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Patent thickets, defensive patenting, and induced R&D: an empirical analysis of the costs and potential benefits of fragmentation in patent ownership

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Abstract Patent thickets are sets of overlapping intellectual property rights that occur in fragmented technology markets. Their potential impacts on innovation have become an increasing concern in recent years. I estimate the direct and indirect effects of patent thickets on market value of publicly traded manufacturing firms. I find that patent thickets decrease the market value of firms, holding R&D and patenting activities of these firms constant. I also find that while firms do not change their R&D activities in response to patent thickets, they do reduce negative cost effects of patent thickets on market value through defensive patenting.

Keywords Innovation · Patent thicket · Patent · Spillovers · Market value · Fragmentation · R&D

JEL Classification L43 · O31 · O33 · O32 · O34 · O38

1 Introduction

Innovation is imperative for technological progress but the presence of positive knowledge spillovers results in a less than socially desired amount of innovation

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investments.[1] To capture spillovers and create incentives for innovation, patent systems grant exclusive rights to innovators. Nevertheless, 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) have created concerns among academics and policy makers that the patent system is actually discouraging innovation.[2]

The argument is that the recent changes have caused a proliferation of patents and higher fragmentation of patent ownership, which discourage subsequent innovation by increasing the enforcement costs of patents (Jaffe and Lerner 2007, p. 10). Subsequent innovators, who build their innovation upon a set of overlapping patents or a "patent thicket" (Shapiro 2001), have to obtain licenses from all the complementary patent holders in their thicket in order to commercialize their innovation.[3] In highly fragmented technology markets, subsequent innovators have to deal with a larger number of right holders in their thickets or their thickets are dense. Consequently, higher fragmentation of patent ownership increases the enforcement costs of patents and discourage innovation.

A part of the large enforcement costs of patents in fragmented technology markets is associated with the complement and double marginalization problems, which increase licensing fees for subsequent innovators.[4] Another reason for the large enforcement costs is the significant transaction costs of identifying and negotiating all the complementary patent holders. Even if all of the right holders are identified, there is a probability of bargaining failure in negotiations with the complementary patent holders because of the large number of parties engaged in the negotiations. The identification process itself is difficult, and innovators often become aware of the complementary patents for their patent only after making large sunk investments in their innovation. This situation implies a potential for holdups and litigation in patent disputes, which also raises the enforcement costs of patents.

Following the concerns about the negative impacts of the US patent system on innovation, several proposals for amendments and legislations were offered to Congress (e.g., the 2007–2010 Patent Reform Acts and the American Invent Act). These amendments themselves generated further disagreements in the economy, which point to a

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[1] The underinvestment argument goes back at least to Nelson (1959) and Arrow (1962). For more studies refer to Grossman and Helpman (1991) and Aghion and Howitt (1992). In an empirical analysis, Bloom et al. (2013) show that social returns of R&D are larger than private returns.

[2] The CAFC unified standards across circuits and granted stronger patent rights (Gallini 2002). The USPTO also started to grant patents extensively 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 (Jaffe and Lerner 2007, p. 11).

[3] A subsequent innovator is in a vertical relation with previous innovators or upstream monopolists. This paper is not about horizontal relations when a new innovation is a substitute instead of a complement to the existing patents. This is because the patent office requires citing all of the previous patents used in the innovation or complementary patents in the patent document when an innovator applies for a patent, and this is when the fragmentation of patent ownership becomes important.

[4] Shapiro (2001) shows subsequent innovators have to pay higher licensing fees in fragmented technology markets because of the presence of multiple right holders in their thicket and the several mark ups due to a long array of previous patent holders.

Fig. 1 Patent thicket and market value analysis
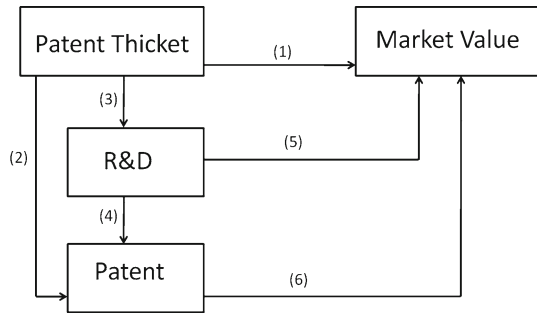
need for an empirical analysis on the presence and the extent of damaging impacts from dense patent thickets.[5]

To address this demand, my paper investigates the economic impacts of dense patent thickets by estimating their effect on manufacturing firms' market value. I argue that dense patent thickets could have two types of impacts on the market value: direct and indirect.[6] The direct impact [Arrow (1): Fig. 1] is the effect of dense patent thickets on firms' market value, while I hold all firms' patenting and R&D behavior constant. The potential costs of patent thickets, explained above, increase the enforcement costs of patents, which lower the expected earnings of firms and their market value.

The indirect impact is the likely effect of dense patent thickets on market value via the influence of thickets on firms' patenting and R&D activities [Arrows (2)–(6): Fig. 1]. On the impact of thickets on patenting [Arrow (2): Fig. 1], there are two possibilities. Patent thickets may encourage firms to patent defensively (the increase in patenting attributed to avoiding thicket costs) in order to decrease enforcement costs of patents and increase bargaining power in negotiations with other right holders (Ziedonis 2004; Lanjouw and Schankerman 2004; Galasso 2012). It is also plausible that higher enforcement costs of patents decrease the profitability of patenting and therefore patenting decreases (Noel and Schankerman 2013).

Patent thickets also influence R&D activities of firms [Arrow (3): Fig. 1]. Thickets may reduce firms' reliance on other firms' innovation by increasing their R&D expenditures. Firms might also increase their R&D to get more patents if they find that patents are helpful for reaching favorable results in patent disputes [Arrow (4): Fig. 1]. The patenting behavior and induced R&D activities of firms in response to their thickets may influence their market value, as they change future earnings of firms [Arrows (5) and (6): Fig. 1]. Therefore, only estimating the direct impact of patent thickets is not

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[5] 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 03 Nov. 2015). 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 03 Nov. 2015).

[6] One might argue that firms could have a third response to patent thickets. They could enter into alliances, such as patent pools, with complementary patent holder's in their thickets. In a patent pool, one entity, who can be one of the patent holders, licenses patents of two or more entities to third parties. However, the high transaction costs of identifying and negotiating all related patents in dense thickets make the formation of such alliances almost impossible (Shapiro 2001).

sufficient to determine the total effects of patent thickets on market value. The indirect impact might reduce or even eliminate the negative direct impact of patent thickets. In this study, using the calculated direct and indirect impacts explained above, I find the total impact of patent thickets.

This paper makes two distinct contributions to the literature. First, I estimate the effects that patent thickets have on patenting, R&D, and market value, using three separate estimating equations, in the manufacturing sector. Hall and Ziedonis (2001) and Ziedonis (2004) examine the impact of patent thickets on patenting in the semi-conductor industry and report evidence of defensive patenting. Graevenitz et al. (2010) uncover a positive effect from fragmentation on European patenting in very complex technology areas. To my knowledge, the only other study that examines the effect of patent thickets on market value, patenting, and R&D activities in separate estimating equations is Noel and Schankerman (2013). They rely on a smaller set of firms (121) specific to a single industry, software. My contribution adds to this existing literature by examining a much larger sample of manufacturing firms which allows me to exploit cross-firm and time-series variation across a larger number of firms (1272) during the sample period. Thus, this sample helps in minimizing potentially confounding effects from unobserved heterogeneities. Additionally, the manufacturing sector, which also includes computer and semiconductor sectors, generally consists of high technology firms with cumulative innovations. Therefore, a highly fragmented technology market in this sector might specifically increase the enforcement costs of patents and make the negative effects of patent thickets more acute.[7]

Second, I find the direct, indirect, and total impacts of patent thickets on manufacturing firms' market value. Noel and Schankerman (2013) and Entezarkheir (2010, ch. 1) quantify a direct negative impact from patent thickets on market value in the software and manufacturing sectors, respectively. As far as I know, no existing paper has quantified the indirect and total impacts of patent thickets on market value similar to my study.[8] Calculating the total impact in my paper for measuring the economic effects of patent thickets is important, as the indirect impact might crowd out the direct negative impact of patent thickets.

Furthermore, the examination of the role of fragmentation in patenting and R&D of manufacturing firms in my paper contributes to the economic literature that provides mixed results on the impact of fragmentation on innovation. Heler and Eisenberg (1998) point to "the tragedy of anti-commons" and argue that the large number of patent

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[7] Table 1 in the appendix also shows that on average firms in the manufacturing sector are R&D and patent intensive (0.83 and 0.54, respectively), which makes them more prone to higher enforcement costs for patents in the fragmented technology market.

[8] Noel and Schankerman (2013) examine the role of patent thickets in R&D and patenting. They define a direct impact from patent thickets on patenting and R&D of software firms via the lower profitability of patents and R&D due to higher enforcement costs of patents. They also define an indirect impact from patent thickets on patenting and R&D via a change in marginal value of accumulating patents. The indirect impact in my study is different from their paper since my paper examines the effect of thickets on R&D and patenting, and then consequently, on market value [Arrows (2)–(6): Fig. 1]. Noel and Schankerman (2013) do not estimates arrows (5) and (6) in Fig. 1, and they also do not estimate the total effect.

holders in the biomedical sector lowers innovation.[9] Murray and Stern (2007) also uncover the anti-commons effect in the biomedical patenting. Galasso and Schankerman (2013) find that patent thickets hinder cumulative innovation, and Williams (2013) provides evidence on the reduction of subsequent innovations as a result of intellectual property rights on current innovations. In contrast, Walsh et al. (2003) find that the anti-commons problem is manageable, and Walsh et al. (2005) report that limited access to intellectual property does not restrict biomedical research. 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. Galasso and Schankerman (2010) find patent thickets decrease the duration of patent disputes. They also find that the increased certainty associated with the CAFC reduced settlement delays.

In my analysis, I use panel data on 1272 publicly traded US manufacturing firms from 1979 to 1996,[10] and build on the methodologies developed in Griliches (1981) and Hall et al. (2005). My results suggest that patent thickets have a negative direct impact on the market value. This conforms with the findings of Noel and Schankerman (2013) and Entezarkheir (2010, ch. 1). I find that patent thickets increase defensive patenting in the manufacturing sector, similar to Hall and Ziedonis (2001) and Ziedonis (2004) for the semiconductor industry and Noel and Schankerman (2013) for the software industry. However, I do not find a statistically significant effect from thickets on R&D. The proliferation of patents in the manufacturing sector seems not to have generated the "tragedy of anti-commons" suggested by Heler and Eisenberg (1998). Hence, these findings imply that obtaining more patents is not the result of more R&D, and patent thickets increase the marginal value of patents. Thus, patent thickets have trigged patenting on marginal innovations to enlarge patent portfolios for bargaining power in patent disputes. While the positive effects of defensive patenting on market value alleviates the direct negative impact that patent thickets have on market value, the total impact stays negative for the manufacturing sector. This finding implies that the concerns in society and economic literature about the negative impacts of patent thickets are valid.

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.

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[9] Heler and Eisenberg (1998) discuss that the large number of patent holders leads to underuse of resources, which leads to underinvestment in innovation.

[10] The original data are from 1976 to 2002. However, I limit the sample to 1976–1996 to avoid problems associated with truncation in the data (for a more detailed explanation see Sect. 3.1 and "Appendix 4"). The sample of publicly traded firms is not an exact representative of all firms in the high technology sectors. However, due to data limitations, it is the best possible approximation of these firms.

2.1 Three functional relationships

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

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

Costs of patent thicket (F) increase the enforcement costs of the firm's patents. Consequently, these costs contribute negatively to future earnings of the firm and lower its market value.

As is depicted in Eq. (1), patent thicket spillovers ($spillF$), R&D, and patenting of the firm also impact its market value. I refer to the effect of complementary patent holders' patent thickets as patent thicket spillovers for the firm. The other right holders in the patent thicket of the firm also have to pay for the large enforcement costs of their own patents, such as transaction costs and risks of bargaining failures, because of the multiple right holders in their own thickets in fragmented markets. As the complementary patent holders are in a vertical relation with the firm, they might pass on at least part of the large enforcement costs of their own thickets to the firm by demanding a larger fee from this firm in negotiations over the use of their complementary patents. Therefore, the higher enforcement costs of complementary patent holders' thickets have a negative spillover effect on the stock market valuation of the firm, as these spillovers lower the expected profit of the firm. Following Griliches (1981) and Hall et al. (2005), R&D and patenting are determinants of the firm's market value as they are measures of its intangible assets.

Since patent thickets may influence R&D expenditures and the patenting behavior of firms, following the explanations in Sect. 1, 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 shows the impact of a firm's patent thicket (F) on its R&D expenditures:

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

and the third functional relationship displays the impact of a firm's patent thicket (F) on its patenting behavior:

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

As is illustrated in relationships (2) and (3), patenting and R&D activities by the firm are also influenced by patent thicket spillovers ($spillF$). Higher enforcement costs of other firms' patent thickets in the fragmented market could also make those firms patent defensively, in order to strengthen their bargaining power in patent disputes or decrease their propensity to patent due to lower benefits of patents. Patent thickets and their costs might also make complementary patent holders increase their R&D to invent around patents in their own thickets. As a result, the change in R&D and

patenting activities of complementary patent holders due to their own thickets will have spillover effects on the given firm's R&D and patenting. Furthermore, the R&D expenditures of the firm in relationship (3) might impact its patenting, as firms might increase their R&D to get more patents if they discover that patents are beneficial for bargaining power in patent disputes in highly fragmented technology markets.[11]

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

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

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

$$INDIRECT(PATENTING) = \frac{\partial Market\,Value}{\partial Patents} \times \frac{\partial Patents}{\partial F} + \frac{\partial Market\,Value}{\partial Patents} \times \frac{\partial Patents}{\partial spillF} \times \frac{\partial spillF}{\partial F}. \tag{6}$$

The total impact of patent thickets on market value is calculated as the sum of the direct impact (4) and the two indirect impacts (5–6).[12]

2.2 Three estimating equations

2.2.1 Market value equation

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

$$log\,q_{it} = \delta_1 log\,F_{it-1} + \delta_2 log\,spillF_{it-1} + \delta_3 log\,spillR\&D_{it-1}$$

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[11] Additionally, Griliches and Pakes (1980) show that successful R&D leads to innovation, and the firm might obtain patents to protect innovation.

[12] In a simple theoretical model, when a firm maximizes market value with respect to R&D and patenting, some components of the indirect effects (the derivative of market value with respect to R&D in particular) might be equal to zero following the theoretical model of Noel and Schankerman (2013). Nevertheless, models with stochastic R&D may deliver predictions closer to the average effects empirically estimated in the paper (Abel 1984, p. 264). Noel and Schankerman (2013) also show that R&D and patenting have effects on market value on average in their empirical analysis.

$$+ \gamma_1 \Psi \left(log \left(\frac{R\&Dstock}{TA} \right)_{it-1} \right) + \gamma_2 \Omega \left(log \left(\frac{PATstock}{R\&Dstock} \right)_{it-1} \right)$$

$$+ \gamma_3 \Gamma \left(log(\frac{CITEstock}{PATstock})_{it-1} \right) + \delta_4 logsale_{it-1} + \delta_5 logsale_{it-2}$$

$$+ \delta_6 logHHI_{it-1} + \alpha_i^{MV} + m_t + \epsilon_{it}^{MV}. \tag{7}$$

For a detailed derivation of Eq. (7) see "Appendix 1".

The dependent variable $logq_{it}$ is the logarithm of Tobin's q.[13] The variables $log F_{it-1}$ and $logspillF_{it-1}$ measure the firm's patent thicket and patent thicket spillovers, respectively. The construction of these variables is explained in Sect. 2.4. The variables $\left(\frac{R\&Dstock}{TA} \right)_{it-1}$, $\left(\frac{PATstock}{R\&Dstock} \right)_{it-1}$, and $\left(\frac{CITEstock}{PATstock} \right)_{it-1}$ are $R\&D$, patent, and citation intensities, respectively. These variables measure the intangible assets of the firm. "Appendix 1" shows how these variables are built. The parameters Ψ, Ω, and Γ denote the polynomials of 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. The R&D activities of other firms raise the available research effort in the economy, which could help the firm achieve more innovation, and consequently, higher future net cash flows and market value. The construction of this variable is discussed in "Appendix 3". The variable $logHHI_{it-1}$ controls for product market competition. This variable is a Herfindahl index (HHI) that utilizes firm-level sales in four-digit SIC codes. The parameters α_i^{MV} and m_t represent firm and time fixed effects, respectively.[14] The variable ϵ_{it}^{MV} is the error term.

The lag structure in the right-hand side variables of Eq. (7) is designed to alleviate the reflection problem (Manski 1993), which could make the estimates of the market value equation inconsistent. This problem highlights the difficulty of determining whether the coefficients on the patent thicket and R&D spillover variables ($logspillR\&D$, $logspillF$) reflect actual spillover effects or contemporaneous (technological) shocks that are correlated across related firms. Additionally, to further address the reflection problem, I try to control for demand shocks with the distributed lag structure in the firm-level sales ($logsale_{it-1}$ and $logsale_{it-2}$).[15] One more concern that might arise here is that value shocks to the technology field at different points of time may encourage firms to patent more and induce denser thickets. Controlling for time fixed effects and using the lagged value of patent fragmentation help decrease this threat to identification. To mitigate the confounding effects due to unobserved firm heterogeneities, I estimate Eq. (7) using a within estimator for panel data.[16]

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[13] The construction of $logq_{it}$ is explained in "Appendix 1".

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

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

[16] Estimates of Eq. (7) imply that the fifth order polynomial is satisfactory. I do not consider the multiplicative terms of the measures of intangible assets because including them does not change the results.

2.2.2 R&D equation

To estimate the relationship (2) for a firm, I apply the equation

$$
\begin{aligned}
log R\&D_{it} = {} & \theta_1 log R\&D_{it-1} + \theta_2 log F_{it-1} + \theta_3 log spill F_{it-1} \\
& + \theta_4 log spill R\&D_{it-1} + \theta_5 log sale_{it-1} + \theta_6 log sale_{it-2} \\
& + \theta_7 log HHI_{it-1} + m_t + \alpha_i^{R\&D} + \epsilon_{it}^{R\&D}.
\end{aligned}
\tag{8}
$$

Most of the right-hand side variables are explained in the previous section. The parameters $\alpha_i^{R\&D}$ and m_t represent firm and time fixed effects (to control for any changes over time such as policy changes), respectively. The variable $\epsilon_{it}^{R\&D}$ is an idiosyncratic error term.

To address the possible inconsistency in estimates due to the reflection problem, the right-hand side variables are in lagged format. Any shock that has an impact on the R&D expenditures of the firm is likely to affect other firms' R&D expenditures and patent thickets in the same technology field. Thus, a correlation between the R&D of other firms and their patent thickets with the firm's R&D expenditures could be related to actual spillover effects on the firm or to technological opportunity shocks that all the firms are experiencing.[17]

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 Eq. (8). To avoid inconsistent estimates due to unobserved firm heterogeneities, I estimate Eq. (8) using a within estimator for panel data.

As an alternative approach, I also estimate the dynamic panel data model of Eq. (8) using the panel generalized method of moments estimator of Arellano and Bond (1991). This approach uses the panel GMM estimator, where the instruments are lags of the dependent variable, and they are assumed to be weakly exogenous.

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[17] One possibility for measurement error could be a change in the direction of research as a result of dense patent thickets rather than changing the amount of R&D expenditures. The direction of research does not often change over time as it is costly to switch research but it varies across firms, and it is controlled for by $\alpha_i^{R\&D}$ or firm fixed effects in Eq. (8).

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

[19] According to Pakes (1985), firms' previous values of R&D expenditures have an impact on their current R&D expenditures. I only consider one lag of the dependent variable in the right-hand side of Eq. (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 difficult.

2.2.3 Patenting equation

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

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

The dependent variable is the number of successful patent applications made by a firm in a given year. Using the method of Cameron and Trivedi (2006, p. 670), I find overdispersion in the data, and consequently inefficient estimates, if I use a Poisson estimator to estimate Eq. (9). Following Hall and Ziedonis (2001), I employ a Poisson estimator with robust standard errors, which overcomes the inefficiency due to overdispersion.[20] One lag of the right-hand side variables is included to mitigate the reflection problem and measurement errors.[21] 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 the 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 heterogeneities. They argue that one reason behind the heterogeneities among firms is the differences 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 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 Eq. (9) are predetermined, I follow the mean-scaling approach of Blundell et al. (1999) to control for the firms' unobserved heterogeneities and include the variable *log pre-sample patents_i* in Eq. (9). This variable is the average of the pre-sample patent counts of firm i.[22]

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[20] To solve the overdispersion problem, some of the studies, such as Ziedonis (2004), suggest using the negative binomial estimator. I also estimate Eq. (9) with a negative binomial estimator with robust standard errors, and I find similar results when I use a Poisson estimator with robust standard errors. Nevertheless, the estimates in the negative binomial approach are consistent if the true distribution of the data is a negative binomial distribution, but the underlying distribution of the data is not evident in my paper.

[21] Any shock that affects the R&D expenditures of the firm, and therefore its patenting, is likely to have an impact on other firms' 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 patenting could be related to actual spillover effects or could be the result of technological opportunity shocks that all firms experience. Additionally, there is a possibility that more patents as a result of dense patent thickets translate into denser patent thickets. Using the lagged regressors is a partial cure for this simultaneity bias.

[22] It is worth mentioning that the investigation of defensive patenting using a citation data-based measure (explained in Sect. 2.4) is only a proxy measure. Ideally, I would like to examine strategic patenting using actual licensing data but I do not have access to such information.

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 regressor X_{it} in the models, the Eqs. (7) through (9) can be rewritten as

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

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

and

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

Using Eqs. (10–12), the direct impact (4) can be calculated as

$$
DIRECT\,IMPACT = \delta_1 + \delta_2, \tag{13}
$$

and the benefits of patent thickets or indirect impacts (5–6) can be calculated as

$$
\begin{aligned}
INDIRECT\,(R\&D) = {}& \frac{\partial logq_i}{\partial logR\&Dstock_i} \times 1 \times \left(\frac{\theta 2 + \theta 3}{1 - \theta_1} \right) \\
& + \frac{\partial logq_i}{\partial logPATstock_i} \times 1 \times \frac{1}{\overline{Patent}} \times \beta_4 \times \left(\frac{\theta 2 + \theta 3}{1 - \theta_1} \right)
\end{aligned} \tag{14}
$$

and

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

respectively, where $\overline{Patent}$ is the average of patent counts in the entire sample. See "Appendix 2" for the detailed steps of deriving Eqs. (14) and (15). The total impact is found by adding Eqs. (13) through (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 patent thicket, using the formula

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

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. The variable $cite_{it}$ is the count of all the citations made by firm i in year t to other firms' patents. Each citation made in a patent document is a reference to a complementary patent.

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.[23] As a robustness check, I also conducted the analysis using the measure of patent thickets in Noel and Schankerman (2013). They employ a 4-firm fragmentation index, which considers the citations of each firm to patents from the four largest rivals in the technology market. Employing this measure in Eqs. (7)–(9) results in similar findings to the case that I employ the measure in Eq. (16).

I employ the methodologies developed in Bernstein and Nadiri (1989), Jaffe (1986), Bloom et al. (2013), and Noel and Schankerman (2013), all of whom examine R&D spillovers, to measure patent thicket spillovers ("Appendix 3"). The patent thicket spillovers for firm i is measured 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 in terms of their technological field and is built based on the uncentered correlation coefficient of the location vectors of firms i and j. Following Noel and Schankerman (2013), the location vectors utilize the distribution of citations across the USPTO technology classes in the patent data (For more explanation on how to build ρ_{ij}, see "Appendix 3").

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[23] In calculating the fragmentation index for a firm, I do not consider citations made to the firm's own patents or to expired patents, as they do not pose any threat from fragmentation on the firm. Therefore, this index is missing for such cases. To control for missing values of F_{it}, I define an indicator variable, which is equal to 1 for missing values. Firms without any patents have missing F_{it}. To control for them, I define an indicator variable which is equal to 1 for firms without any patent.

3 Data

3.1 Data sources

I build the sample in my analysis based on three different data sets. The first data set is the updated National Bureau of Economic Research (NBER) data, consisting of information on utility patents granted from 1963 to 2002 and their citations.[24] The second data set is the Compustat North American Annual Industrial data from Standard and Poors on US publicly traded firms.[25] This data set includes information on firms' R&D expenditures, sales, and components of firms' book and market values.[26] The third data set is a company identifier file, which facilitates linking the updated NBER patent and citation files to Compustat data by firm names.[27]

This link file is required because patent 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 updated 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 updated NBER data, and its equivalent identifier in the Compustat data.

I combine the updated patent and citation data files of the NBER together. After accounting for withdrawn patents and considering only the patents of publicly traded firms, my sample from the NBER data yields almost 19 million observations on patents and their citations from 1976 to 2002. As the Compustat data are for publicly traded firms, I consider only the patents of publicly traded firms from the updated NBER data but for citations I consider citations to all types of firms. Since the citation file only contains patents that are granted in 1976 and afterward, I am forced to use the updated NBER data from 1976.

I consider manufacturing firms (SIC 2000–3999) from the publicly traded US firms in Compustat data from 1976 to 2002. This results in an unbalanced panel of 19,868 firms with 365,589 observations over this time period. I focus on the manufacturing sector, as it allows me to exploit cross-firm and time-series variation across a large number of firms during the sample period and thus minimizes potentially confounding effects from unobserved heterogeneity. Additionally, this sector generally includes firms with cumulative innovation and higher fragmentation which has more acute effects on these firms. Table 1 in the appendix also shows that an average manufacturing firm is R&D and patent intensive (0.83 and 0.54, respectively), which makes manufacturing firms more prone to higher enforcement costs for patents in the

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[24] The NBER patent and citation data files were originally built for patents from 1963 to 1999 and 1976 to 1999, respectively, 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/.

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

[26] The variables used in building firms' market and book values are explained in "Appendix 1".

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

fragmented technology market. The sample of publicly traded firms is not an exact representation of all firms in high technology sectors; however, due to the data limitations, it is the best approximation of these firms.

I link the sample from the updated NBER data, explained above, to corresponding observations of publicly traded US manufacturing firms from Compustat, explained above, by using Hall's identifier file. Dropping missing observations on market value ($Market\ Value_{it}$) and book value (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 1976 to 2002 (almost 2000 firms in each year).[28] 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 occurs because 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 at the beginning of the sample, as citation data are available only for the patents granted since 1976 from the updated NBER data.

The data have been corrected for these truncations. The correction procedures are explained in "Appendix 4". After these changes, I further limit the sample to 1979–1996 to avoid any potential problems arising from truncations and the possible edge effects suggested by Hall et al. (2005).[29] As a result, I focus only on when the data are the least problematic, leaving me with an unbalanced panel of 1272 manufacturing firms with 14,214 observations from 1979 to 1996. The result is a longitudinal firm-level data set over years on firm-level financial variables and patenting activities.

Table 1 presents the descriptive statistics of all variables. The average firm in the sample is large and R&D intensive.[30] 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 very similar. Figures 2 and 3 illustrate that variables F_{it} and $spillF_{it}$ were increasing on average from 1979 to 1996.

3.2 Exogenous sources of identifying variation

While not all of the variation in patent thickets 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 Sect. 1) and the pure randomness of having successful innovations.

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[28] 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 1".) 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.

[29] Following Bloom et al. (2013), 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.

[30] 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	SE	Min	Max
$MarketValue_{it}$	Market value	14,214	867	78	3073	0	70,772
TA_{it}	Book value	14,214	1222	108	3721	0	61,659
q_{it}	$(Market\,Value/TA)_{it}$	14,207	1.14	0.67	4.76	0	390
F_{it}	Fragmentation index	9110	0.70	0.81	0.291	0	0.98
$spill\,F_{it}$	Patent thicket spillovers	14,135	18.73	16.36	11.47	0.21	0.78
$spill\,R\&D_{it}$	R&D spillovers	14,126	19,516	14,910	16,107	79.63	117,631.70
$R\&D\,flow_{it}$	The level of R&D	12,533	80.03	8.24	296	0	6099.34
$R\&D\,stock_{it}$	The stock of R&D	14,214	307.20	21.46	1250	0	28,958.23
$Patent_{it}$	Patent counts	14,214	14	1	58	0	1256
$PATstock_{it}$	Stock of patents	14,214	64.22	5.64	260	0	5415.17
$CITEstock_{it}$	Stock of citations	9110	1152	126	4232	1.19	79,115.08
$(R\&Dstock/TA)_{it}$	R&D intensity	14,207	0.83	0.26	5.29	0	383.98
$(PATstock/R\&Dstock)_{it}$	Patent intensity	12,523	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	13,986	1766	186	5888	0	146,991
HHI_{it}	Market structure	14,214	0.428	0.357	0.260	0	1
$Pre\text{-}samplepatents_i$	Firm's pre-sample patents	14,214	14	1.78	43.84	0	6.29
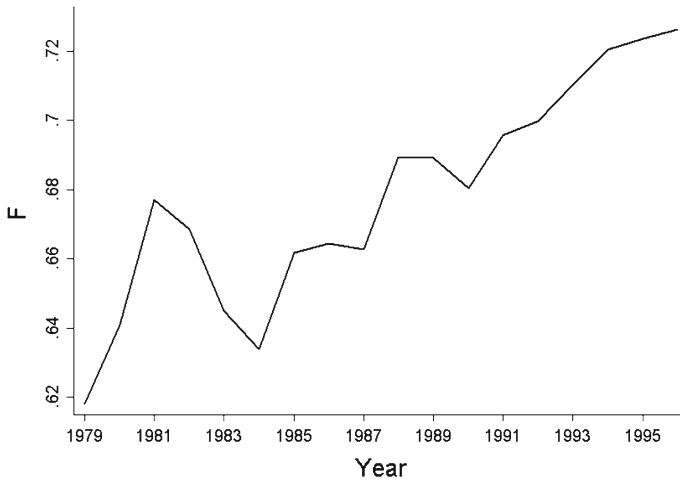
Fig. 2 Own patent thicket over time
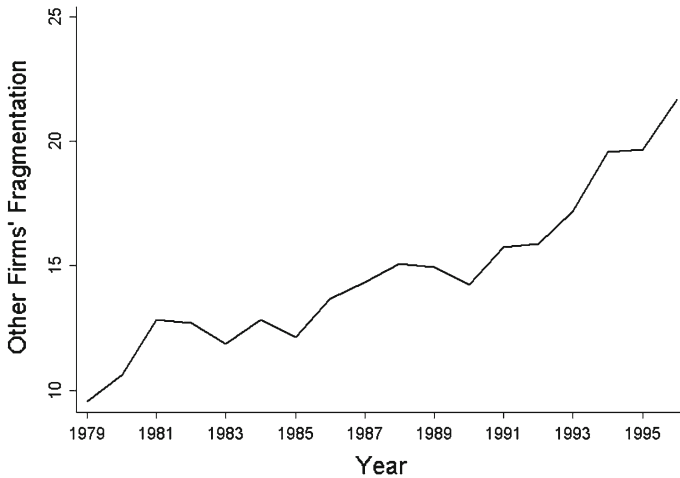
**Fig. 3** Patent thicket spillovers over time

To analyze the impact of pro-patent shifts following the establishment of the CAFC, I investigate 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, 1979–1986 and 1987–1996, 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 6–58 patents (medium firms), and firms with more than 58 patents (large firms).

Figures 4 and 5 illustrate the effect of the pro-patent shifts on F_{it} and $spillF_{it}$ for medium firms. 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. For the Kernel densities of the rest of the groups refer to Entezarkheir (2010, ch. 1). These densities show 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.
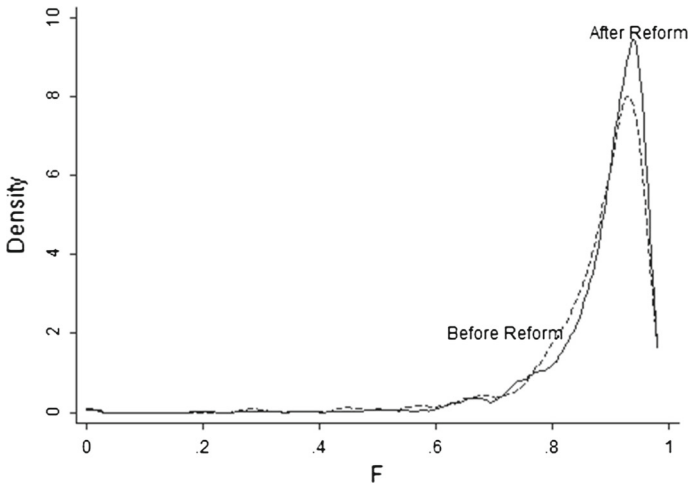
Fig. 4 Density of F_{it} for medium firms (firms with 6–58 patents)
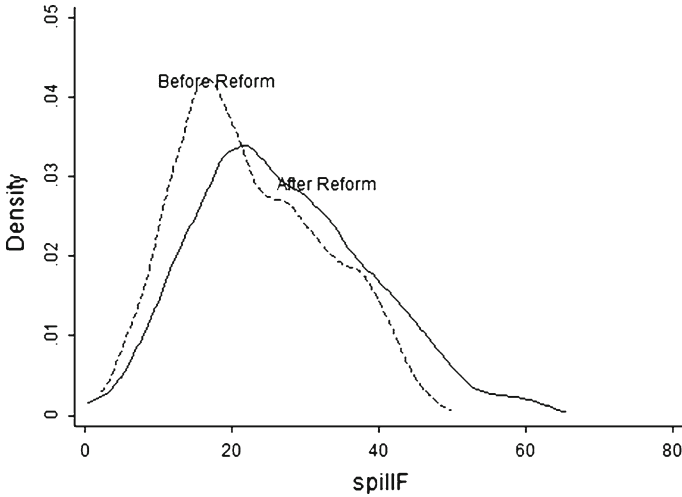
Fig. 5 Density of $spill\,F_{it}$ for medium firms (firms with 6–58 patents)

4 Results

4.1 Market value equation

Table 2 contains estimates of patent thickets on market value (the direct impact or Eq. (4)) based on the estimating Eq. (7). Standard errors are clustered at the firm-level.[31] Both the estimated coefficients on a firm's patent thicket ($log\,F_{it-1}$) and patent thicket

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

Table 2 Patent thicket and market value

Dependent variable $logq_{it}$	(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)
$[log(\frac{PATstock}{R\&Dstock})_{it-1}]^4$	−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
$log(\frac{CITEstock}{PATstock})_{it-1}$	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)
	(0.055)	(0.000)	(0.000)	(0.000)

Table 2 continued

Dependent variable $logq_{it}$	(1)	(2)	(3)	(4)
$[log(\frac{CITEstock}{PATstock})_{it-1}]^4$	−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	11,773	11,773	11,773	11,773
R^2	0.1364	0.1366	0.1397	0.2785

The signs ***, **, and * mean significance at 1, 5, and 10 %, respectively

The numbers in the parentheses are the cluster-robust standard errors (clustered at the firm-level)

The reported R^2 in the first three columns are within R^2 for a panel fixed effects estimator

spillovers ($logspillF_{it-1}$) indicate that patent thickets have a negative direct impact on market value. The coefficient of $logF_{it-1}$ in column 3, which contains estimates with firm fixed effects, shows that market value declines by 0.22 % as fragmentation increases by a 10 percentage point. This result implies that an increase in fragmentation raises the cost of negotiating with other patent holders. Thus, higher transaction costs increase enforcement costs of patents and thereby, lower market value. However, I put limited emphasis on this result because the coefficient estimate is not statistically significant. The coefficient of $logspillF_{it-1}$ shows that if fragmentation increases by 10 % for other firms in the same technology space, the given firm experiences a statistically significant decrease in market value by 0.69 %. This finding indicates that the other right holders in the patent thicket of the given firm transfer at least part of the costs of their own thickets to the given firm.

The estimated negative impacts of patent thickets are robust to the use of industry dummies in column 4. As firms in the manufacturing sector are assigned into different SIC industry classifications, I include four-digit industry dummies to control for unobserved heterogeneities due to the higher possibility of having dense patent thickets in some industries than others. In summary, the results in Table 2 support the hypothesis that patent thickets lower a firm's market value directly.

In a comparison of these results to the previous literature, Noel and Schankerman (2013) find a negative impact from patent thickets on the market value of software firms from 1980 to 1999. They show that a 10 percentage point increase in fragmentation of patent ownership decreases the market value of software firms by 3.44 %. Similarly,
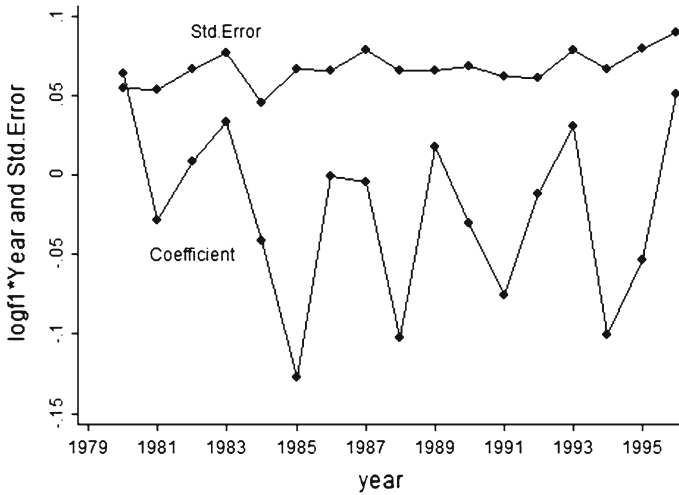
Fig. 6 Fragmentation impact by year

Entezarkheir (2010, ch. 1) finds a direct negative impact from patent thickets on the market value of manufacturing firms, without considering the impact of patent thicket spillovers, from 1979 to 1996. This study shows that a 10 percentage point increase in fragmentation lowers the market value of manufacturing firms by 0.76 %. Noel and Schankerman's (2013) measure for patent thickets, explained in Sect. 2.4, is different from mine and is a 4-firm fragmentation index. As a robustness check, I also used Noel and Schankerman's (2013) measure of patent thickets for manufacturing firms. My empirical findings are robust to this measure.

The explained US pro-patent shifts after 1982 raise the question of whether patent thickets had any noticeable impact on manufacturing firms' market value after these changes. To investigate this question, I will first interact key variables of interest, $logF_{it-1}$ and $logspillF_{it-1}$, with year dummies (D_t, where $t = 1979, \ldots, 1996$) in Eq. (7) and then plot the estimated coefficients and their standard errors in Figs. 6 and 7. As the figures show, the first change due to the pro-patent shifts happened around 1983 and 1986. Thus, I divide the sample once into two sub-periods, 1979–1986 and 1987–1996, and once into 1979–1983 and 1984–1996. Next, I estimate Eq. (7) for each case. The results for 1979–1986 show that the estimated coefficients on $logF_{it-1}$ and $logspillF_{it-1}$ are −0.004 (standard error = 0.020) and −0.033 (standard error = 0.016), respectively. The estimates of $logF_{it-1}$ and $logspillF_{it-1}$ for 1987–1996 are −0.050 (standard error = 0.024) and −0.128 (standard error = 0.049), respectively. The results for 1979–1983 show that the estimated coefficients on $logF_{it-1}$ and $logspillF_{it-1}$ are 0.032 (standard error = 0.024) and −0.017 (standard error = 0.015), respectively. The estimates of $logF_{it-1}$ and $logspillF_{it-1}$ for 1984–1996 are −0.049 (standard error = 0.023) and −0.127 (standard error = 0.049), respectively. Whether if I consider 1983 or 1986 as the breaking point, these findings show that the negative effects of patent thickets on market value increase after the pro-patent shifts.

One might worry that the negative effects of patent thicket and patent thicket spillovers on market value are simply due to higher product market competition,
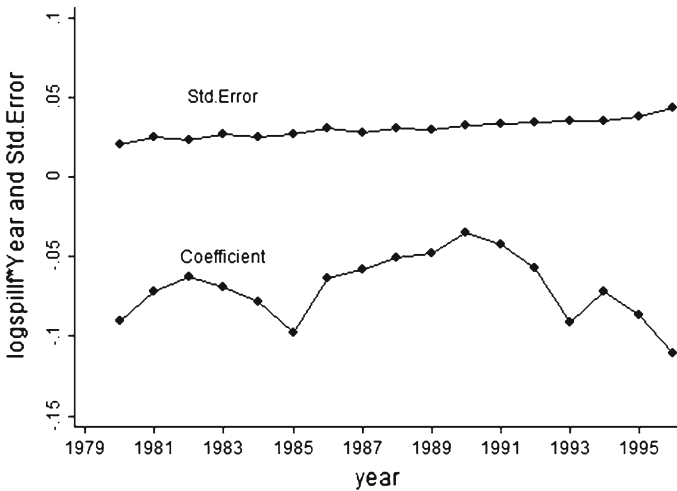
Fig. 7 Fragmentation spillover impact by year

not higher patent enforcement costs, if fragmentation is also correlated with product market competition. To address this concern, following Noel and Schankerman (2013), I estimate Eq. (7) with and without a control for product market competition. As explained in Sect. 2.2.1, I measure product market competition with a Herfindahl index that utilizes firm-level sales in four-digit SIC codes ($logHHI_{it-1}$). Column 3 of Table 2 reports the estimates with the variable $logHHI_{it-1}$. I also estimate the same model as column 3 without the variable $logHHI_{it-1}$. In this model, the estimated coefficients on $log F_{it-1}$ and $logspill F_{it-1}$ are -0.021 (standard error $= 0.020$) and -0.076 (standard error $= 0.024$), respectively. Since the estimated coefficients in models with and without a control for product market competition are similar, I might be able to conclude that the negative effects of patent thicket variables do not reflect the product market competition. There is a caveat here that the HHI index based on sales at the 4-digit SIC codes might not be a good estimator of the product market competition. Nevertheless, based on the available data, $logHHI_{it-1}$ is the possible measure. Another concern might be that these findings are the result of changes in technological opportunities that vary across industries over time. However, the results are robust when I control for interactions between the industry and time fixed effects.

Additionally, the positive impact of $logHHI_{it-1}$ in column 3 of Table 2 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 in a cross-sectional data (Lindenberg and Ross 1981; Hirschey 1985).

The knowledge intensity variables in Table 2, explained in "Appendix 1", also have positive effects on market value, and this is similar to the findings of Noel and Schankerman (2013) for the software industry and Hall et al. (2005) for the manufacturing sector. R&D spillovers ($logspillR\&D_{it-1}$) do not have a statistically

Table 3 Patent thicket and R&D

Dependent variable $log R\&D_{it}$	(1)	(2)	(3)	(4)	(5) Arrellano Bond GMM
$log F_{it-1}$		0.024	0.023	0.015	−0.012
		(0.019)	(0.020)	(0.018)	(0.019)
$logspill F_{it-1}$			0.008	0.012	0.020
			(0.017)	(0.010)	(0.017)
$logspill R\&D_{it-1}$			−0.004	0.010	0.004
			(0.005)	(0.006)	(0.006)
$log R\&D_{it-1}$	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)
$D(log F_{it} = 0)$		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	

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

significant effect on market value in columns 3 and 4. This differs from previous literature. Hall et al. (2005) and Bloom et al. (2013) find a positive and statistically significant impact from R& D spillovers in a sample based on various industries.

4.2 R&D equation

Table 3 reports estimates of the potential benefits of patent thickets for R&D activities, employing Eq. (8). All columns of Table 3 include time fixed effects to control for any relevant policy changes over time in the sample. The results in Column 3 of Table 3 show that the major determinant of R&D expenditures for a given firm is its past R&D expenditures.[32] While the coefficients on the patent thicket variables, $log F_{it-1}$ and $logspill F_{it-1}$, are both positive, they are not statistically significant, and

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[32] When I estimate Eq. (8) with an Ordinary Least Squares estimator, the estimated coefficient of the lagged dependent variable is 0.981 (SE = 0.005), which is very similar to the estimate in column 3 of Table 3.

their magnitude is very small. Noel and Schankerman (2013) also find a statistically insignificant effect from fragmentation in a model similar to Column 3 for software firms (the coefficient of their fragmentation measure is 0.124 with SE = 0.14). The estimated coefficient of $log F_{it-1}$ in column 3 implies that a 10 % increase in the firms' own patent thicket increases R&D expenditure by only 0.23 %, and the coefficient estimate on the variable $logspill F_{it-1}$ in the same column suggests that a 10 % increase in others' patent thickets increases R&D expenditures of a firm by only 0.08 %.

One interpretation of statistically insignificant effects of thickets on R&D is that the proliferation of patents has not generated the "tragedy of anti-commons" suggested by Heler and Eisenberg (1998) in the manufacturing sector. It is also plausible that patent thickets do not change the amount of R&D expenditures but rather the direction of research for firms. Nevertheless, the direction of research varies mostly across firms and does not change that frequently over time, as it is costly. Therefore, the use of firm fixed effects in estimations of Eq. (8) provides a partial remedy for this measurement error.

Policy changes over time are controlled by time fixed effects, and the estimated coefficients of time dummies (not reported) do not show systematic changes in R&D over the sample period. I cannot reject the hypothesis that the estimated coefficients of time dummies are jointly zero. The findings of Table 3 are robust when I use Noel and Schankerman's measure for patent thickets. I do not find any effect from R& D spillovers ($logspill R\&D_{it-1}$) on the R&D activities of manufacturing firms similar to Noel and Schankerman (2013) for software firms. This finding is robust to all the specifications of Table 3.

An alternative approach for estimating dynamic panel data models, such as Eq. (8), is to use the panel generalized method of moments estimator of Arellano and Bond (1991). Column 5 of Table 3 shows the results using this estimator where the instruments are lags of the dependent variable and assumed to be weakly exogenous. The statistically insignificant impact of patent thickets on R&D persists in Column 5.

4.3 Patent equation

Table 4 reports estimates of patent thicket effects on patenting activity, using Eq. (9). The estimated coefficient on the variable *log pre-sample patents$_i$* in Table 4, which is used to control for firm unobserved heterogeneities following Blundell et al. (1999), is positive and statistically significant in columns 1 to 3. This result confirms the need to control for heterogeneity across firms with respect to their patenting behavior in Eq. (9).

The results in columns 3 and 4 indicate that patent thickets have a positive effect on patenting in models both with and without controls for firm fixed effects. These results imply that manufacturing firms patent more in fragmented technology markets to increase their bargaining power with other right holders in their thickets. In other words, these results provide evidence for defensive patenting behavior of firms in response to patent thickets. Noel and Schankerman (2013) for the software industry, and Hall and Ziedonis (2001) and Ziedonis (2004) for the semiconductor industry, also report evidence of defensive patenting with respect to fragmentation in patent

Table 4 Patent thicket and patent propensity

Dependent variable $Patent_{it}$	(1) Poisson Mean-scaling	(2) Poisson Mean-scaling	(3) Poisson Mean-scaling	(4) Poisson No mean-scaling
$\log F_{it-1}$		1.250***	1.151***	1.022
		(0.117)	(0.116)	(0.103)
		[2.066]	[1.932]	[1.395]
$\log spill F_{it-1}$			0.023**	0.525***
			(0.048)	(0.061)
			[0.039]	[0.716]
$\log spill R\&D_{it-1}$			0.127***	0.041**
			(0.027)	(0.020)
$\log R\&Dstock_{it-1}$	0.585***	0.552***	0.534***	0.709***
	(0.018)	(0.018)	(0.017)	(0.020)
	[1.822]	[0.913]	[0.896]	[0.967]
$\log Sale_{it-1}$	−0.079***	−0.080***	−0.090***	−0.044***
	(0.014)	(0.014)	(0.013)	(0.014)
$\log Sale_{it-2}$	−0.023**	−0.024**	−0.015	−0.015**
	(0.010)	(0.010)	(0.010)	(0.007)
$\log HHI_{it-1}$			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)	
$D(\log F_{it} = 0)$		-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	11,760	11,760	11,760	11,760

The signs ***, **, and * mean significance at 1, 5, and 10 %, respectively

Numbers in the brackets are marginal effects. The numbers in the parentheses are robust standard errors

ownership. The coefficient of the variable $\log spill F_{it-1}$ is also positive and statistically significant but the marginal effect of this variable is small. This result implies that when technology rivals are faced with denser patent thickets, firms patent more to strengthen their position in negotiations. The standard errors in Table 4 are robust standard errors to avoid the inefficiency resulting from over-dispersion in the data, explained in Sect. 2.2.3.

The other result is that firms' R&D stock has a positive and statistically significant impact on their patenting. R&D spillovers have a positive and statistically significant effect on patenting as well. A 10 % increase in spillovers boosts patenting by 1.3 %.

Table 5 Direct and indirect impacts of F_{it} and $spill F_{it}$

Specification	Direct impact	Indirect impact		Total impact
		INDIRECT (R&D)	INDIRECT (PATENTING)	
Firm FE	−0.091	+0.002	+0.008	−0.081
	(0.030)[a]	(0.005)	(0.003)	(0.032)
	[0.031][b]	[0.007]	[0.001]	[0.030]

[a] Nonparametric bootstrapped standard errors
[b] Wild bootstrapped standard errors

The positive effect of knowledge spillovers on patenting is much larger (6.4 %) for software firms, according to Noel and Schankerman (2013).

Similar to the market value equation, one might be concerned that the positive effects of patent thicket and patent thicket spillovers on patenting are the result of higher product market competition, rather than higher enforcement costs resulting from fragmentation. Following NS13, I estimate Eq. (9) with and without a control for product market competition (explained in 2.2.1). Column 3 of Table 4 reports the estimates with the variable $logHHI_{it-1}$. The estimates on the variables $log F_{it-1}$ and $logspill F_{it-1}$ without $logHHI_{it-1}$ in the model of column 3 of Table 4 are 1.1 (standard error = 0.117) and 0.062 (standard error = 0.048), respectively. Since the results of models with and without $logHHI_{it-1}$ are similar, the positive effects of patent thickets on patenting do not reflect the product market competition.

4.4 Calculated direct, indirect, and total impacts

Table 5 displays the calculated direct, indirect, and total impacts obtained using Eqs. (13), (14), and (15) in the manufacturing sector. I calculate these effects using the estimates with firm fixed effects (column 3 of Tables 2, 3, 4). Standard errors of direct, indirect, and total impacts are estimated with nonparametric bootstrapping (the numbers in parentheses). As a robustness check, I also report the standard errors based on wild bootstrapping (the numbers in brackets).[33]

The direct impacts of patent thickets on market value is negative, and the indirect impacts of patent thickets through R&D and patenting on market value are positive. The direct impact shows that a 10 % increase in patent thickets is associated with a 0.9 % decrease in firms' market value. As I explained earlier, Noel and Schankerman (2013) and Entezarkheir (2010, ch. 1) also estimate a direct impact from patent thickets on market value in the software and manufacturing industries, respectively. They show that a 10 % increase in fragmentation lowers market value by 3.44 % for software firms and 0.76 % for manufacturing firms. Their estimated statistically significant

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

direct impact similar to my study implies that higher fragmentation translates to lower market value for software and manufacturing firms.

The indirect impact of patent thickets on market value through R&D (induced R&D) is very small and statistically insignificant in Table 5. However, the indirect impact of patent thickets on market value through patenting is positive and statistically significant. The beneficial indirect impact of patent thickets on market value through an increase in patenting (defensive patenting) only partially offsets the negative direct impact of patent thickets on the market value in the manufacturing sector. The total impact of patent thickets on market value is negative and statistically significant in the manufacturing sector. The estimates in Table 5 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 (column 4 of Tables 2, 3, 4) result in similar findings.

Noel and Schankerman (2013) report an indirect impact from fragmentation but this effect is different from the estimated indirect impact here. They define a direct impact from fragmentation on R&D and patenting via lower profitability due to higher enforcement costs, and an indirect impact from fragmentation on R&D and patenting via the change in marginal value of accumulating patents in fragmented technology markets.

Table 6 provides estimates of the direct, indirect, and total effects of fragmentation of patent ownership by industry. The industry classifications are defined based on Hall and Vopel (1997) and Hall et al. (2005) that group firms in the manufacturing sector into 6 broad categories by their 4-digit SIC codes. The chemical industry includes chemical products, the computer industry includes the computers and computing equipment, the drugs sector consists of optical and medical instruments, and pharmaceuticals. The electrical sector includes electrical machinery and electrical instrument as well as communication equipment, while the mechanical sector includes primary metal products, fabricated metal products, machinery and engines, transportation equipment, motor vehicles, and auto parts.[34] Although the direct and total impacts are both negative across all industries except for computers, they are statistically insignificant. Fragmentation has a higher penalty in terms of total effect for the chemical and drugs sectors.

In order to compare these results to the previous literature, Noel and Schankerman (2013) use a sample of 121 software firms, where two third of firms in their sample have 4-digit SIC code of 7372 (prepackaged software) and only 22 of their firms belong to the manufacturing sector with the same 4-digit SIC codes as firms in my computer sector. The computer sector in Table 6 includes firms with four-digit SIC codes 3570 to 3578.[35] Noel and Schankerman (2013) find a direct negative impact from fragmentation on market value. My estimated positive impact of fragmentation

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[34] The percentage of each industry in my sample is: chemical 5 %, computers 6 %, drugs 18 %, electrical 28 %, and mechanical 23 %. I focus on these industries, as subsequent innovations are more common for them. The rest of the firms are in other industries in the manufacturing sector and they constitute approximately 21 % of the sample.

[35] The titles of these SIC codes are: 3570 Computer and Office Equipment, 3571 Electronic Computers, 3572 Computer Storage Devices, 3575 Computer Terminals, 3576 Computer Communications Equipment, 3577 Computer Peripheral Equipment—NEC, 3578 Calculating and Accounting Machines - except Electronic Computers.

Table 6 Direct and indirect impacts of F_{it} and $spill F_{it}$ by industry

Industry	Direct impact	Indirect impact		Total impact
		INDIRECT (R&D)	INDIRECT (PATENTING)	
Chemical	−0.081	−0.158	0.027	−0.212
	(0.216)[a]	(0.120)	(0.016)	(0.274)
Computers	0.226	+0.026	−0.017	0.235
	(0.132)	(0.005)	(0.011)	(0.178)
Drugs	−0.123	+0.013	−0.001	−0.111
	(0.122)	(0.024)	(0.005)	(0.124)
Electrical	−0.080	+0.012	+0.053	−0.015
	(0.066)	(0.005)	(0.018)	(0.122)
Mechanical	−0.039	−0.010	+0.010	−0.039
	(0.050)	(0.015)	(0.012)	(0.052)

Effects are calculated based on models with firm fixed effects

[a] Nonparametric bootstrapped standard errors

on market value for the computer sector in Table 6 might be justified by the fact that software firms with cumulative innovations (firms with the SIC code 7372 for prepackaged software) are not included in this sector but I put only limited emphasis on this result as it is not statistically significant. Following Bessen and Meurer (2008, p. 190), the included firms in the computer sector might have counteracted the negative effect of fragmentation by having more patents and using fewer patents from other firms. The insignificant impact on the drug sector is likely due to the fact that in the pharmaceutical sector, firms use patents to block the development of alternative drugs by rivals and, therefore, patents are not used for expropriating rivals (Cohen et al. 2000).

Even though the time span of the sample does not cover some of the recent shifts in patent policies, such as AMP v. Myriad (2013), Prometheus v. Mayo (2012), and Bilski v. Kappos (2010), the findings of this paper might provide some predictions for the consequences of these policy changes. The ruling of Bilski v. Kappos invalidates some of the business and software claims, which restricts patenting in this area. Following Dreyfuss and Evans (2011), the Bilski v. Kappos ruling has further implications for invalidating some of the gene patents, which have profound downstream impacts, as these patents are built upon each other. The ruling of AMP v. Myriad on isolated genes is an example of the subsequent effects of the Bilski v. Kappos for gene patents. The ruling of Promtheus v. Mayo on ineligibility of the dosage and methods of giving a drug as well as finding metabolites of the drug for patenting also restricts obtaining diagnostic patents (Thomas 2000).

Ziedonis (2004) links patent proliferation of the US economy with fragmentation of patent ownership. Jaffe and Lerner (2007, p. 15) also discuss that proliferation of patents can imply holdup risks, which is one of the costs of patent thickets for innovators with subsequent innovation. The recent rulings on gene, business, software patents imply alleviation in the current patent proliferation. Following Ziedonis (2004),

the decrease in the proliferation might imply less fragmentation of patent ownership for firms with subsequent innovations, such as firms in the biotechnology sector. Assuming that everything else is constant, the findings of this paper imply that these patent policy shifts might result in an increase in market valuation and a decrease in defensive patenting for firms with sequential innovations. However, the amount of R&D investments of such firms is not expected to change following the results here. The total impact of patent fragmentation for firms will change, depending on the magnitude of the direct and indirect effects.

5 Conclusion

The economic effects of patent thickets have been at the center 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, indirect, and total impact of patent thickets. The direct impact is the negative effect that patent thicket costs have on firms' market value, while holding R&D and patenting activities of firms constant. The indirect impact is the potential benefit of patent thickets for market value through patent thicket induced changes in R&D and through a patent thicket prompted increase in defensive patenting. The analysis is conducted using unbalanced panel data on 1272 publicly traded US manufacturing firms from 1979 to 1996.

The results show that patent thickets lower the market value of manufacturing firms directly. Noel and Schankerman (2013) and Entezarkheir (2010, ch. 1) also find a direct negative impact on software and manufacturing industries, respectively. However, to my knowledge, there is no prior study that examines the indirect and total impacts of patent thickets. This paper shows that 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 in the manufacturing sector.

The merit of my analysis for intellectual property policy is that it quantifies the indirect and total impacts of patent thickets in addition to the direct impact. As the USA 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.

Appendix 1: 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

$$log\, Market\, Value_{it} = log\, SV_{it} + \sigma\, log(TA_{it} + \gamma INA_{it}). \tag{18}$$

The variable $log\,Market\,Value_{it}$ is the log of the market value of firm i in year t.[36] 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 $log\,SV_{it}$ 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 Eq. (18) allows the left-hand side of this equation to be written as $log\left(\frac{Market\,Value_{it}}{TA_{it}}\right)$ or Tobin's q.[37] Eq. (18) then becomes

$$logq_{it} = log\left(1 + \gamma\frac{INA_{it}}{TA_{it}}\right) + m_t + \epsilon_{it}^{MV}. \tag{19}$$

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.[38] 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 %.[39] 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 $R\&D$, patent, and citation intensities to measure INA_{it}, following Hall et al. (2005), and, Eq. (19) becomes

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[36] According to Hall et al. (2005), one important advantage of this specification is the equalization of the marginal shadow value of assets across firms.

[37] 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.

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

[39] 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 (2013). I select the parameter δ or depreciation rate equal to 15 %. Most researchers settled with this deprecation rate (Hall et al. 2000, 2005, 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.

$$logq_{it} = log\left(1 + \gamma_1 \times \left[\left(\frac{R\&Dstock}{TA}\right)_{it}\right] + \gamma_2 \times \left[\left(\frac{PATstock}{R\&Dstock}\right)_{it}\right]\right.$$
$$\left. + \gamma_3 \times \left[\left(\frac{CITEstock}{PATstock}\right)_{it}\right]\right) + m_t + \epsilon_{it}^{MV}. \tag{20}$$

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 happens 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 4" for detailed correction procedures.

To estimate the impact of patent thicket on the market value of firms, I augment Eq. (20) 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 or patent thicket spillovers (the construction of these variables is explained in Sect. 2.4). To control for R&D spillovers, I include $logspillR\&D_{it}$ in Eq. (20), and the construction of this variable is explained in "Appendix 4". The distributed lag structure in the firm-level sales ($logsale_{it}$ and $logsale_{it-1}$) decreases the potential for inconsistent estimates due to demand shocks. To control for product market competition, 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.[40] To control for the firm's unobserved heterogeneities, I include α_i^{MV} in Eq. (20). Adding the above variables to Eq. (20) results in the specification

$$logq_{it} = log\left(1 + \gamma_1 \times \left(\frac{R\&Dstock}{TA}\right)_{it} + \gamma_2 \times \left(\frac{PATstock}{R\&Dstock}\right)_{it}\right.$$
$$\left. + \gamma_3 \times \left(\frac{CITEstock}{PATstock}\right)_{it}\right) + \delta_1 logF_{it} + \delta_2 logspillF_{it}$$
$$+ \delta_3 logspillR\&D_{it} + \delta_4 logsale_{it} + \delta_5 logsale_{it-1}$$
$$+ \delta_6 logHHI_{it} + m_t + \alpha_i^{MV} + \epsilon_{it}^{MV}. \tag{21}$$

Equation (21) could be estimated with a nonlinear least squares estimator, but it is easier to substitute the nonlinear terms with series expansions and estimate the equation with a linear estimator, following Bloom et al. (2013) and Noel and Schankerman (2013).[41] This approach makes the incorporation of firm fixed effects easier. Therefore, Eq. (21) becomes

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[40] 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.

[41] 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.

$$logq_{it} = \delta_1 logF_{it} + \delta_2 logspillF_{it} + \delta_3 logspillR\&D_{it}$$
$$+ \gamma_1\Psi\left(log\left(\frac{R\&Dstock}{TA}\right)_{it}\right) + \gamma_2\Omega\left(log(\frac{PATstock}{R\&Dstock})_{it}\right)$$
$$+ \gamma_3\Gamma\left(log\left(\frac{CITEstock}{PATstock}\right)_{it}\right) + \delta_4 logsale_{it} + \delta_5 logsale_{it-1}$$
$$+ \delta_6 logHHI_{it} + \alpha_i^{MV} + m_t + \epsilon_{it}^{MV}, \tag{22}$$

where the parameters Ψ, Ω, and Γ denote the polynomials of the measures of intangible assets. Equation (22) is used to build Eq. (7).

Appendix 2: Indirect impacts through R&D and patenting

$$INDIRECT(R\&D)$$
$$= \left[\frac{\partial logq_i}{\partial logR\&Dstock_i} \times \frac{\partial logR\&Dstock_i}{\partial logR\&D_i} \times \left(\frac{\partial logR\&D_i}{\partial logF_i} + \frac{\partial logR\&D_i}{\partial logspillF_i}\right)\right]$$
$$+ \left[\frac{\partial logq_i}{\partial logPATstock_i} \times \frac{\partial logPATstock_i}{\partial logPatent_i} \times \frac{\partial logPatent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial logR\&Dstock_i}\right.$$
$$\left. \times \frac{\partial logR\&Dstock_i}{\partial logR\&D_i} \times \left(\frac{\partial logR\&D_i}{\partial logF_i} + \frac{\partial logR\&D_i}{\partial logspillF_i}\right)\right]$$
$$= \frac{\partial logq_i}{\partial logR\&Dstock_i} \times 1 \times \left(\frac{\theta2 + \theta3}{1 - \theta_1}\right)$$
$$+ \frac{\partial logq_i}{\partial logPATDstock_i} \times 1 \times \frac{1}{Patent} \times \beta_4 \times 1 \times \left(\frac{\theta2 + \theta3}{1 - \theta_1}\right). \tag{23}$$

$$INDIRECT(PATENTING) = \left[\frac{\partial logq_i}{\partial logPATDstock_i} \times \frac{\partial logPATDstock_i}{\partial logPatent_i}\right.$$
$$\left. \times \frac{\partial logPatent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial logF_i}\right]$$
$$+ \left[\frac{\partial logq_i}{\partial logPATDstock_i} \times \frac{\partial logPATDstock_i}{\partial logPatent_i} \times \frac{\partial logPatent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial logspillF_i}\right]$$
$$= \frac{\partial logq_i}{\partial logPATDstock_i} \times 1 \times \frac{1}{Patent} \times (\beta_1 + \beta_2). \tag{24}$$

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

$$R\&Dstock_{it} = (1 - \delta)R\&Dstock_{it-1} + R\&D_{it}. \tag{25}$$

Using the steady state condition ($R\&Dstock_{it} = R\&Dstock_{it-1} = R\&Dstock_i$), and taking the logarithm of both sides, Eq. (25) becomes

$$logR\&Dstock_i = logR\&D_i - log\delta, \tag{26}$$

where

$$\frac{\partial logR\&Dstock_i}{\partial logR\&D_i} = 1. \tag{27}$$

I use Eq. (27) in Eq. (23). The same applies to the patent variable as this variable is a stock variable in Eq. (10) and is a count variable in Eq. (12).

Appendix 3: 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 Sect. 1, and I measure the R&D spillovers of firm i at time t as

$$SpillR\&D_{it} = \sum_{j \neq i} \rho_{ij} \times R\&Dstock_{jt}. \tag{28}$$

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). 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 $S_i = \{s_{i1}, s_{i2}, \ldots, s_{iN}\}$, where s_{ik} shows firm i's share of patents in the technology class k.

Bloom et al. (2013) use a modified version of Jaffe's (1986) measure for the parameter ρ_{ij}. Their measure is

$$\rho_{ij} = \frac{S_i' S_j}{(S_i' S_i)^{1/2} (S_j' S_j)^{1/2}}. \tag{29}$$

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.[42] Noel and Schankerman (2013) 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

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[42] The proximity measure is symmetric to the ordering of firms ($\rho_{ij} = \rho_{ji}$).
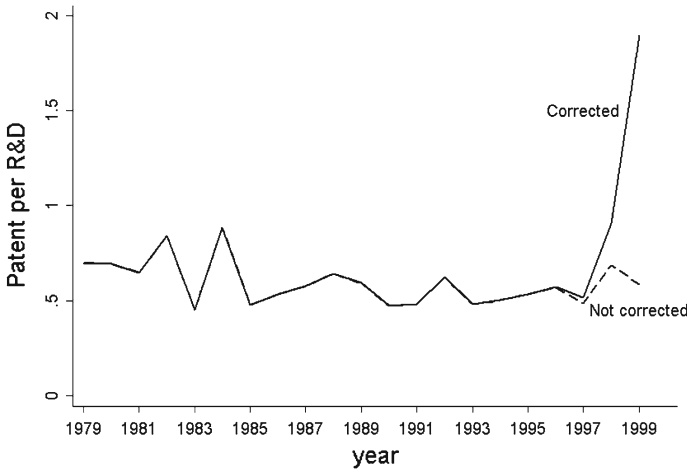
Fig. 8 Patents per *R&D* with corrected and not corrected patent counts

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 (2013) 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 Eq. (29) to calculate the R&D spillovers that firm *i* receives at time *t* from other firms based on Eq. (28).

Appendix 4: 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

$$
patent_t^* = \frac{patent_t}{\sum_{k=0}^{1999-t} weight_k}
$$
$$
1996 \leq t \leq 1999, \tag{30}
$$

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.[43] 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 1996 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

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[43] 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.
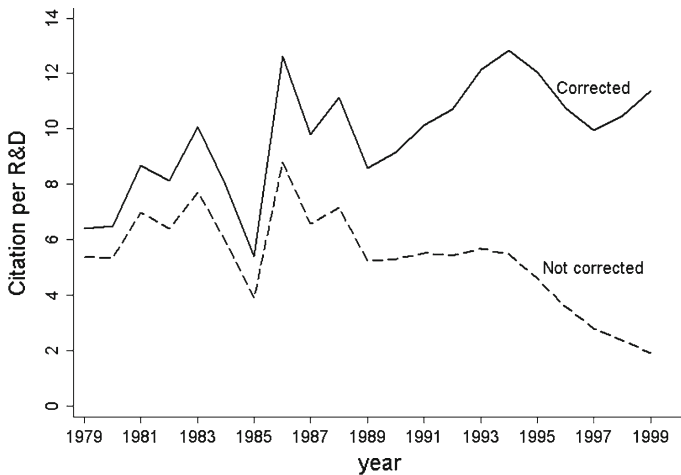
Fig. 9 Citations per *R&D* with corrected and not corrected citation counts

the 2001 data will have large variance. Figure 8 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, up to 40 years after the grant date of the patent. Figure 9 displays a comparison of original and corrected citation counts. I use the truncation corrected patent and citation counts in my analysis.

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