it} as a set of regressors, argue that if the hypothesis H_0: $\alpha = 0$ in the specification of over-dispersion or $var(y_{it}|X_{it})$=$exp(X'_{it}\beta)$+$\alpha exp(X_{it}\beta)^2$ cannot be rejected, equi-dispersion assumption holds. Therefore, to test for equi-dispersion, they suggest building an auxiliary regression

$$\frac{(y_{it} - \hat{\mu_{it}})^2 - y_{it}}{\hat{\mu_{it}}} = \alpha \frac{\hat{\mu_{it}}^2}{\hat{\mu_{it}}} + u_{it},$$

where $\hat{\mu_{it}}$ is $exp(X'_{it}\hat{\beta})$, which is the fitted value of the Poisson model, assuming that the first moment in the Poisson model is $E(y_{it}|X_{it}) = exp(X'_{it}\beta)$. Therefore, following Cameron and Trivedi (2006, p. 670), I estimate equation (9) with Poisson estimator and calculate the fitted value. Then using the fitted value, I build the auxiliary regression, and estimate it with a linear Least Squares estimator. The results show that α is statistically significant and over-dispersion exists in the data of this paper.

The over-dispersion problem leads to inefficiency of estimates in the Poisson model, but the Poisson-based estimates remain consistent. According to Gourieroux et al. (1984), consistency of estimates holds as long as the conditional mean is correctly specified because the Poisson model belongs to the linear exponential class of models. Following Hall and Ziedonis (2001), I use the Poisson model, and to overcome the inefficiency, I employ the robust standard errors. To solve the over-dispersion problem, some of the studies such as Ziedonis (2004), suggest using the negative binomial estimator. The estimates in the negative binomial approach are consistent if the true distribution of the data is a negative binomial distribution. Nevertheless, the underlying distribution of the data is not evident.

[22]Any shock that has impact on the R&D investments of the firm and therefore, its patenting propensity is likely to have an impact on other firm's R&D and consequently their patenting in the same technology field. Thus, a correlation between R&D spillovers and patent thicket spillovers with the given firm's patent propensity could be related to actual spillover effects or could be the result of technological opportunity shocks that all firms experience.

information on the patenting propensity of firms to construct a pre-sample average to measure firms' entry level of innovation. Since the right-hand side variables in equation (9) are pre-determined, I follow the mean-scaling approach of Blundell et al. (1999) to control for firms' unobserved heterogeneities and include the variable $log\ pre-sample\ patents_i$ in equation (9). This variable is the average of the pre-sample patent counts of firm i.

2.3 Using the Estimates to Calculate the Direct, Indirect, and Total Impacts

Assuming the steady state condition, which is $X_{it} = X_{it-1} = X_i$, holds for any variable X_{it}, the equations (7) through (9) can be rewritten as

$$\begin{aligned} logq_i &= \delta_1 logF_i + \delta_2 logspillF_i + \delta_3 logspillR\&D_i \\ &+\gamma_1\Psi(log(\frac{R\&Dstock}{TA})_i) \\ &+\gamma_2\Omega(log(\frac{PATstock}{R\&Dstock})_i) \\ &+\gamma_3\Gamma(log(\frac{CITEstock}{PATstock})_i) \\ &+(\delta_4+\delta_5)logsale_i + \delta_6 logHHI_i \\ &+\alpha_i^{MV} + \epsilon_i^{MV}, \end{aligned} \tag{10}$$

$$\begin{aligned} logR\&D_i &= \frac{\theta_2}{1-\theta_1}logF_i + \frac{\theta_3}{1-\theta_1}logspillF_i + \frac{\theta_4}{1-\theta_1}logspillR\&D_i \\ &+\frac{\theta_5+\theta_6}{1-\theta_1}logsale_i + \frac{\theta_7}{1-\theta_1}logHHI_i \\ &+\alpha_i^{R\&D} + \epsilon_i^{R\&D}, \end{aligned} \tag{11}$$

and

$$E(Patent_i|X_i^{RHS}) = exp(\beta_1 logF_i + \beta_2 logspillF_i + \beta_3 logspillR\&D_i + \beta_4 logR\&Dstock_i + (\beta_5 + \beta_6)logsale_i + \beta_7 logHHI_i + \beta_8 log\ pre - sample\ patents_i). \quad (12)$$

Using equations (10-12) the direct impact (4) can be calculated as

$$DIRECT = \delta_1 + \delta_2, \quad (13)$$

and the indirect impacts (5-6) can be calculated as

$$INDIRECT\ (R\&D) = \frac{\partial logq_i}{\partial logR\&Dstock_i} \times 1 \times (\frac{\theta 2 + \theta 3}{1 - \theta_1}) + \frac{\partial logq_i}{\partial logPATstock_i} \times 1 \times \frac{1}{\overline{\overline{Patent}}} \times \beta_4 \times (\frac{\theta 2 + \theta 3}{1 - \theta_1}) \quad (14)$$

and

$$INDIRECT\ (PATENTING) = \frac{\partial logq_i}{\partial logPATstock_i} \times 1 \times \frac{1}{\overline{\overline{Patent}}} \times (\beta_2 + \beta_3), \quad (15)$$

respectively, where $\overline{Patent}$ is the average of patent counts in the entire sample. See Appendix B for the detailed steps of deriving equations (14) and (15).

2.4 Measuring Patent Thickets

To measure the extent of fragmentation in patent ownership, I employ the fragmentation index used by Ziedonis (2004). This measure is based on a normalized Herfindahl index, which is usually used for measuring the level of competition in the market. The index is calculated as a measure of a firm's own patent thicket, using the formula

$$F_{it} = 1 - \sum_{j=0}^{J} (\frac{cite_{ijt}}{cite_{it}})^2. \tag{16}$$

The variable $cite_{ijt}$ is the number of citations made by firm i in its patent documents to the patents of firm j at time t.[23] The index F_{it} is zero when all the citations are made to the patents of one firm, and this measure is one when every citation is to the patents of a different firm. Figure 1 displays the change in the fragmentation index of a hypothetical firm as a function of the number of external right holders that this firm cites their patents, assuming that the total number of citations made in the patents of this firm remains constant at 20.[24,25]

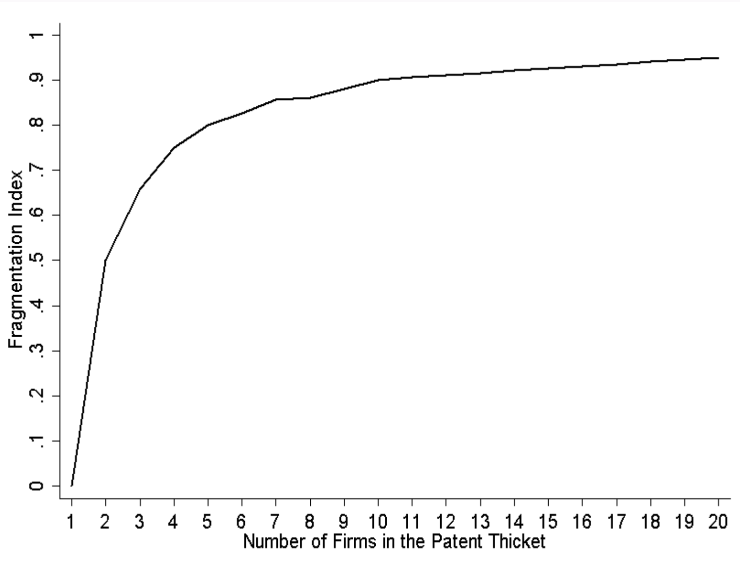
Similar to the measurement of R&D spillovers (Appendix C), I measure the extent of

[23] Each citation made in a patent document is a reference to a complementary patent. In calculating the fragmentation index for a firm, I do not consider citations made to the firm's own patents or to expired patents.

[24] Assuming the number of complementary patents or external right holders in the patent thicket of the hypothetical firm is N, I plot Figure 1 making the following assumptions about the citations that external right holders' patents receive from the hypothetical firm: If N=1, the only right holder receives all the citations and $F_{it} = 0$. If N=2, each of the right holders receives 10 citations to its patents and $F_{it} = 0.5$. If N=4, each of them receives 5 citations and $F_{it} = 0.75$. If N=6, 5 of them receive 3 citations and one of them receives 5 citations ($F_{it} = 0.8$). If N=8, 6 of them receive 3 citations and one of them receives 2 citations ($F_{it} = 0.86$). If N=10, each of them receives 2 citations and $F_{it} = 0.9$. If N=12, 8 of them receive 2 citations and four of them receive one citation ($F_{it} = 0.91$). If N=14, 6 of them receive 2 citations and the rest receive one citation ($F_{it} = 0.92$). If N=16, 4 of them receive 2 citations and the rest get only one citation ($F_{it} = 0.93$). If N=18, 2 of them receive 2 citations and the rest receive one citation ($F_{it} = 0.94$). If N=20, all of them receive one citation and $F_{it} \approx 1$

[25] I also conducted the analyses using the measure of patent thickets in Noel and Schankerman (2006). Employing this measure in equations (7) to (9) did not change the empirical results. Noel and Schankerman (2006) employ a measure which considers only the citations of each firm to patents of the four largest rivals in the technology market. However, the measure of fragmentation that I use is based on the citations to the patents of all firms. Therefore, my employed measure is able to capture heterogeneity among the small and large firms in terms of their hold-up probabilities. The smaller firms might hold up larger firms with higher probability than large firms because smaller firms may assume that the likelihood of dealing with the same large firm is quite low in the future. However, larger firms might assume a correspondingly higher likelihood and therefore an enhanced probability of retaliation.

Figure 1: Fragmentation Index and External Right Holders.



related firms' patent thickets for firm i or the patent thicket spillovers for firm i by

$$spillF_{it} = \sum_{j \neq i} \rho_{ij} \times F_{jt}, \tag{17}$$

which is a weighted sum of other firms' patent thickets. The weight parameter, ρ_{ij}, measures the distance between firm i and j (Appendix C). Following Noel and Schankerman (2006), the construction of ρ_{ij} is based on the distribution of citations across technology classes in the patent data.

3 Data

3.1 Data sources

I build the sample in my analysis based on three different data sets. The first data is the National Bureau of Economic Research (NBER) data, consisting of information on patents granted from 1963 to 2002 and their citations.[26] The second data is the Compustat North American Annual Industrial data from Standard and Poors, consisting of 500,000 observations on 26,000 US publicly traded firms from 1979 to 2002.[27] This data includes information on firms' $R\&D$ expenditures, sales, and components of firms' book and market values.[28] The third data is a company identifier file, which facilitates linking the patent and citation files from the NBER to Compustat data by firm names.[29] This link file is required because assignees apply for patents either under their own name or under their subsidiaries' names. The patent and citation information from the USPTO, which are used for building the NBER data, do not specify a unique code for each patenting identity. However, Compustat has a unique code for each publicly traded firm. The link file contains the assignee number of each firm mentioned on patents in the NBER data, and its equivalent identifier in the Compustat data.

I select a sample of manufacturing firms (SIC 2000-3999) from the publicly traded US firms in Compustat data from 1979 to 2002. This selection results in an unbalanced panel of 19,868 firms with 365,589 observations.[30] Manufacturing firms are selected because this sector includes high technology firms, and the patent-related issues and fragmented technology markets are usually more important for them. Additionally, the sample of publicly traded firms is not an exact representative of all firms in the high technology sectors. However, due to the data limitation, it is the best possible approximation of these firms. I also select a sample from the NBER data. After accounting for withdrawn patents, cited patents granted

[26]The NBER patent and citation data files were originally built for the data from 1963 to 1999, and they are available in http://www.nber.org/patents. Hall et al. (2001) provide a detailed explanation of these files. Bronwyn H. Hall later updated these files from 1999 to 2002. I use the updated files, which are available at: http://elsa.berkeley.edu/∼bhhall/.

The Patent file contains information on utility patents granted between 1963 to 2002. The patent file has information on citations in patents granted between 1975 to 2002.

[27]The publicly traded firms are those traded on the New York, American, and regional stock exchanges, as well as over-the-counter in NASDAQ.

[28](The variables used in building $Market\ Value_{it}$ and TA_{it} are defined in Appendix A.

[29]The company identifier file is available at http://elsa.berkeley.edu/∼bhhall.

[30]SIC is the Standard Industrial Classification by the United States Government.

before 1963, and considering only the patents of publicly traded firms, my sample from the NBER data yields almost 19 million observations from 1979 to 2002.[31]

I link the selected sample from the NBER data, explained above, to corresponding observations of publicly traded US manufacturing firms in the sample from Compustat by using Hall's identifier file. Dropping missing observations on $Market\ Value_{it}$ and TA_{it} of firms results in a sample that consists of 68,203 observations relating to 6,402 unique patenting and non-patenting firms from 1979 to 2002 (almost 2000 firms in each year).[32] This sample includes 20,852 missing observations on $R\&D$.

The patent and citation data are truncated. The truncation in the patent data is the result of the difference between the application and grant dates of patents. The truncation in citation counts is the result of the fact that patents receive citations for a long period after they are granted. Therefore, some citations to patents are received out of the range of the analyzed sample. Moreover, there is a further truncation in citation counts in the beginning of the sample as citation data is available only for the patents granted since 1976 from the NBER data.

The data has been corrected for these truncations. The correction procedures are explained in Appendix D. After these changes, I further limit the sample to 1979-1996 to avoid any potential problems arising from truncations.[33] As a result, I focus only on when the data

[31] I do not consider patents without any citations to previous patents or patents with only self-citations in my sample from the NBER data because these patents do not face problems related to fragmentation in the technology market. As a result, I do not have a patenting firm without any citation to previous patents in my sample.

According to the USPTO's website, withdrawn patents are the patents that are not issued (http://www.uspto.gov/patents/process/search/withdrawn.jsp).

[32] I have replaced the missing observations of the variables that I use in the construction of $Market\ Value_{it}$ and TA_{it} (The variables used in building $Market\ Value_{it}$ and TA_{it} are defined in Appendix A) with zero and then I have built the variables $Market\ Value_{it}$ and TA_{it}. In the next step, I have dropped observations for which the value of variables $Market\ Value_{it}$ and TA_{it} are zero. If I calculated the variables $Market\ Value_{it}$ and TA_{it} before replacing the missing observations of their components with zero, and dropped the missing observations on $Market\ Value_{it}$ and TA_{it}, this would only leave me with 52,736 observations and would lead to a loss of information.

[33] Following Bloom et al. (2005), I exclude firms with less than four consecutive years of data. This issue facilitates calculating the knowledge stock variables in a sample of patenting and non-patenting firms.

Figure 2: Own Patent Thicket over Time.

is the least problematic, leaving me with an unbalanced panel of 1,272 manufacturing firms with 14,214 observations from 1979 to 1996. The result is a longitudinal firm-level data set on firm-level financial variables and patenting activity.

Table 1 presents the descriptive statistics of all variables. The average firm in the sample is large and R&D intensive.[34] On average, a firm experiences a large fragmentation index of 0.70 and has 14 patents. The mean and median of variables $spillF_{it}$ and $spillR\&D_{it}$ are not that different.

Figures 2 and 3 illustrate that variables F_{it} and $spillF_{it}$ were increasing on average from 1979 to 1996. Using corrected patent counts, Figure 4 displays the distribution of patent counts by each firm in the sample. Consistent with previous studies, the distribution of patents across firms is highly skewed (e.g., Hall et al., 2005).

[34]The average firm is large, because it has 13,000 employees. This firm is R&D intensive, since its R&D intensity is 0.83.

Table 1: Descriptive Statistics

Variable	Description	Obs	Mean	Median	Std.Error	Min	Max
$Market\ Value_{it}$	Market Value	14214	867	78	3073	0	70772
TA_{it}	Book Value	14214	1222	108	3721	0	61659
q_{it}	$(Market\ Value\ /TA)_{it}$	14207	1.14	0.67	4.76	0	390
F_{it}	Fragmentation Index	9110	0.70	0.81	0.291	0	0.98
$spillF_{it}$	Patent Thicket Spillovers	14135	18.73	16.36	11.47	0.21	0.78
$spillR\&D_{it}$	R&D Spillovers	14126	19516	14910	16107	79.63	117631.70
$R\&Dflow_{it}$	The Level of R&D	12533	80.03	8.24	296	0	6099.34
$R\&Dstock_{it}$	The Stock of R&D	14214	307.20	21.46	1250	0	28958.23
$Patent_{it}$	Patent Counts	14214	14	1	58	0	1256
$PATstock_{it}$	Stock of Patents	14214	64.22	5.64	260	0	5415.17
$CITEstock_{it}$	Stock of Citations	9110	1152	126	4232	1.19	79115.o8
$(R\&Dstock/ TA)_{it}$	R&D Intensity	14207	0.83	0.26	5.29	0	383.98
$(PATstock/ R\&Dstock)_{it}$	Patent Intensity	12523	0.54	0.23	1.55	0	104.50
$(CITEstock/ PATstock)_{it}$	Citation Intensity	9110	13.5	8.47	19.49	1.17	416.98
$Sale_{it}$	Firm-Level Sales	13986	1766	186	5888	0	146991
HHI_{it}	Market Structure	14214	0.428	0.357	0.260	0	1
$pre-sample\ patents_i$	Firm's Pre-Sample Patents	14214	14	1.78	43.84	0	6.29

Figure 3: Other Firms' Patent Thickets over Time.

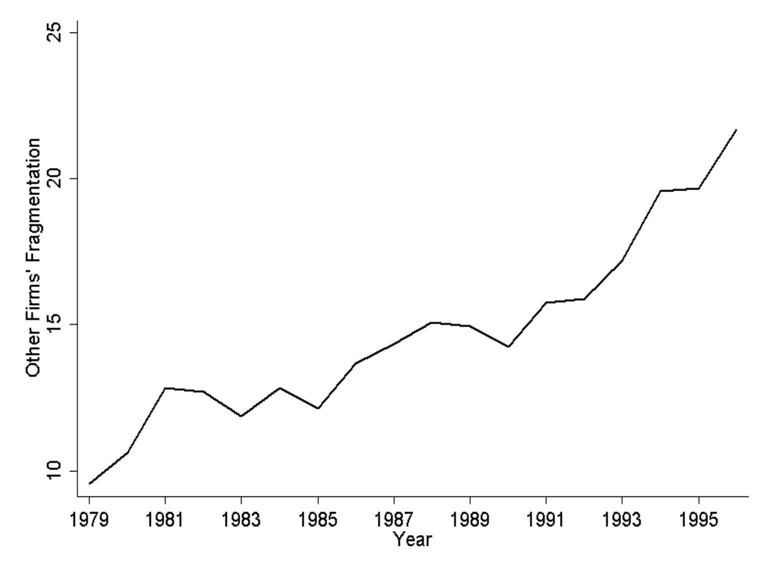
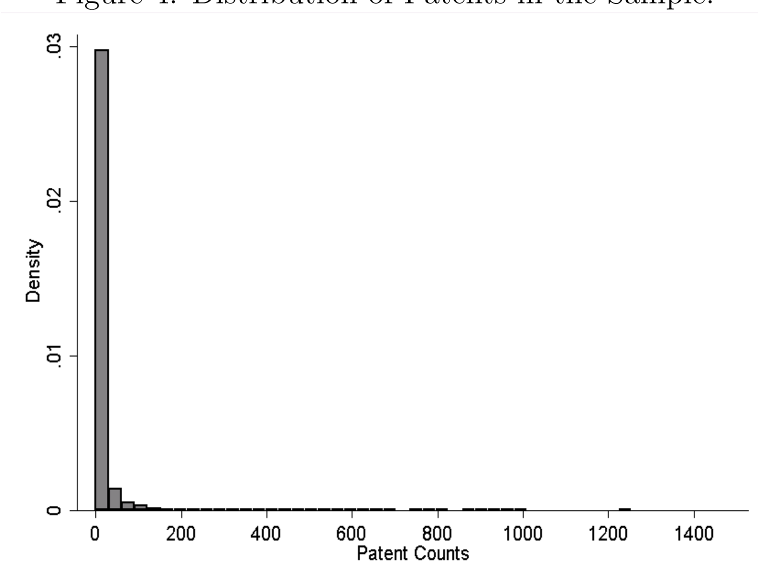


Figure 4: Distribution of Patents in the Sample.



3.2 Exogenous Sources of Identifying Variation

While not all of the variation in the fragmentation is necessarily exogenous to the unobserved characteristics of firms, some is driven by two sources that are arguably exogenous to unobserved firm characteristics: the pro-patent shifts in the US patent system (see introduction) and the pure randomness of having successful innovations.

To analyze the impact of pro-patent shifts following the establishment of the CAFC, I illustrate the Kernel density distributions of the variables F_{it} (patent thicket) and $spillF_{it}$ (patent thicket spillovers) for the periods before and after the reforms, 1979-1985 and 1986-1996, respectively. In these analyses, I group firms based on their patent portfolio size into three categories: firms with fewer than 5 patents (small firms), firms with 6 to 58 patents (medium firms), and firms with more than 58 patents (large firms). Figures 5 to 10 investigate the effect of the pro-patent shifts on F_{it} and $spillF_{it}$ for each group. In Figures 5 to 10 except for Figure 9, the kernel densities experience a shift to the right following the pro-patent policy changes, which imply higher F_{it} and $spillF_{it}$ after the establishment of the CAFC.[35]

[35] Figures 5 to 10 display that the impact of pro-patent policies depends on the number of patents owned by the firm. Therefore, there is both over-time and cross-firm variation in F_{it} and $spillF_{it}$ that help in identifying the empirical estimates. The different finding of Figure 9 is quite puzzling as it points to the fact that firms with a large patent portfolio size experience a lower fragmentation index following reforms. This finding might imply that large firms change their type of innovation from cumulative to non-cumulative following reforms and therefore, they do not have to cite other firms' patents, which makes their fragmentation index lower.

Figure 5: Kernel Density of F_{it} for Small Firms.

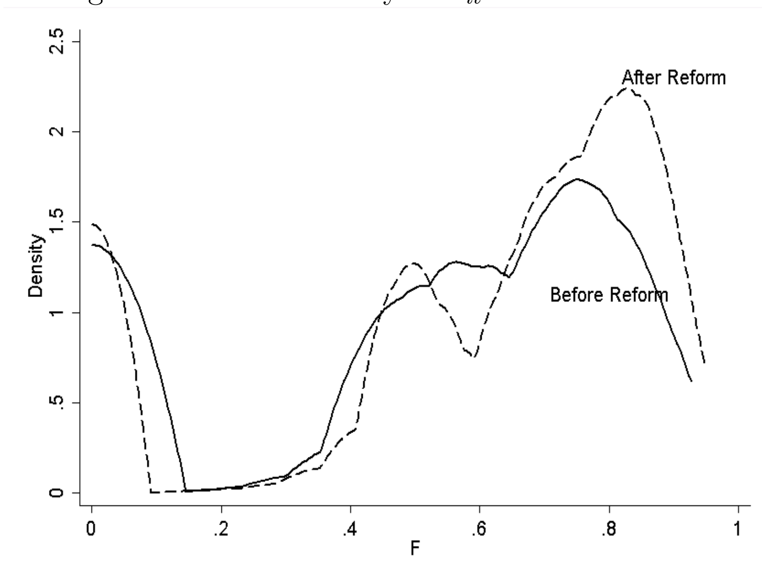


Figure 6: Kernel Density of $spillF_{it}$ for Small Firms.

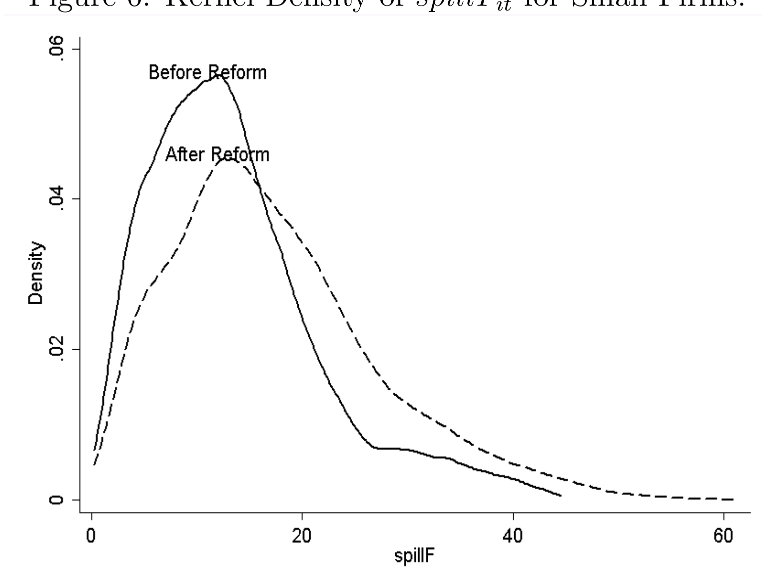


Figure 7: Kernel Density of F_{it} for Medium Firms.

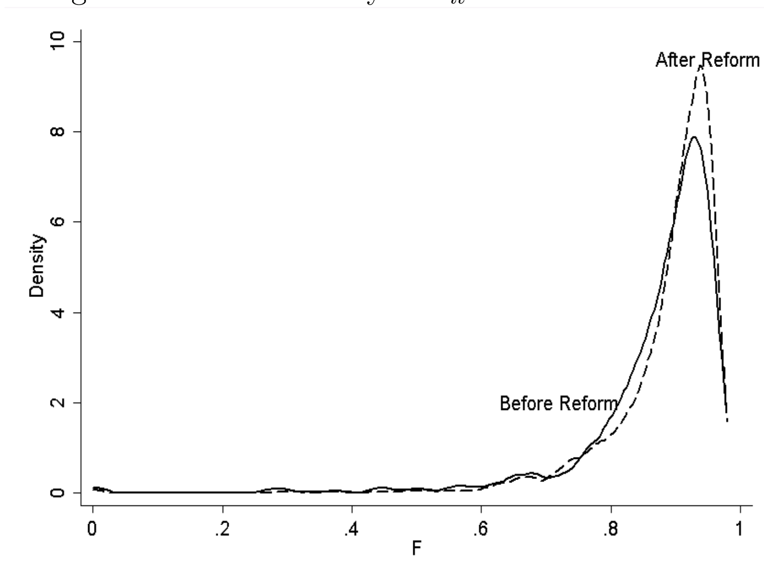


Figure 8: Kernel Density of $spillF_{it}$ for Medium Firms.

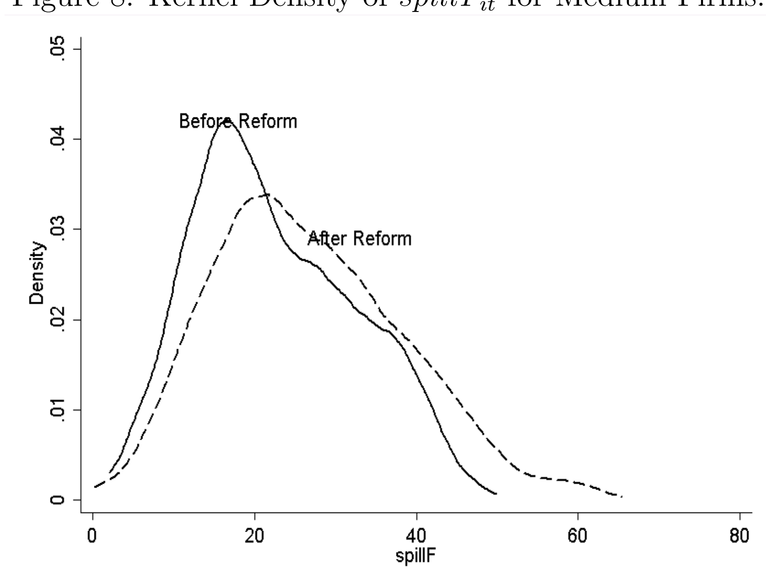


Figure 9: Kernel Density of F_{it} for Large Firms.

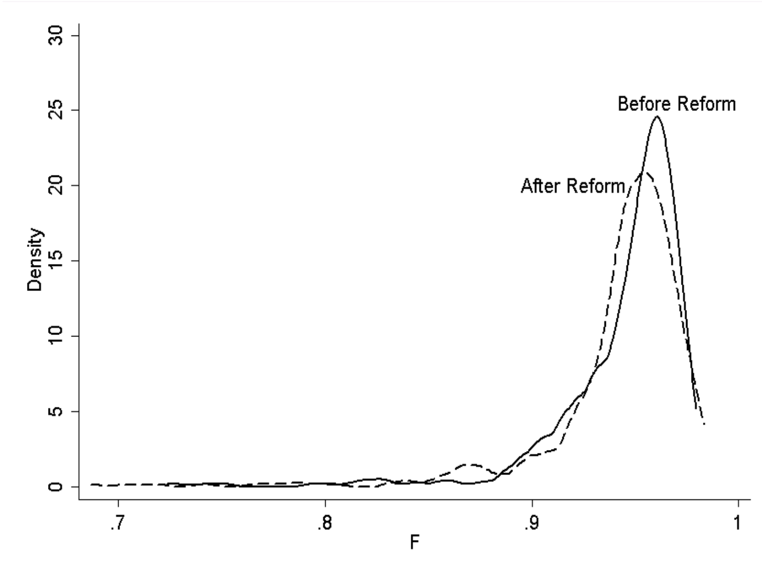
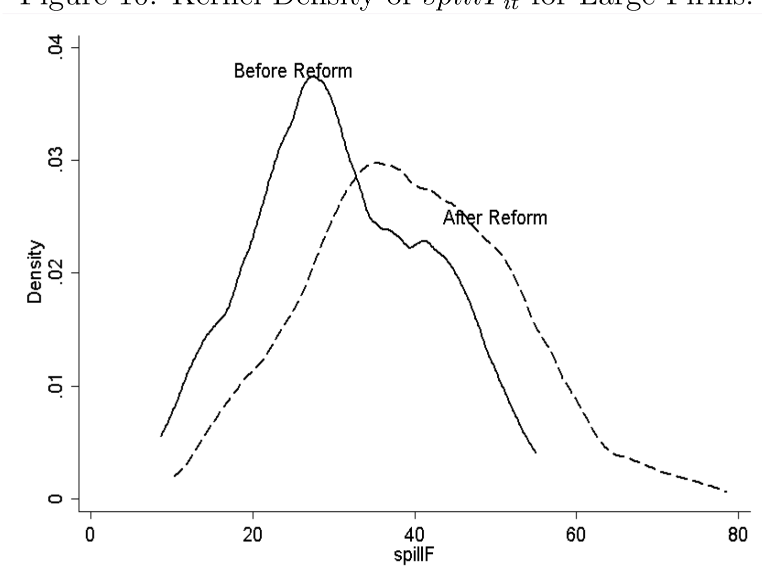


Figure 10: Kernel Density of $spillF_{it}$ for Large Firms.



4 Results

4.1 Estimates of the Market Value, Patenting, and R&D Equations

Table 2 contains estimates of patent thickets on market value (direct impacts) based on equation (7). Standard errors are clustered at the firm-level.[36] Both the estimated coefficients on a firm's own patent thicket ($logF_{it-1}$) and others' patent thickets ($logspillF_{it-1}$) indicate that patent thickets have a negative direct impact on market value. For example, in Column 3, which contains estimates with firm fixed effects, the coefficient of $logF_{it-1}$ implies that market value declines by 0.22% as fragmentation increases by 10%. However, I lay limited emphasis on this result because the coefficient estimate is not statistically significant. The coefficient of $logspillF_{it-1}$ shows that if fragmentation in the technology market increases by 10% for other firms, the given firm experiences lower market value by 0.69%. This finding is statistically significant at a 1% level of significance. The estimated negative impacts on patent thickets are robust to the use of industry fixed effects in column 4.[37] The results in Table 2 support the hypothesis that patent thickets lower a firm's market value directly.[38]

Table 3 reports estimates of the effect of patent thickets on R&D expenditures, employing equation (8). The results in Column 1 show that the major determinant of R&D expenditures of a given firm is its past R&D expenditures. While the coefficients on the patent thicket

[36] Clustering at the industry level (based on four-digit SIC codes) generates similar results to clustering at the firm-level.

[37] The estimation is based on equation (7), but instead of controlling for firm fixed effects, I control for industry fixed effects, which are based on four-digit SIC codes. The industry fixed effects are for controlling the possibility of dense patent thickets, which may be more likely in some industries than others.

[38] Since columns 3 and 4 allow for interactions among firms, there are controls for R&D spillover ($logspillR\&D_{it-1}$) and market structure ($logHHI_{it-1}$) in these columns. In both columns, the variable $logspillR\&D_{it-1}$ has a statistically insignificant impact on market value, but with different signs and sizes. The market structure has a positive and statistically significant impact on market value in column 3. The finding on the market structure variable corresponds to the notion that in highly concentrated markets, firms have higher market power that leads to larger future expected earnings for those firms and consequently, higher market value. This result is interesting as, to the best of my knowledge, there are few studies that focus on the impact of market structure on the market value of firms, and they do not find a statistically significant impact (Lindenberg and Ross, 1981 and Hirschey, 1985).

variables, $logF_{it-1}$ and $logspillF_{it-1}$, are both positive, they are not statistically significant, and even their magnitude is very small. The estimated coefficient of $logF_{it-1}$ in column 3 implies that a 10% increase in firms' own patent thicket lowers R&D expenditure by only 0.23%, and the coefficient estimate on the variable $logspillF_{it-1}$ in the same column suggests that a 10% increase in others' patent thickets increases R&D expenditures of a firm by only 0.08%. Hence, the proliferation of patents seems not to have generated the "tragedy of anti-commons" suggested by Heller and Eisenberg (1998) in the manufacturing sector.

Table 4 reports estimates of patent thicket impacts on patenting activity, using equation (9). The results in columns 3 and 4 indicate that patent thickets have a positive and statistically significant effect on patenting. The reported standard errors in Table 4 are robust standard errors. The reason for using these standard errors is the over-dispersion problem in the sample that leads to inefficiency in estimates.[39] The estimated coefficient on the variable $log\ pre-sample\ patents_i$, which is used to control for firm unobserved heterogeneity, is positive and statistically significant in columns 1 to 3. This result confirms the need to control heterogeneity across firms with respect to their patenting behavior.[40]

[39] For a detailed explanation of the over-dispersion problem, refer to section 2.2

[40] For a detailed explanation of the reason behind using the variable $pre-sample\ patents_i$ to control for firm unobserved heterogenities, refer to section 2.2

[41] The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are the cluster-robust standard error (clustered at the firm-level).

[42] The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are the cluster-robust standard error at the firm-level).

Table 2: Patent Thicket and Market Value

Dependent Variable $logq_{it}$[41]	(1)	(2)	(3)	(4)
$logF_{it-1}$		-0.022	-0.022	-0.026
		(0.020)	(0.018)	(0.028)
$logspillF_{it-1}$			-0.069***	-0.039***
			(0.017)	(0.013)
$logspillR\&D_{it-1}$			-0.003	0.011
			(0.005)	(0.007)
$logSale_{it-1}$	0.003	0.004	0.005	0.001
	(0.005)	(0.005)	(0.005)	(0.007)
$logSale_{it-2}$	0.005	0.005	0.005	0.012**
	(0.005)	(0.005)	(0.004)	(0.006)
$logHHI_{it-1}$			0.058***	0.019
			(0.014)	(0.021)
$log(\frac{R\&Dstock}{TA})_{it-1}$	0.151***	0.152***	0.159***	0.314***
	(0.031)	(0.030)	(0.011)	(0.020)
$[log(\frac{R\&Dstock}{TA})_{it-1}]^2$	0.047***	0.047***	0.048***	0.132***
	(0.012)	(0.011)	(0.004)	(0.008)
$[log(\frac{R\&Dstock}{TA})_{it-1}]^3$	0.003	0.003	0.002**	0.006**
	(0.002)	(0.002)	(0.000)	(0.002)
$[log(\frac{R\&Dstock}{TA})_{it-1}]^4$	-0.001	-0.001	-0.001***	-0.003***
	(0.001)	(0.001)	(0.000)	(0.000)
$[log(\frac{R\&Dstock}{TA})_{it-1}]^5$	-0.001*	-0.000*	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$log(\frac{PATstock}{R\&Dstock})_{it-1}$	0.054**	0.055**	0.053***	0.044***
	(0.021)	(0.022)	(0.010)	(0.012)
$[log(\frac{PATstock}{R\&Dstock})_{it-1}]^2$	0.006	0.006	0.005	0.006
	(0.010)	(0.009)	(0.004)	(0.006)
$[log(\frac{PATstock}{R\&Dstock})_{it-1}]^3$	-0.002	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)

Table 2 Continued

Dependent Variable $logq_{it}$	(1)	(2)	(3)	(4)
$[log(\frac{PATstock}{R\&Dstock})_{it-1}]^4$	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
$[log(\frac{PATstock}{R\&Dstock})_{it-1}]^5$	0.010	0.000	0.000	-0.000
	(0.055)	(0.000)	(0.000)	(0.000)
$log(\frac{CITEstock}{PATstock})_{it-1}$	0.068	0.055	0.051	0.233*
	(0.129)	(0.130)	(0.100)	(0.132)
$[log(\frac{CITEstock}{PATstock})_{it-1}]^2$	-0.092	-0.081	-0.077	-0.358*
	(0.191)	(0.191)	(0.143)	(0.191)
$[log(\frac{CITEstock}{PATstock})_{it-1}]^3$	0.040	0.035	0.035	0.172*
	(0.097)	(0.097)	(0.072)	(0.098)
$[log(\frac{CITEstock}{PATstock})_{it-1}]^4$	-0.007	-0.006	-0.007	-0.035*
	(0.021)	(0.020)	(0.015)	(0.021)
$[log(\frac{CITEstock}{PATstock})_{it-1}]^5$	0.005	0.000	0.000	0.003*
	(0.015)	(0.001)	(0.001)	(0.002)
$D(logF_{it} = 0)$		-0.006	-0.007	-0.003
		(0.012)	(0.011)	(0.018)
$D(R\&D_{it} = 0)$	-0.094**	-0.094***	-0.100***	-0.081***
	(0.034)	(0.035)	(0.023)	(0.024)
$D(Patent_{it} = 0)$	0.016	0.019	0.017	0.029
	(0.011)	(0.012)	(0.011)	(0.018)
Firm Fixed Effects	Yes	Yes	Yes	No
Industry Fixed Effects	No	No	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observation	11773	11773	11773	11773
R^2	0.1364	0.1366	0.1397	0.2785

Table 3: Patent Thicket and R&D

Dependent Variable $logR\&D_{it}$[42]	(1)	(2)	(3)	(4)	(5) Panel GMM
$logF_{it-1}$		0.024	0.023	0.015	-0.012
		(0.019)	(0.020)	(0.018)	(0.019)
$logspillF_{it-1}$			0.008	0.012	0.020
			(0.017)	(0.010)	(0.017)
$logspillR\&D_{it-1}$			-0.004	0.010	0.004
			(0.005)	(0.006)	(0.006)
$logR\&D_{it-1}$	0.726***	0.727***	0.726***	0.944***	0.329***
	(0.018)	(0.023)	(0.023)	(0.007)	(0.127)
$logSale_{it-1}$	0.187***	0.186***	0.187***	0.181***	0.078
	(0.030)	(0.037)	(0.037)	(0.023)	(0.049)
$logSale_{it-2}$	-0.038	-0.037	-0.038	-0.144***	0.103***
	(0.027)	(0.027)	(0.027)	(0.021)	(0.029)
$logHHI_{it-1}$			-0.024	0.002	-0.023
			(0.016)	(0.015)	(0.020)
$D(logF_{it} = 0)$		0.029**	0.029**	0.024*	0.021
		(0.012)	(0.012)	(0.013)	(0.014)
Firm Fixed Effects	Yes	Yes	Yes	No	No
Industry Fixed Effects	No	No	No	Yes	No
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	7340	7340	7340	7340	5496
R^2	0.7294	0.7298	0.7299	0.9933	

4.2 Calculated Direct, Indirect, and Total Impacts

Table 5 displays the calculated direct and indirect impacts obtained using equations (13), (14) and (15). I calculate these effects using both the estimates with firm fixed effects (column 3 of Tables 2, 3, and 4) and the estimates with industry fixed effects (column 4 of Tables 2, 3, and 4). Standard errors of direct, indirect, and total impacts are estimated with non-parametric bootstrapping (the numbers in parentheses). As a robustness check, I also report the standard errors based on wild bootstrapping (the numbers in brackets).[41]

In models with firm fixed effects, the direct impact is negative, and indirect impacts through R&D and patenting are positive. The direct impact shows that a 10% increase in patent thickets is associated with a 0.9% decrease in firms' market value. The indirect impact of patent thickets on market value through R&D is very small and statistically insignificant. However, the indirect impact of patent thickets on market value through patenting is positive and statistically significant. As is expected, the beneficial indirect impact of patent thickets on the market value through an increase in patenting only partially offsets the negative direct impact of patent thickets. The total impact of patent thickets on market value is negative and statistically significant. The estimates imply that a 10% increase in the fragmentation of patent ownership decreases the market value of firms by 0.81%. The models with industry fixed effects result in similar findings.

[40]The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in parenthesis are standard errors, which are robust to heteroskedasticity. Numbers in the brackets are marginal effects.

[41]The number of replications in both of non-parametric bootstrapping and wild bootstrapping is 1000. For a detailed explanation of non-parametric and wild bootstrapping procedures, refer to Cameron et al. (2007).

Table 4: Patent Thicket and Patent Propensity

Dependent Variable $Patent_{it}{}^{40}$	(1) Poisson Mean-scaling	(2) Poisson Mean-scaling	(3) Poisson Mean-scaling	(4) Poisson No Mean-scaling
$logF_{it-1}$		1.250***	1.151***	1.022
		(0.117)	(0.116)	(0.103)
		[2.066]	[1.932]	[1.395]
$logspillF_{it-1}$			0.023**	0.525***
			(0.048)	(0.061)
			[0.039]	[0.716]
$logspillR\&D_{it-1}$			0.127***	0.041**
			(0.027)	(0.020)
$logR\&Dstock_{it-1}$	0.585***	0.552***	0.534***	0.709***
	(0.018)	(0.018)	(0.017)	(0.020)
	[1.822]	[0.913]	[0.896]	[0.967]
$logSale_{it-1}$	-0.079***	-0.080***	-0.090***	-0.044***
	(0.014)	(0.014)	(0.013)	(0.014)
$logSale_{it-2}$	-0.023**	-0.024**	-0.015	-0.015**
	(0.010)	(0.010)	(0.010)	(0.007)
$logHHI_{it-1}$			0.143***	-0.188**
			(0.023)	(0.068)
$log\ pre-sample\ patents_i$	0.441***	0.361***	0.340***	
	(0.016)	(0.016)	(0.016)	
$D(logF_{it}=0)$		-2.317***	-2.300***	-2.363***
		(0.049)	(0.049)	(0.049)
$D(R\&D_{it}=0)$	0.175*	0.270**	0.282***	0.583***
	(0.091)	(0.100)	(0.096)	(0.113)
Industry Fixed Effects	No	No	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	11760	11760	11760	11760

Table 5: Direct and Indirect Impacts of F_{it} and $spillF_{it}$

Specification[41]	Direct Impact	Indirect Impact		Total Impact
		INDIRECT (R&D)	INDIRECT (PATENTING)	
Firm FE	-0.091	+0.002	+0.008	-0.081
	(0.030)	(0.005)	(0.003)	(0.032)
	[0.031]	[0.007]	[0.001]	[0.030]
Industry FE	-0.065	+0.004	+0.018	-0.043
	(0.045)	(0.007)	(0.006)	(0.047)
	[0.044]	[0.018]	[0.002]	[0.044]

5 Conclusion

The economic costs of patent thickets have been at the centre of ongoing debates on reforming the US patent system. Economic analyses of patent thickets have provided differing views on patent thickets' effects. In this paper, I estimate the direct and indirect costs of patent thickets. The direct impact is the effect that patent thickets have on firms' market value, while I hold R&D and patenting activities of firms constant. The indirect impact is the effect that patent thickets potentially have on market value through patent thicket induced changes in R&D and through a patent thicket prompted increase in defensive patenting. In the empirical models, I also incorporate the influence that other firms' patent thickets have on market value of a given firm. The analysis is conducted using panel data on 1,272 publicly

[41]Direct impact is calculated based on equation (13). Indirect impact via R&D is calculated based on equation (14). The indirect impact via patents is based on equation (15). The numbers in the parentheses are the non-parametric bootstrapped standard errors. The numbers in the brackets are the wild bootstrapped standard errors. In the models with industry fixed effects, the maximum likelihood Poisson estimator of the patent equation encountered non-convergence 16 times out of 1000 bootstrapped observations, when I measured standard errors. Models with firm FE are based on Column 3 of Tables 2, 3, and 4. Models with industry FE are based on Column 4 of Tables 2, 3, and 4.

traded US manufacturing firms from 1979 to 1996.

The results show that patent thickets lower the market value of firms. The total impact on market value is smaller in magnitude than the direct impact because firms avoid some of the potential costs of patent thickets through defensive patenting. Hence, exclusively focusing on patent thickets' direct impact on market value overstates patent thickets' negative impact on firms' market value. Moreover, I find that thickets have no statistically significant impact on firms' R&D expenditures.

The merit of my analysis for intellectual property policy is that it quantifies the costs of patent thickets. As the US considers potential patent reforms, the benefit of lowering costs of patent thickets through, for example, lowering fragmentation in patent ownership by increasing the requirements for obtaining patents must be weighed against the negative effects that making patenting harder might have on the incentives to innovate.

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Appendices

A Derivation Steps of the Market Value Equation

Following the studies of Griliches (1981) and Hall et al. (2005), the general specification for market value function is

$$logMarket\ Value_{it} = logSV_{it} + \sigma log(TA_{it} + \gamma INA_{it}). \tag{A.1}$$

The variable $logMarket\ Value_{it}$ is the log of the market value of firm i in year t. Following Hall et al. (2005), the market value of a firm is calculated as the sum of the current market value of common and preferred stocks, long-term debt adjusted for inflation, and short-term debts of the firm net of assets. In the analysis of Hall et al. (2005), the variable $logSV_{it}$ includes time fixed effects (m_t) and the error term (ϵ_{it}). The term ϵ_{it} denotes the other factors that influence the market value of firm i in year t. I assume that error terms ϵ_{it} are additive, independently and identically distributed across firms and over time, and serially uncorrelated. The variables TA_{it} and INA_{it} are tangible and intangible assets, respectively. Their measurement is discussed shortly. The coefficient γ is the shadow price of the intangible to tangible asset ratio. Moving the variable TA_{it} to the left-hand side in equation (A.1) allows left-hand side of this equation to be written as $log(\frac{Market\ Value_{it}}{TA_{it}})$ or Tobin's q.[42] Equation (A.1) then becomes

$$logq_{it} = log(1 + \gamma \frac{INA_{it}}{TA_{it}}) + m_t + \epsilon_{it}^{MV}. \tag{A.2}$$

Following Hall et al. (2005), the variable TA_{it} is measured by the book value of firms based on their balance sheet. The book value of a firm is calculated as the sum of net plant and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles and others. All of the components of TA_{it} are adjusted for inflation.[43] INA_{it} is measured based on the approach of Hall et al. (2005), who measure the variable INA_{it} with $R\&D$ intensity ($R\&Dstock_{it}/TA_{it}$), patent intensity ($PATstock_{it}/R\&Dstock_{it}$), and citation yield per patent or citation intensity ($CITEstock_{it}/PATstock_{it}$). The variables $R\&Dstock_{it}$, $PATstock_{it}$, and $CITEstock_{it}$ measure the stock of $R\&D$, patents, and citations, respectively. These variables are constructed based on a declining balance formula with the depreciation rate of 15%.[44] Hall et al. (2005) justify their method for measuring INA_{it} of a firm by arguing that the firm's $R\&D$ expenditures show the intention of the firm to innovate. The $R\&D$ expenditures might become successful and result in an innovation. Patents of the firm catalogue the success of the innovative activity, and the importance of each patent is measured by the number of times it is cited in subsequent patents. Therefore, I employ $R\&D$,

[42] The parameter σ is a scale factor in the value function. According to Hall et al. (2005), the assumption of constant returns to scale with respect to assets usually holds in the cross-section. Thus, σ becomes one.

[43] Inflation adjustments are based on the CPI urban US index for 1992 (Source: http://www.bls.gov).

[44] Following Hall et al. (2005), the employed declining balance formula is $K_t = (1 - \delta)K_{t-1} + flow_t$. The variables K_t and $flow_t$ stand for knowledge stock and knowledge flow at time t, respectively. I define the initial stock of knowledge variables as the initial sample values of the knowledge variables similar to Noel and Schankerman (2006). I select the parameter δ or depreciation rate equal to 15%. Most researchers settled with this deprecation rate (Hall et al., 2000, 2005, and 2007). Hall and Mairesse (1995) show experiments with different deprecation rates, and they conclude that changing the rate from 15% does not make a difference. As a result, I select $\delta = 15\%$, and this selection further assists in easy comparisons to previous studies.

patent, and citation intensities to measure INA_{it}, following Hall et al. (2005), and, equation (A.2) becomes

$$\begin{aligned} logq_{it} &= log(1+\gamma_1 \times [(\frac{R\&Dstock}{TA})_{it}] + \gamma_2 \times [(\frac{PATstock}{R\&Dstock})_{it}] \\ &\quad +\gamma_3 \times [(\frac{CITEstock}{PATstock})_{it}]) + m_t + \epsilon_{it}^{MV}. \end{aligned} \tag{A.3}$$

There is usually a difference between the application and grant date of patents. Out of the patents applied close to the end date of the sample, only a small fraction is granted, and the rest are granted outside the reach of the sample. This issue indicates truncation in patent counts. Citation counts are also truncated. Truncation in citation counts happen since only citations that occur within the sample are observable. I correct for these truncations. As a result, the $PATstock_{it}$ and $CITEstock_{it}$ variables are corrected for truncations in patent and citation counts. See Appendix D for detailed correction procedures.

To estimate the impact of patent thicket on the market value of firms, I augment equation (A.3) with the variables $logF_{it}$ as a measure of the firm's own patent thicket, and $logspillF_{it}$ as a measure of other firms' patent thickets (the construction of these variables is explained in section 2.4). To control for R&D spillovers, I include $logspillR\&D_{it}$ in equation (A.3), and the construction of this variable is explained in Appendix C. The distributed lag structure in the firm level sales ($logsale_{it}$ and $logsale_{it-1}$) decrease the potential for inconsistent estimates due to demand shocks. To control for the effect of market structure on the market value of firms, I use a Herfindahl index that utilizes firm-level sales in four-digit SIC codes ($logHHI_{it}$). Finally, some firms might have a permanently higher market value than others due to omitted firm specific effects.[45] To control for the firm unobserved heterogeneities, I include α_i^{MV} in equation (A.3). Adding the above variables to equation (A.3) results in the specification

$$\begin{aligned} logq_{it} &= log(1+\gamma_1 \times (\frac{R\&Dstock}{TA})_{it} + \gamma_2 \times (\frac{PATstock}{R\&Dstock})_{it} \\ &\quad +\gamma_3 \times (\frac{CITEstock}{PATstock})_{it}) + \delta_1 logF_{it} + \delta_2 logspillF_{it} \\ &\quad +\delta_3 logspillR\&D_{it} + \delta_4 logsale_{it} + \delta_5 logsale_{it-1} \\ &\quad +\delta_6 logHHI_{it} + m_t + \alpha_i^{MV} + \epsilon_{it}^{MV}. \end{aligned} \tag{A.4}$$

Equation (A.4) could be estimated with a non-linear least squares estimator, but it is easier to substitute the non-linear terms with series expansions and estimate the equation with a linear estimator, following Bloom et al. (2005) and Noel and Schankerman (2006).[46] This approach makes the incorporation of firm fixed effects easier. Therefore, equation (A.4) becomes

$$\begin{aligned} logq_{it} &= \delta_1 logF_{it} + \delta_2 logspillF_{it} + \delta_3 logspillR\&D_{it} \\ &\quad +\gamma_1 \Psi(log(\frac{R\&Dstock}{TA})_{it}) + \gamma_2 \Omega(log(\frac{PATstock}{R\&Dstock})_{it}) \\ &\quad +\gamma_3 \Gamma(log(\frac{CITEstock}{PATstock})_{it}) + \delta_4 logsale_{it} + \delta_5 logsale_{it-1} \\ &\quad +\delta_6 logHHI_{it} + \alpha_i^{MV} + m_t + \epsilon_{it}^{MV}, \end{aligned} \tag{A.5}$$

where the parameters Ψ, Ω, and Γ denote the polynomials of the measures of intangible assets. Equation (A.5) is used to build equation (7).

[45] For example, this could be the result of the stock of past innovations at the beginning of the sample, or a better ability of absorbing external technologies for reasons that are not explained by independent variables.

[46] I would not approximate $log(1+\theta\frac{INA_{it}}{TA_{it}})$ with $\theta(\frac{INA_{it}}{TA_{it}})$ because such an approximation is right if the ratio of intangible assets to tangible assets is small. However, this ratio is large for high technology firms in the manufacturing sector.

B Indirect Impacts through R&D and Patenting

$$\begin{aligned}
INDIRECT(R\&D) &= [\frac{\partial logq_i}{\partial logR\&Dstock_i} \times \frac{\partial logR\&Dstock_i}{\partial logR\&D_i}(\frac{\partial logR\&D_i}{\partial logF_i} + \frac{\partial logR\&D_i}{\partial logspillF_i})] \\
&+ [\frac{\partial logq_i}{\partial logPATstock_i} \times \frac{\partial logPATstock_i}{\partial logPatent_i} \times \frac{\partial logPatent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial logR\&Dstock_i} \\
&\times \frac{\partial logR\&Dstock_i}{\partial logR\&D_i} \times (\frac{\partial logR\&D_i}{\partial logF_i} + \frac{\partial logR\&D_i}{\partial logspillF_i})] \\
&= \frac{\partial logq_i}{\partial logR\&Dstock_i} \times 1 \times (\frac{\theta 2 + \theta 3}{1-\theta_1}) \\
&+ \frac{\partial logq_i}{\partial logPATDstock_i} \times 1 \times \frac{1}{\overline{\overline{Patent}}} \times \beta_4 \times 1 \times (\frac{\theta 2 + \theta 3}{1-\theta_1}). \qquad (B.1)
\end{aligned}$$

$$\begin{aligned}
INDIRECT(PATENTING) &= [\frac{\partial logq_i}{\partial logPATDstock_i} \times \frac{\partial logPATDstock_i}{\partial logPatent_i} \times \frac{\partial logPatent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial logF_i}] \\
&+ [\frac{\partial logq_i}{\partial logPATDstock_i} \times \frac{\partial logPATDstock_i}{\partial logPatent_i} \times \frac{\partial logPatent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial logspillF_i}] \\
&= \frac{\partial logq_i}{\partial logPATDstock_i} \times 1 \times \frac{1}{\overline{\overline{Patent}}} \times (\beta_2 + \beta_3). \qquad (B.2)
\end{aligned}$$

One point to note is that the $R\&D$ variable is a stock variable in equations (10) and (12), and is a flow variable in equation (11). Following Hall et al. (2005), I define the relation between the $R\&D$ stock and flow as

$$R\&Dstock_{it} = (1-\delta)R\&Dstock_{it-1} + R\&D_{it}. \qquad (B.3)$$

Using the steady state condition ($R\&Dstock_{it} = R\&Dstock_{it-1} = R\&Dstock_i$), and taking the logarithm of both sides, equation (B.3) becomes

$$logR\&Dstock_i = logR\&D_i - log\delta, \qquad (B.4)$$

where

$$\frac{\partial logR\&Dstock_i}{\partial logR\&D_i} = 1. \qquad (B.5)$$

I use equation (B.5) in equation (B.1). The same applies to the patent variable as this variable is a stock variable in equation (10) and is a count variable in equation (12).

C Measuring Technology Spillovers

Firms in different industries interact with each other. These interactions imply the possibility of R&D spillovers among firms. In order to measure the R&D spillovers, I follow the R&D spillovers literature that I explain in section 1, and I measure the R&D spillovers of firm i at time t as

$$SpillR\&D_{it} = \sum_{j \neq i} \rho_{ij} \times R\&Dstock_{jt}. \qquad (C.1)$$

The parameter ρ_{ij} measures the closeness between firm i and j, and the variable $R\&Dstock_{jt}$ stands for the R&D stock of firm j at time t. According to Jaffe (1986), firms mostly benefit from R&D of the firms that are closer to them in their technological field. Jaffe names ρ_{ij} the technological proximity between firms i and j, and he explains that ρ_{ij} is built based on the uncentered correlation coefficient of the location vectors of firms i and j (S_i and S_j).[47] For example, the location vector of each firm i (S_i) based on the distribution of the share of the firm i's patents across N different technology classes is $S_i = \{s_{i1}, s_{i2}, ..., s_{iN}\}$, where s_{ik} shows firm i's share of patents in the technology class k.

Bloom et al. (2005) use a modified version of Jaffe's (1986) measure for the parameter ρ_{ij}. Their measure is

$$\rho_{ij} = \frac{S_i' S_j}{(S_i' S_i)^{1/2} (S_j' S_j)^{1/2}}. \tag{C.2}$$

The range of ρ_{ij} is between 0 and 1. It is closer to 1 for the firms that are closer to each other in their technological field, and it is zero if the location vectors of firms are orthogonal.[48] Noel and Schankerman (2006) suggest using the distribution of the citations in the patents of each firm across N different technology classes for location vectors. This means s_{ik} is the share of all citations in the patents of firm i that belong to a technology class k. These citations reflect the benefits that the firm enjoys from the research activity of others in the same technology field, because they exactly show the previous patents that the firm is using in its innovation. Therefore, I follow Noel and Schankerman (2006) and utilize the distribution of citations across 426 different technology classes of the USPTO in the sample of my analysis to build the location vectors. Then, I use the proximity measure in equation (C.2) to calculate the R&D spillovers that firm i receives at time t from other firms based on equation (C.1).[49]

D Correcting Truncation in Patent and Citation Counts

To correct for truncation in patent counts, I follow the approach of Hall et al. (2000), which defines weight factors to correct for truncation in patent counts. Their weight factors are calculated according to

$$\begin{aligned} patent_t^* &= \frac{patent_t}{\sum_{k=0}^{1999-t} weight_k} \\ 1996 &\leq t \leq 1999, \end{aligned} \tag{D.1}$$

where $patent_t$ is the number of patents granted at time t to all firms and $weight_k$ is built based on the average of citations in each lag for the patents of firms.[50] Hall et al. (2000) multiply patent counts in ending years of the sample with the inverse of the weight factors ($1/patent_t^*$) and correct for the truncation. I only correct patent counts for 1997 to 1999 because from 2000 to 2002 (end of my sample) the results are under the "edge effect"(Hall et al., 2000). This means the 2002 data will not be usable and 2001 data will have large variance. Figure D.1 displays a comparison of original and corrected patent counts for truncation.

To correct for truncations in citations, I have employed the method of Hall et al. (2000). I calculate the distribution of the fraction of citations received by each patent at a time between the grant year of the citing patents and the grant year of the cited patent. Using this distribution, I predict the number of citations received for each patent outside the range of the sample, maximum to 40 years after the grant date of the patent. Figure D.2 displays a comparison of original and corrected citation counts. I use the truncation

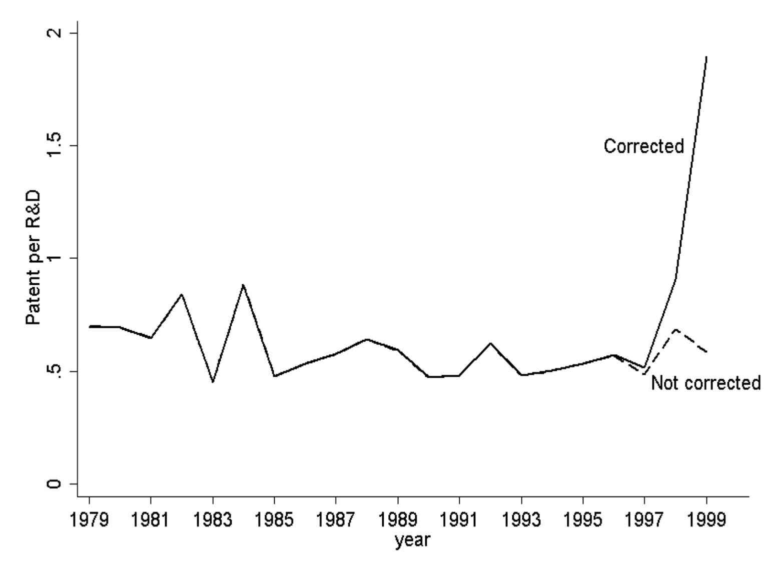
[47] The proximity measure of Jaffe (1986) is not directly under the impact of the length of the location vectors, which are dependent on the concentration of firms in research fields. Other forms of proximity measures such as Euclidean distance are highly dependent on the length of the location vector. For example, in a Euclidean distance measure, diversified firms with orthogonal location vectors are counted as close, since they are close to the origin of the coordinate system (Jaffe, 1986).

[48] The proximity measure is symmetric to the ordering of firms ($\rho_{ij} = \rho_{ji}$).

[49] In the proximity measure based on citation distribution, I exclude the self-citations, because they do not impose any of the potential costs of patent thickets.

[50] Lags are defined as the difference between the ending years of the sample and year 1999. Therefore, lags are 1999-1996=3, 1999-1997=2, 1999-1998=1, and 1999-1999=0.

Figure D.1: Patents per $R\&D$ with Corrected and Not Corrected Patent Counts.



corrected patent and citation counts in my analysis.

Figure D.2: Citations per $R\&D$ with Corrected and Not Corrected Citation Counts.