Patent Thicket and Market Value: An Empirical Analysis*

Mahdiyeh Entezarkheir†

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Abstract

The pro-patent shifts of the United States Patent and Trademark Office since 1982 have fragmented patent ownership in the technology market. Fragmentation builds overlapping property rights or patent thickets for firms with cumulative innovations. This has made the use of other firms' innovations costlier, due to higher transaction costs, licensing fees, and the possibility of hold-up. Using a panel data on 1,975 publicly traded US manufacturing firms from 1979 to 1996, I find that a denser patent thicket for a firm leads to lower expected profit and, consequently, reduced stock market valuation. I also find that firms with a large patent portfolio size experience a smaller effect, likely because stronger bargaining position lowers the occurrence of the hold-up problem for these firms. In addition there is no systematic time effect from patent thickets on market value of firms with a large patent portfolio size.

Keywords: Innovation, Patent Thicket, Market Value, Fragmentation
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†PhD in Economics and Lecturer, Department of Economics, University of Waterloo, 200 University Avenue West, ON N2L 3G1, Canada. Email: mentezar@uwaterloo.ca.

1 Introduction

The United States Court of Appeals for the Federal Circuit (CAFC) was established in 1982 to strengthen patent rights and unify standards across circuits.[1] The establishment of the CAFC and the subsequent pro-patent shifts in the United States Patent and Trademark Office (USPTO) increased the benefits and ease of obtaining patents.[2] These changes caused a proliferation of patents and a higher fragmentation of patent ownership in the technology market (Jaffe and Lerner, 2007, p. 10). Figure 1 displays the upward trend of patenting in the US from 1979 to 1996.[3] The total number of patent applications granted by the USPTO grew at an average annual rate of 2.2% from 1976 to 1985 and increased to 5.8% from 1986 to 1996.

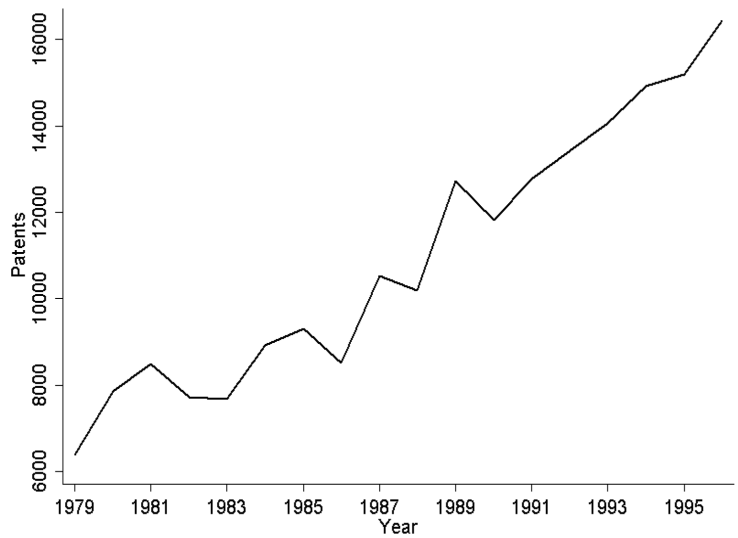
Highly fragmented technology markets result in dense patent thickets for subsequent innovators. A subsequent (cumulative) innovator builds innovation upon a set of complementary patents, owned by previous innovators. Shapiro (2001) refers to a set of complementary patents faced by a subsequent innovator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

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

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

[3]The original data is from 1975 to 2002. However, I limit the sample to 1979-1996 to avoid problems associated with truncation in the data (For a more detailed explanation see Section 3 and Appendix A).

Figure 1: Total Number of Patents by Grant Year.



discussed below.

The costs imposed on subsequent innovators by dense patent thickets arise from the high licensing fees associated with the complement problem and double marginalization, the transaction costs, and the possibility of hold-up and prolonged litigation, all explained below. The origin of the complement problem goes back to Cournot (1838); he analyzed a manufacturer of brass who needed two inputs: zinc and copper. He showed that the price of brass is lower, when the inputs are controlled by a single monopolist than when each input is controlled by a separate monopolist. Shapiro (2001) illustrates the negative impacts of fragmentation in patent ownership by applying the complement analysis of Cournot (1838) to the case of intellectual property rights. Shapiro (2001) shows subsequent innovators in fragmented technology markets have to pay a considerable licensing fee due to the presence of multiple right holders in their thicket. In other words, these innovators pay higher licensing fees when the complementary patents in their thicket are owned by multiple licensors than when the complementary patents are owned by only one licensor. Consequently, the existence of separate licensors for complementary patents leads to higher prices of final goods. Fragmentation in patent ownership therefore lowers both the licensors' profits and consumers' welfare.

Another potential consequence of patent thickets is underinvestment in subsequent innovation because subsequent innovators pay higher licensing fees when the ownership of complementary patents in their patent thicket is fragmented. This aspect is emphasized by Heller and Eisenberg (1998), who discuss the potential impacts of patent thickets on innovative activities in the biomedical sector, and compare the problem to the tragedy of commons, that is, the overuse of resources.[4] They argue that the large number of intellectual property rights in the biomedical sector leads to underuse of knowledge resources, because subsequent innovators should obtain permission from patent holders in their thicket if they want to use the complementary patents. Heller and Eisenberg (1998) call this phenomenon "the tragedy of anti-commons."

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

Patent thickets also imply larger transaction costs for identifying and negotiating licenses for complementary patents (Shapiro, 2001). The difficulty in identification makes the use of ex-ante solutions costly or even impossible.[5] Firms often become aware of related existing patents only after making large sunk investments in their own innovation process. The associated potential for hold-up and litigation further discourages firms from investing in

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

[5]An example of an ex-ante solution is the formation of a patent pool. According to Shapiro (2001), in a patent pool, one entity, who can be one of the patent holders, licenses patents of two or more entities to third parties.

manufacturing facilities and innovation.

This paper evaluates the economic impact of fragmentation in the ownership of complementary patents by estimating the effect of patent thickets on the market value of firms. Costs of patent thickets, including large licensing fees, large transaction costs, and the increased likelihood of being held-up can be expected to decrease future profits, and consequently, lower the market value of firms. This further implies that firms become less profitable, and this aspect might lower innovation.

Using panel data on 1,975 publicly traded US manufacturing firms from 1979 to 1996, this chapter exploits firm level data over a relatively long time period. The analysis builds on the methodologies developed in Griliches (1981) and Hall et al. (2005).[6] To my knowledge, the only other study that examines the impact of patent thickets on market value is Noel and Schankerman (2006), who employ data from the US software industry. While Noel and Schankerman use data over longer time period (1980-1999), they rely on a smaller set of firms (121) specific to a single industry (the software industry). My analysis, in contrast, uses firm level data across a variety of manufacturing industries.[7]

To assess the impact of patent thickets on the market value of firms, I estimate a nonlinear Tobin's q equation. My results suggest that more fragmentation in the technology market decreases the market value of firms. I also find that firms with a large patent portfolio size are penalized less than other firms, probably because a larger patent portfolio size increases their bargaining power in licensing negotiations and lowers the risk of the hold-up problem. The likelihood of the hold-up problem for these firms might also be lower since other firms in the

[6]My analysis expands the studies of Griliches (1981) and Hall et al. (2005), since it includes a measure of fragmentation of patent ownership as a possible determinant of firms' market value. In addition, the samples of these studies have a shorter time span than my sample of analysis.

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

[7]Further, the measure of patent thicket in my analysis is different from that of Noel and Schankerman (2006). For more explanation, see section 2.

thicket have an incentive to avoid possible future retaliations. Further, I examine whether the effect of fragmentation changes over time and whether the effect of fragmentation varies across industries. I relate these analyses to changes in patent policies and differences in the nature of innovations across industries. The results show that patent thickets do not have systematic time effects on firms' market value, and this finding holds even for firms with a large patent portfolio size. The other result is that the impacts of patent thickets on firms' market value are independent of industry.[8]

The prior empirical evidence on the effects of patent thickets, which is summarized in Table 1, is mixed. Murray and Stern (2007) find only a modest anti-commons effect in biomedical patenting. Walsh et al. (2005) perform a survey on 414 biomedical researchers in universities, government, and non-profit institutions. They find that limited access to intellectual property does not restrict biomedical research. Walsh et al. (2003) perform 70 interviews with personnel in universities, the biotechnology sector, and pharmaceutical firms. According to their interviews, the anti-commons problem is manageable. Hall and Ziedonis (2001) and Ziedonis (2004) examine the semiconductor industry, and find that firms patent aggressively in more fragmented technology markets and that this effect is more pronounced for capital-intensive firms.

The main contributions of my analysis are two-fold. First, I measure the impact of patent thickets on the market value of firms in the manufacturing sector. As stated beforehand, Noel and Schankerman (2006), who focus on software industry, have previously examined the impact of patent thickets on firms' market value. I instead examine these impacts in the manufacturing sector. Second, I analyze the heterogeneous impact of patent thickets

[8]Additionally, I find that market structure does not play a role in how the stock market values firms, when I control for patent thicket effect. This result holds, when I also control for the effect of possible heterogeneity at the firm level as a result of the patent portfolio size of firms, time, or both time and patent portfolio size. The statistically insignificant impact of the market structure variable on the market value remains robust, when I control for heterogeneity across industries at the firm level. According to Lindenberg and Ross (1981), a possible explanation is that markets with high concentration do not necessarily reflect market power, and consequently, the market structure has no impact on the market value.

Table 1: A Summary of Previous Findings in the Literature

Author	Data	Main finding
Murray and Stern (2007)	340 peer-reviewed scientific articles from 1997 to 1999 (Observations= 1,688).	They find only a modest anti-commons effect exists in biomedical patenting.
Noel and Schankerman (2006)	Unbalanced panel of 121 US software firms from 1980 to 1999 (Observations= 865).	Patent thickets have statistically significant negative impacts on Tobin's q in the software industry.
Hall et al. (2005)	Unbalanced panel of 4,864 US publicly traded manufacturing firms from 1979 to 1988 (Observations= 12,118).	Intangible assets of firms [measured by *R&D*-, patent-, and citation intensities] have statistically significant positive impact on Tobin's q.
Walsh et al. (2005)	A survey on 414 biomedical researchers in universities, government, and non-profit institutions.	They find that limited access to intellectual property does not restrict biomedical research.
Ziedonis (2004)	67 US semiconductor firms from 1980 to 1994 (Observation= 667).	Patent thickets have statistically significant positive effects on the patent propensity of semiconductor firms.
Walsh et al. (2003)	70 interviews with personnel in universities, biotechnology sector, and pharmaceutical firms.	The anti-commons problem is manageable.
Hall and Ziedonis (2001)	95 US semiconductor firms from 1979 to 1995 based on data collected from interviews with industry representatives (Observation= 946).	They find evidence of positive impacts of patent thickets on patenting propensity of firms.

on the market value of firms in terms of firms' different patent portfolio sizes, the different industries they belong to, and over time. To my knowledge, no prior study has evaluated these heterogeneities in the effect of patent thickets on market value.

2 Empirical Framework

The empirical model that I employ to assess the impacts of patent thickets on market value of firms is based on Griliches (1981) and Hall et al. (2005). The general empirical framework used in these studies is

$$logMarket\ Value_{it} = logSV_{it} + \sigma\ logTA_{it} + \sigma\ log\left(1 + \gamma\,\frac{INA_{it}}{TA_{it}}\right). \qquad (1)$$

The variable $logMarket\ Value_{it}$ is the log of the market value of firm i in year t. Following Hall et al. (2005), the market value of a firm is calculated as the sum of the current market value of common and preferred stocks, long-term debt adjusted for inflation, and short-term debts of the firm net of assets. In the analysis of Hall et al. (2005), the variable $logSV_{it}$ includes time fixed effects (m_t) and the error term (ϵ_{it}). The term ϵ_{it} denotes the other factors that influence market value of firms. I assume that ϵ_{it} is 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 asset to tangible asset ratio. Moving the variable TA_{it} to the left-hand side in equation (1) allows left-hand side of this equation to be written as $log\left(\frac{Market\ Value_{it}}{TA_{it}}\right)$ or Tobin's q.[9] Equation (1) then becomes

$$logq_{it} = log\left(1 + \gamma\,\frac{INA_{it}}{TA_{it}}\right) + m_t + \epsilon_{it}. \qquad (2)$$

[9]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.

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 components of TA_{it} are adjusted for inflation.[10] 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%.[11] 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 equation (2) becomes

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

There is usually a difference between the application and grant date of patents. Out of the patents applied close to the end date of the sample, only a small fraction is granted,

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

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

and the rest are granted outside the reach of the sample. This issue indicates truncation in patent counts. Citation counts are also truncated. Truncations in citations happen since only citations that occur within the sample are observable. I correct for these truncations. As a result, the $PATstock_{it}$ and $CITEstock_{it}$ variables are built based upon patent and citation counts, which are corrected for the truncation problems. See Appendix A for a more detailed analysis of correction procedures.

To estimate the impact of patent thicket on the market value of firms, I augment equation (3) with the fragmentation index variable used by Ziedonis (2004). The measurement of the fragmentation variable ($logF_{it}$) is discussed shortly. To control for the effects of market structure on market value, I also add the log of a Herfindahl index for market structure ($logHHI_{it}$) to equation (3). This results in the specification

$$\begin{aligned} logq_{it} &= log\left(1+\gamma_1\left(\frac{R\&Dstock}{TA}\right)_{it}+\gamma_2\left(\frac{PATstock}{R\&Dstock}\right)_{it}+\gamma_3\left(\frac{CITEstock}{PATstock}\right)_{it}\right) \\ &\quad +\delta_1\, logF_{it}+\delta_2\, logHHI_{it}+m_t+\epsilon_{it}. \end{aligned} \quad (4)$$

The variable HHI_{it} is calculated using firm-level sales based on 4-digit SIC codes. Equation (4) is estimated using a nonlinear least squares estimator.[12]

Some firms might have a permanently higher market value than others due to omitted firm specific effects.[13] With the inclusion of the firm fixed effects, equation (4) becomes

$$\begin{aligned} logq_{it} &= log\left(1+\gamma_1\left(\frac{R\&Dstock}{TA}\right)_{it}+\gamma_2\left(\frac{PATstock}{R\&Dstock}\right)_{it}+\gamma_3\left(\frac{CITEstock}{PATstock}\right)_{it}\right) \\ &\quad +\delta_1\, logF_{it}+\delta_2\, logHHI_{it}+\alpha_i+m_t+\epsilon_{it}. \end{aligned} \quad (5)$$

[12] There are several issues worth noting with respect to equation (4). I do not approximate $log\left(1+\gamma\,\frac{INA_{it}}{TA_{it}}\right)$ with $\left(\gamma\,\frac{INA_{it}}{TA_{it}}\right)$ because such an approximation is correct only if the ratio of intangible assets to tangible assets is very small. However, this ratio is large for high technology firms in the manufacturing sector. The other issue is that I use contemporaneous $R\&D$ because, according to Hausman et al. (1984), the within firm correlation of $R\&D$ over time is not large and many firms have short $R\&D$ histories.

[13] 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.

Parameters α_i capture firm unobserved heterogeneities. Following Bloom et al. (2005) and Noel and Schankerman (2006), I replace the non-linear terms in equation (5) with series expansions. Thus, equation (5) becomes

$$\begin{aligned} logq_{it} &= \gamma_1 \, \Psi\left(log\left(\frac{R\&Dstock}{TA}\right)_{it}\right) + \gamma_2 \, \Omega\left(log\left(\frac{PATstock}{R\&Dstock}\right)_{it}\right) \\ &\quad + \gamma_3 \, \Gamma\left(log\left(\frac{CITEstock}{PATstock}\right)_{it}\right) + \delta_1 \, logF_{it} + \delta_2 \, logHHI_{it} \\ &\quad + m_t + \alpha_i + \epsilon_{it}, \end{aligned} \tag{6}$$

where the parameters Ψ, Ω, and Γ denote the polynomials of the measures of intangible assets. To avoid the omitted variable bias due to unobserved firm heterogeneities, I estimate equation (6) using a within estimator for panel data. Estimates of equation (6) imply that the fifth order polynomial is satisfactory. I do not consider the multiplicative terms of the measures of intangible assets in equation (6), because including them do not change the results.

Hall et al. (2005) argue against including firm fixed effects in equation (6). They indicate that an important factor that creates heterogeneity across firms is the difference in their $R\&D$ expenditures, which implies R&D intensity is highly related to firms' individual characteristics. Therefore, controlling for firm fixed effects removes this source of difference among firms and implies over-correction. Hall et al. (2005) further explain that the explanatory variables are predetermined and changing very slowly over time, which require the use of a first-differences estimator in order to obtain consistent estimates.[14] However, according to Griliches and Hausman (1984), a small measurement error could lead to a large downward bias in first-differences estimates. Despite the argument in Hall et al. (2005) against controlling for the firm unobserved heterogeneities, I estimate equation (6) as a robustness

[14] A predetermined or weakly exogenous variable is a variable that its current and lagged values are not correlated with the current period error terms, but its future values might be correlated with the current period error terms (Cameron and Trivedi, 2006, p. 748).

check.

Equations (4) and (6) are employed as base models for estimation in this paper. To capture the heterogeneity of the impact of the patent thickets on the market value of firms in terms of firms' different patent portfolio sizes, the different industries they belong to and over time, I will add relevant variables to equations (4) and (6).

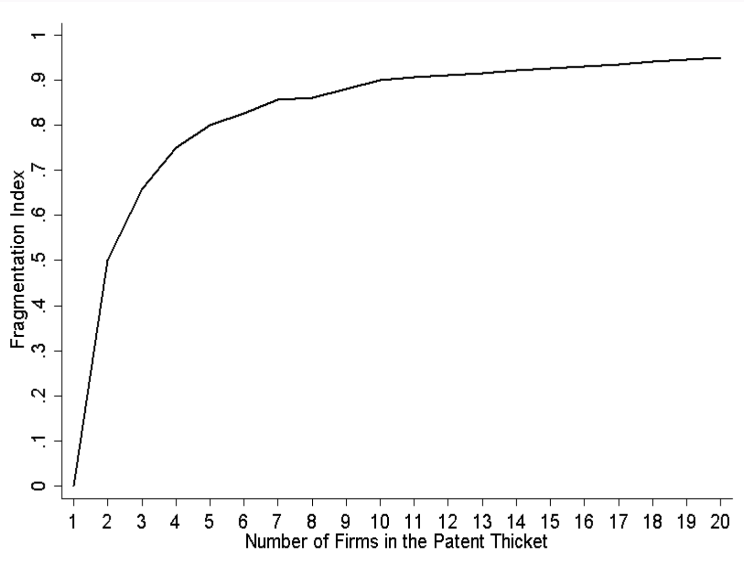
A question I have not explored yet is measuring the extent of fragmentation in patent ownership. I employ the fragmentation index used by Ziedonis (2004). This measure is based on a normalized Herfindahl index, which is usually used for measuring the level of competition in the market. The index is calculated using the formula

$$F_{it} = 1 - \sum_{j=0}^{J} \left(\frac{cite_{ijt}}{cite_{it}} \right)^2 . \tag{7}$$

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.[15] The variable $cite_{it}$ is the count of all the citations made by firm i in year t. he index F_{it} is zero when all the citations are made to the patents of one firm, and this measure is one when every citation is to the patents of a different firm. Figure 2 displays the change in the fragmentation index of a hypothetical firm as a function of the number of external right holders that this firm cites their patents, assuming that the total

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

Figure 2: Fragmentation Index and External Right Holders.



number of citations made in the patents of this firm remains constant.[16,17]

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

[17]I also conducted the analyses in Chapter 1 using the measure of patent thickets in Noel and Schankerman (2006). Using this measure in equations (4) and (6) did not change the empirical results. Noel and Schankerman (2006) employ a measure which considers only the citations of each firm to patents of the four largest rivals in the technology market. However, the measure of fragmentation that I use is based on the citations to the patents of all firms. Therefore, my employed measure is able to capture heterogeneity among the small and large firms in terms of their hold-up probabilities. The smaller firms might hold up larger firms with higher probability than large firms because smaller firms may assume that the likelihood of dealing with the same large firm is quite low in the future. However, larger firms might assume a correspondingly higher likelihood and therefore an enhanced probability of retaliation.

3 Data

3.1 Data Sources

I build the sample in my analysis based on three different data sets. The first data is the National Bureau of Economic Research (NBER) data, consisting of information on patents granted from 1963 to 2002 and their citations.[18] The second data is the Compustat North American Annual Industrial data from Standard and Poors, consisting of 500,000 observations on 26,000 US publicly traded firms from 1979 to 2002.[19] This data set includes information on firms' $R\&D$ expenditures, sales, and components of firms' book and market values.[20] The third data is a company identifier file, which facilitates linking the patent and citation files from the NBER to Compustat data by firm names.[21] This link file is required because assignees apply for patents either under their own name or under their subsidiaries' names. The patent and citation information from the USPTO, which are used for building the NBER data, do not specify a unique code for each patenting identity. However, Compustat has a unique code for each publicly traded firm. The link file contains the assignee number of each firm mentioned on patents in the NBER data, and its equivalent identifier in the Compustat data.

I select a sample of manufacturing firms (SIC 2000-3999) from the publicly traded US

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

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

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

[20] Following Hall et al. (2005), I measure the book value of firms (TA_{it}) 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 variables are adjusted for inflation. Following Hall et al. (2005), I measure the market value of a firm ($Market\ Value_{it}$)as the sum of the market value of common and preferred stocks, long-term debt adjusted for inflation, and short-term debts of the firm net of assets.

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

firms in Compustat data from 1979 to 2002. This selection results in an unbalanced panel of 19,868 firms with 365,589 observations.[22] Manufacturing firms are selected because this sector includes high technology firms, and the patent-related issues and fragmented technology markets are usually more important for them. Additionally, the sample of publicly traded firms is not an exact representative of all firms in the high technology sectors. However, due to the data limitation, it is the best possible approximation of these firms. I also select a sample from the NBER data. After accounting for withdrawn patents, cited patents granted before 1963, and considering only the patents of publicly traded firms, my sample from the NBER data yields almost 19 million observations from 1979 to 2002.[23]

I link the selected sample from the NBER data, explained above, to corresponding observations of publicly traded US manufacturing firms in the sample from Compustat by using Hall's identifier file. Dropping missing observations on $Market\ Value_{it}$ and TA_{it} of firms results in a sample that consists of 68,203 observations relating to 6,402 unique patenting and non-patenting firms from 1979 to 2002 (almost 2000 firms in each year).[24] This sample includes 20,852 missing observations on $R\&D$.

The patent and citation data are truncated. The truncation in the patent data is the result of the difference between the application and grant dates of patents. The truncation in citation counts is the result of the fact that patents receive citations for a long period after they are granted. Therefore, some citations to patents are received out of the range of the

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

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

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

[24]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 section 2) with zero and then I have built the variables $Market\ Value_{it}$ and TA_{it}. In the next step, I have dropped observations for which the value of variables $Market\ Value_{it}$ and TA_{it} are zero. If I calculated the variables $Market\ Value_{it}$ and TA_{it} before replacing the missing observations of their components with zero, and dropped the missing observations on $Market\ Value_{it}$ and TA_{it}, this would only leave me with 52,736 observations and would lead to a loss of information.

analyzed sample. Moreover, there is a further truncation in citation counts in the beginning of the sample as citation data is available only for the patents granted since 1975 from the NBER data.

The data has been corrected for these truncations. The correction procedures are explained in the Appendix A. After these changes, I further limit the sample to 1979-1996 to avoid any potential problems arising from truncations. As a result, I focus only on when the data is the least problematic, leaving me with an unbalanced panel of 1,975 patenting manufacturing firms with 10,273 observations from 1979 to 1996.[25] The result is a longitudinal firm-level data set on firm-level financial variables and patenting activity.

Table 2 presents the descriptive statistics of all variables. The average firm in the sample is R&D intensive.[26] On average, a firm experiences a fairly large fragmentation index of 0.61 and a patent portfolio size of 19 patents.[27] Using corrected patent counts, Figure 3 illustrates the distribution of patent counts by each firm in the sample. Consistent with previous studies, the distribution of patents is highly skewed (e.g., Hall et al., 2005). Figure 4 demonstrates that variable F_{it} was increasing on average from 1979 to 1996.

[25]This sample includes firms that have at least one patent. Considering these firms facilitates measuring the variables: $PATstock_{it}$ and $CITEstock_{it}$.

[26]The average firm is R&D intensive. The average of R&D intensity in the sample is 0.90.

[27]In the sample the variable F_{it} is missing if the firm has only self-citations or do not cite anything in its patent. The reason is that in constructing F_{it}, I do not consider patents that only self-cite or they do not have any citation in their patent as the owners of such patents do not come across with the risk of being held-up. As a result, the variable F_{it} for the firms who owns such patents is missing in the sample. This situation is equivalent to no impact from fragmentation, and I replace these observations with zero. Some of the observations of the variable F_{it} are zero. These observations are for the firms that all of the citations in their patents are made to the patents of one entity or they have only one patent with one citation in year t. The variable $logF_{it}$ in equations (4) and (6) is missing in both of the cases that F_{it} is missing or is zero. Therefore, to control for this issue, I adopt the indicator method for handling missing data on explanatory variables (for the detailed explanation of this method refer to Chapter 3 of the thesis). I define an indicator variable which takes the value one, if the variable $logF_{it}$ is missing and takes the value zero otherwise. Then, I replace the missing observations of the variable $logF_{it}$ with an arbitrary value, here zero.

Table 2: Descriptive Statistics

Variable	Description	Obs	Mean	Median	Min	Max	Std.er
$Market\ Value_{it}$	Market Value	10273	1052.30	103	0.022	70772	3439
TA_{it}	Book Value	10273	1410.27	113	0	57532	4122
q_{it}	$(Market\ Value/TA)_{it}$	10271	1.33	0.67	0.05	660	10.55
F_{it}	Fragmentation Index	10273	0.61	0.75	0	0.98	0.35
$R\&Dstock_{it}$	Stock of R&D	9178	346	34	0	28865	1270
$PATstock_{it}$	Stock of Patents	10273	85.54	10.87	1	5426	290.1
$CITEstock_{it}$	Stock of Citations	10273	826	89	1.19	79115	3460
$(R\&Dstock/TA)_{it}$	R&D Intensity	9176	0.90	0.29	0	184.8	4.30
$(PATstock/R\&Dstock)_{it}$	Patent Intensity	9178	0.98	0.44	0	100.24	2.40
$(CITEstock/PATstock)_{it}$	Citation Intensity	10273	10.66	6.45	1.17	346.11	14.71
$Patent\ Portfolio\ Size_{it}$	Number of Patents	10273	19	3	1	1256	66.82
HHI_{it}	Market Structure	10273	0.47	0.40	0	1	0.27

Figure 3: Distribution of Patents in the Sample.

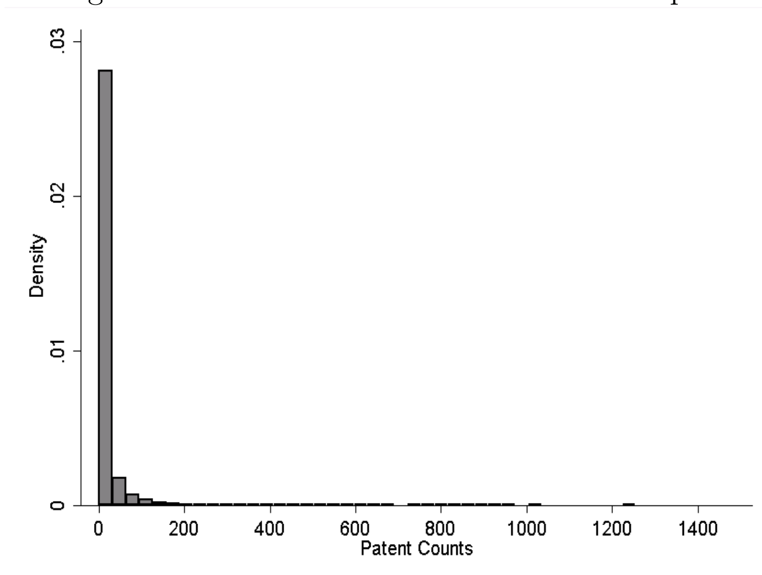


Figure 4: Patent Thicket over Time.

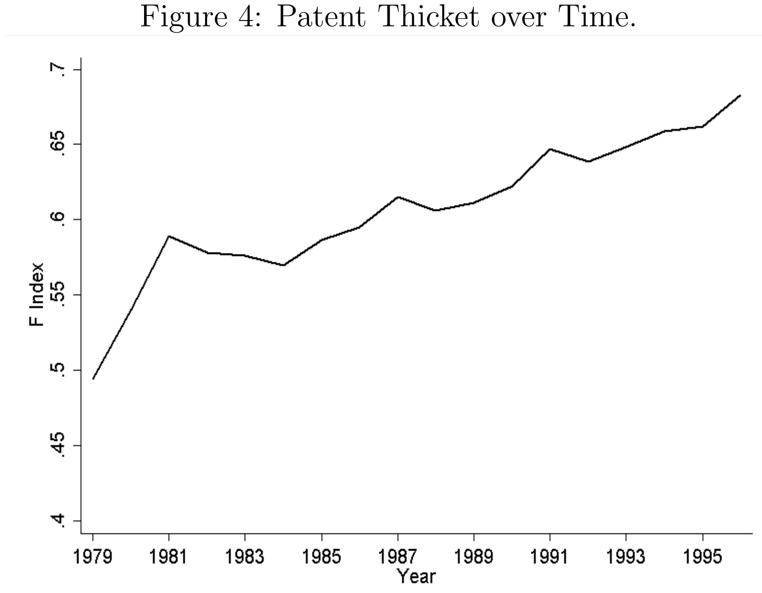
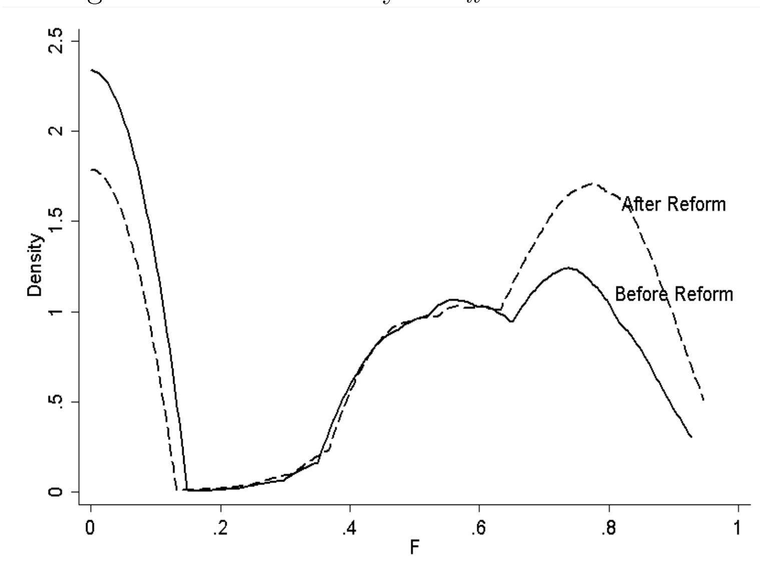


Figure 5: Kernel Density of F_{it} for Small Firms.



3.2 Exogenous Sources of Identifying Variation

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

To analyze the impact of pro-patent shifts following the establishment of the CAFC, I illustrate the Kernel density distributions of the variable F_{it} for the periods before and after the reforms, 1979-1985 and 1986-1996, respectively. In these analyses, I group firms based on their patent portfolio size into three categories: firms with fewer than 3 patents (small firms), firms with 4 to 42 patents (medium firms), and firms with more than 42 patents (large firms). Figures 5 to 7 investigate the effect of the pro-patent shifts on F_{it} for each group. In Figures 5 to 7 except for Figure 7, the kernel densities experience a shift to the right following the pro-patent policy changes, which imply higher F_{it} after the establishment of the CAFC.[28]

[28]Figures 5 to 7 display that the impact of pro-patent policies depends on the number of patents owned

Figure 6: Kernel Density of F_{it} for Medium Firms.

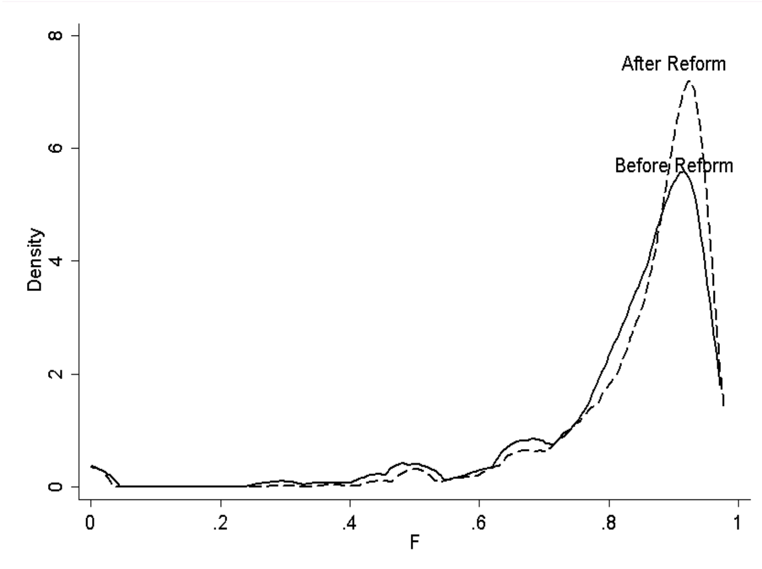
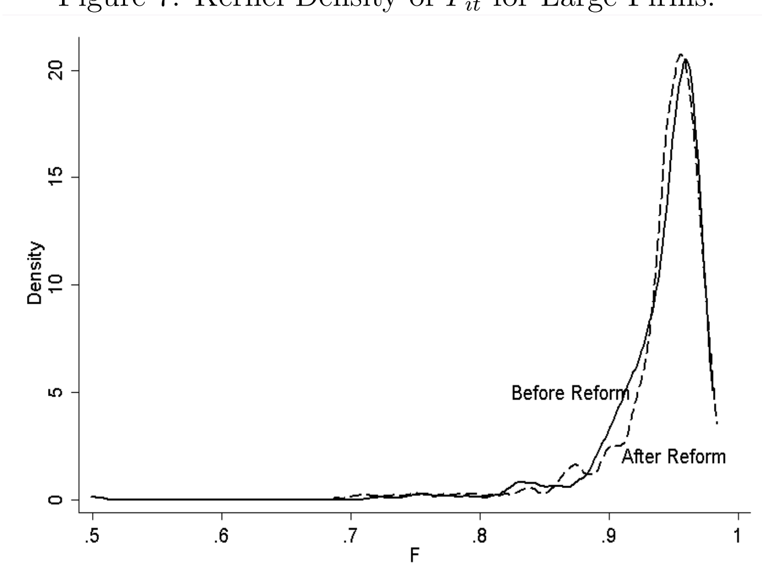


Figure 7: Kernel Density of F_{it} for Large Firms.



4 Results

Table 3 contains estimates of the effect of patent thickets ($logF_{it}$) on the market value of firms. Column 1 contains the nonlinear least squares estimates of equation (4), column 2 reports estimates for equation (6) with firm fixed effects, and column 3 shows estimates for the same model as equation (6) but with industry fixed effects as a robustness check.[29] I include industry fixed effects to control for the possibility of dense patent thickets which may be more likely in some industries relative to others.[30] Standard errors are clustered at the firm level.[31]

The nonlinear least squares estimator in column 1 of Table 3 shows that the patent thicket ($logF_{it}$) has a negative and statistically significant impact on the market value of the firm at the 10% level of significance. The coefficient of $logF_{it}$ implies that market value declines by 0.8% as fragmentation increases by 10%.[32] The other key finding of this column is that all of the knowledge stock variables have a positive and statistically significant impact on the market value, and this finding is consistent with previous studies in the literature.[33]

I also estimate the impact of patent thickets on the market value of firms with controls for firms fixed effects as a robustness check in column 2 of Table 3 (using equation, 6). With the inclusion of firms fixed effects, the variable $logF_{it}$ keeps its negative impact on the market

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by the firm. Therefore, there is both over-time and cross-firm variation in F_{it} that help in identifying the empirical estimates. The different finding of Figure 7 is quite puzzling as it points to the fact that the impact of the pro-patent changes following the establishment of the CAFC is not that important for firms with a large patent portfolio size. This finding might imply that large firms change their type of innovation from cumulative to non-cumulative following reforms. Therefore, they do not have to cite other firms' patents, which keeps their fragmentation index unchanged.

[29] Industry fixed effects are defined based on four-digit SIC codes.

[30] One example is the semiconductor industry (SIC3674), which is characterized with highly cumulative innovations (Ziedonis, 2004 and Hall and Ziedonis, 2001).

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

[31] The sample includes 1,975 patenting firms with 10,273 observations from 1979 to 1996. The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are the cluster-robust standard error (clustered at the firm level).

[32] The standardized estimated impact is that a one deviation increase in $logF_{it}$ lowers $logMarket\ Value_{it}$ by 0.113 standard deviation units (1.10%).

[33] One example of studies with similar results is Hall et al. (2005).

Table 3: Patent Thicket and Market Value

Dependent Variable: $logq_{it}$[31]	NLS	Fixed Effect Estimation	Pooled with Industry Fixed Effects
$logF_{it}$	-0.076*	-0.042	-0.062*
	(0.042)	(0.028)	(0.033)
$log(\frac{R\&Dstock}{TA})_{it}$	0.309***	0.206***	0.206***
	(0.052)	(0.038)	(0.038)
$[log(\frac{R\&Dstock}{TA})_{it}]^2$		0.077***	0.098***
		(0.020)	(0.013)
$[log(\frac{R\&Dstock}{TA})_{it}]^3$		0.013**	0.010***
		(0.004)	(0.003)
$[log(\frac{R\&Dstock}{TA})_{it}]^4$		-0.001	-0.001
		(0.001)	(0.001)
$[log(\frac{R\&Dstock}{TA})_{it}]^5$		-0.000**	-0.000
		(0.000)	(0.000)
$log(\frac{PATstock}{R\&Dstock})_{it}$	0.036***	0.124***	0.069***
	(0.010)	(0.025)	(0.013)
$[log(\frac{PATstock}{R\&Dstock})_{it}]^2$		0.018	0.014**
		(0.012)	(0.007)
$[log(\frac{PATstock}{R\&Dstock})_{it}]^3$		-0.001	-0.000
		(0.003)	(0.002)
$[log(\frac{PATstock}{R\&Dstock})_{it}]^4$		-0.000	0.000
		(0.001)	(0.001)
$[log(\frac{PATstock}{R\&Dstock})_{it}]^5$		-0.000	0.000
		(0.000)	(0.000)
$log(\frac{CITEstock}{PATstock})_{it}$	0.004**	-0.492	0.347
	(0.002)	(0.387)	(0.307)
$[log(\frac{CITEstock}{PATstock})_{it}]^2$		0.429	-0.351
		(0.384)	(0.316)
$[log(\frac{CITEstock}{PATstock})_{it}]^3$		-0.152	0.130
		(0.168)	(0.144)
$[log(\frac{CITEstock}{PATstock})_{it}]^4$		0.024	-0.022
		(0.033)	(0.029)
$[log(\frac{CITEstock}{PATstock})_{it}]^5$		-0.001	0.001
		(0.002)	(0.002)

Table 3 Continued

Dependent Variable: $logq_{it}$	NLS	Fixed Effect Estimation	Pooled with Industry Fixed Effects
$logHHI_{it}$	0.037*	0.035	-0.037
	(0.022)	(0.026)	(0.023)
$D(logF_{it} = 0)$	0.054*	0.017	0.046**
	(0.028)	(0.017)	(0.020)
$D(R\&D_{it} = 0)$	0.106***	-0.267***	-0.167***
	(0.033)	(0.084)	(0.039)
Firm Fixed Effects	No	Yes	No
Industry Fixed Effects	No	No	Yes
Time Fixed Effects	Yes	Yes	Yes
Adjusted-R^2	0.3536	0.1546	0.2772

value but not its statistically significant effect. The coefficient suggests that an increase in fragmentation by 10% is associated with a market value decrease by 0.4%.[34] In column 3, the patent thicket has a negative and statistically significant impact on the market value controlling for industry fixed effects (using equation (6) with industry fixed effects rather than firm fixed effects). A 10% rise in fragmentation is significantly correlated with a 0.6% decrease in the market value. In summary, the results from different specifications indicate a negative impact from patent thickets on the market value of firms.[35]

Using the estimates of column 1 of Table 3, I calculate the semi-elasticities of knowledge stock variables as well as the elasticity of the variable $logF_{it}$ at both the mean and median of the covariates in Table 4. These elasticities allow me to evaluate the size of the impacts of

[34]Empirical results suggest that the fifth order polynomial is satisfactory. The reason is that the coefficients of the polynomials higher than the fifth order are not statistically significant.

[35]Another finding from Table 3 is that the market structure ($logHHI_{it}$) does not have a statistically significant impact on how the stock market values the firm. This finding is in contrast to the common notion that in highly concentrated markets, firms have higher market power that lead to larger expected earnings for firms and consequently, higher market value. This result further implies that the market structure measure does not reflect market power. To the best of my knowledge there are few studies in the economic literature that focus specifically on the impact of market structure on market value of firms. My results are similar to previous findings (Lindenberg and Ross, 1981 and Hirschey, 1985). According to Lindenberg and Ross (1981), a possible reason for the statistical insignificance of the $logHHI_{it}$ is that markets with high concentration do not necessarily reflect market power.

Table 4: Calculating the Impact of Knowledge Stocks and Patent Thicket on Market Value

	Ratios Evaluated at[37]	
Ratios	Mean	Median
$(\frac{R\&Dstock}{TA})_{it}$	0.711	0.241
$(\frac{PATstock}{R\&Dstock})_{it}$	0.872	0.375
$(\frac{CITEstock}{PATstock})_{it}$	10.946	6.688
F_{it}	0.612	0.750
$logF_{it}$	-0.217	-0.130
	Semi-elasticities	
$(\partial logq_{it}/\partial(\frac{R\&Dstock}{TA})_{it})$	0.238***	0.277***
	(0.034)	(0.044)
$(\partial logq_{it}/\partial(\frac{PATstock}{R\&Dstock})_{it})$	0.027***	0.032***
	(0.008)	(0.009)
$(\partial logq_{it}/\partial(\frac{CITEstock}{PATstock})_{it})$	0.003**	0.004**
	(0.001)	(0.001)
	Elasticity	
$(\partial logq_{it}/\partial \log F_{it})$	-0.076*	-0.076*
	(0.042)	(0.042)

the explanatory variables on the firms' market value.[36] According to Table 4, an increase of 1% in the $R\&D$ intensity of the firm increases $Market\ Value_{it}$ by 2.3%, an extra patent per million \$ of $R\&D$ raises $Market\ Value_{it}$ by 3%, and an additional citation per patent boosts $Market\ Value_{it}$ by 0.3%. Market value also declines by 0.8% as fragmentation increases by 10%.

Table 5 analyzes the possible heterogeneity in the impact of patent thicket on the market value of firms as a result of the patent portfolio size of firms. To analyze the impact of this heterogeneity, I add the variable $logF_{it} \times logPatent\ Portfolio\ Size_{it}$ to equation (4)

[36] I consider both the mean and median because of the skewness in the distribution of the knowledge stock variables.

[37] The sample includes 1,975 patenting firms with 10,273 observations from 1979 to 1996. The numbers in parentheses are clustered robust standard errors (clustered at the firm level).

and use the resulting equation for the estimates in column 1 of Table 5. The results show that the estimated coefficient of the variable $logF_{it} \times logPatent\ Portfolio\ Size_{it}$ is positive and statistically significant, while $logF_{it}$ preserves its negative and significant impact on the market value of firms in column 1. This finding implies that firms with a large patent portfolio size in a fragmented technology market have higher market values than other firms, probably because a larger patent portfolio size increases such firms' bargaining power in licensing negotiations and lowers the risk of being held-up. Moreover, the likelihood of the hold-up problem for these firms might be lower, since other firms have incentives to avoid possible future retaliations. The results of column 1 of Table 5 are robust to the models with firm fixed effects and industry fixed effects in columns 2 and 3 (based on equation (6)).

To capture the heterogeneous impact of patent thickets on market value over time, I analyze the effect of patent thickets on the market value of firms before and after the establishment of the CAFC in 1982. I divide the sample into two sub-samples, which consist of observations for the period before the establishment of the CAFC and the period after the establishment of the CAFC. However, using equation (4) for each sub-sample, the results are sensitive to the selection of the year in which reforms become effective. In order to avoid this problem and examine whether the impact of patent thickets on the market value of firms has been increasing over time as a result of the pro-patent shifts, I augment equation (4) with variables $D_{year} \times logF_{it}$, where the variable D_{year} ($year$ =1979,...,1996) is a dummy variable for each year.

Table 6 contains the results of this exercise and reports only the coefficients of the new variables added to equation (4). Most of the coefficients of these variables are not statistically significant. Figure 8 plots the scatter plot of the estimated coefficients of variables $D_{year} \times logF_{it}$, where $year$ =1979,...,1996, with their upper and lower 95% confidence intervals.

[38]The sample includes 1,975 patenting firms with 10,273 observations from 1979 to 1996. The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are the cluster-robust standard error (clustered at the firm level).

Table 5: Patent Thicket, Patent Portfolio Size, and Market Value

Dependent Variable: $logq_{it}$[38]	(1) NLS	(2) Fixed Effect Estimation	(3) Pooled with Industry Fixed Effects
$logF_{it}$	-0.121***	-0.085***	-0.111***
	(0.045)	(0.033)	(0.035)
$(\frac{R\&Dstock}{TA})_{it}$	0.308***	0.208***	0.266***
	(0.052)	(0.038)	(0.020)
$(\frac{PATstock}{R\&Dstock})_{it}$	0.036***	0.129***	0.072***
	(0.010)	(0.025)	(0.013)
$(\frac{CITEstock}{PATstock})_{it}$	0.004***	-0.487	0.363
	(0.002)	(0.387)	(0.309)
$logF_{it} \times$ $logPatent$	0.161***	0.084***	0.148***
$Portfolio\ Size_{it}$	(0.040)	(0.025)	(0.030)
$logHHI_{it}$	0.035	0.033	-0.039*
	(0.022)	(0.026)	(0.023)
$D(logF_{it} = 0)$	0.024	0.014	0.025
	(0.028)	(0.017)	(0.020)
$D(R\&D_{it} = 0)$	0.101***	-0.275***	-0.173***
	(0.033)	(0.084)	(0.039)
Firm Fixed Effects	No	Yes	No
Industry Fixed Effects	No	No	Yes
Time Fixed Effectss	Yes	Yes	Yes
Adjusted-R^2	0.3558	0.1563	0.2793

Table 6: Time Effect of Patent Thickets on Market Value

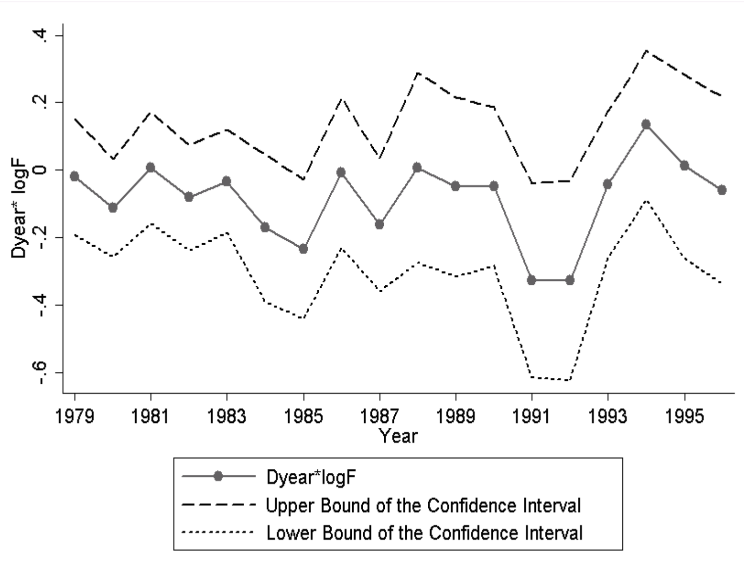
Dependent Variable: $logq_{it}$[39]			
$D_{1979} \times logF_{it}$	-0.024	$D_{1988} \times logF_{it}$	0.001
	(0.087)		(0.143)
$D_{1980} \times logF_{it}$	-0.117	$D_{1989} \times logF_{it}$	-0.055
	(0.074)		(0.136)
$D_{1981} \times logF_{it}$	0.004	$D_{1990} \times logF_{it}$	-0.059
	0.083		(0.120)
$D_{1982} \times logF_{it}$	-0.089	$D_{1991} \times logF_{it}$	-0.334**
	(0.079)		(0.146)
$D_{1983} \times logF_{it}$	-0.040	$D_{1992} \times logF_{it}$	-0.336**
	(0.078)		(0.150)
$D_{1984} \times logF_{it}$	-0.180	$D_{1993} \times logF_{it}$	-0.048
	(0.111)		(0.110)
$D_{1985} \times logF_{it}$	-0.241**	$D_{1994} \times logF_{it}$	0.131
	(0.105)		(0.112)
$D_{1986} \times logF_{it}$	-0.016	$D_{1995} \times logF_{it}$	0.003
	(0.113)		(0.138)
$D_{1987} \times logF_{it}$	-0.167*	$D_{1996} \times logF_{it}$	-0.066
	(0.100)		(0.141)

The results do not offer evidence in favour of a systematic time effect in the impact of fragmentation index on the market value of firms.

Table 7 takes into account two heterogeneities (time and patent portfolio size) in the impact of patent thickets. This table evaluates how the impact of patent thickets on the market value changes over time for firms with a large patent portfolio size. The estimating equation is based on equation (4) with extra variables $D_{year} \times logF_{it} \times logPatent\ Portfolio\ Size_{it}$, and $D_{year} \times logF_{it}$, where $year$ =1979,...,1996 and D_{year} is a dummy variable for each year. Table 7 displays the results of this exercise and reports only the coefficients of the new variables added to equation (4). The estimated coefficients of these variables in Table 7 are statistically insignificant with respect to most years. Figure 9 plots the scatter plot of the estimated

[39] The estimating specification of Table 6 is based on equation (4) and is estimated with a non-linear least squares estimator. The sample includes 1,975 patenting firms with 10,273 observations from 1979 to 1996. The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are the cluster-robust standard error (clustered at the firm level).

Figure 8: Estimated Coefficients of Variables $D_{year} \times \log F_{it}$.



coefficients of variables $D_{year} \times logF_{it} \times logPatent\ Portfolio\ Size_{it}$ with their upper and lower 95% confidence intervals. The findings of Tables 6 and 7 imply that I cannot find a systematic time effect from patent thickets on the market value of firms, and this result even applies to firms with a large patent portfolio size.

Table 8 provides the estimates of patent thickets on the market value of firms by industry.[37] Column 1 illustrates the impact of fragmentation on the market value for the average industry, while the remaining columns report the impact of patent thickets on firms in each industry. Although the estimates are negative, they are statistically insignificant. Fragmentation has a higher than average penalty on the market value of firms in the chemical and

[36]The estimating specification of Table 7 is based on equation (4) and is estimated with a non-linear least squares estimator. The sample includes 1,975 patenting firms with 10,273 observations from 1979 to 1996. 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).

[37]The industry classifications are based on Hall and Vopel (1997). In Table 8, 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 Pharmaceutical. The electrical sector includes Electrical machinery and electrical instrument & communication equipment. The mechanical sector includes Primary metal products, fabricated metal products, machinery & engines, transportation equipment, motor vehicles, and auto parts. The percentage of each industry in my sample is: chemical 3.5%, computers 7%, drugs 22%, electrical 28%, and mechanical 19%.

Table 7: Time Effect of Patent Thickets, Patent Portfolio Size, and Market Value

Dependent Variable: $logq_{it}$[36]			
$D_{1979} \times logF_{it}$	-0.112	$D_{1979} \times logF_{it}$	0.182**
	(0.083)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.072)
$D_{1980} \times logF_{it}$	-0.211**	$D_{1980} \times logF_{it}$	0.184***
	(0.084)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.067)
$D_{1981} \times logF_{it}$	-0.104	$D_{1981} \times logF_{it}$	0.216**
	(0.091)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.090)
$D_{1982} \times logF_{it}$	-0.105	$D_{1982} \times logF_{it}$	0.089
	(0.092)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.084)
$D_{1983} \times logF_{it}$	-0.020	$D_{1983} \times logF_{it}$	0.012
	(0.086)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.069)
$D_{1984} \times logF_{it}$	-0.184	$D_{1984} \times logF_{it}$	0.068
	(0.122)	$\times\ log\ Patent\ Portfolio\ Size_{it}$	(0.105)
$D_{1985} \times logF_{it}$	-0.209*	$D_{1985} \times logF_{it}$	-0.017
	(0.119)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.091)
$D_{1986} \times logF_{it}$	-0.068	$D_{1986} \times logF_{it}$	0.182*
	(0.123)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.102)
$D_{1987} \times logF_{it}$	-0.211*	$D_{1987} \times logF_{it}$	0.159*
	(0.109)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.087)
$D_{1988} \times logF_{it}$	-0.022	$D_{1988} \times logF_{it}$	0.087
	(0.187)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.132)
$D_{1989} \times logF_{it}$	-0.156	$D_{1989} \times logF_{it}$	0.241*
	(0.165)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.137)
$D_{1990} \times logF_{it}$	-0.084	$D_{1990} \times logF_{it}$	0.159
	(0.127)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.120)
$D_{1991} \times logF_{it}$	-0.377**	$D_{1991} \times logF_{it}$	0.220*
	(0.152)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.129)

Table 7 Continued

Dependent Variable: $logq_{it}$			
$D_{1992} \times logF_{it}$	-0.343**	$D_{1992} \times logF_{it}$	0.101
	(0.147)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.190)
$D_{1993} \times logF_{it}$	-0.084	$D_{1993} \times logF_{it}$	0.158
	(0.107)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.109)
$D_{1994} \times logF_{it}$	0.051	$D_{1994} \times logF_{it}$	0.225*
	(0.113)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.128)
$D_{1995} \times logF_{it}$	-0.056	$D_{1995} \times logF_{it}$	0.372***
	(0.138)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.140)
$D_{1996} \times logF_{it}$	-0.105	$D_{1996} \times logF_{it}$	0.185
	(0.146)	$\times\ logPatent\ Portfolio\ Size_{it}$	(0.135)

Figure 9: Estimated Coefficients of Variables $D_{year} \times logF_{it} \times logPatent\ Portfolio\ Size_{it}$.

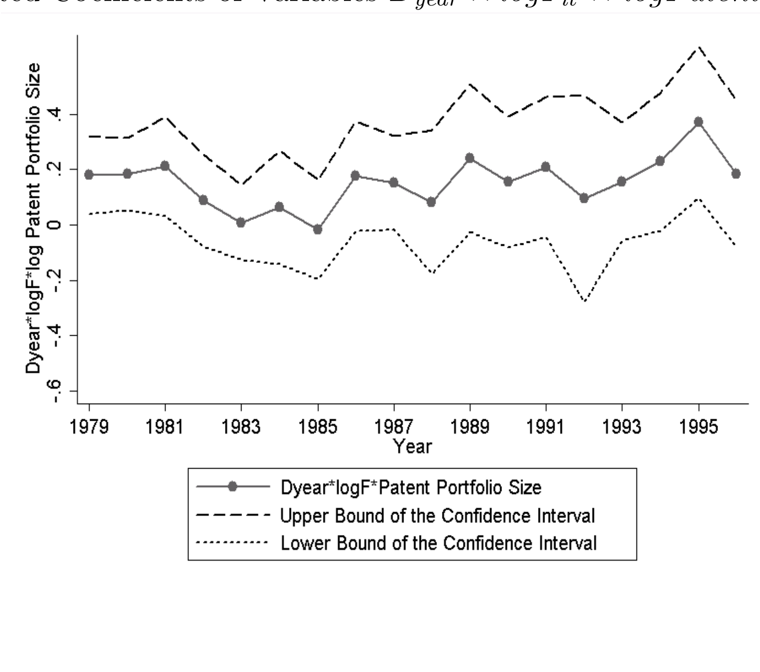


Table 8: The Impact of Patent Thicket across Industries

Dependent Variable $logq_{it}$[37]	Average	Chemical	Computers	Drugs	Electrical	Mechanical
$logF_{it}$	-0.076*	-0.370	-0.080	-0.050	-0.068	-0.066
	(0.042)	(0.226)	(0.163)	(0.118)	(0.081)	(0.076)
$(\frac{R\&Dstock}{TA})_{it}$	0.309***	1.139	0.061	0.357***	0.350***	0.634***
	(0.052)	(0.893)	(0.049)	(0.083)	(0.129)	(0.223)
$(\frac{PATstock}{R\&Dstock})_{it}$	0.036***	-0.016	0.096*	0.112**	0.046**	0.020
	(0.010)	(0.011)	(0.056)	(0.045)	(0.021)	(0.020)
$(\frac{CITEstock}{PATstock})_{it}$	0.044**	0.027	-0.000	0.000	0.008**	0.003
	(0.002)	(0.042)	(0.001)	(0.002)	(0.003)	(0.006)
$logHHI_{it}$	0.037*	0.003	-0.180*	0.042	-0.034	0.027
	(0.022)	(0.089)	(0.098)	(0.053)	(0.045)	(0.048)
$D(R\&D_{it} = 0)$	0.054*	0.428**	0.058	1.039***	0.257***	0.058
	(0.028)	(0.173)	(0.118)	(0.186)	(0.092)	(0.073)
$D(logF_{it} = 0)$	0.106***	0.034	0.063	0.013	0.086*	0.066
	(0.033)	(0.176)	(0.102)	(0.086)	(0.047)	(0.045)
Observation	10273	545	694	1850	2800	2348
Number of firms	1975	69	138	437	548	384
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.3536	0.6791	0.2102	0.2415	0.3517	0.4384

computers sectors. The insignificant impact on the drugs 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).

I conduct a joint hypothesis test of the equality of the impact of the variable $logF_{it}$ on the market value of firms across industries.[38] Even though the point estimates for the coefficient of $logF_{it}$ are different across industries, the estimates are not statistically significantly

[37]The sample includes 1,975 patenting firms with 10,273 observations from 1979 to 1996. The signs ***, **, and * mean significance at 1%, 5%, and 10%, respectively. The numbers in the parentheses are the cluster-robust standard error (clustered at the firm level).

[38]To perform this test, I define a separate dummy variable for each industry ($D_{industry}$). Then, I include the dummy variables for each industry and the multiplication of these dummy variables with the key variables of equation (4) in equation (4). Then I test for the equality of the coefficients of the variables $D_{industry} \times logF_{it}$ across industries.

different from each other across industries (F-statistics=1.24)– possibly because of the lack of the power of the test. As a robustness check, I also weight the variables with the patent portfolio size of firms and estimate equation (4) with a weighted nonlinear least squares estimator. This specification also cannot reject the joint hypothesis of the equality of the coefficient of the variable $logF_{it}$ across industries.[39] There are also differences across sectors in the knowledge stock variables, and these results are also consistent with the findings of Hall et al. (2005).

5 Conclusion

This study provides empirical evidence on the negative impact of patent ownership fragmentation on firms' market value. The analysis contributes to the literature on the determinants of the market value of firms and research on the patent thicket problem.

My results show that firms experience a statistically and economically significant decrease in their market value when the technology market is fragmented. My results expand on the work of Noel and Schankerman (2006) and show that the negative impact of patent thickets on the market value of firms is not restricted to a single industry.

In this paper, I analyze the heterogeneous impact of patent thickets on the market value of firms in terms of firms' different patent portfolio sizes, the different industries they belong to, and over time. To my knowledge, no prior study has evaluated these heterogeneities in the effect of patent thickets on market value. The findings indicate that firms with a large patent portfolio size experience a smaller negative impact from patent thickets on their market value. This finding is possibly because firms with a large patent portfolio size have fewer problems in cross-licensing negotiations. Their larger patent portfolio size increases their bargaining power in the licensing negotiations and lowers the risk of being held-up. The other result of this chapter is that patent thickets do not have systematic time effects on

[39] A similar result holds when I estimate equation (4) with a Weighted Pooled Least Squares estimator.

the market value of firms, and this finding even holds for firms with a large patent portfolio size. Another outcome of this chapter is that market structure does not have a statistically significant impact on how the stock market values firms after controlling for fragmentation in the technology market. This finding holds, when I analyze the effect of possible heterogeneity at the firm level as a result of the patent portfolio size of firms, time, or both time and patent portfolio size. This result also holds, when I control for heterogeneity across industries at the firm level. The insignificant impact of market structure on market value is similar to the few studies available in the literature, such as Lindenberg and Ross's (1981) and Hirschey's (1985). Finally, my results suggest that the impact of patent thickets on the market value of firms is independent of industry.

The findings of this paper can help policy makers in devising appropriate patent policies because this chapter quantifies the costs of patent thickets. The smaller negative impact of fragmentation on market value of firms with a large patent portfolio size signals to policy makers that the current US patent system is encouraging aggressive patenting to counter the negative costs of fragmentation. This problem might divert the resources of firms from R&D activities to legal activities aimed at obtaining patents on marginal innovation and increasing the patent portfolio size of firms. To avoid forming incentives for firms to obtain patents on marginal innovations, policy makers can change the patenting requirements to decrease the costs of patent thickets.

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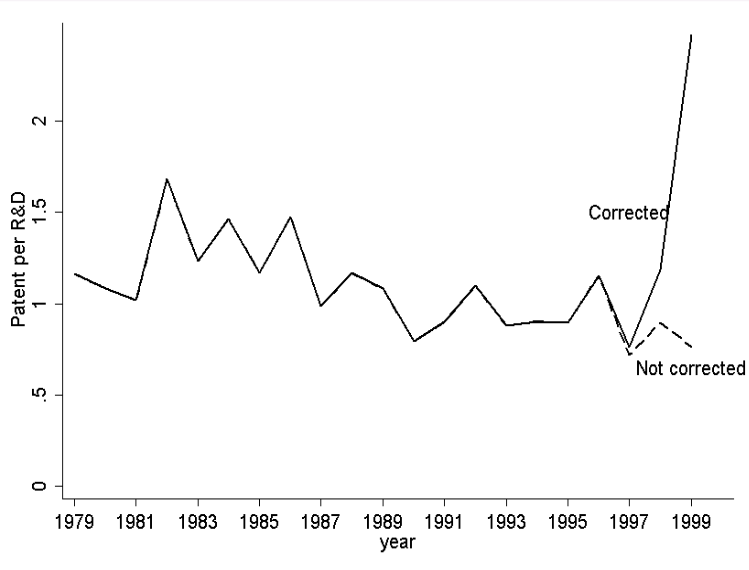
Figure A.1: Correction for Truncation in the Patent Counts.



Appendices

A Correcting for truncation in the patent and citation counts

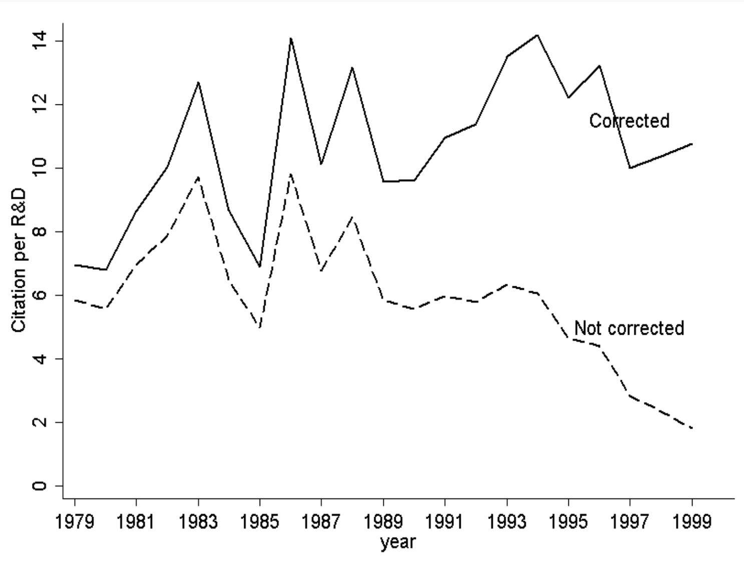
To correct for truncation in patent counts, I follow the approach of Hall et al. (2000), which defines weight factors to correct for truncation in patent counts. Their weight factors are calculated according to

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

where $patent_t$ is the number of patents granted at time t to all firms and $weight_k$ is built based on the average of citations in each lag for the patents of firms.[40] Hall et al. (2000) multiply patent counts in ending years of the sample with the inverse of the weight factors ($1/patent_t^*$) and correct for the truncation. I only correct patent counts for 1997 to 1999 because from 2000 to 2002 (end of my sample) the results are under the "edge effect"(Hall et al., 2000). This means the 2002 data will not be usable and 2001 data will have large variance. Figure A.1 displays a comparison of original and corrected patent counts for truncation. To correct for truncations in citations, I employ the method of Hall et al. (2000). I calculate the distribution of the fraction of citations received by each patent at a time between the grant year of the citing patents and the grant year of the cited patent. Using this distribution, I predict the number of citations received for each patent outside the range of the sample, maximum to 40 years after the grant date of the patent. Figure A.2 displays a comparison of original and corrected citation counts. I use the truncation corrected

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

Figure A.2: Correction for Truncation in the Citation Counts.



patent and citation counts in my analysis.