# Essays on Innovation, Patents, and Econometrics

by

Mahdiyeh Entezarkheir

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Applied Economics

Waterloo, Ontario, Canada, 2010

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

## Abstract

This thesis investigates the impact of fragmentation in the ownership of complementary patents or patent thickets on firms' market value. This question is motivated by the increase in the patent ownership fragmentation following the pro-patent shifts in the US since 1982. The first chapter uses panel data on patenting US manufacturing firms from 1979 to 1996, and estimates the impact of patent thickets on firms' market value. I find that patent thickets lower firms' market value, and firms with a large patent portfolio size experience a smaller negative effect from their thickets. Moreover, no systematic difference exists in the impact of patent thickets on firms' market value over time. The second chapter extends this analysis to account for the indirect impacts of patent thickets on firms' market value. These indirect effects arise through the effects of patent thickets on firms' R&D and patenting activities. Using panel data on US manufacturing firms from 1979 to 1996, I estimate the impact of patent thickets on market value, R&D, and patenting as well as the impacts of R&D and patenting on market value. Employing these estimates, I determine the direct, indirect, and total impacts of patent thickets on market value. I find that patent thickets decrease firms' market value, while I hold the firms R&D and patenting activities constant. I find no evidence of a change in R&D due to patent thickets. However, there is evidence of defensive patenting (an increase in patenting attributed to thickets), which helps to reduce the direct negative impact of patent thickets on market value.

The data sets used in Chapters 1 and 2 have a number of missing observations on regressors. The commonly used methods to manage missing observations are the listwise deletion (complete case) and the indicator methods. Studies on the statistical properties of these methods suggest a smaller bias using the listwise deletion method. Employing Monte Carlo simulations, Chapter 3 examines the properties of these methods, and finds that in some cases the listwise deletion estimates have larger biases than indicator estimates. This finding suggests that interpreting estimates arrived at with either approach requires caution.

*Keywords:* Innovation, Fragmentation, Market Value, Patent, Patent Thicket, R&D, Spillovers, Missing Data, Unobserved Error Terms, Censored Regressors, Listwise Deletion, Dummy Indicator

*JEL Classification Numbers:* L43, O31, O33, O32, O34, O38, C01, C13, C15, and C31.

**Acknowledgements**

This thesis would not have been possible without the support of many people. I would like to express my gratitude to my supervisor, Professor Mikko Packalen, who was abundantly helpful, and offered invaluable assistance, support, and guidance. Deepest gratitude is also due to the members of the supervisory committee, Professor Lutz-Alexander Busch and Professor Anindya Sen. Without their knowledge and assistance this study would not have been successful. I would also like to express my gratitude to my parents and my husband for their understanding and endless love through the duration of my studies. Special thanks also to Professor John Burbidge, Pat Shaw, Professor Victor Aguirregabiria, Professor Brian Cozzarin, and the Economics Department at the University of Waterloo for their invaluable assistance.

## Dedication

This thesis is dedicated to my wonderful parents, Nahideh Aslanzadeh and Gholamreza Entezarkheir, who have raised me to be the person I am today. You have been with me every step of the way, through good times and bad. Thank you for all the unconditional love, guidance, and support that you have always given me, helping me to succeed and instilling in me the confidence that I am capable of doing anything I put my mind to. Thank you for everything. I love you!

Also, this thesis is dedicated to my husband, Mohammad Mahdi Roghanizad, who has been a great source of motivation and inspiration.

Finally, I would like to dedicate this thesis to my country Iran, and all of my mentors and teachers throughout my life.

# Contents

# List of Tables

# List of Figures

# Introduction

Economic growth is a key objective in economic policy. Accordingly, identifying factors that contribute positively to growth is a central aim in economic analysis. The literature suggests innovation as one of the major forces behind growth. For instance, Solow (1957) finds that technological changes play an important role in economic growth, and Schumpeter (1942) argues that innovation is a key factor, and the replacement of old ideas with new ideas generates growth.

Patent systems play an important role in fostering innovation. Patents grant innovators the right to prevent others from the unauthorized use of their innovation for a limited time. Such rights promote innovation by allowing innovators to recover their costs and perhaps experience profit. Patents also encourage innovation by disclosing knowledge via the publication of patent documents. All innovators are able to benefit from the public stock of knowledge. However, knowledge spillovers can also lead to underinvestment in innovation as innovators cannot reap all the benefits associated with their innovation (Nelson, 1959 and Arrow, 1962). Patents help promote innovation by capturing the positive knowledge spillovers and alleviating the underinvestment in innovative activities.

However, despite the crucial roles that patents play in encouraging innovation and economic growth, they may also have counter effects. Patent systems can grant a large number of patents, and generate a technology market with highly fragmented patent ownership. Each 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 thickets, which means they have to deal with a large number of patent holders in their patent thicket. The costs of dense patent thickets, which are discussed below, can act as a disincentive to innovation.

The costs imposed on subsequent innovators by dense patent thickets arise from the high licensing fees associated with the complement problem and double marginalization, the transaction costs, and the possibility of hold-up and prolonged litigation, all explained below. The origin of the complement problem goes back to Cournot (1838); he analyzed a 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 that in more fragmented technology markets, subsequent innovators pay higher licensing fees because of the 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 those patents are owned by only one licensor. The large licensing fees associated with dense patent thickets can lead to underinvestment in subsequent innovation. This aspect is emphasized by Heller and Eisenberg (1998) for the biomedical sector. They compare the underinvestment problem to the tragedy of commons, that is, the overuse of resources.[1] Arguing that the large number of intellectual property rights in the biomedical sector leads to underuse of knowledge resources, they 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.

Another cost of dense patent thickets is the transaction cost for identifying and negotiating licenses for complementary patents (Shapiro, 2001). Due to the difficulty in identification, firms often become aware of related existing patents only after making large sunk investments into their own innovation process. The associated potential for both hold-up and prolonged litigation discourages firms from investing in innovation.

Subsequent innovators in the current US patent system are experiencing dense patent thickets, because of the huge number of patents and a high degree of fragmentation in patent ownership. The story behind the current situation in the US patent system goes back to the 1970s. In those years, there was a concern that United States' technology had fallen behind other industrialized countries (Meador, 1992). Thus, the United States Court of Appeals for the Federal Circuit (CAFC) was established in 1982 (Gallini, 2002). Prior to

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

this, 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. This situation created considerable incentives for obtaining patents, and the pro-patent attitude of the CAFC led to a proliferation of patents in the US economy (Jaffe and Lerner, 2007, p. 10). Jaffe and Lerner (2007, p. 11) argue that the proliferation of patents was further intensified by the decision of Congress in the early 1990s that changed the United States Patent and Trademark Office (USPTO) from an agency funded by tax revenues to an agency funded by fees that the USPTO collects. Thus, the USPTO also started to grant patents extensively, feeding the proliferation of patents. According to Jaffe and Lerner (2007, p. 10) the large number of patents generated following the CAFC and the pro-patent shifts led to a considerable fragmentation of patent ownership in the US technology market. This situation left subsequent innovators to deal with dense patent thickets and their costs.

The current status of the US patent system has become an increasing concern in recent years and has led to several proposals for amendments (e.g., the 2005, 2007, and 2009 Patent Reform Acts). These proposals have created considerable debate. The reform supporters, represented by the Coalition for Patent Fairness, argue that the resources used to cover the costs of dense patent thickets would be better spent on job creation and innovation.[2] Innovation Alliance, in contrast, argues that the reform would weaken patent rights, which would decrease innovation and have a negative impact on US technology leadership at the

[2]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 30 Sept. 2009 )

global level.[3] Both sides of this debate are represented in economic literature on patent thickets. As discussed previously, Heller and Eisenberg (1998) and Shapiro (2001) argue that dense patent thickets deter innovation. In contrast, Merges (2001) argues that firms largely avoid potential problems induced by patent thickets via establishing institutions such as patent pools in which to conduct their transactions with other right holders.[4]

These arguments are pointing to the fact that the US patent system is acting like a double-edged sword. On the one hand, the system is promoting innovation by protecting the rights of innovators, and on the other hand, it is hindering innovation by building dense patent thickets. This situation indicates a need for analysis to determine whether any reform is needed in the current US patent system, and to examine how negatively the dense patent thickets, formed following the CAFC, impact the economy. Therefore, the presence and the extent of damaging impacts caused by dense patent thickets constitute an empirical question.

The purpose of Chapters 1 and 2 of my thesis is to quantify the economic consequences of dense patent thickets. To do so, I consider the impact of such thickets on the market outcome of firms, which is measured by market value. Ideally, I would find the impact of patent thickets on firms' economic profits. However, the available information deals with business profits. Therefore, employing market value as a measure of firms' market outcome is a better proxy than business profit. The rationale behind the effect of patent thickets on firms' market value is that the potential costs of patent thickets might change the expected earnings of firms, and thereby change their market value.

[3]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 25 Oct. 2007)

[4]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.

In Chapter 1, I measure the impact of patent thickets on the market value of firms in the manufacturing sector, assuming that the R&D and patenting behavior of firms do not change with dense patent thickets. The sample of analysis is longitudinal data on 1,975 patenting publicly traded US manufacturing firms from 1976 to 1996. To my knowledge, only Noel and Schankerman (2006), who focus on the software industry, have previously examined the impacts of patent thickets on market value of firms. I instead examine these impacts in the manufacturing sector. Moreover, 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. As far as I am aware, no prior study has analyzed these heterogeneities in the impact of patent thickets on firms' market value.

The results of Chapter 1 suggest that denser patent thickets decrease firms' market value, but patent thickets penalize market value of firms with a large patent portfolio size less than other firms. This advantage is probably because a large patent portfolio size increases such firms' bargaining power in licensing negotiations, and lowers the risk of hold-up. The other findings of Chapter 1 are that no systematic difference exists in the impact of patent thickets on firms' market value over time, and this finding even holds for firms with a large patent portfolio size. The findings of this chapter can help policy makers in devising appropriate patent policies. 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 patent ownership 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. In order to prevent the formation of incentives for obtaining patents on marginal innovations, policy makers can change the requirements for obtaining patents to decrease costs of patent thickets.

Chapter 2 extends the analysis of the first chapter by arguing that dense patent thickets in highly fragmented technology markets could have two types of impacts: direct and indirect. The direct impact is the effect of patent thickets on market value of firms, while I hold all firms' patenting and R&D behavior constant. This impact occurs because the potential costs of patent thickets might lower the expected earnings of firms, and consequently, lower their market value. Estimating the direct impact of patent thickets is not sufficient to determine the effects of patent thickets, because patent thickets might also change the behavior of firms in terms of their patenting and R&D activities, and the changes in these activities could contribute to future earnings of firms and their market value. Patent thickets may encourage defensive patenting (the increase in patenting attributed to avoiding costs of thickets) in order to increase bargaining power in negotiations with other right holders (Ziedonis, 2004). Patent thickets may also make firms reduce their reliance on other firms' innovations by increasing their own R&D expenditures. Hence, I estimate the indirect impacts of patent thickets on market value through the likely effects that thickets have on patenting and R&D activities of firms.

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

To find the direct and indirect impacts of patent thickets and patent thicket spillovers in Chapter 2, I estimate the impacts of patent thickets on three outcome variables: market value, patent, and R&D as well as the impacts of R&D and patenting on market value, using longitudinal data on 1,272 publicly traded US manufacturing firms from 1979 to 1996. To my knowledge, only Noel and Schankerman (2006), who focused on the software industry, have previously examined the impact of firms' own patent thicket on these three outcome variables. Then, after estimating the impact of patent thickets on the outcome variables as well as the impacts of R&D and patenting on market value, I use these estimates to determine the direct, indirect, and total impacts of patent thickets on firms' market value. To my knowledge, no prior study has quantified the indirect and total impacts of patent thickets on firms' market value as well as the impact that other firms' patent thickets may have on a firm's market value or behavior.

My results suggest that firms' own patent thicket and patent thicket spillovers have direct negative impacts on the market value of firms. I also find that patent thickets and their spillovers increase defensive patenting, but do not have a statistically significant effect on firms' R&D activities. While defensive patenting alleviates the negative impact that patent thickets and their spillovers have on market value, the total impact of patent thickets and their spillovers on firms' market value is still negative. The findings of Chapter 2 indicate to policy makers that the ongoing concerns and debates over the negative economic impacts of patent thickets are valid. They also indicate that any consideration of patent reforms, such as increasing the requirements for obtaining patents, must weigh any potential benefits of lowering the costs of dense patent thickets against the negative effects that making patenting harder might have on the incentives to innovate.

While I was working on Chapters 1 and 2, I noticed a large number of missing observations on some of the regressors. In the sample of each chapter, about 30% of observations of R&D was missing. To handle this problem, the two common approaches employed by the empirical research are either dropping the missing observations and using the resulting complete sample (the listwise deletion method or LW), or adding an indicator variable for missing observations of a regressor and replacing the missing observations with a constant (the indicator method or DI). The dropping of the missing observations leads to loss of information and lower variation in the data. Moreover, if the missing observations are not missing at random, the LW method could lead to selection bias and inconsistent estimates, since the employed complete sample becomes a non-representative sample from the original population. Nevertheless, the DI method uses all the available information, including the missing observations on regressors (Cohen and Cohen, 1975 and Chow, 1979), and avoids selection bias in the estimates. The comparisons between the two methods indicate a need for an analysis of the performance of these methods.

Only a few studies analyze the performance of the DI and LW methods in models with censored regressors and regressors with missing observations. The findings of these studies suggest a smaller bias from using the LW method (Rigobon and Stoker, 2007 and Jones, 1996). Nevertheless, as has been observed by Jones (1996), the DI method is widely used in empirical research in fields such as epidemiology, sample survey research, behavioral science, and business and economics.

The common employment of the DI method in empirical studies implies that it is likely that the bias in estimates of the DI method is smaller than the bias of the LW method. To examine this question, Chapter 3 studies the case of when the missing observations of a regressor are assumed to be correlated with unobserved error terms and the value of the regressor. The reason for focusing on this type of missingness is that it reflects many economic conditions, and further, the existing literature does not analyze the performance of the DI and LW methods when missingness is dependent on unobserved error terms and the value of a regressor. Therefore, this study seeks to fill this gap using Monte Carlo simulations, and benefits all the different fields within the applied economics literature.

The results of Chapter 3 show conditions in which the bias of the LW method is much bigger than the DI method, when the probability of missingness on a regressor is dependent on unobserved error terms and values of the regressor. The results imply that the recommendation of the existing literature for using the LW method is not supported when missingness is dependent on unobserved error terms and the value of a regressor. Therefore, the third chapter of my thesis indicates that the selection of one approach over the other one and interpreting the estimates under each method require greater care than what exists in the current literature and the applications which generally employ these methods.

# Chapter 1

# Patent Thicket and Market Value: An Empirical Analysis

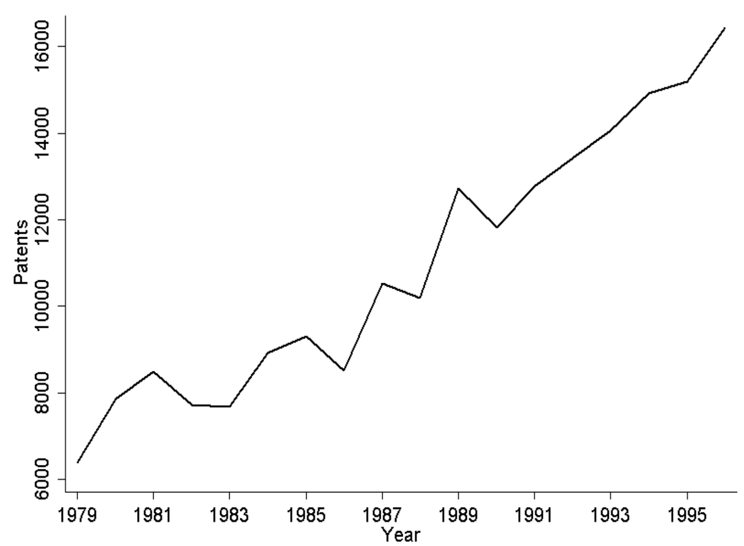
## 1.1 Introduction

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

[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.

Figure 1.1: Total Number of Patents by Grant Year.




caused a proliferation of patents and a higher fragmentation of patent ownership in the technology market (Jaffe and Lerner, 2007, p. 10). Figure 1.1 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

[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 1.3 and Appendix A.1).

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 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 manufacturing facilities and innovation.

This chapter evaluates the economic impact of fragmentation in the ownership of complementary patents by estimating the effect of patent thickets on the market value of

[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.

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 thicket have an incentive to avoid possible future retaliations.

[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 1.2.

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 1.1, 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

[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 1.1: 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. |

impacts in the manufacturing sector. Second, 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.

## 1.2 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

$$logMarket\ Value_{it} = logSV_{it} + \sigma\ logTA_{it} + \sigma\ log\left(1 + \gamma\ \frac{INA_{it}}{TA_{it}}\right). \tag{1.1}$$

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 ($\epsilon_{it}$). The term $\epsilon_{it}$ denotes the other factors that influence market value of firms. I assume that $\epsilon_{it}$ 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 $\gamma$ is the shadow price of the intangible asset to tangible asset ratio. Moving the variable $TA_{it}$ to the left-hand side in equation (1.1) 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 (1.1) then becomes

$$logq_{it} = log\left(1 + \gamma\,\frac{INA_{it}}{TA_{it}}\right) + m_t + \epsilon_{it}. \tag{1.2}$$

Following Hall et al. (2005), the variable $TA_{it}$ is measured by the book value of firms based on their balance sheet. The book value of a firm is calculated as the sum of net plant and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles and others. All 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

[9] The parameter $\sigma$ 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, $\sigma$ becomes one.

[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 $\delta$ 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.

al. (2005), and equation (1.2) becomes

$$\begin{aligned} logq_{it} &= log\left(1+\gamma_1\left(\frac{R\&Dstock}{TA}\right)_{it}+\gamma_2\left(\frac{PATstock}{R\&Dstock}\right)_{it}+\gamma_3\left(\frac{CITEstock}{PATstock}\right)_{it}\right) \\ &\quad +m_t+\epsilon_{it}. \end{aligned} \tag{1.3}$$

There is usually a difference between the application and grant date of patents. Out of the patents applied close to the end date of the sample, only a small fraction is granted, and the rest are granted outside the reach of the sample. This issue indicates truncation in patent counts. Citation counts are also truncated. 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.1 for a more detailed analysis of correction procedures.

To estimate the impact of patent thicket on the market value of firms, I augment equation (1.3) 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 (1.3). This results in the specification

$$\begin{aligned} logq_{it} &= log\left(1+\gamma_1\left(\frac{R\&Dstock}{TA}\right)_{it}+\gamma_2\left(\frac{PATstock}{R\&Dstock}\right)_{it}+\gamma_3\left(\frac{CITEstock}{PATstock}\right)_{it}\right) \\ &\quad +\delta_1\ logF_{it}+\delta_2\ logHHI_{it}+m_t+\epsilon_{it}. \end{aligned} \tag{1.4}$$

The variable $HHI_{it}$ is calculated using firm-level sales based on 4-digit SIC codes. Equation (1.4) is estimated using a nonlinear least squares estimator.[12]

[12]There are several issues worth noting with respect to equation (1.4). I do not approximate

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 (1.4) becomes

$$
\begin{aligned}
logq_{it} &= log\left(1+\gamma_1\left(\frac{R\&Dstock}{TA}\right)_{it}+\gamma_2\left(\frac{PATstock}{R\&Dstock}\right)_{it}+\gamma_3\left(\frac{CITEstock}{PATstock}\right)_{it}\right) \\
&\quad +\delta_1\, logF_{it}+\delta_2\, logHHI_{it}+\alpha_i+m_t+\epsilon_{it}. \qquad (1.5)
\end{aligned}
$$

Parameters $\alpha_i$ capture firm unobserved heterogeneities. Following Bloom et al. (2005) and Noel and Schankerman (2006), I replace the non-linear terms in equation (1.5) with series expansions. Thus, equation (1.5) becomes

$$
\begin{aligned}
logq_{it} &= \gamma_1\,\Psi\left(log\left(\frac{R\&Dstock}{TA}\right)_{it}\right)+\gamma_2\,\Omega\left(log\left(\frac{PATstock}{R\&Dstock}\right)_{it}\right) \\
&\quad +\gamma_3\,\Gamma\left(log\left(\frac{CITEstock}{PATstock}\right)_{it}\right)+\delta_1\, logF_{it}+\delta_2\, logHHI_{it} \\
&\quad +m_t+\alpha_i+\epsilon_{it}, \qquad (1.6)
\end{aligned}
$$

where the parameters $\Psi$, $\Omega$, and $\Gamma$ denote the polynomials of the measures of intangible assets. To avoid the omitted variable bias due to unobserved firm heterogeneities, I estimate equation (1.6) using a within estimator for panel data. Estimates of equation (1.6) imply that the fifth order polynomial is satisfactory. I do not consider the multiplicative terms of the measures of intangible assets in equation (1.6), because including them do not change the results.

---

$log\left(1+\gamma\,\frac{INA_{it}}{TA_{it}}\right)$ 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.

Hall et al. (2005) argue against including firm fixed effects in equation (1.6). 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 (1.6) as a robustness check.

Equations (1.4) and (1.6) are employed as base models for estimation in Chapter 1. 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 (1.4) and (1.6).

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

$$F_{it} = 1 - \sum_{j=0}^{J} \left( \frac{cite_{ijt}}{cite_{it}} \right)^2 . \tag{1.7}$$

[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).

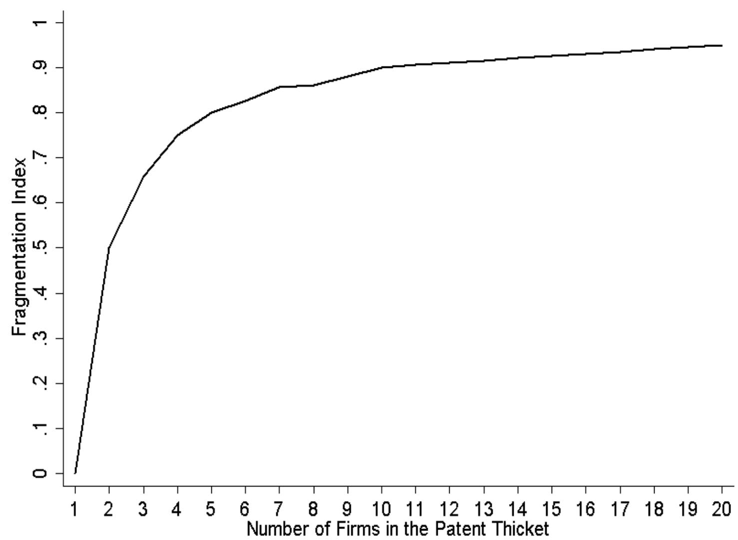
The variable $cite_{ijt}$ is the number of citations made by firm $i$ in its patent documents to the patents of firm $j$ at time $t$.[15] The variable $cite_{it}$ is the count of all the citations made by firm $i$ in year $t$. The index $F_{it}$ is zero when all the citations are made to the patents of one firm and one when every citation is to a patent of a different firm. Figure 1.2 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, assuming that the total number of citations made in the patents of this firm remains constant at 20.[16,17]

[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.

[16] Assuming the number of complementary patents or external right holders in the patent thicket of the hypothetical firm is N, I plot Figure 1.2 making the following assumptions about the citations that external right holders' patents receive from the hypothetical firm: If N=1, the only right holder receives all the citations and $F_{it} = 0$. If N=2, each of the right holders receives 10 citations to its patents and $F_{it} = 0.5$. If N=4, each of them receives 5 citations and $F_{it} = 0.75$. If N=6, 5 of them receive 3 citations and one of them receives 5 citations ($F_{it} = 0.8$). If N=8, 6 of them receive 3 citations and one of them receives 2 citations ($F_{it} = 0.86$). If N=10, each of them receives 2 citations and $F_{it} = 0.9$. If N=12, 8 of them receive 2 citations and four of them receive one citation ($F_{it} = 0.91$). If N=14, 6 of them receive 2 citations and the rest receive one citation ($F_{it} = 0.92$). If N=16, 4 of them receive 2 citations and the rest get only one citation ($F_{it} = 0.93$). If N=18, 2 of them receive 2 citations and the rest receive one citation ($F_{it} = 0.94$). If N=20, all of them receive one citation and $F_{it} \approx 1$

[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 (1.4) and (1.6) 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. This is because smaller firms may assume that the likelihood of dealing with the same large firm is quite low in the future. However, larger firms might assume a correspondingly higher likelihood and therefore an enhanced probability of retaliation.

Figure 1.2: Fragmentation Index and External Right Holders.




# 1.3 Data

## 1.3.1 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

[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.

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 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

[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.

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

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 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.1. 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

[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 1.2) 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.

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 1.2 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 1.3 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 1.4 demonstrates that variable $F_{it}$ was increasing on average from 1979 to 1996.

### 1.3.2 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

[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 (1.4) and (1.6) 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 1.2: 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 1.3: Distribution of Patents in the Sample.

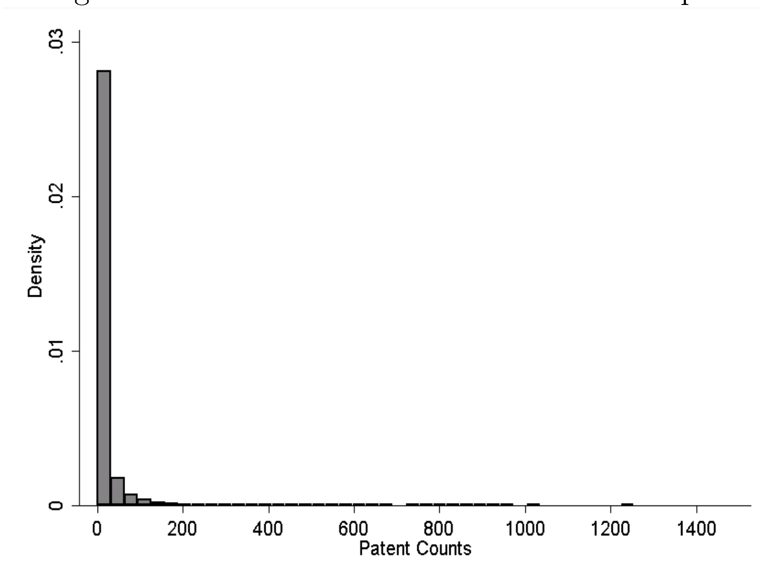



Figure 1.4: Patent Thicket over Time.

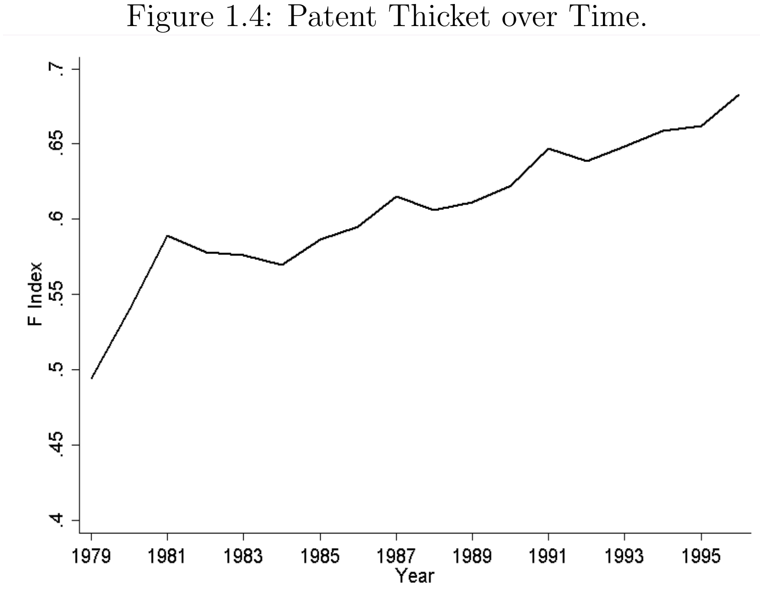
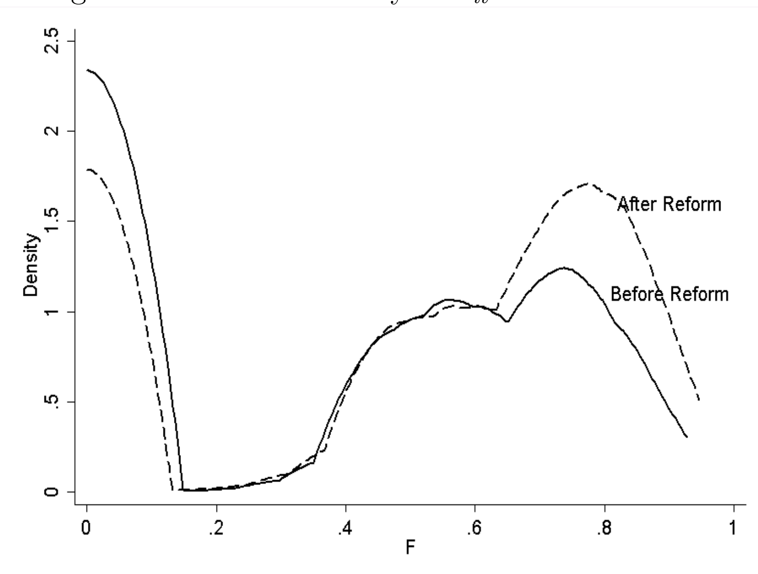


Figure 1.5: Kernel Density of $F_{it}$ for Small Firms.




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 1.5 to 1.7 investigate the effect of the pro-patent shifts on $F_{it}$ for each group. In Figures 1.5 to 1.7 except for Figure 1.7, 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 1.5 to 1.7 display that the impact of pro-patent policies depends on the number of patents owned by the firm. Therefore, there is both over-time and cross-firm variation in $F_{it}$ that help in identifying the empirical estimates. The different finding of Figure 1.7 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

Figure 1.6: Kernel Density of $F_{it}$ for Medium Firms.

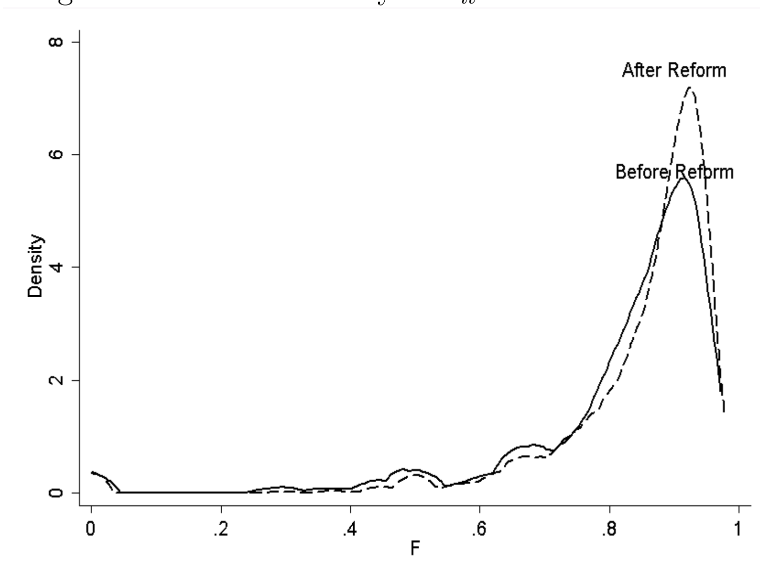
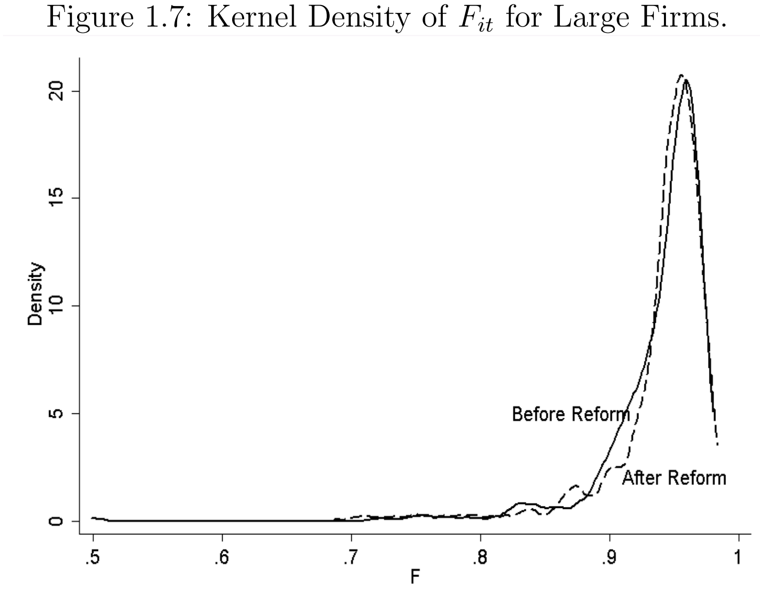



Figure 1.7: Kernel Density of $F_{it}$ for Large Firms.



## 1.4 Results

Table 1.3 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 (1.4), column 2 reports estimates for equation (1.6) with firm fixed effects, and column 3 shows estimates for the same model as equation (1.6) 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 1.3 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 1.3 (using equation,

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 1.3: 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 1.3 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 |

1.6). With the inclusion of firms fixed effects, the variable $logF_{it}$ keeps its negative impact on the market 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 (1.6) 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 1.3, I calculate the semi-elasticities of knowl-

[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 1.3 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 1.4: 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) |

edge stock variables as well as the elasticity of the variable $logF_{it}$ at both the mean and median of the covariates in Table 1.4. These elasticities allow me to evaluate the size of the impacts of the explanatory variables on the firms' market value.[36] According to Table 1.4, 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%.

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

Table 1.5 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 (1.4) and use the resulting equation for the estimates in column 1 of Table 1.5. 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 1.5 are robust to the models with firm fixed effects and industry fixed effects in columns 2 and 3 (based on equation (1.6)).

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 (1.4) 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

[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).

[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 1.5: 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 1.6: 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) |

value of firms has been increasing over time as a result of the pro-patent shifts, I augment equation (1.4) with variables $D_{year} \times logF_{it}$, where the variable $D_{year}$ ($year$ =1979,...,1996) is a dummy variable for each year.

Table 1.6 contains the results of this exercise and reports only the coefficients of the new variables added to equation (1.4). Most of the coefficients of these variables are not statistically significant. Figure 1.8 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. 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.

[39]The estimating specification of Table 1.6 is based on equation (1.4) and is estimated with a non-linear

Figure 1.8: Estimated Coefficients of Variables $D_{year}\times\ logF_{it}$.

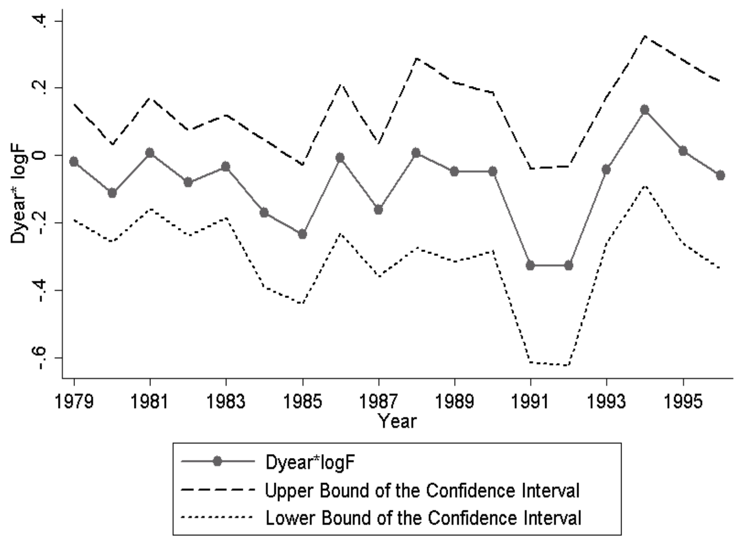
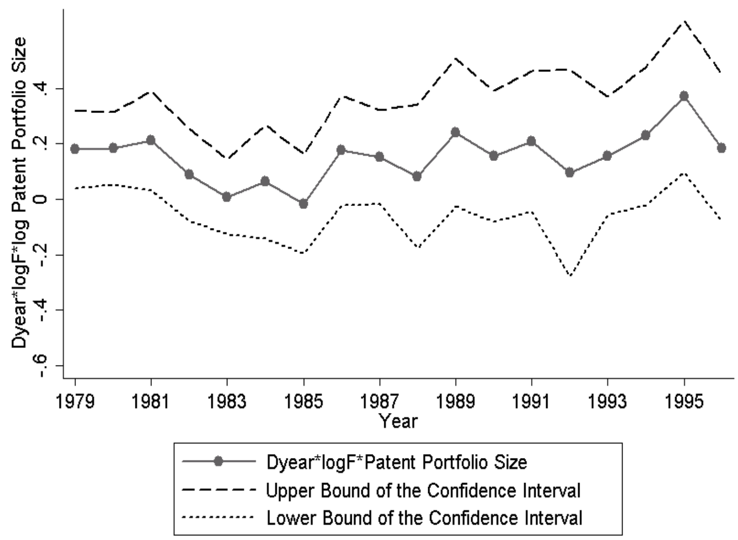



Table 1.7 takes into account two heterogeneities (time and patent portfolio size) in the impact of patent thickets. This table evaluates how the impact of patent thickets on the market value changes over time for firms with a large patent portfolio size. The estimating equation is based on equation (1.4) 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 1.7 displays the results of this exercise and reports only the coefficients of the new variables added to equation (1.4). The estimated coefficients of these variables in Table 1.7 are statistically insignificant with respect to most years. Figure 1.9 plots the scatter plot of the estimated 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 1.6 and 1.7 imply that I cannot find a systematic time

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




effect from patent thickets on the market value of firms, and this result even applies to firms with a large patent portfolio size.

Table 1.8 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

[36]The estimating specification of Table 1.7 is based on equation (1.4) 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 1.8, 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 1.7: 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 1.7 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) |

chemical and 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 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 (1.4) with a weighted nonlinear least squares estimator. This specification also cannot reject the joint hypothesis of the equality

[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 (1.4) in equation (1.4). Then I test for the equality of the coefficients of the variables $D_{industry} \times logF_{it}$ across industries.

Table 1.8: 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 |

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).

## 1.5 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 chapter, 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 the market value of firms, and this finding even holds for firms

[39] A similar result holds when I estimate equation (1.4) with a Weighted Pooled Least Squares estimator.

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 Chapter 1 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.

# Chapter 2

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

## 2.1 Introduction

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

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

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

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

My results suggest that patent thickets, both firms' own as well as other firms', have a negative direct impact on the market value of firms. I also find that both firms' own and other firms' patent thickets increase defensive patenting, but do not have a statistically significant effect on firms' R&D activities. While defensive patenting alleviates the direct negative impact that patent thickets have on market value, the total impact of patent thickets on the market value of firms is still negative. This finding implies that the concerns over the negative impacts of patent thickets are valid. The prior empirical evidence on the effects of patent thickets is mixed. For a detailed summary of the previous findings in the literature refer to section 1.1 of Chapter 1.

[1] 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.

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

## 2.2 Empirical Framework

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

### 2.2.1 Three Functional Relationships

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

$$Market\ Value = f(F, spillF, R\&D, Patents, ...). \tag{2.1}$$

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

$$R\&D = g(F, spillF, ...), \tag{2.2}$$

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

$$Patent = h(F, spillF, R\&D, ...). \tag{2.3}$$

As is illustrated in relationship (2.3), patenting activity by a firm is also influenced by its R&D expenditures.[2]

The estimating equations for the relationships (2.1) through (2.3) 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

$$DIRECT = \frac{\partial Market\ Value}{\partial F} + \frac{\partial Market\ Value}{\partial spillF} \times \frac{\partial spillF}{\partial F}, \tag{2.4}$$

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

$$\begin{aligned} INDIRECT(R\&D) &= \frac{\partial Market\ Value}{\partial R\&D} \times \frac{\partial R\&D}{\partial F} \\ &+ \frac{\partial Market\ Value}{\partial R\&D} \times \frac{\partial R\&D}{\partial spillF} \times \frac{\partial spillF}{\partial F}, \end{aligned} \tag{2.5}$$

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

$$\begin{aligned} INDIRECT(PATENTING) &= \frac{\partial Market\ Value}{\partial Patents} \times \frac{\partial Patents}{\partial F} \\ &+ \frac{\partial Market\ Value}{\partial Patents} \times \frac{\partial Patents}{\partial spillF} \times \frac{\partial spillF}{\partial F}. \end{aligned} \tag{2.6}$$

The total impact of patent thickets on market value is calculated as the sum of direct impact (2.4) and the two indirect impacts (2.5-2.6).

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

### 2.2.2 Three Estimating Equations

**Market Value Equation**

To estimate the relationship (2.1) depicting the direct impacts of patent thickets on the market value of a firm, I use

$$
\begin{aligned}
logq_{it} \;=\;& \delta_1 \, logF_{it-1} + \delta_2 \, logspillF_{it-1} + \delta_3 \, logspillR\&D_{it-1} \\
& + \gamma_1 \, \Psi\left( log \left( \frac{R\&Dstock}{TA} \right)_{it-1} \right) + \gamma_2 \, \Omega\left( log \left( \frac{PATstock}{R\&Dstock} \right)_{it-1} \right) \\
& + \gamma_3 \, \Gamma\left( log \left( \frac{CITEstock}{PATstock} \right)_{it-1} \right) + \delta_4 \, logsale_{it-1} + \delta_5 \, logsale_{it-2} \\
& + \delta_6 \, logHHI_{it-1} + \alpha_i^{MV} + m_t + \epsilon_{it}^{MV}.
\end{aligned} \tag{2.7}
$$

For a detailed derivation of equation (2.7) see Appendix B.1. The dependent variable $logq_{it}$ is the logarithm of Tobin's q.[3] The variables $logF_{it-1}$ and $logspillF_{it-1}$ measure the firm's own patent thicket and the other firms' patent thickets, respectively. The construction of these variables is explained in section 2.2.4. The variables $(R\&Dstock/TA)_{it-1}$, $(PATstock/R\&Dstock)_{it-1}$, and $(CITEstock/PATstock)_{it-1}$ are $R\&D$ intensity, patent intensity, and citation yield per patent (citation intensity), respectively. These variables measure the intangible assets of the firm. The construction of these variables is discussed in Appendix B.1. The parameters $\Psi$, $\Omega$, and $\Gamma$ denote the polynomials of the measures of intangible assets. The variable $logspillR\&D_{it-1}$ captures potential (positive) spillovers from other firms' R&D expenditures on the firm's market value.[4] The construction of

[3] This variable is explained in Appendix B.1.

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

this variable is discussed in Appendix B.3. The variable $logHHI_{it-1}$ controls for market structure impacts.[5] The parameters $\alpha_i^{MV}$ and $m_t$ represent firm and time fixed effects, respectively.[6] The variable $\epsilon_{it}^{MV}$ is the error term.

The lag structure in the right-hand side variables of equation (2.7) is designed to alleviate the reflection problem (Manski, 1993), which could make the estimates of the market value equation inconsistent.[7] This problem points to the fact that it is difficult to distinguish whether the coefficients on the spillover variables ($logspillR\&D_{it-1}$, $logspillF_{it-1}$) reflect actual spillover effects or (technological opportunity) shocks that are correlated across related firms. The distributed lag structure in the firm-level sales ($logsale_{it-1}$ and $logsale_{it-2}$) decrease the potential inconsistency from demand shocks.[8] To avoid the omitted variable bias due to unobserved firm heterogeneities, I estimate equation (2.7), using a within estimator for panel data.[9]

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

[6]I assume that $\alpha_i^{MV}$ is additive, time-invariant and not correlated across firms.

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

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

[9]Estimates of equation (2.7) imply that the fifth order polynomial is satisfactory. I do not consider the multiplicative terms of the measures of $INA_{it-1}$ in equation (2.7) because including them does not change the results.

**R&D Equation**

To estimate the relationship (2.2), I apply the equation

$$\begin{aligned} logR\&D_{it} \;=\;& \theta_1\, logR\&D_{it-1} + \theta_2\, logF_{it-1} + \theta_3\, logspillF_{it-1} \\ & +\theta_4\, logspillR\&D_{it-1} + \theta_5\, logsale_{it-1} \\ & +\theta_6\, logsale_{it-2} + \theta_7\, logHHI_{it-1} \\ & +m_t + \alpha_i^{R\&D} + \epsilon_{it}^{R\&D}. \end{aligned} \tag{2.8}$$

The parameters $\alpha_i^{R\&D}$ and $m_t$ represent firm and time fixed effects, respectively. The variable $\epsilon_{it}^{R\&D}$ is an idiosyncratic error term.[10]

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

The distributed lag structure in the firm-level sales decreases the inconsistency from possible demand shocks.[11] 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.[12] Based on the argument in Nickell (1981), the long time dimension in the

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

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

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

panel data used in Chapter 2 prevents inconsistent estimates due to the lagged dependent variable in equation (2.8).[13] To avoid the omitted variable bias due to unobserved firm heterogeneities, I estimate equation (2.8) using a within estimator for panel data.

### Patenting Equation

As the patent data is inherently count data, I adapt the approach in Hausman et al. (1984) by estimating the relationship (2.3) using

$$\begin{aligned} E(Patent_{it}|X_{it}^{RHS}) \;=\; & \exp(\beta_1 \, logF_{it-1} + \beta_2 \, logspillF_{it-1} + \beta_3 \, logspillR\&D_{it-1} \\ & + \beta_4 \, logR\&Dstock_{it-1} + \beta_5 \, logsale_{it-1} + \beta_6 \, logsale_{it-2} \\ & + \beta_7 \, logHHI_{it-1} + \beta_8 \, logpre\text{-}sample\ patents_i \\ & + m_t). \end{aligned} \tag{2.9}$$

The dependent variable is the number of successful patent applications made by a firm in a given year. A Poisson estimator is the appropriate estimator for equation (2.9).[14]

(2.8) because, according to Griliches (1979), the R&D expenditures are highly correlated over the years, and estimating the separate contribution from each lag with precision is hard.

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

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

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

where $\hat{\mu_{it}}$ is $exp(X'_{it}\hat{\beta})$, which is the fitted value of the Poisson model, assuming that the first moment in the Poisson model is $E(y_{it}|X_{it}) = exp(X'_{it}\beta)$. Therefore, following Cameron and Trivedi (2006, p. 670), I

One lag of the right hand side variables is included to mitigate the reflection problem.[15] The distributed lags of firm-level sales are included to capture demand shocks. The parameter $m_t$ represents time fixed effects.

Firms' unobserved heterogeneities could make estimates of patent thicket impacts on patenting inconsistent. Firms might differ because of their pre-sample stock of innovations, or their abilities to absorb external technologies for reasons that are not explained by independent variables. Blundell et al. (1999) use a mean-scaling approach to control for firm fixed effects. They argue that one interpretation of such effects is the entry level of innovation of each firm, and this innovation is uncorrelated with subsequent shocks to innovation. Therefore, they use the pre-sample information on the patenting propensity of firms to construct a pre-sample average. Since the right-hand side variables in equation (2.9) are pre-determined, I follow the mean-scaling approach of Blundell et al. (1999) to control for firm fixed effects and include the variable $logtextitpre - samplepatents_i$ in equation (2.9). This variable is the average of the pre-sample patent counts of firm $i$.

estimate equation (2.9) with Poisson estimator and calculate the fitted value. Then using the fitted value, I build the auxiliary regression, and estimate it with a linear Least Squares estimator. The results show that $\alpha$ is statistically significant and over-dispersion exists in the data of this paper.

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

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

### 2.2.3 Using the Estimates to Calculate the Direct, Indirect, and Total Impacts

Assuming the steady state condition, which is $X_{it} = X_{it-1} = X_i$, holds for any variable $X_{it}$, the equations (2.7) through (2.9) can be rewritten as

$$\begin{aligned} logq_i &= \delta_1\, logF_i + \delta_2\, logspillF_i + \delta_3\, logspillR\&D_i \\ &+\gamma_1\, \Psi\left( log\left(\frac{R\&Dstock}{TA}\right)_i \right) \\ &+\gamma_2\, \Omega\left( log\left(\frac{PATstock}{R\&Dstock}\right)_i \right) \\ &+\gamma_3\, \Gamma\left( log\left(\frac{CITEstock}{PATstock}\right)_i \right) \\ &+(\delta_4+\delta_5)\, logsale_i + \delta_6\, logHHI_i \\ &+\alpha_i^{MV} + \epsilon_i^{MV}, \end{aligned} \tag{2.10}$$

$$\begin{aligned} logR\&D_i &= \frac{\theta_2}{1-\theta_1}\, logF_i + \frac{\theta_3}{1-\theta_1}\, logspillF_i + \frac{\theta_4}{1-\theta_1}\, logspillR\&D_i \\ &+\frac{\theta_5+\theta_6}{1-\theta_1}\, logsale_i + \frac{\theta_7}{1-\theta_1}\, logHHI_i \\ &+\alpha_i^{R\&D} + \epsilon_i^{R\&D}, \end{aligned} \tag{2.11}$$

and

$$\begin{aligned} E(Patent_i|X_i^{RHS}) &= exp(\beta_1\, logF_i + \beta_2\, logspillF_i + \beta_3\, logspillR\&D_i \\ &+\beta_4\, logR\&Dstock_i + (\beta_5+\beta_6)\, logsale_i \\ &+\beta_7\, logHHI_i + \beta_8\, logpre\text{-}sample\ patents_i). \end{aligned} \tag{2.12}$$

Using equations (2.10-2.12) the direct impact (2.4) can be calculated as

$$DIRECT = \delta_1 + \delta_2, \tag{2.13}$$

and the indirect impacts (2.5-2.6) can be calculated as

$$\begin{aligned} INDIRECT\ (R\&D) \quad &= \quad \frac{\partial logq_i}{\partial logR\&Dstock_i} \times 1 \times \left(\frac{\theta 2 + \theta 3}{1 - \theta_1}\right) \\ &+ \quad \frac{\partial logq_i}{\partial logPATstock_i} \times 1 \times \frac{1}{\overline{\overline{Patent}}} \times \beta_4 \times \left(\frac{\theta 2 + \theta 3}{1 - \theta_1}\right) \end{aligned} \tag{2.14}$$

and

$$INDIRECT\ (PATENTING) = \frac{\partial logq_i}{\partial logPATstock_i} \times 1 \times \frac{1}{\overline{\overline{Patent}}} \times (\beta_2 + \beta_3), \tag{2.15}$$

respectively, where $\overline{Patent}$ is the average of patent counts in the entire sample. See Appendix B.2 for the detailed steps of deriving equations (2.14) and (2.15).

### 2.2.4 Measuring Patent Thickets

To measure the extent of fragmentation in patent ownership, I employ the fragmentation index used by Ziedonis (2004). This measure is explained in Chapter 1 in section 1.2. Similar to the measurement of R&D spillovers (Appendix B.3), I measure the extent of related firms' patent thickets for firm $i$, the patent thicket spillovers, by

$$spillF_{it} = \sum_{j \neq i} \rho_{ij} \times F_{jt}, \tag{2.16}$$

which is a weighted sum of other firms' patent thickets. The weight parameter, $\rho_{ij}$, measures the distance between firm $i$ and $j$ (Appendix B.3). Following Noel and Schankerman (2006), the construction of $\rho_{ij}$ is based on the distribution of citations across technology classes in the patent data.

## 2.3 Data

### 2.3.1 Data sources

The sample of analysis in Chapter 2 is same as the sample in Chapter 1 except that I include both patenting and non-patenting firms in the sample to facilitate estimation of equation (2.9). Following Bloom et al. (2005), I further exclude firms with less than four consecutive years of data. This aspect facilitates the calculation of the knowledge stock variables in the sample of patenting and non-patenting firms.[16] As a result, the sample of analysis in Chapter 2 is an unbalanced panel of 1,272 manufacturing firms with 14,214 observations from 1979 to 1996. Table 2.1 presents the descriptive statistics of all variables. The average firm in the sample is large and R&D intensive.[17] On average, a firm experiences a large fragmentation index of 0.70 and has 14 patents. The mean and median of variables $spillF_{it}$ and $spillR\&D_{it}$ are not that different.

Figures 2.2 and 2.3 illustrate that variables $F_{it}$ and $spillF_{it}$ were increasing on average from 1979 to 1996. The distribution of patent counts by each firm in Chapter 2 is similar to Figure 1.3 in Chapter 1.

[16] I also correct for the truncation in the patent and citation counts as I explained in section 1.3 of Chapter 1. The correction procedures are in Appendix B.4.

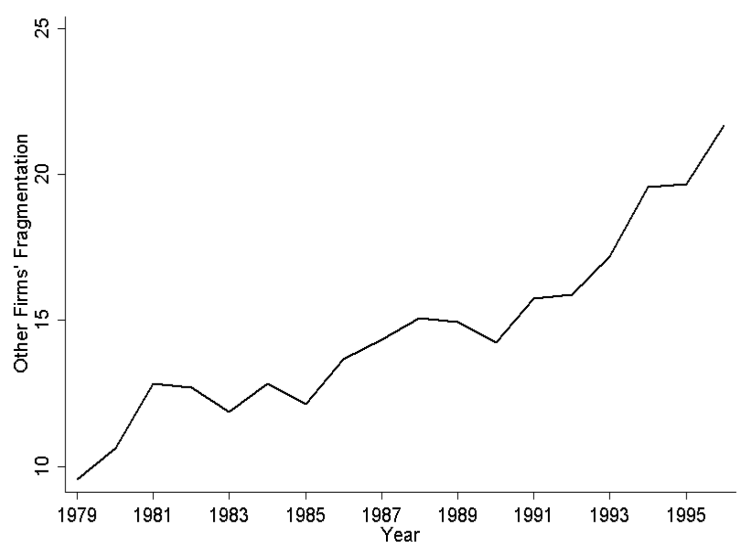
[17] The average firm is large, because it has 13,000 employees. This firm is R&D intensive, since its R&D intensity is 0.83.

Table 2.1: Descriptive Statistics

| Variable | Description | Obs | Mean | Median | Std.er | Min | Max |
|---|---|---|---|---|---|---|---|
| $Market\ Value_{it}$ | Market Value | 14214 | 867 | 78 | 3073 | 0 | 70772 |
| $TA_{it}$ | Book Value | 14214 | 1222 | 108 | 3721 | 0 | 61659 |
| $q_{it}$ | $(Market\ Value/TA)_{it}$ | 14207 | 1.14 | 0.67 | 4.76 | 0 | 390 |
| $F_{it}$ | Fragmentation Index | 9110 | 0.70 | 0.81 | 0.291 | 0 | 0.98 |
| $spillF_{it}$ | Others' Thicket | 14135 | 18.73 | 16.36 | 11.47 | 0.21 | 0.78 |
| $spillR\&D_{it}$ | R&D Spillovers | 14126 | 19516 | 14910 | 16107 | 79.63 | 117631 |
| $R\&Dflow_{it}$ | The Level of R&D | 12533 | 80.03 | 8.24 | 296 | 0 | 6099.34 |
| $R\&Dstock_{it}$ | The Stock of R&D | 14214 | 307.2 | 21.46 | 1250 | 0 | 28958 |
| $Patent_{it}$ | Patent Counts | 14214 | 14 | 1 | 58 | 0 | 1256 |
| $PATstock_{it}$ | Stock of Patents | 14214 | 64.22 | 5.64 | 260 | 0 | 5415.17 |
| $CITEstock_{it}$ | Stock of Citations | 9110 | 1152 | 126 | 4232 | 1.19 | 79115.o8 |
| $(R\&Dstock/TA)_{it}$ | R&D Intensity | 14207 | 0.83 | 0.26 | 5.29 | 0 | 383.98 |
| $(PATstock/R\&Dstock)_{it}$ | Patent Intensity | 12523 | 0.54 | 0.23 | 1.55 | 0 | 104.50 |
| $(CITEstock/PATstock)_{it}$ | Citation Intensity | 9110 | 13.5 | 8.47 | 19.49 | 1.17 | 416.98 |
| $Sale_{it}$ | Firm-Level Sales | 13986 | 1766 | 186 | 5888 | 0 | 146991 |
| $HHI_{it}$ | Market Structure | 14214 | 0.43 | 0.36 | 0.26 | 0 | 1 |
| $pre\text{-}sample\ patents_i$ | Firm's Pre-Sample Patents | 14214 | 14 | 1.78 | 43.84 | 0 | 6.29 |

Figure 2.1: Own Patent Thicket over Time.


Figure 2.2: Other Firms' Patent Thickets over Time.



### 2.3.2 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 use the Kernel density distributions of the variables $F_{it}$ and $spillF_{it}$ 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 5 patents (small firms), firms with 6 to 58 patents (medium firms), and firms with more than 58 patents (large firms). The effect of the pro-patent shifts on $F_{it}$ in Chapter 2 are roughly the same as Figures 1.5 to 1.7 in Chapter 1. Figures 2.4 to 2.6 investigate the effect of the pro-patent shifts on $spillF_{it}$ for each group. In all of these figures, the kernel densities experience a shift to the right following the pro-patent policy changes, which imply higher $spillF_{it}$ after the establishment of the CAFC.

Figure 2.3: Kernel Density of $spillF_{it}$ for Small Firms.

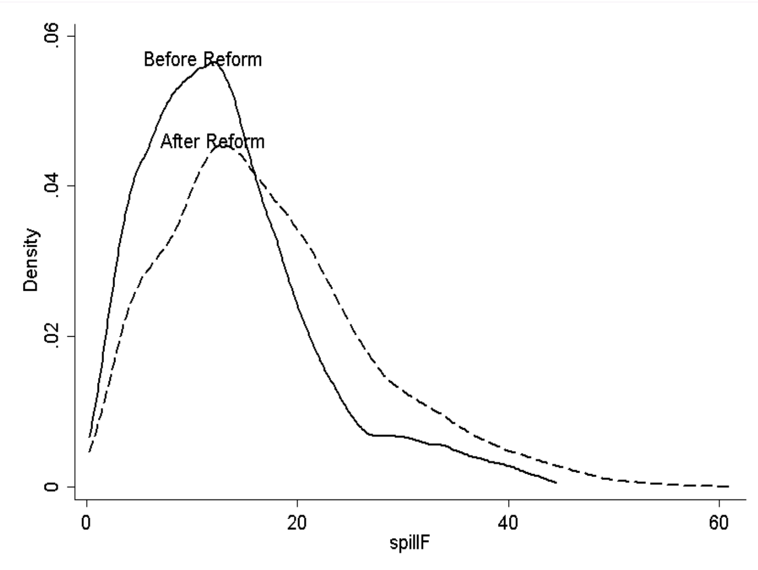



Figure 2.4: Kernel Density of $spillF_{it}$ for Medium Firms.

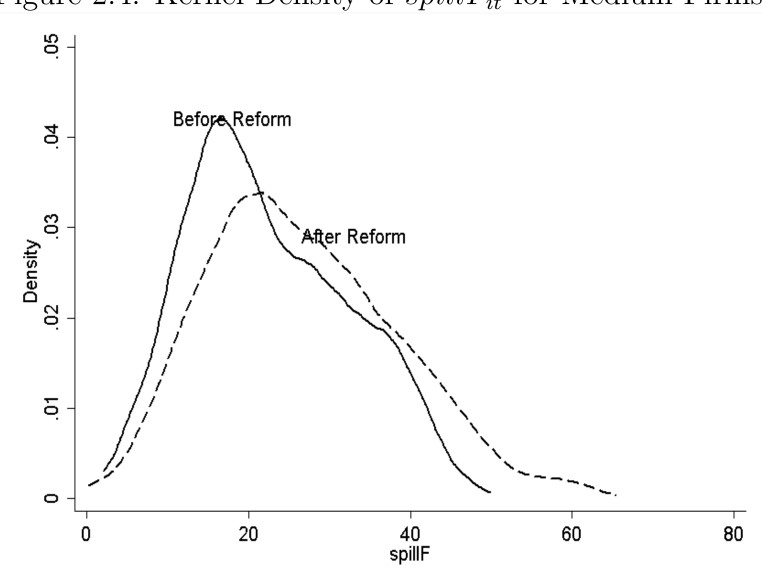
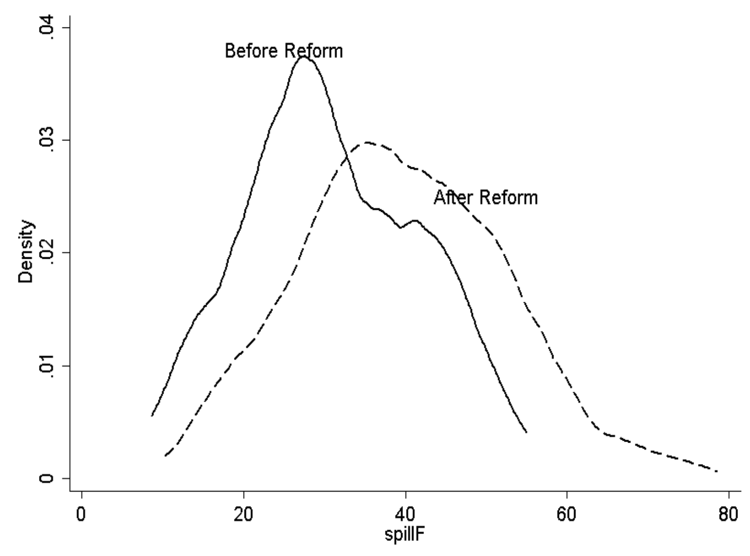


Figure 2.5: Kernel Density of $spillF_{it}$ for Large Firms.




## 2.4 Results

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

Table 2.2 contains estimates of patent thickets on market value (direct impact) based on equation (2.7). Standard errors are clustered at the firm-level.[18] Both the estimated coefficients on a firm's own patent thicket ($logF_{it-1}$) and others' patent thickets ($logspillF_{it-1}$) indicate that patent thickets have a negative direct impact on market value. For example, in Column 3, which contains estimates with firm fixed effects, the coefficient of $logF_{it-1}$ implies that market value declines by 0.22% as fragmentation increases by 10%. However, I lay limited emphasis on this result because the coefficient estimate is not statistically

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

significant. The coefficient of $logspillF_{it-1}$ shows that if fragmentation in the technology market increases by 10% for other firms, the given firm experiences lower market value by 0.69%. This finding is statistically significant at a 1% level of significance. The estimated negative impacts og patent thickets are robust to the use of industry fixed effects in column 4.[19] The results in Table 2.2 support the hypothesis that patent thickets lower a firm's market value directly.[20]

Table 2.3 reports estimates of the effect of patent thickets on R&D expenditures, employing equation (2.8). The results in Column 1 show that the major determinant of R&D expenditures of a given firm is its past R&D expenditures. While the coefficients on the patent thicket variables, $logF_{it-1}$ and $logspillF_{it-1}$, are both positive, they are not statistically significant, and even their magnitude is very small. The estimated coefficient of $logF_{it-1}$ in column 3 implies that a 10% increase in firms' own patent thicket lowers R&D expenditure by only 0.23%, and the coefficient estimate on the variable $logspillF_{it-1}$ in the same column suggests that a 10% increase in others' patent thickets increases R&D expenditures of a firm by only 0.08%. Hence, the proliferation of patents seems not to have generated the "tragedy of anti-commons" in the manufacturing sector.

Table 2.4 reports estimates of patent thicket impacts on patenting activity, using equation (2.9). The results in columns 3 and 4 indicate that patent thickets have a positive and

[19]The estimation is based on equation (2.7), but instead of controlling for firm fixed effects, I control for industry fixed effects, which are based on four-digit SIC codes. The industry fixed effects are for controlling the possibility of dense patent thickets, which may be more likely in some industries than others.

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

statistically significant effect on patenting. The reported standard errors in Table 2.4 are robust standard errors. The reason for using these standard errors is the over-dispersion problem in the sample that leads to inefficiency in estimates.[21] The estimated coefficient on the variable *logpre-sample patents*$_i$, which is used to control for firm unobserved heterogeneity, is positive and statistically significant in columns 1 to 3. This result confirms the need to control heterogeneity across firms with respect to their patenting behavior.[22]

[21]For a detailed explanation of the over-dispersion problem, refer to section 2.2.2

[22]For a detailed explanation of the reason behind using the variable *pre-sample patents*$_i$ to control for firm unobserved heterogenities, refer to section 2.2.2

[28]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).

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

Table 2.2: Patent Thicket and Market Value

| Dependent Variable $logq_{it}$[28] | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $logF_{it-1}$ | | -0.022 | -0.022 | -0.026 |
| | | (0.020) | (0.018) | (0.028) |
| $logspillF_{it-1}$ | | | -0.069*** | -0.039*** |
| | | | (0.017) | (0.013) |
| $logspillR\&D_{it-1}$ | | | -0.003 | 0.011 |
| | | | (0.005) | (0.007) |
| $logSale_{it-1}$ | 0.003 | 0.004 | 0.005 | 0.001 |
| | (0.005) | (0.005) | (0.005) | (0.007) |
| $logSale_{it-2}$ | 0.005 | 0.005 | 0.005 | 0.012** |
| | (0.005) | (0.005) | (0.004) | (0.006) |
| $logHHI_{it-1}$ | | | 0.058*** | 0.019 |
| | | | (0.014) | (0.021) |
| $log(\frac{R\&Dstock}{TA})_{it-1}$ | 0.151*** | 0.152*** | 0.159*** | 0.314*** |
| | (0.031) | (0.030) | (0.011) | (0.020) |
| $[log(\frac{R\&Dstock}{TA})_{it-1}]^2$ | 0.047*** | 0.047*** | 0.048*** | 0.132*** |
| | (0.012) | (0.011) | (0.004) | (0.008) |
| $[log(\frac{R\&Dstock}{TA})_{it-1}]^3$ | 0.003 | 0.003 | 0.002** | 0.006** |
| | (0.002) | (0.002) | (0.000) | (0.002) |
| $[log(\frac{R\&Dstock}{TA})_{it-1}]^4$ | -0.001 | -0.001 | -0.001*** | -0.003*** |
| | (0.001) | (0.001) | (0.000) | (0.000) |
| $[log(\frac{R\&Dstock}{TA})_{it-1}]^5$ | -0.001* | -0.000* | -0.000*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $log(\frac{PATstock}{R\&Dstock})_{it-1}$ | 0.054** | 0.055** | 0.053*** | 0.044*** |
| | (0.021) | (0.022) | (0.010) | (0.012) |
| $[log(\frac{PATstock}{R\&Dstock})_{it-1}]^2$ | 0.006 | 0.006 | 0.005 | 0.006 |
| | (0.010) | (0.009) | (0.004) | (0.006) |
| $[log(\frac{PATstock}{R\&Dstock})_{it-1}]^3$ | -0.002 | -0.002 | -0.001 | -0.001 |
| | (0.002) | (0.002) | (0.001) | (0.001) |

Table 2.2 Continued

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

Table 2.3: Patent Thicket and R&D

| Dependent Variable $logR\&D_{it}$[29] | (1) | (2) | (3) | (4) | (5) Panel GMM |
|---|---|---|---|---|---|
| $logF_{it-1}$ | | 0.024 | 0.023 | 0.015 | -0.012 |
| | | (0.019) | (0.020) | (0.018) | (0.019) |
| $logspillF_{it-1}$ | | | 0.008 | 0.012 | 0.020 |
| | | | (0.017) | (0.010) | (0.017) |
| $logspillR\&D_{it-1}$ | | | -0.004 | 0.010 | 0.004 |
| | | | (0.005) | (0.006) | (0.006) |
| $logR\&D_{it-1}$ | 0.726*** | 0.727*** | 0.726*** | 0.944*** | 0.329*** |
| | (0.018) | (0.023) | (0.023) | (0.007) | (0.127) |
| $logSale_{it-1}$ | 0.187*** | 0.186*** | 0.187*** | 0.181*** | 0.078 |
| | (0.030) | (0.037) | (0.037) | (0.023) | (0.049) |
| $logSale_{it-2}$ | -0.038 | -0.037 | -0.038 | -0.144*** | 0.103*** |
| | (0.027) | (0.027) | (0.027) | (0.021) | (0.029) |
| $logHHI_{it-1}$ | | | -0.024 | 0.002 | -0.023 |
| | | | (0.016) | (0.015) | (0.020) |
| $D(logF_{it} = 0)$ | | 0.029** | 0.029** | 0.024* | 0.021 |
| | | (0.012) | (0.012) | (0.013) | (0.014) |
| Firm Fixed Effects | Yes | Yes | Yes | No | No |
| Industry Fixed Effects | No | No | No | Yes | No |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 7340 | 7340 | 7340 | 7340 | 5496 |
| $R^2$ | 0.7294 | 0.7298 | 0.7299 | 0.9933 | |

### 2.4.2 Calculated Direct, Indirect, and Total Impacts

Table 2.5 displays the calculated direct and indirect impacts obtained using equations (2.13), (2.14) and (2.15). I calculate these effects using both the estimates with firm fixed effects (column 3 of Tables 2.2, 2.3, and 2.4) and the estimates with industry fixed effects (column 4 of Tables 2.2, 2.3, and 2.4). Standard errors of direct, indirect, and total impacts are estimated with non-parametric bootstrapping (the numbers in parentheses). As a robustness check, I also report the standard errors based on wild bootstrapping (the numbers in brackets).[23]

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

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

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

Table 2.4: Patent Thicket and Patent Propensity

| Dependent Variable: $Patent_{it}$[27] | (1) Poisson Mean-scaling | (2) Poisson Mean-scaling | (3) Poisson Mean-scaling | (4) Poisson No Mean-scaling |
|---|---|---|---|---|
| $logF_{it-1}$ | | 1.250*** | 1.151*** | 1.022 |
| | | (0.117) | (0.116) | (0.103) |
| | | [2.066] | [1.932] | [1.395] |
| $logspillF_{it-1}$ | | | 0.023** | 0.525*** |
| | | | (0.048) | (0.061) |
| | | | [0.039] | [0.716] |
| $logspillR\&D_{it-1}$ | | | 0.127*** | 0.041** |
| | | | (0.027) | (0.020) |
| $logR\&Dstock_{it-1}$ | 0.585*** | 0.552*** | 0.534*** | 0.709*** |
| | (0.018) | (0.018) | (0.017) | (0.020) |
| | [1.822] | [0.913] | [0.896] | [0.967] |
| $logSale_{it-1}$ | -0.079*** | -0.080*** | -0.090*** | -0.044*** |
| | (0.014) | (0.014) | (0.013) | (0.014) |
| $logSale_{it-2}$ | -0.023** | -0.024** | -0.015 | -0.015** |
| | (0.010) | (0.010) | (0.010) | (0.007) |
| $logHHI_{it-1}$ | | | 0.143*** | -0.188** |
| | | | (0.023) | (0.068) |
| $logpre\text{-}sample$ $patents_i$ | 0.441*** | 0.361*** | 0.340*** | |
| | (0.016) | (0.016) | (0.016) | |
| $D(logF_{it} = 0)$ | | -2.317*** | -2.300*** | -2.363*** |
| | | (0.049) | (0.049) | (0.049) |
| $D(R\&D_{it} = 0)$ | 0.175* | 0.270** | 0.282*** | 0.583*** |
| | (0.091) | (0.100) | (0.096) | (0.113) |
| Industry Fixed Effects | No | No | No | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 11760 | 11760 | 11760 | 11760 |

Table 2.5: Direct and Indirect Impacts of $F_{it}$ and $spillF_{it}$

| Specification[29] | Direct Impact | Indirect Impact | | Total Impact |
|---|---|---|---|---|
| | | INDIRECT (R&D) | INDIRECT (PATENTING) | |
| Firm FE | -0.091 | +0.002 | +0.008 | -0.081 |
| | (0.030) | (0.005) | (0.003) | (0.032) |
| | [0.031] | [0.007] | [0.001] | [0.030] |
| Industry FE | -0.065 | +0.004 | +0.018 | -0.043 |
| | (0.045) | (0.007) | (0.006) | (0.047) |
| | [0.044] | [0.018] | [0.002] | [0.044] |

## 2.5 Conclusion

The economic costs of patent thickets have been at the centre of ongoing debates on reforming the US patent system. Economic analyses of patent thickets have provided differing views on patent thickets' effects. In this chapter, I estimate the direct and indirect costs of patent thickets. The direct impact is the effect that patent thickets have on firms' market value, while I hold R&D and patenting activities of firms constant. The indirect impact is the effect that patent thickets potentially have on market value through

[29]Direct impact is calculated based on equation (2.13). Indirect impact via R&D is calculated based on equation (2.14). The indirect impact via patents is based on equation (2.15). The numbers in the parentheses are the non-parametric bootstrapped standard errors. The numbers in the brackets are the wild bootstrapped standard errors. In the models with industry fixed effects, the maximum likelihood Poisson estimator of the patent equation encountered non-convergence 16 times out of 1000 bootstrapped observations, when I measured standard errors. Models with firm FE are based on Column 3 of Tables 2.2, 2.3, and 2.4. Models with industry FE are based on Column 4 of Tables 2.2, 2.3, and 2.4.

patent thicket induced changes in R&D and through a patent thicket prompted increase in defensive patenting. In the empirical models, I also incorporate the influence that other firms' patent thickets have on market value of a given firm. The analysis is conducted using panel data on 1,272 publicly traded US manufacturing firms from 1979 to 1996.

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

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

# Chapter 3

# Missing Observations on a Variable: A Comparison of the Listwise Deletion and Indicator Approaches

## 3.1 Introduction

Censored regressors and explanatory variables with missing observations are quite common in applied research. Applied studies usually employ the listwise deletion method (LW), which is also called complete case analysis, or the indicator method (DI) in models with such regressors.[1] The LW method deletes observations with missing values on one or more of the regressors. The DI approach adds an indicator variable for missing observations of a regressor and replaces all missing observations of the regressor with a constant.

[1] Little (1992) and Little and Rubin (2002) offer a summary of the methods used for solving the problem of missing data in the literature.

Only few studies have analyzed the performance of the DI and LW methods in models with censored regressors or regressors with missing observations. In economics literature, Rigobon and Stoker (2007) employ a model of censoring to a single value in the case of censored regressors, and find unbiased estimates for the LW method and biased estimates for the DI method.[2] In statistics literature, Jones (1996) assumes missing completely at random (MCAR) and finds that unlike the LW method, the DI method generates biased estimates unless the regressors are uncorrelated.[3] Jones (1996) further observes that if the missing data mechanism is dependent on all explanatory variables, the estimates obtained using the DI method are biased, while the LW estimates are unbiased.

Nevertheless, as has been observed by Jones (1996), the DI method is widely used in empirical research in fields such as epidemiology, sample survey research, behavioral science, and business and economics. Some of the examples in the economics literature that employ the DI method are Hall and Ziedonis (2001), Ziedonis (2004), Bloom et al. (2005), and Noel and Schankerman (2006).

One potential justification for the abundant use of the DI method in empirical research might be the dependence of the mechanisms on whether observations on a regressor are missing on unobserved error terms, and on the value of the regressor. When missing observations on a regressor are dependent on unobserved error terms and the value of the

[2]Rigobon and Stoker (2007) assume exogenous censoring for censored regressors. To analyze the performance of the DI and LW methods, Rigobon and Stoker (2007) employ a top-coding censoring mechanism to generate censored data. In this mechanism, the observations of a regressor $X_i$, which are larger than a single fixed value, for example $\xi$, are missing. Rigobon and Stoker also analyze the properties of the DI and LW methods using a bottom-coding censoring and determine that the observations on the regressor $X_i$ are missing if $X_i < \xi$.

[3]Rubin (1976) categorizes the random missingness to missing completely at random (MCAR), and missing at random (MAR). MCAR means the probability of being missing for the kth observation, $x_{ik}$, of an explanatory variable $X_i$ neither depends on its own value nor on the value of other fully observed variables in the data set. If the probability of $x_{ik}$ being missing does not depend on its realized value, but depends on the values of other fully observed variables in the data set, the type of missingness is MAR.

regressor, using the LW method could lead to selection bias and inconsistent estimates. Due to the dependence of the missingness mechanism on the error term and on the regressor, the complete sample – which is employed in the LW method – becomes a non-representative sample of the population.

In contrast, the DI method uses all the available information, including the missing observations on regressors (Cohen and Cohen, 1975 and Chow, 1979), and may avoid the bias. Even if the missing observations are MCAR and the LW estimates are consistent, the deletion of missing observations, when the LW method is used, implies an inherent loss of information.

In this chapter, I examine whether cases can be found in which the estimates obtained using the DI method are less biased than estimates obtained using the LW method. In my analysis, whether an observation on a variable is missing depends both on the value of the error term and on the value of the regressor. To my knowledge, the performance of the DI and LW methods, in this case of missingness, has not been previously examined. Using Monte Carlo simulations, this chapter seeks to fill this gap in the literature.[4]

The findings of Chapter 3 reveal conditions under which the biases of the estimates in the LW method are bigger than the biases in the DI method, when the probability of whether an observation on an explanatory variable is missing depends on the value of the

[4] Imputation methods are sometimes used for solving the problem of missing observations of explanatory variables. These methods predict the missing observations of each variable from the observed values of that variable. According to Little and Rubin (2002), the cost of imputation methods comes from their requirement for making (possibly wrong) assumptions on the procedure which should be used for filling the missing observations. This approach has approximation errors, which should be taken into account in the inferences (Cameron and Trivedi, 2006, p. 923). Such errors make statistical inferences more complicated.

Maximum Likelihood approach is another suggested method to correct for missing observations in the literature. The limitation of this method is related to its requirement for making an assumption on the joint distribution of all variables with missing observations. Usually the multivariate normal distribution is assumed, but this assumption might not be realistic (Allison, 2001). Moreover, ML generates different results every time it is used. This happens since a random variation is deliberately added to the process.

unobserved error term and on the (possibly unobserved) value of the regressor itself. The results imply that recommendations in the existing literature to use the LW method are not supported when missingness is dependent on unobserved error terms and the value of a regressor. Therefore, the selection of a proper method and interpretation of the estimates under each method requires greater care than is implied by the existing literature.

## 3.2 The Model

To analyze the biases in the DI and LW methods, I assume that the true model is of the form

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + U_i, \tag{3.1}$$

where the variables $Z_i$ and $U_i$ are uniformly distributed on the interval [-0.5, 0.5] and [-1, 1], respectively. The variables $Y_i$ and $Z_i$ are always fully observed. The only variable with missing observations is $X_i$. For each observation on $X_i$, one of two mechanisms is used to set whether the observation on $X_i$ is missing. I assume that with probability $\alpha$, the variable $X_i$ has missing observations if $X_i > U_i$, and with probability $(1 - \alpha)$, the variable $X_i$ has missing observations if $X_i U_i < 0$. With this missing data mechanism, both the unobserved error term $U_i$ and the value of $X_i$ influence whether an observation on $X_i$ is missing. Following Jones (1996), I set $\beta_0 = 1$, $\beta_1 = 2$, and $\beta_2 = 1$.

As has been observed by Jones (1996), the correlation of regressors is an important determinant of whether the DI estimators of the parameters $\beta_1$ and $\beta_2$ are biased. Therefore, to generate a correlation between regressors, I assume that the relation between the variable $X_i$ and the variable $Z_i$ is given by

$$X_i = \gamma(\delta Z_i + W_i), \tag{3.2}$$

where $W_i$ is uniformly distributed on the interval [-0.5, 0.5], and $\gamma$ and $\delta$ are parameters.

Employing these assumptions in Monte Carlo simulations, I examine the conditions that lead to a smaller bias in the DI estimates than the LW estimates, when missingness depends on unobserved error term $U_i$ and on the variable $X_i$.[5]

## 3.3 Properties of the DI and the LW Methods

This section employs the Monte Carlo simulations and examines the bias in the DI and LW estimates, when the missing data mechanism is dependent on unobserved error term $U_i$ and on the variable $X_i$.

The true model employed in the simulations for the DI and the LW methods is equation (3.1), and the relationship between $X_i$ and $Z_i$ is defined as equation (3.2). The DI method includes a dummy variable, denoted by $D_i$, in the estimating equation to control for missing observations. The variable $D_i$ is equal to one for observations for which $X_i$ is observed and zero for observations for which $X_i$ is missing. This method replaces the missing observations of $X_i$ with a constant, which I set to be zero. Thus, the estimating equation for the DI method is

$$Y_i = \beta_0^{DI} + \beta_1^{DI} X_{0i} \times D_i + \beta_2^{DI} Z_i + \beta_3^{DI}(1 - D_i) + U_i, \tag{3.3}$$

[5]The results of the Monte Carlo simulations are quantitatively similar if I change the distribution of the variable $X_i$ to standard normal distribution, or if I alter equation (3.2).

where the missing observations of the variable $X_{0i}$ are replaced with 0. The variables $Y_i$ and $Z_i$ have no missing values.

The estimating equation for the LW method is

$$\tilde{Y}_i = \beta_0^{LW} + \beta_1^{LW} \tilde{X}_i + \beta_2^{LW} \tilde{Z}_i + \tilde{U}_i, \tag{3.4}$$

where the variables $\tilde{Y}_i$, $\tilde{X}_i$, $\tilde{Z}_i$, and $\tilde{U}_i$ are the variables $Y_i$, $X_i$, $Z_i$, and $U_i$, respectively, from the complete sample (the sample without any missing observations). For each reported parameter combination, I perform 10,000 Monte Carlo simulations with a sample size of 1,000. For each simulation, I calculate the estimates of the parameters $\beta_1$ and $\beta_2$, while I use the estimating equations (3.3) and (3.4) for the DI and LW methods, respectively.

Figures 3.1 and 3.2 display the average of the estimates of the coefficients $\beta_1$ and $\beta_2$ in the LW and DI methods across the 10,000 simulated samples assuming $\gamma = 0.5$ and $\delta = 0.5$. These figures also report the averages of the 95% confidence intervals from simulations for $\beta_1$ and $\beta_2$.

As is illustrated by Figures 3.1 and 3.2, there are cases in which the bias of the estimates of the parameters $\beta_1$ and $\beta_2$, which are obtained using the DI method, are smaller than the bias of the corresponding estimates, which are obtained using the LW method. For example, when the parameter $\alpha$ is in the range 0.6 to 1, the bias in the DI method is smaller than the bias in the LW method for both coefficients. The results of the Monte Carlo simulations are almost quantitatively similar if the value of $\gamma$ is decreased or if the value of $\delta$ is either increased or decreased, while I hold the other parameter constant. However, for very large values of $\gamma$, the smaller bias of the DI method in comparison to the LW method disappears, as is illustrated in Figures 3.3 and 3.4, in which values of $\gamma$

Figure 3.1: Average of $\widehat{\beta_1}$ in the LW and DI Methods ($\gamma = \delta = 0.5$).

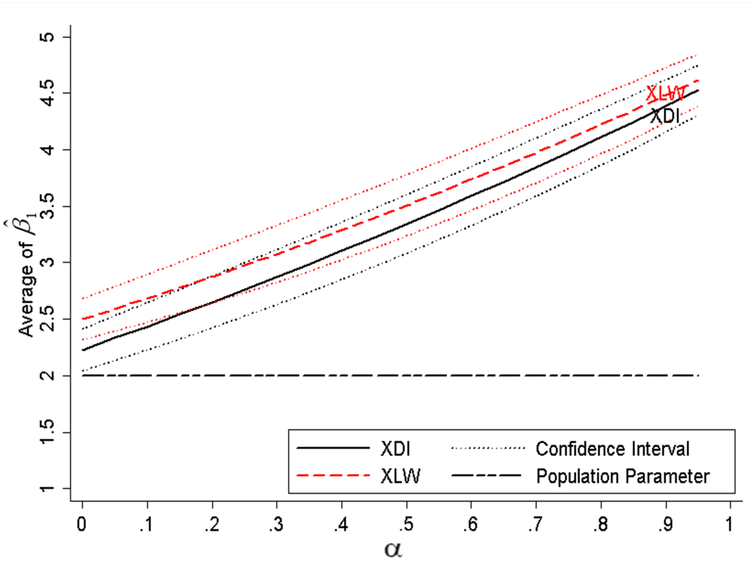



Figure 3.2: Average of $\widehat{\beta_2}$ in the LW and DI Methods ($\gamma = \delta = 0.5$).

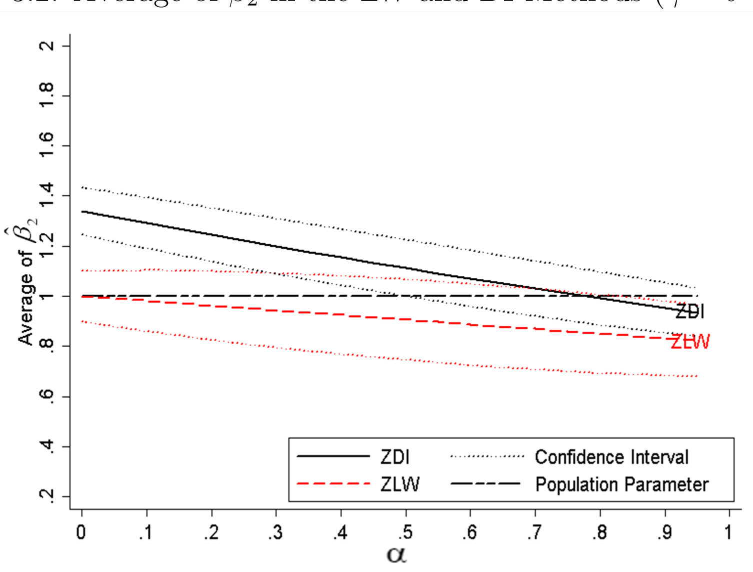
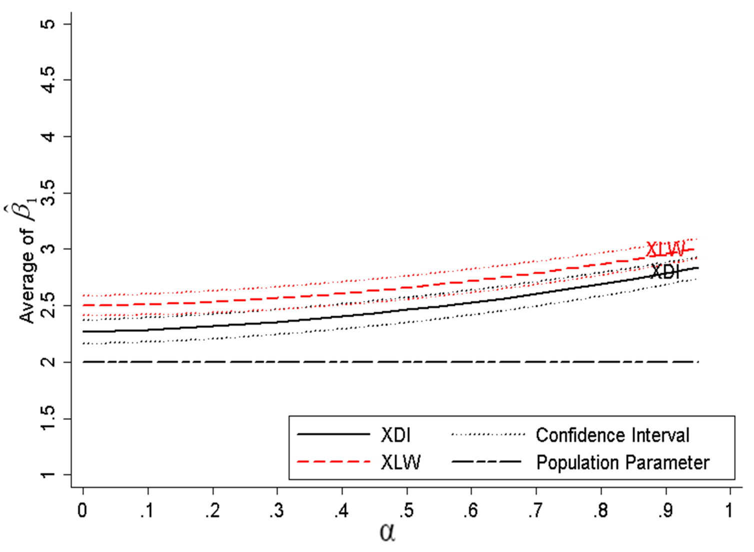


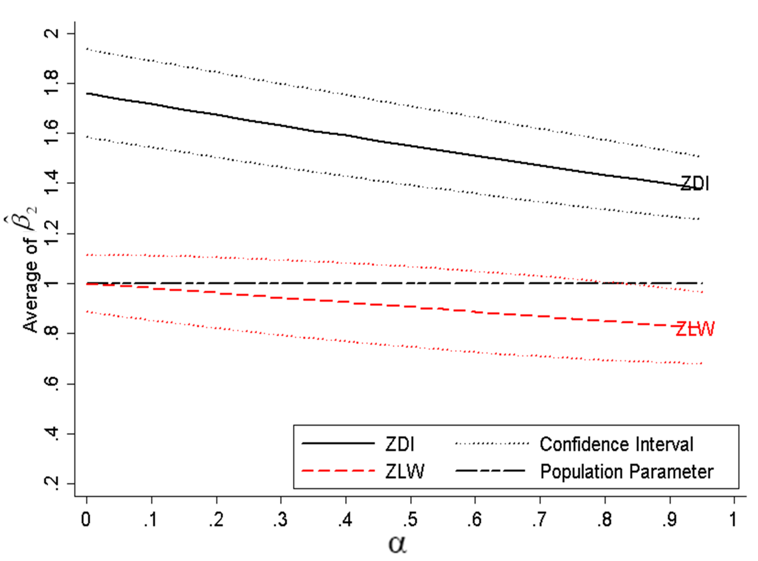
Figure 3.3: Average of $\widehat{\beta_1}$ in the LW and DI Methods ($\gamma = 1.3, \delta = 0.5$).




and $\delta$ are 1.3 and 0.5, respectively. With this value of $\gamma$, the DI method generates much larger bias than the LW method on the coefficient of the variable $Z_i$ in Figure 3.4.

The observed smaller bias in the DI estimates of the parameters $\beta_1$ and $\beta_2$ in comparison to the LW estimates of these parameters in Figures 3.1 and 3.2 indicates that the LW method is not a better choice than the DI method. Sometimes, the DI method can indeed alleviate the selection bias associated with missing observations as is often implicitly and in some cases even explicitly implied in the applied economics literature. The next step is gaining a better understanding of why these results are found based on different values of $\gamma$ and $\delta$ in terms of the variances and covariance of $X_i$ and $Z_i$.

Figure 3.4: Average of $\widehat{\beta_2}$ in the LW and DI Methods ($\gamma = 1.3, \delta = 0.5$).




## 3.4 Conclusion

It is surprising that few studies in the literature have addressed the estimation problems associated with censored regressors and explanatory variables with missing observations, as such regressors are quite common in applied work. Studies usually recommend using the listwise deletion approach (LW) over the dummy indicator approach (DI) for estimation. Despite the findings of these studies, the DI method is widely used in empirical research as is observed by Jones (1996). The abundant use of the DI method in practice implies the likelihood of cases in which the bias of the DI method is smaller than that of the LW method.

This study illustrates cases that lead to smaller bias in the estimates of the DI method than the LW method, when the missingness on a regressor is correlated with unobserved error terms and the values of the regressor. The examined cases of this research imply that the suggestion of the existing literature on selecting the LW method over the DI method does not help with these specific types of missingness. Therefore, the selection of one approach over the other one needs careful consideration.

In the end, the simulated samples in Monte Carlo simulations are samples of cross-sectional data, and only one of the regressors has missing observations. Further research is required to analyze the bias of the estimates of the DI and LW methods in the context of longitudinal data, and when there are several regressors with missing observations.

# APPENDICES

# Appendix A

# Appendix for Chapter 1

## A.1 Correcting Truncation in Patent and Citation Counts

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

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

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.[1] 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 patent and citation counts in my analysis.

[1] 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.1: Correction for Truncation in the Patent Counts.

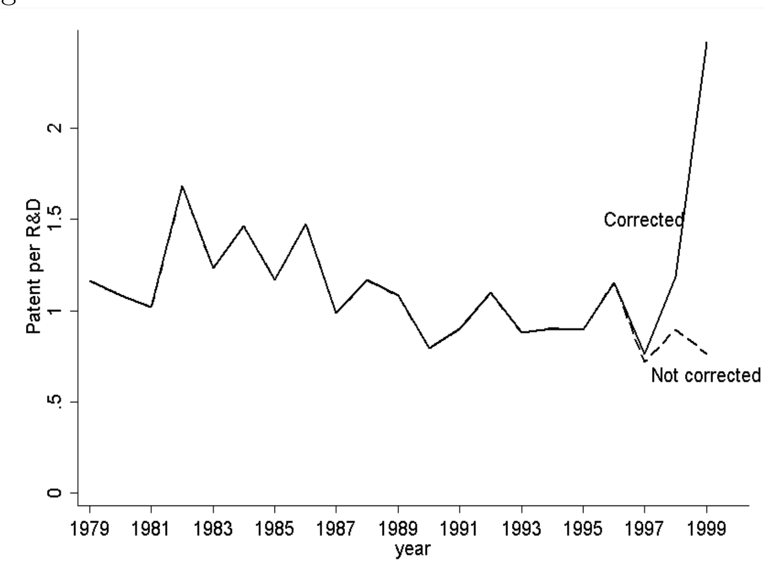
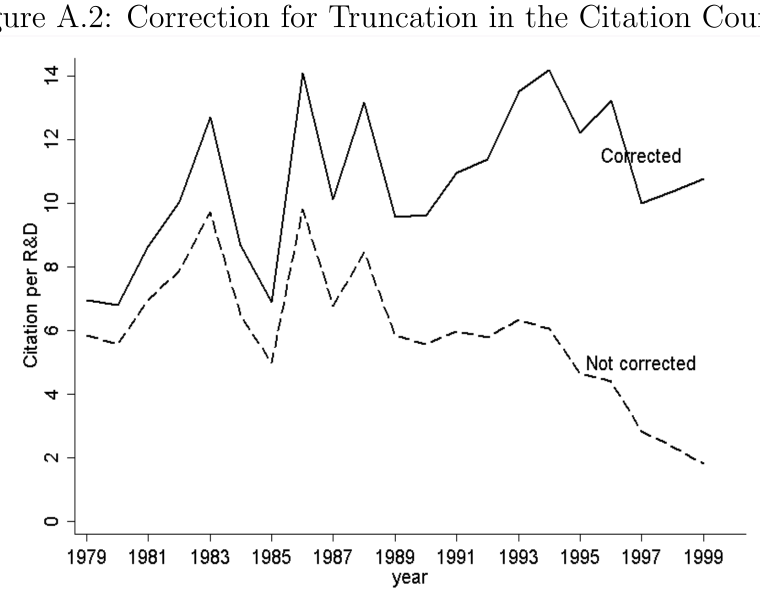



Figure A.2: Correction for Truncation in the Citation Counts.



# Appendix B

# Appendix for Chapter 2

## B.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

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

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 ($\epsilon_{it}$). The term $\epsilon_{it}$ denotes the other factors that influence the market value of firm $i$ in year $t$. I assume that error terms $\epsilon_{it}$ 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 $\gamma$ is the shadow price of the intangible to tangible asset ratio. Moving the variable $TA_{it}$ to the left-hand side in equation (B.1) allows left-hand side of this equation to be written as $log(\frac{Market\ Value_{it}}{TA_{it}})$ or Tobin's q.[1] Equation (B.1) then becomes

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

Following Hall et al. (2005), the variable $TA_{it}$ is measured by the book value of firms based on their balance sheet. The book value of a firm is calculated as the sum of net plant and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles and others. All of the components of $TA_{it}$ are adjusted for inflation.[2] $INA_{it}$ 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 $R\&Dstock_{it}$,

[1]The parameter $\sigma$ 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, $\sigma$ becomes one.

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

$PATstock_{it}$, 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%.[3] 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 $R\&D$ intensity, patent intensity, and citation intensity to measure $INA_{it}$, following Hall et al. (2005), and, equation (B.2) becomes

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

There is usually a difference between the application and grant date of patents. Out of the patents applied close to the end date of the sample, only a small fraction is granted, and the rest are granted outside the reach of the sample. This issue indicates truncation in patent counts. Citation counts are also truncated. Truncation in citation counts happen since only citations that occur within the sample are observable. I correct for these truncations. As a result, the $PATstock_{it}$ and $CITEstock_{it}$ variables are corrected for truncations in patent and citation counts. See Appendix B.4 for detailed correction procedures.

To estimate the impact of patent thicket on the market value of firms, I augment equation (B.3) with the variables $logF_{it}$ as a measure of the firm's own patent thicket, and $logspillF_{it}$ as a measure of other firms' patent thickets (the construction of these variables is explained in section 2.2.4). To control for R&D spillovers, I include $logspillR\&D_{it}$ in equation (B.3), and the construction of this variable is explained in Appendix B.3. The distributed lag structure in the firm level sales ($logsale_{it}$ and $logsale_{it-1}$) decrease the potential for inconsistent estimates due to demand shocks. To control for the effect of market structure on the market value of firms, I also add the log of a Herfindahl index for market structure ($logHHI_{it}$). Finally, some firms might have a permanently higher market value than others due to omitted firm specific effects.[4] To control for the firm unobserved heterogeneity, I include $\alpha_i^{MV}$ in equation (B.3). Adding the above variables to equation (B.3) results in the specification

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

[3]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 $\delta$ or depreciation rate equal to 15%. Most researchers settled with this deprecation rate (Hall et al., 2000, 2005, and 2007). Hall and Mairesse (1995) show experiments with different deprecation rates, and they conclude that changing the rate from 15% does not make a difference. As a result, I select $\delta = 15\%$, and this selection further assists in easy comparisons to previous studies.

[4]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.

Equation (B.4) could be estimated with a non-linear least squares estimator, but it is easier to substitute the non-linear terms with series expansions and estimate the equation with a linear estimator, following Bloom et al. (2005) and Noel and Schankerman (2006).[5] This approach makes the incorporation of firm fixed effects easier. Therefore, equation (B.4) becomes

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

where the parameters $\Psi$, $\Omega$, and $\Gamma$ denote the polynomials of the measures of intangible assets. Equation (B.5) is used to build equation (2.7).

## B.2 Indirect Impacts through R&D and Patenting

$$\begin{aligned} INDIRECT(R\&D) \quad = \quad & [\frac{\partial logq_i}{\partial logR\&Dstock_i} \times \frac{\partial logR\&Dstock_i}{\partial logR\&D_i}(\frac{\partial logR\&D_i}{\partial logF_i} + \frac{\partial logR\&D_i}{\partial logspillF_i})] \\ & +[\frac{\partial logq_i}{\partial logPATstock_i} \times \frac{\partial logPATstock_i}{\partial logPatent_i} \times \frac{\partial logPatent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial logR\&Dstock_i} \\ & \times \frac{\partial logR\&Dstock_i}{\partial logR\&D_i} \times (\frac{\partial logR\&D_i}{\partial logF_i} + \frac{\partial logR\&D_i}{\partial logspillF_i})] \\ & = \frac{\partial logq_i}{\partial logR\&Dstock_i} \times 1 \times (\frac{\theta 2 + \theta 3}{1-\theta_1}) \\ & + \frac{\partial logq_i}{\partial logPATDstock_i} \times 1 \times \frac{1}{\overline{Patent}} \times \beta_4 \times 1 \times (\frac{\theta 2 + \theta 3}{1-\theta_1}). \end{aligned} \tag{B.6}$$

[5] 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.

$$
\begin{aligned}
INDIRECT(PATENTING) &= [\frac{\partial log q_i}{\partial log PATDstock_i} \times \frac{\partial log PATDstock_i}{\partial log Patent_i} \times \frac{\partial log Patent_i}{\partial Patent_i} \\
&\times \frac{\partial Patent_i}{\partial log F_i}] + [\frac{\partial log q_i}{\partial log PATDstock_i} \times \frac{\partial log PATDstock_i}{\partial log Patent_i} \\
&\times \frac{\partial log Patent_i}{\partial Patent_i} \times \frac{\partial Patent_i}{\partial log spill F_i}] \\
&= \frac{\partial log q_i}{\partial log PATDstock_i} \times 1 \times \frac{1}{\overline{\overline{Patent}}} \times (\beta_2 + \beta_3). \qquad \text{(B.7)}
\end{aligned}
$$

One point to note is that the $R\&D$ variable is a stock variable in equations (2.10) and (2.12), and is a flow variable in equation (2.11). Following Hall et al. (2005), I define the relation between the $R\&D$ stock and flow as

$$R\&Dstock_{it} = (1-\delta)R\&Dstock_{it-1} + R\&D_{it}. \qquad \text{(B.8)}$$

Using the steady state condition ($R\&Dstock_{it} = R\&Dstock_{it-1} = R\&Dstock_i$), and taking the logarithm of both sides, equation (B.8) becomes

$$log R\&Dstock_i = log R\&D_i - log\delta, \qquad \text{(B.9)}$$

where

$$\frac{\partial log R\&Dstock_i}{\partial log R\&D_i} = 1. \qquad \text{(B.10)}$$

I use equation (B.10) in equation (B.6). The same applies to the patent variable as this variable is a stock variable in equation (2.10) and is a count variable in equation (2.12).

## B.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 section 2.1, and I measure the R&D spillovers of firm $i$ at time $t$ as

$$Spill R\&D_{it} = \sum_{j \neq i} \rho_{ij} \times R\&Dstock_{jt}. \qquad \text{(B.11)}$$

The parameter $\rho_{ij}$ 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 $\rho_{ij}$ the technological proximity between firms $i$ and $j$, and he explains that $\rho_{ij}$ is built based on the uncentered correlation coefficient of the location vectors of firms $i$ and $j$ ($S_i$ and $S_j$).[6] For example, the location vector of each firm $i$

[6] The proximity measure of Jaffe (1986) is not directly under the impact of the length of the location vectors, which are dependent on the concentration of firms in research fields. Other forms of proximity measures such as Euclidean distance are highly dependent on the length of the location vector. For

($S_i$) based on the distribution of the share of the firm $i$'s patents across N different technology classes is $S_i = \{s_{i1}, s_{i2}, ..., s_{iN}\}$, where $s_{ik}$ shows firm $i$'s share of patents in the technology class $k$.

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

$$\rho_{ij} = \frac{S_i' S_j}{(S_i' S_i)^{1/2} (S_j' S_j)^{1/2}}. \tag{B.12}$$

The range of $\rho_{ij}$ 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.[7] Noel and Schankerman (2006) suggest using the distribution of the citations in the patents of each firm across N different technology classes for location vectors. This means $s_{ik}$ is the share of all citations in the patents of firm $i$ that belong to a technology class $k$. These citations reflect the benefits that the firm enjoys from the research activity of others in the same technology field, because they exactly show the previous patents that the firm is using in its innovation. Therefore, I follow Noel and Schankerman (2006) and utilize the distribution of citations across 426 different technology classes of the USPTO in the sample of my analysis to build the location vectors. Then, I use the proximity measure in equation (B.12) to calculate the R&D spillovers that firm $i$ receives at time $t$ from other firms based on equation (B.11).[8]

## B.4 Correcting Truncation in Patent and Citation

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

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

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.[9] 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 B.1 displays a comparison of original and corrected patent counts for truncation.

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

example, in a Euclidean distance measure, diversified firms with orthogonal location vectors are counted as close, since they are close to the origin of the coordinate system (Jaffe, 1986).

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

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

[9] 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 B.1: Patents per $R\&D$ with Corrected and Not Corrected Patent Counts.

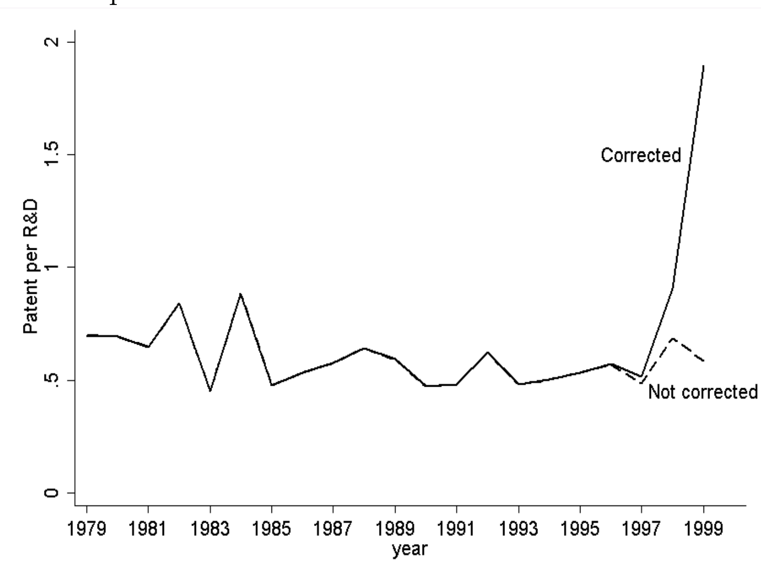
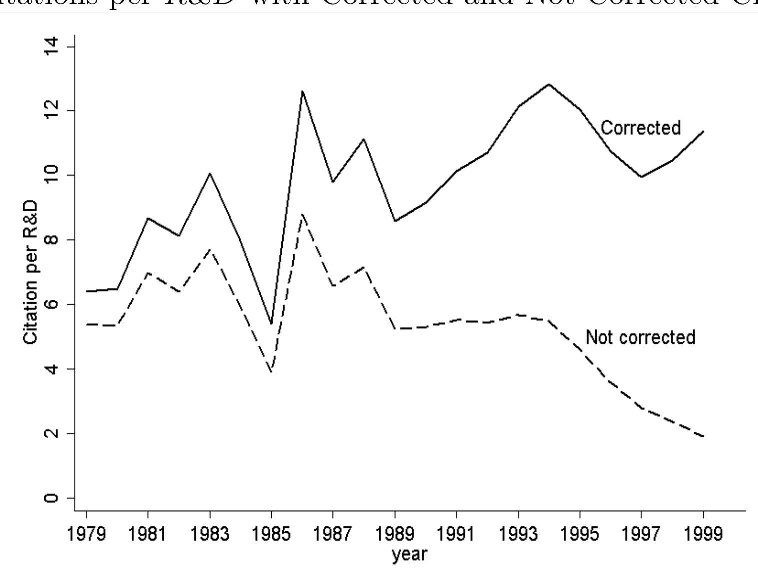



Figure B.2: Citations per $R\&D$ with Corrected and Not Corrected Citation Counts.



# Bibliography

**Allison, Paul.** 2001. *Missing Data.* Vol. 136 of *Quantitative Applications in Social Sciences*, Thousand Oaks, California: Sage Publications, Inc.

**Arellano, Manuel, and Stephen Bond.** 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, 58(2): 277–298.

**Arrow, Kenneth.** 1962. "Economic Welfare and Allocation of Resources to Invention." In *The Rate and Direction of Inventive Activity,* ed. Richard Nelson. Princeton, New Jersey: Princeton University Press.

**Bernstein, Jeffrey, and Ishaq Nadiri.** 1989. "Research and Development and Intra-Industry Spillovers: An Empirical Application of Dynamic Duality." *Review of Economic Studies*, 56(2): 249–267.

**Bloom, Nick, Mark Schankerman, and John Van Reenen.** 2005. "Identifying Technology Spillovers and Product Market Rivalry." *CEPR Discussion Paper 3916.*

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

**Cameron, Colin, and Pravin Trivedi.** 2006. *Microeconometrics: Methods and Applications.* New York, New York: Cambridge University Press.

**Cameron, Colin, Jonah Gelbach, and Douglas Miller.** 2007. "Bootstrap-Based Improvements for Inference with Clustered Errors." National Bureau of Economic Research Technical Working Paper No. 344.

**Chow, Winston.** 1979. "A Look at Various Estimators in Logistic Model in the Presence of Missing Values." In *Proceedings of Business and Economics Section, American Statistical Association*: 417-420.

**Cohen, Wesley, Richard Nelson, and John Walsh.** 2000. "Protecting their Intellectual Assets: Appropriability Conditions and Why US Manufacturing Firms Patent (or Not)." National Bureau of Economic Research Working Paper No. 7552.

**Entezarkheir, Mahdiyeh.** 2010. "Patent Thickets and Market Value: An Empirical Analysis." http://www.economics.uwaterloo.ca/grad/Mahdiyeh-JobCandidate.htm.

**Gallini, Nancy.** 2002. "The Economics of Patents: Lessons from Recent U.S. Patent Reform." *Journal of Economic Perspectives*, 16(2): 131–154.

**Gourieroux, Christian, Alain Montfort, and Alain Trognon.** 1984. "Pseudo Maximum Likelihood Methods: Application to Poisson Models." *Econometrica*, 52(3): 701–720.

**Griliches, Zvi.** 1979. "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics*, 10(1): 92–116.

**Griliches, Zvi.** 1980. "Returns to R&D Expenditures in the Private Sector." In *New Developments in Productivity Measurement* ed. John Kendrick and Beatrice Vaccara. Cambridge, Massachusetts: UMI in National Bureau of Economic Research book series.

**Griliches, Zvi.** 1981. "Market Value, R&D, and Patents." *Economic Letters*, 7(2): 183–187.

**Griliches, Zvi, and Ariel Pakes.** 1980. "Patents and R&D at the Firm Level: A First Look." National Bureau of Economic Research Working Paper No. 561.

**Griliches, Zvi, and Jerry Hausman.** 1984. "Errors in Variables in Panel Data." National Bureau of Economic Research Working Paper Technical Working Paper No. 37.

**Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg.** 2000. "Market Value and Patent Citations: A First Look." National Bureau of Economic Research Working Paper No. 7741.

**Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg.** 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools." National Bureau of Economic Research Working Paper No. 8498.

**Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg.** 2005. "Market Value and Patent Citations." *RAND Journal of Economics*, 36(1): 16–38.

**Hall, Bronwyn, and Jacques Mairesse.** 1995. "Exploring the Relationship Between R&D and Productivity in French Manufacturing Firms." *Journal of Econometrics*, 65(1): 263–293.

**Hall, Bronwyn, and Katrin Vopel.** 1997. "Innovation, Market Share, and Market Value." http://elsa.berkeley.edu/∼bhhall/papers/HallVopel97.pdf.

**Hall, Bronwyn, and Rosemarie Ziedonis.** 2001. "The Patent Paradox Revisited: An Empirical Study of Patenting in the Semiconductor Industry, 1979-1995." *RAND Journal of Economics*, 32(1): 101–128.

**Hall, Bronwyn, Grid Thoma, and Salvatore Torrisi.** 2007. "The Market Value of Patents and R&D: Evidence From European Firms." National Bureau of Economic Research Working Paper No. 13426.

**Hausman, Jerry, Bronwyn Hall, and Zvi Griliches.** 1984. "Econometric Models for Count Data with an Application to the Patents-R&D Relationship." *Econometrica*, 52(4): 909–938.

**Heler, Michael, and Rebecca Eisenberg.** 1998. "Can Patents Deter Innovation? The Anti-commons in Biomedical Research." *Science*, 280(5364): 698–701.

**Hirschey, Mark.** 1985. "Market Structure and Market Value." *Journal of Business*, 58(1): 89–98.

**Jaffe, Adam.** 1986. "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value." *American Economic Review*, 76(5): 984–1001.

**Jaffe, Adam, and Josh Lerner.** 2007. *Innovation and its Discontents: How our Broken Patent System is Endangering Innovation and Progress, and What to do About it.* Princeton, New Jersey: Princeton University Press.

**Jaffe, Adam, and Manuel Trajtenberg.** 1996. "Flows of Knowledge form Universities and Federal Labs: Modeling the Flow of Patent Citations over Time and across Institutional and Geographic Boundaries." National Bureau of Economic Research Working Paper No. 5712.

**Jones, Michael.** 1996. "Indicator and Stratification Methods for Missing Explanatory Variables in Multiple Linear Regression." *Journal of the American Statistical Association*, 91(433): 222–230.

**Lindenberg, Eric, and Stephen Ross.** 1981. "Tobin's q Ratio and Industrial Organization." *Journal of Business*, 54(1): 1–32.

**Little, Roderick.** 1992. "Regression with Missing X's: A Review." *Journal of the American Statistical Association*, 87(420): 1227–1237.

**Little, Roderick, and Donald Rubin.** 2002. *Statistical Analysis with Missing Data.* Hoboken, New Jersey: JohnWiley and Sons.

**Mansfield, Edwin.** 1980. "Basic Research and Productivity Increase in Manufacturing." *American Economic Review*, 70(5): 863–873.

**Manski, Charles.** 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies*, 60(3): 531–542.

**Meador, Daniel.** 1992. "The Origin of the Federal Circuit: A Personal Account." *American University Law Review*, 41(4): 581–620.

**Merges, Robert.** 2001. "Institutions for Intellectual Property Transactions: The Case of Patent Pools." In *Expanding the Boundaries of Intellectual Property: Innovation Policy for the Knowledge Society,* ed. Rochelle Dreyfuss, Diane Zimmerman and Harry First. New York, New York: Oxford University Press.

**Murray, Fiona, and Scott Stern.** 2007. "Do Formal Intellectual Property Rights Hinder the Free Flow of Scientific Knowledge? An Empirical Test of the Anti-commons Hypothesis." *Journal of Economic Behavior and Organization*, 63(4): 648–687.

**Nelson, Richard.** 1959. "The Simple Economics of Basic Scientific Research." *Journal of Political Economy*, 67(3): 297–306.

**Nickell, Stephen.** 1981. "Biases in Dynamic Models with Fixed Effects." *Econometrica*, 49(6): 1417–1426.

**Noel, Michael, and Mark Schankerman.** 2006. "Strategic Patenting and Software Innovation." http://sticerd.lse.ac.uk/dps/ei/EI43.pdf.

**Pakes, Ariel.** 1985. "On Patents, R&D, and the Stock Market Rate of Return." *Journal of Political Economy*, 93(2): 390–409.

**Rigobon, Roberto, and Thomas M. Stoker.** 2001. "Estimation with Censored Regressors: Basic Issues." *International Economic Review*, 48(4): 1441–1466.

**Rubin, Donald.** 1976. "Inferences and Missing Data." *Biometrika*, 63(3): 581–592.

**Schumpeter, Joseph.** 1942. *Capitalism, Socialism and Democracy.* New York, New York: Harper & Brothers.

**Scotchmer, Suzanne.** 1991. "Standing on the Shoulders of Giants: Cumulative Research and the Patent Law." *Journal of Economic Perspective*, 5(1): 29–41.

**Shapiro, Carl.** 2001. "Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard-Setting." In *Innovation Policy and the Economy,* ed. Adam Jaffe, Joshua Lerner, and Scott Stern. Cambridge, Massachusetts: MIT Press.

**Solow, Robert.** 1957. "Technical Change and the Aggregate Production Function." *Review of Economics and Statistics*, 39(3): 312–20.

**Varian, Hal.** 2010. *Intermediate Microeconomics.* New York, New York: W. W. Norton & Company, Inc.

**Ziedonis, Rosemarie.** 2004. "Don't Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms." *Management Science*, 50(6): 804–820.