# INNOVATION, FIRM STRATEGY AND PATENT LITIGATION

by

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## Abstract

This thesis comprises three chapters with the enforcement of intellectual property rights as a central theme. The first chapter explores the effect of patent 'thickets' on litigation propensity. Patent thickets, involve fragmented ownership rights, which lead to the anticommons problem, and unclear property boundaries which lead to uncertainty. I distinguish between these two aspects of patent thickets and argue that an important reason for unclear claims is the increase in technological diversity associated with multi-component technologies. I develop theory that predicts that both ownership fragmentation and technological diversity have a positive causal impact on litigation propensity and that these effects are higher for small firms. Empirical analysis provides evidence for the hypotheses.

In the second chapter, I examine the appropriation hazards inherent in strategic alliances. Adopting a network perspective, I develop and test a theoretical framework that predicts when knowledge appropriation is likely to occur between partners. I show that different types of embeddedness in the network (relational, structural or positional) affect the likelihood that firms will engage in knowledge appropriation and litigious behavior. I also show that, not only is the competitive environment between a firm and its partner relevant (in that firms are more likely to sue each other if they are competitors), but that the competitive environment of all firms in the network affects litigation hazard.

The third chapter investigates whether small firms are at a disadvantage in seeking to enforce patents and whether an aspect of the market for innovation, the trading of patents, helps small firms to overcome difficulties in enforcement. The first part examines whether small firms are more likely to litigate their patents and whether lawsuit durations are greater than large firms, establishing that small firms do incur a disproportionately large burden of cost in protecting their intellectual property. I extend previous work in this area by considering case outcomes and differences across industries. I then examine whether traded patents by small firms to large firms are more likely to be litigated, and find that the market for innovation in the form of patent trades is associated with increased litigation.

## Preface

This thesis is based on datasets obtained from Lex Machina IPLC and from the NBER Patent Data Project. Supplemental data from S&P Capital IQ's Compustat and Thompson's SDC Platinum commercial databases are used in Chapters 2 and 3 respectively. For Chapter 4, I am grateful for data on patent renewals provided by Ed Egan and the data made available on the Patent Network Dataverse, particularly the data pertaining to the paper by Lai, D'Amour, Yu, Sun and Fleming 'Disambiguation and Co-authorship Networks of the U.S. Patent Inventor Database (1975 - 2010)'. I was responsible for the merging of these databases and all empirical analyses presented in this thesis.

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## Acknowledgements

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# Chapter 1: Introduction

## 1.1 The growth in patent litigation and its cost to firms

Firms rely on intellectual property protection to appropriate their investments in research and development. Yet, whilst the patent system is generally regarded as an indispensable mechanism to provide incentives to innovate, recent research on innovation and markets for technology has highlighted aspects of the system that may be undermining these incentives (e.g. Lemley and Shapiro 2007, Bessen and Maskin 2009, Hall and Ziedonis 2001). One characteristic of the patent system which is potentially reducing incentives to innovate is the dramatic recent increase in patent litigation[1] (see Figure 1.1). Patent infringement lawsuits are expensive undertakings for those involved, typically costing over $1 million in legal fees alone (Bessen and Meurer 2008, AIPLA 2011). These costs are even higher when cases go to trial and when accounting for other factors such as losses from the imposition of temporary injunctions (Lanjouw and Lerner 2001); the diversion of management attention (Somaya 2003); difficulties obtaining finance (Bhagat et al 1994); damage to reputation (Lerner 1995); and lost opportunities (Bhagat et al 1994). Litigation is not only costly to those accused of patent infringement but is also costly to those who protect their intellectual property. Legal fees in enforcement, costs associated with monitoring, and the acquisition of defensive patent portfolios to mitigate the risk of retaliatory lawsuits, place a significant burden on firms. In one study, the protection of intellectual property is estimated to typically constitute a third of firms' R&D budgets (Lerner 1995). Recent estimates in the mobile communications industry suggest that $20 billion was spent by firms on defensive patent portfolios and patent litigation between 2010 and 2012; and in 2011 two of the largest firms, Apple Inc. and Google Inc., spent more on patent purchases and litigation than they spent on R&D of new products (The New York Times Oct 18, 2012). The increased prevalence of patent lawsuits and the burden that they are placing on firms is indicative that "patents and patent enforcement strategies have become essential part of a firm's competitive strategies" (Paik and Zhu 2013). The increase in patent litigation and associated strategic behavior are particularly pertinent to small firms since enforcement costs are likely to be disproportionately higher for small firms who lack the resources of larger firms and who may be more reliant on intellectual property for their competitive advantage (Lanjouw and Schankerman 2004, Gallini 2002).

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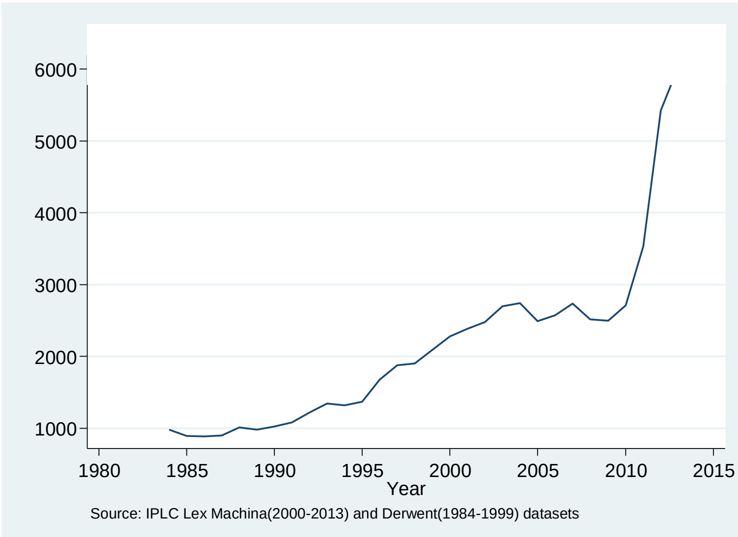
[1] Litigation reduces incentives to innovate by diminishing the private value of innovations (Lanjouw and Schankerman 1998, Scotchmer 2004).

**Figure 1.1 Patent infringement lawsuits filed by year**




This thesis aims to provide improved understanding as to the causes of patent litigation. In the first two essays, I explore core themes that have important implications for litigation propensity: the growth of patent ‘thickets’, firm strategy and the role of inter-organizational alliances. In the third essay I focus specifically on small firms to examine whether small firms have disproportionately greater costs of participation in the patent system.

## 1.2 The changing nature of technological innovation

In the first essay of this thesis, I explore how patent ‘thickets’[2], caused by a changes in technological paradigms, are affecting the propensity of firms to be engaged in patent litigation. I develop theory that predicts that patent thickets increase rates of litigation, distinguishing between the two distinct aspects of thickets: 1) ownership fragmentation which leads to the “tragedy of the anticommons” and 2) the overlapping of claims. I argue that a major cause of the increased uncertainty regarding intellectual property claims is the recent shift from a “discrete” to a “combinative” innovation paradigm. This shift involves a change from local search recombination and extension of familiar technologies to long distance search involving expansion and recombination of technologies outside a firm’s principal technology field.

[2] Patent thickets are described by Shapiro (2001) as a “dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology”

Innovative products are now often complex and modular (Hall et al 2013), consisting of multiple components from a diverse set of technologies, which causes difficulties in establishing claim boundaries. An empirical analysis using data drawn from three separate sources provides support for the hypotheses that both ownership fragmentation and technological diversity aspects of thickets cause litigation and furthermore, that the effect of ownership fragmentation is greater for small firms. These findings have a number of implications for policy which are discussed.

## 1.3 Inter-organizational networks and appropriation

Strategic alliances can provide substantial benefits to firms, facilitating the acquisition of new knowledge and capabilities (Mowery et al 1996). However, by participating in alliances firms induce the risk of knowledge appropriation by partner firms (e.g. Gulati and Singh 1998, Kale et al 2000). This tradeoff between access to new knowledge and the loss of proprietary knowledge through appropriation is the subject of the second essay in this thesis. Since firm outcomes are arguably best understood by appreciating that organizations can be seen as systems of inter-related social behaviors between participants both inside and outside the firm (March and Simon 1958), I adopt a network perspective with an inter-organizational scope. I show that the embeddedness of partner firms within the alliance network affects the likelihood that firms will engage in knowledge appropriation and litigious behavior, but that its effect depends on the type (relational, structural or positional) and relative degree of embeddedness between potential litigants. I also show that the competitive environment of all firms in the network affects litigation hazard, not only the direct competitive environment between partnering firms. Furthermore, I find that network embeddedness and competition are inter-related and that the effect of power imbalances caused by asymmetrical network positions depends on the intensity of competition within alliance portfolios.

## 1.4 Small firms and the patent system

As part of the first essay (Chapter 2) I examine whether the detrimental effects of ownership fragmentation and knowledge diversity, in terms of increased litigation hazard, are stronger for small firms. In the final essay of this thesis I return to the subject of whether small firms are at a disadvantage in the patent system and extend the scope of study to encompass strategic actions in the market for innovation.

Small firms are reliant on strong intellectual property rights to commercialize their inventions. Often lacking the complementary assets required to develop new products and get them to market, small firms rely on intellectual property rights to prevent imitation and to facilitate partnerships that enable them to appropriate their innovations. In this essay, I pursue several objectives. First, following work by Lanjouw and Schankerman (2004), I determine whether small firms are more likely to litigate their patents and whether lawsuit outcomes are different for them. This enables inferences as to the relative cost of patent enforcement to be made, thus evaluating whether small firms are at a disadvantage. Second, the empirical results are assessed with respect to current theoretical perspectives and conclusions drawn as to the degree to which current theory is consistent with the data. Finally, I investigate whether participation in markets for innovation through patent trades, is associated with litigation. It is hoped that the contemporaneous nature of the study can inform current policy debate on small firms and the patent system.

# Chapter 2: Ownership Fragmentation, Technological Diversity and Patent Litigation

## 2.1 Background and synopsis

Historically, most inventions represented discreet distinct progress within a dominant technological area. Such progress typically resulted in a significantly new product or a class of highly related products. To encourage such inventive activity and provide incentives for further refinement of inventions, patents were awarded to protect inventors from appropriation of the benefits of their inventions by others. However, in recent times, technologies have become more sophisticated and complex, with innovations often drawing from more than one technological area and comprising the recombination of existing knowledge elements in new ways, together with the recombination of old elements with newer elements (Fleming 2001).

Initially, the search of new combinations of technologies tended to be local – i.e. innovators recombining a familiar set of technological elements. Over time, as technological opportunities became exhausted (or the search of new combinations became less economically viable), firms have broadened their search horizons outside of their field of technology (Fleming 2001). Innovation processes have shifted from the more certain "exploitation" mode of innovation that relies heavily on existing familiar knowledge into the more uncertain "exploration" mode, searching for opportunities to combine different knowledge sources that often span multiple technological fields, with their promise of higher rewards (March 1991, Fleming 2001, Leiponen and Helfat 2010, Singh and Agrawal 2011, Singh and Fleming 2010). This shift in the nature of innovation, however, is presenting a challenge to the intellectual property protection system on which inventors have relied to be able to appropriate the fruits of their investments in research and development.

Two distinct but related phenomena have emerged as a result of the combinative process of innovation and its increasing reliance on recombination across technological boundaries: (1) the emergence of new modular products that include an increasing number of complimentary elements with highly fragmented ownership of the intellectual property rights of the elements necessary for their commercialization, and (2) the emergence of complex technologies based on a large number of patents typically from numerous different technological areas. The first phenomenon (fragmented ownership) gives rise to the ‘anticommons’ problem (Heller and Eisenberg 1998), whereby agreement from an increasing number of property owners is required to commercialize new technologies. The second has the effect of increasing uncertainty over intellectual property boundaries. Taken together, these phenomena result in patent ‘thickets’, where there exists “a dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology” (Shapiro 2001). Thickets potentially undermine innovation incentives by increasing the cost of intellectual property protection and there is evidence to suggest that they have particularly detrimental effects for small firms and potential entrants (Cockburn and MacGarvie 2009, 2011). However, whilst the presence of patent thickets is increasingly being acknowledged, a number of scholars have challenged whether the fragmentation of property rights and the growth of thickets actually affect incentives to innovate. For example, Shapiro (2001) suggests that the formation of institutional mechanisms such as patent pools and cross-licenses mitigates the effects of fragmentation and Lichtman (2006) argues that that the presence of multiple overlapping rights can lessen the incentives to enforce intellectual property since gains become diluted amongst owners. The questions as to whether increased levels of patenting and litigation are the result of ownership fragmentation and overlapping intellectual property rights, and whether this warrants policy change in the patent system, are central in the critical debate on how to provide efficient incentives for innovation. This study contributes to the debate.

Despite the general contention regarding the causal effects of thickets on innovation incentives, and despite increased litigation activity and the substantial cost that lawsuits place on firms, the effects of ownership fragmentation and the increased overlapping of rights on litigation have yet to be explored. Whilst it has been shown that the fragmentation of property rights results in greater patenting activity (Ziedonis 2004) and that it reduces the time taken for firms to reach ex post settlements (Galasso and Schankerman 2010), the effect of fragmentation on the likelihood that firms will be sued is not known. Whether firms have increased litigation hazards as a result of patent thickets is of critical interest since this suggests that ex ante bargaining is failing and that innovation incentives are being undermined.

Patent thickets are associated with multiple inter-related phenomena and scholars have experienced challenges in operationalizing them in empirical studies (Cockburn and MacGarvie 2009). They are characterized by complexity, complimentarity and dispersed ownership. The density and growth of thickets has been measured using counts of ‘triples’[3] (Graevenitz et al 2011, 2013) and Hall et al 2013 show that, using this measure, certain industries such as telecommunications, audio and visual technology

[3] Patents which cite prior art from two other firms, which in turn have cited each other.

and computer technology have particularly dense patent thickets. I show that key characteristics of thickets, ownership fragmentation and unclear and overlapping claims, can apply across all industries, not just those associated with dense thickets. Moreover, I explore a hitherto neglected aspect of thickets: uncertainty caused by innovative activity that spans multiple technological fields. Thus, I also contribute to the literature that seeks to understand the essence of patent thickets.

In brief, I build on a broad base of existing management, legal and economics literature to develop a theory of how patent thickets impact litigation. I distinguish between two distinct aspects of thickets, ownership fragmentation and increased uncertainty through technological diversity, thus helping to ‘untangle the patent thicket’. I then extend the theory to show how the effects of thickets differ with firm size. I test my hypotheses using a novel, contemporary and highly complete firm level panel dataset. Constructed by combining legal data from Lex Machina’s IPLC database, with patent data from the National Bureau of Economic Research (NBER) and firm data from Compustat, the combined dataset comprises information on almost all public firms for the period 1999-2005 and incorporates all patent infringement lawsuits during the period.

I find that both the fragmentation of ownership rights and knowledge diversity have an economically and statistically significant effect on the number of lawsuits filed against firms. I also find that fragmentation of ownership has a greater effect on small firms. The results are robust to a number of alternative model specifications including models that account for individual firm heterogeneity and industry fixed effects. The results have important implications for patent policy. By showing the impact of the separate effects of thickets on litigation, and by demonstrating its disproportionate effect on small firms, it is hoped that this study may aid policy makers in their efforts to provide an effective intellectual property protection system.

## 2.2 Theory and hypotheses

According to neoclassical economic theory, in a world of no transaction costs and under conditions of perfect information, symmetrical stakes and certainty, legal disputes should not occur. However, when these assumptions are relaxed, for example when allowing for costly monitoring of infringement (Crampes and Langinier 2002); costs to “invent around” infringing patents (Bessen and Meurer 2006); enforcement costs (Meurer 1989, Lanjouw and Schankerman 1998); asymmetrical information (P’ng 1983, Bebchuk 1984, Schweizer 1989, Spier 1992); asymmetrical stakes (Meurer 1989); self-serving biases and perceptions of fairness (Loewenstein et al 1993, Babcock et al 1995); and different expectations of outcomes (Priest and Klein 1984); then it has been shown that that ex ante agreements that avoid litigation may not be in the best interests of one or both of the parties involved.

Ex ante contractual bargaining failure becomes more likely with increased transaction costs (Williamson 1981). In the context of the enforcement of intellectual property, the likelihood of bargaining failure increases when licenses are required from multiple owners to commercialize a new cumulative technology since negotiation with multiple intellectual property owners generates higher overall direct and transaction costs (Coase 1937) and longer bargaining delays (Galasso and Schankerman 2010). Negotiation of each license extorts a cost both in terms of direct financial cost such as through royalty payments and in intangible cost such as through delays in getting products to market. At some point, the number of patent owners is large enough that the total transaction and direct costs associated with all contractual negotiations exceeds the commercial value of the innovation. At this point, downstream innovations are not commercialized, leading to what has been termed 'the tragedy of the anticommons' (Heller and Eisenberg 1998).

The tragedy of the anticommons is the antithesis of Hardin's (1968) tragedy of the commons. Hardin's well known metaphor describes how a lack of property rights can lead to the over-use of a common resource. By contrast, in the anticommons perspective, too many property rights to exclude can lead to the under use of a common resource, causing a sub-optimal social outcome (Heller 1998). One example of the tragedy of the anticommons is the adversity in starting new businesses when approval from multiple stakeholders is needed (Buchanan and Yoon 2000).

In the application of anticommons theory to intellectual property, the proliferation of upstream property rights in the form of patents stifles downstream cumulative innovations (Heller and Eisenberg 1998). This is closely related to Shapiro's (2001) notion of patent thickets and also to 'royalty stacking', where "a single product potentially infringes on many patents and thus may bear multiple royalty burdens" (Lemley and Shapiro 2007). Both of these concepts are related to the proliferation of patents in general and an increase in the number of owners of intellectual property. These entwined concepts have been defined differently in extant literature causing a lack of clarity in theoretical conceptualization. For example, Shapiro (2001) and Burk and Lemley (2003) refer to thickets as the "overlap of existing rights" whereby Galasso and Schankerman (2010) and Ziedonis (2004) refer to thickets in terms of the "fragmentation of patent rights" and "fragmentary patent owners" respectively. Are thickets primarily a result of increased numbers of owners or are they a result of a proliferation of overlapping rights?

In this chapter, I follow the original definition of thickets by Shapiro (2001) and distinguish between ownership fragmentation and overlapping claims. This distinction matters since the implications of each concept to patent policy differ. The occurrence of overlapping claims implies that patent law should ensure the clearance of these overlapping rights (for instance by narrowing them so that overlapping scope does not arise in the first instance) whereas the solution to the anticommons is to consolidate rights to reduce the number of owners or to issue fewer, broader patents (Burk and Lemley 2003).

### 2.2.1 Litigation and the fragmentation of ownership – the anticommons

The anticommons problem increases litigation hazard through two principal mechanisms. First, as previously discussed, transaction costs associated with licensing existing technology are higher when there are more owners of the rights of that existing technology. When transaction costs associated with licensing existing technology in order to commercialize a new cumulative technology exceed the value of the new technology, markets for technology fail and firms are faced with two main options: they either switch R&D resources to other projects or they proceed at a risk of litigation. Furthermore, with many owners, cooperative agreements such as patent pools become harder to form as negotiations become complex and the likelihood that a cooperative agreement will be in the best interests of all diminishes since each have the option to opt out of the pool and assert its patents separately (Lemley and Shapiro 2007). Second, when licenses from multiple owners that each have blocking patents (i.e. those which cannot be invented around or where the costs to do so are prohibitively high) are required, the total cost of licensing exceeds the optimal cost associated with an efficient market for technology. Each owner of the downstream technology seeks to extract a disproportionately high share of future profits through their license, leading to a 'royalty stacking' effect (Lemley and Shapiro 2007). This is analogous to the Cournot 'complements problem' (Cournot 1838) in which multiple input owners charge more than the marginal cost for their product which increases the final cost of the downstream product and reduces the number of units sold. This occurs when inputs are complements such as when multiple blocking patents need to be licensed for a new product. In Cournot's model at the limit where there are a 'large' number of input owners, no units are produced. In the application to intellectual property, markets for technology fail and innovations do not reach consumers.

Although royalty stacking and high transaction costs associated with large numbers of intellectual property owners may discourage firms from innovating in the first place they do have another option: to proceed at risk of patent infringement litigation. Since patents are probabilistic (Lemley and Shapiro 2004), with significant uncertainty associated with litigation outcomes, firms may choose to proceed to market with their innovations even if firms have not managed to secure all licensing agreements. Firms may gamble that infringement may not be detected (Crampes and Langinier 2002). They may rely on defensive strategies such as the filing of counter-suits that challenge the validity of the patent or that allege infringement of the litigating party themselves. Hence, where royalty stacking and high transaction costs result in the failure of markets for technology, firms are more likely to be the subject of litigation.

*Hypothesis 2.1 – The fragmentation of intellectual property rights causes an increased propensity for the firm to be the subject of litigation*

### 2.2.2 Knowledge diversity, overlapping and uncertain claims

Shapiro (2001: 120) observed that the patent system has created "a patent thicket: an overlapping set of patent rights requiring that those seeking to commercialize new technology obtain licenses from multiple patentees." His focus was on the notion of cumulative innovation that characterizes the design of new complex products. I argue that the shift from local search recombination and extension of familiar technologies to long distance search involving expansion and recombination of technologies outside a firm's technology field has created a "thornier" patent thicket problem. The increases in technology diversity in complex product innovation have not only exacerbated the anticommons problem described in the previous section increasing the occurrence of hold up, transaction costs, and royalty stacking, but also have increased the uncertainty of claim boundaries and the danger of inadvertent infringement on patents issued before and after new complex products are designed.

Increases in overlapping claims and uncertainty about claim boundaries (patent scope) arising as a consequence of technology diversity in complex products (i.e. products based on multiple patents, typically from diverse technological fields) are due to a variety of reasons including (1) bounded rationality of innovators and uncertainties inherent in differences between cultures and languages of different technology communities; (2) different interpretations and applications of legal standards and doctrines concerning judicial decisions with respect to alleged patent infringements; and (3) the high pace of innovation in technology-diverse fields.

#### 2.2.2.1 Bounded rationality and cultural / language differences between technological communities

The recent shift from a "discrete" to a "combinative" innovation paradigm has created complex products (Fleming and Sorenson 2001) consisting of numerous modular components often with partial or complete overlap in functionality of components and the patents protecting them. Bounded search and information processing capabilities of innovating firms make it almost impossible to identify all relevant technologies and consequent threats of hold-up, even if due diligence has been done when designing these complex products (Hall et al. 2012). The sheer number of possible patents that must be evaluated and the costly process of finding whether the new product might infringe on any of them, makes a 'fool proof' search impractical and prohibitively expensive.

The rapid increases in technological sophistication and in the rates of technology change and the wide expansion in the domains of technology applications has been accompanied by increased specialization of innovators and more generally the fragmentation of knowledge production and application. As a consequence, semi-autonomous innovator communities have emerged with their own professional networks, cultures, languages, assumptions and practices. Knowledge that "occurs in the distributed communities through the conscious and unconscious acts of social interaction" is an important input into the innovative process (Amin and Cohendet 2004). However, the meaning of scientific and technical terms used to describe claims of patents can differ significantly among these isolated technology communities and even "change significantly over the life of a patent" (Menell et al. 2010). Furthermore, terms of degree such as 'about', 'approximately' and 'essentially' which are important in describing patent claims and specifications within each community also vary by industry (Menell et al. 2010).

The ambiguity of language within a technology field can be often resolved through the application of accepted conventions and common knowledge. However, in complex innovations that draw from multiple technologies, descriptive terms and conventions may have different interpretations and applications across technological fields. This inherent limitation of language in cross-disciplinary communications creates uncertainty in compliance with existing intellectual property rights. Thus, achieving clarity vis-à-vis property boundaries when distant technologies are concerned is difficult.

#### 2.2.2.2 Differences in judicial application of legal standards and doctrines among industries

The shift in the innovation paradigm in the past two decades and the consequent increases in the economic importance of complex products containing diverse technologies has presented the patent system with great challenges. Evolving differences in the nature and dynamics of innovation processes among industries arguably requires adaptation of the patent system to accommodate them. Burk and Lemley (2003) observed that ‘a one size fits all’, undifferentiated intellectual property protection system does not meet the complex needs of the modern era and that as a result, different rules and doctrines are applied by judges dealing with cases related to patenting innovations in different industries.

The evolution of a differentiated application of patent law based on industry specific precedent has had a counter-productive impact on the clarity of claims particularly when innovations relate to more than one separate field of technology. Misperceptions of patent practitioners about standards of innovativeness required and scope of patents granted in other fields of technology have led to a proliferation of overlapping claims. “Patent practitioners often focus on a single technology area and take courts’ rules in that area for granted” irrespective of the field of technology they deal with (Burk and Lemley 2003). Not surprisingly, advice and actions of patent practitioners (e.g. patent examiners) working in a technology field with less stringent standards of innovativeness and more stringent constraints on the scope of patents are likely to increase the incidence of overlapping claims when evaluating infringements of patents granted in a field characterized by stringent innovation requirements but with lax constraints on the breadth of patents’ scope. Consider, for example, differences in the treatment of innovation in the field of biotechnology and computer programming. The Federal Circuit Court in the U.S. has tended to have a low non-obviousness standard in biotechnology inventions, the requirement that to be patentable, an innovation must be a non-obvious extension of prior art to ‘a person having ordinary skills in the art’ (PHOSITA). On the other hand, the court has imposed stringent requirements on disclosing the best means to recreate the invention and its claims . Such requirements have served to constrain the scope of patents in this industry. In contrast, the computer software industry has relatively high non-obviousness standards and a low disclosure requirement (Burke and Lemley 2003). Patent examiners and practitioners in biotechnology evaluating a multi-component innovation that includes some software components of a previously protected software innovation are likely to arrive at different conclusions with respect to the definition of claim boundaries than those in computer software. There is therefore considerable uncertainty in technologies, such as next generation DNA sequencing, which span both of these technology fields. Lawsuits such as Resonant Sensors Inc et al v Sru Biosystems Inc[4], in which thirty-one different patents were asserted in the case, covering six different technological fields (including such diverse fields as optics, biotechnology, instruments and software) are indicative of the high degree of uncertainty associated with complex, cross-industry technologies.

#### 2.2.2.3 The high pace of innovation in technology-diverse fields

Industries characterized by high knowledge diversity tend to be fast-changing and market information is often unavailable or incomplete (Bourgeois and Eisenhardt 1988). Innovations by firms in this type of environment are often motivated by common problems and opportunities. The lack of complete knowledge concerning other firms' innovation activities makes it more likely that firms will infringe on each other's intellectual property and make similar innovations more likely to occur independently by different firms in different industries. Burke and Lemley (2003), for example, in their commentary on the semiconductor business, note that "because many different companies are attempting to do the same thing… at about the same time, they will often obtain patents on similar inventions with overlapping claims."

This situation is compounded by the relatively high numbers of "submarine" patents in high velocity industries (Shapiro 2001). Submarine patents are patents whose grant and publication are intentionally delayed; so that once they emerge they surprise the market, creating opportunities for hold-up. Further incentives exist for innovators to hide technologies within the patenting registration process, such as the strategic advantages that result from delaying disclosure of patent specification that enable competitors to invent around them. As described earlier in this section, within specialized technology focused communities information flows rapidly so competitors may discover relevant information about submarine patents early on in the patenting process. However, firms in knowledge diverse environments are more likely to be outside specialized technology communities. Thus, they are less likely to have access to information that is exchanged within communities and may invest in developing technology components that will be deemed to infringe on submarine patents[5].

In summary, the bounded rationality of innovators and uncertainties inherent in differences between technology cultures and languages undermine efforts by innovators of multi-component diverse

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[4] Civil case no. 3:08-cv-01978-M (Tex. 2008).
[5] It should, however, be noted that initiating submarine patents has become more difficult since the requirement for pre-grant publication for all patent applications from November 19, 2000.

technologies to avoid infringement. The evolution of technology differentiated application of the patent law vis-à-vis standards of innovativeness required for issuing patents and decisions about the scope of claims granted to such innovations has increased uncertainty about the legitimacy of patents issued and the boundaries of their claims. The high pace of innovation which is characteristic to multi component technologically diverse industries has increased the probability that similar inventions are created independently by firms in the same and different industries. All of the above characteristics of knowledge diverse innovation regimes lead to overlapping claims and hence the probability that a firm's innovations infringe on prior art in such environments is increased.

*Hypothesis 2.2 – Firms that innovate using highly knowledge diverse information sources have an increased propensity of being the subject of litigation.*

### 2.2.3 Firm size, knowledge diversity and the fragmentation of ownership rights

Despite significant interest and numerous popular accounts in the affirmative, the question as to whether the burden of litigation falls disproportionately on small firms has received only limited attention in scholarly work. Smaller public firms, defined as those with less than 500 employees, are four times more likely per patent and six times more likely per R&D dollar to be sued for patent infringement (Bessen and Meurer 2005). Lanjouw and Lerner (2001) show that they are often the target of injunction threats by large firms seeking to impose financial stress. This section of the essay examines whether small firms have other sources of disadvantage that are associated with the anticommons problem and thickets in intellectual property.

Patent protection is particularly important to smaller firms since they often lack complementary assets (Arora and Ceccagnoli 2006) and small firms differ significantly from large firms in their attitudes to intellectual property protection. For example, Hall and Ziedonis (2001) find that in the semi-conductor business, large firms tend to be vertically integrated and engage in the cross-licensing of their intellectual property, whereas small firms tend to be litigious and exclusionary towards other industry members. This suggests that small firms may be unable or unwilling to enter into collaborative ex ante agreements that avoid litigation. Several characteristics of small firms suggest that they are less likely to form collaborative agreements that mitigate the problems of the fragmentation of intellectual property rights and the overlapping of claims.

First, smaller firms tend to have smaller patent portfolios and as a result pose less of a retaliatory threat to litigation (Meurer and Bessen 2005) and have less to offer in any cross-licensing agreements (Lanjouw and Schankerman 2004). Smaller portfolios result in higher licensing costs due to the effects of "balancing costs" (Cockburn, MacGarvie and Muller 2010). Higher licensing costs resulting from smaller portfolios are compounded with royalty stacking effects when there are multiple owners of intellectual property that a firm must seek agreement with.

Second, small firms have fewer financial, legal and managerial resources both to fight lawsuits, negotiate ex ante licenses and to search for overlapping technologies. Large corporations have lower costs of litigation through economies of scale (Lanjouw and Schankerman 2004) and have substantial legal departments with greater resources for negotiating licenses on a case-by-case basis (Heller and Eisenberg 1998). In contrast, smaller firms have resource constraints associated with negotiating ex ante licenses and the effect of these constraints intensifies as the number of required licenses increases (i.e. as ownership rights become more fragmented).

The resource limitations of small firms also apply to the search for technologies with overlapping claims, such as the investigation of prior art at the time of the patent applications. Large firms are better equipped to conduct thorough investigations of adjacent intellectual property and are likely to take more care to accurately delineate claims, especially since they tend to have higher capital investments and are thus more vulnerable to ex post hold-up (Ziedonis 2004). In knowledge diverse environments, these resource limitations are particularly acute as multiple industries must be investigated, requiring significant resources to be employed to search a relatively wide technological area.

Hence, due to portfolio size effects and limitations in financial, legal and managerial resources, the effect of the fragmentation of intellectual property rights and knowledge diversity on firm litigation hazard is predicted to be greater for small firms.

*Hypothesis 2.3 – The effects of fragmentation of intellectual property rights and knowledge diversity are moderated by firm size, such that ceteris paribus, the effects of the fragmentation (Hypothesis 2.3a) and knowledge diversity (Hypothesis 2.3b) on litigation hazard are greater for smaller firms.*

## 2.3 Empirical analysis

This research focuses on two distinct aspects of thickets, the fragmentation of ownership and the overlapping of claims resulting from technological diversity. In order to operationalize these concepts, data that captures both a firm's reliance on previous technologies and its obligations to current owners of overlapping technology is required. I use the citation characteristics of a firm's patent portfolio to derive these measures since patent infringement lawsuits are directly related to the intellectual property assets that firms possess and the technological antecedents of that intellectual property. Patent citations embody significant information about knowledge dependencies (Jaffe 2000), indicating the range of prior knowledge that a new innovation draws upon (Schildt et al 2012) and the other organizations that may need to be approached as licensors of prior cumulative technology (Ziedonis 2004). Moreover, patent based measures enable comparison with previous studies (e.g., Galasso and Schankerman 2010).

The hypotheses predict that ownership fragmentation and technological diversity increase the propensity of firms to be the subject of patent infringement litigation and that these effects are greater for smaller firms. Thus, litigation data on firms as well as patent data is required to test the hypotheses. Furthermore, in order to control for individual firm heterogeneity, information on important firm characteristics such as firm revenue and capital intensity needs to be incorporated into the analysis. To meet these data requirements I compile a unique dataset that draws from three separate sources: legal data from Lex Machina's IPLC database which contains information on all patent infringement cases from 2000 to present, data from Capital IQ's Compustat database which provides financial variables and key firm characteristics such as firm size, and patent data from the National Bureau of Economic Research (NBER) Patent Project.

This empirical analysis offers a number of improvements on extant research. First, in contrast to most previous studies that have tended to focus on the patent or the legal dispute as the unit of analysis, a firm-level approach is used, which allows a better understanding of the firm characteristics that have a causal effect on litigation hazard. Second, the Lex Machina legal data provides information on all patent infringement cases within the sample period. Other legal databases that have been used in prior research have tended to be reliant on the registration of lawsuits at the US Patent and Trademark Office (USPTO) which typically only constitute 60% of all cases. Finally, the analysis is not limited to a single industry, allowing for comparisons of key variables and parameters across industries and the confidence to generalize conclusions across industries without the context specific caveats required for single industry analysis.

### 2.3.1 Sample

The sample of firms used in the analysis is the 3408 publically traded firms that are listed in the National Bureau of Economic Research (NBER) Patent Project datasets and that have positive matches to patent data within the period 1999 to 2005. I selected this sample since this set of firms constitutes the vast majority of publically listed firms during the data period. This limits concerns over any sample selection bias and enables data on a relatively large range of variables to be gathered. In order to ensure that corporate entities are followed throughout the data period, firms were tracked through various types of re-organization and changes in security references. Duplicate results, such as multiple listings of consolidated subsidiaries and parent companies, were eliminated.

I selected a data period of 1999 to 2005 for the analysis which provided a contemporaneous window within the recent trend of high litigation levels and ensured that a high complement of patent and other firm variables could be accessed. For each sample firm I collected financial information from Compustat for each year within the data period. All financial variables are converted to 2005 US dollars to ensure equivalence throughout the sample. This was supplemented by time invariant data such as six digit NAICS industry codes from the same source. I then collected patent data for each firm from the NBER patent data project, compiling detailed records of each firm's patent portfolio for each year. These records contained information on the number of patents, forward citations, backward and claims, as well as the list of patent numbers in each firm's portfolio. To develop this data further, I matched patent numbers to cited patent numbers and then matched the cited patents to patent owners and to the technology classes that the cited patents were assigned by the USPTO. Thus the data on the firms includes information on the distribution of the owners of cited patents and the distribution of cited technology classes. Finally, the Lex Machina IPLC legal data, which contains information on all patent infringement cases from 2000 to present, was incorporated into the dataset, with counts of lawsuits against firms for each firm year observation being added. The Lex Machina data identifies all parties in each lawsuit and distinguishes between patent infringement lawsuits where the patent holder is the plaintiff (claimant) and declaratory lawsuits, whereby the patent holder is the defendant in a claim of invalidity, infringement or unenforceability. Only patent infringement lawsuits are retained in the analysis and thus litigation counts exclude instances where firms file counter lawsuits for patent invalidity.

The final (unbalanced) panel consisted of 3408 firms and 15385 observations. The main variables used in the empirical analysis are described below.

### 2.3.2 Dependent variable

In this study, the dependent variable $NCASES_{it}$ is defined as the number of patent infringement lawsuits instigated against firm *i* in year *t*.

### 2.3.3 Independent variables

Following Ziedonis (2004) and Noel and Schankerman (2013), a firm specific, time varying fragmentation index is used to measure the fragmentation of ownership. $FRAG_{it}$ is the fragmentation of firm *i* in year *t* and is defined as

$$FRAG_{it} = 1 - \sum_{j=1}^{J} \left( \frac{NBCITES_{ijt}}{NBCITES_{it}} \right)^2, \qquad i \neq j,$$

Where *j* is each firm in the set of firms with patents cited within firm *i*'s patent portfolio. Since litigation tends to occur during the first few years after patents are issued (Allison et al 2003), patents obtained within the past three years are used in the analysis. $NBCITES_i$ refers to the total number of back citations in the portfolio and $NBCITES_{ij}$ is the number of citations where firm *i* cites firm *j*. Again, in accordance with previous studies, only citations to *patents* of other firms are included in the analysis. For an illustration of how the index is calculated, consider a firm with 10 patents that has an equal distribution of 100 citations to 4 different firms. This firm has a fragmentation index of 0.75, whereas if the same firm has 10 patents with 50 citations to each of 2 firms, the fragmentation index is 0.50. Similarly, in the case where the same number of patents and citations cite 100 different entities, the fragmentation index is 0.99.

As in previous studies (Hall 2005, Ziedonis 2004, Galasso and Schankerman 2010), the index is adjusted to account for bias in Herfindahl based measures for firms with few patents by multiplying the index by $\frac{NBCITES_i}{(NBCITES_i)-1}$.

Whilst the Ziedonis fragmentation measure does capture the anticommons dimension of thickets it does not identify the "web of overlapping rights" (Hall et al 2012). I derive a new measure that captures the effects overlapping rights caused by the multiplicity of technologies which now characterizes innovation. Using the distribution of USPTO technical classes of the patents cited in the firm's portfolio, I construct a Herfindahl based measure of knowledge that represents the extent to which the knowledge that a firm relies upon to innovate is diversified. Since patent back citations reveal some of the technological antecedents (Ziedonis 2004), the number of technical areas of cited patents reflects the breadth of knowledge "flows" into the organization (Jaffe and Trajtenberg 2002). Firms in high knowledge diversity environments will cite patents in a wide range of technological fields. The measure is, in effect, similar to Trajtenberg, Jaffe and Henderson's (1997) "generality" measure that has been applied to individual patents. However, I extend this measure to cover the firm's entire patent portfolio, thus forming a time varying, firm level construct that captures the theoretical prediction of Hypothesis 2.2. The measure of knowledge diversity is thus as follows:

$$KNOW_{it} = 1 - \sum_{c=1}^{C} {S_{ijt}}^2$$

Where $S_{ijt}$ denotes the fraction of citations from patent portfolio of firm that belong to patent class $j$, out of $C$ patent classes (Jaffe and Trajtenberg 2002). As with the fragmentation index, a similar correction was made to account for bias associated with Herfindahl-based measures.

In order to ensure robustness of any results, an alternative analysis was undertaken using a different, more conventional measure of technological complexity and diversity. Patents have become increasingly complex over the past 40 years and one such indicator of this increased complexity is the increase in the average number of claims in a patent (Allison and Lemley 2002). Claims delineate the boundaries of the intellectual property embodied in a patent and distinguish it from prior art and complex technologies require extensive patent refinement which is seen in a relatively high number of claims in patent applications (Meurer and Bessen 2005). Thus the more complex a technology and the greater the number of technological areas that form technological antecedents, the greater the number of claims required in the patent documentation. This alternative measure is therefore constructed by taking the number of claims contained in the patents of a firm's portfolio, normalized by the number of patents in that portfolio.

### 2.3.4 Control variables

The following control variables are used in the analysis:

*Patents_ln*. The size of the firm's patent portfolio, measured as the logarithm of the number of patents. A control for the size of a firm's patent portfolio an important requirement as it has been found to affect litigation hazard (Bessen and Meurer 2005) and it is likely to be correlated with both fragmentation and the number of technological classes cited.

*Employment_ln.* Firm size, measured as the log of the employment (in thousands)

*Fwdcitations/patents.* Higher quality patents are more likely to be litigated (Allison et al 2003) and firms with more valuable intellectual property, as measured by the number of forward citations, are more likely to be the subject of lawsuits (Bessen and Meurer 2005). The number of forward citations (other firms citing patents from the firm's portfolio) is therefore included as a variable in the analysis. The measure is normalized by the number of patents in the portfolio and is adjusted for truncation (newer patents tend to have fewer forward citations).

*Bwdcitations/patents.* Both of the main explanatory variables, FRAG and KNOW, are positively correlated with the number of back citations. Firms with higher rates of citing prior art will tend to have higher values fragmentation and knowledge diversity and to ensure that these key variables are not simply acting as proxies for patenting and citation rates, a control for the average number of back citations in a firm's portfolio is included. In order to match this control variable closely to the independent variables, the measure was calculated on the firm's patent portfolio comprising patents issued over the past 3 years.

Total assets (*Assets*), earnings before interest, tax, dividends and amortization (*Earnings*) and revenue (*Revenue*) are included to reflect firm financial characteristics that may affect litigation risk. These variables are measured in $billion.

*Capintensity_ln.* Capital intensity, defined as the log of the value of the firm's plant, property and equipment (in 2005 $million), normalized by the number of employees (in thousands).

*Time fixed effects*. Annual time dummies to account for the general increase in litigation over the sample period. Note that these are omitted from the results output for brevity.

*MISS.* As demonstrated by Ziedonis (2004), omitting missing observations of the main explanatory variables, such as the fragmentation index, can generate a sample with a higher proportion of larger firms that obtain more patents. To avoid restricting the sample and losing observations relating to firms with low patenting activity, dummy variables (MISS) for missing fragmentation and missing knowledge diversity  are included, following the approach of previous studies (e.g. Galasso and Schankerman 2010, Ziedonis 2004).

### 2.3.5 Methodology

Since the dependent variable is an event count, a Poisson or Negative Binomial model is the appropriate specification for the analysis. It can be seen from Table 1 that the variance of the cases count is greater than the mean indicating the presence of overdispersion (a Poisson model assumes that the variance is equal to the mean). A Lagrange multiplier test (Greene 2012) confirms the presence of overdispersion and hence a Negative Binomial specification rather than a Poisson model is used. Further inspection of the distribution of the dependent variable indicates an excess of zeros. A common means of adjusting for an excess of zeros is to use a zero inflation model which supplements the count density with a binary process which models whether the count is zero. A zero outcome can occur either through the negative binomial process or the binary process. A Vuong (1989) test which compares the fit of a zero inflated negative binomial (ZINB) model to that of a Negative Binomial (NB) model without the inflation process gives a large, positive test statistic (z= 6.94, p-value= 0.0000) confirming that the ZINB model is preferred .

It is worth noting that there are a number of theoretical reasons why an excess of zeros are observed the data and why this should be taken into account using a dual process specification. For example, firms may choose to avoid commercializing technologies where property rights are uncertain, particularly if they risk inviting the wrath of an aggressive or powerful litigator.

Appendix A presents the conditional probabilities associated with the zero inflated negative binomial specification and outlines the assumed probability form of the negative binomial process.

### 2.3.6 Endogeneity and robustness tests

Litigation rates vary substantially across industries and much of the recent rise in patent infringement lawsuits is associated with the Information Communications Technology (ICT) sector which has seen high rates of patenting activity over the past 30 years. Other industries such as the pharmaceutical industry and the sector associated with electric components and devices have also seen increases in the number of patent lawsuits. One alternative explanation to the effect of thickets on litigation is that there exist particular environmental conditions (e.g. a high level of technological opportunity, a culture of aggressive litigious behavior) within industries that lead to high rates of litigation. I control for this by using unconditional industry fixed effects in the modeling. Classification is achieved by grouping firms into 11 industry areas using NAICS 6-digit code assignments.

One possible source of endogeneity in the model is through reverse causality. It is possible that firms change their patenting behavior in response to patent infringement lawsuits that are filed against them. They may, for instance, decide to be more careful in their citation of prior art, or conversely, they may strategically cite less in the hope that potentially overlapping claims go unnoticed[6]. This potential simultaneity is accounted for by lagging the independent variables from the dependent variable in the analysis. There can be autocorrelation following the lagging of the explanatory variables, however further econometric analysis suggests that this is not likely to be a major problem. For example, clustering standard errors to account for possible autocorrelation caused no significant change to the results. For example, re-running the logit model (2.6) in Table 2.5 results in the significance of all explanatory variables being maintained. The use of GMM estimators in this case is limited by the derth of appropriate instruments.

A number of scholars have highlighted further examples of strategic patenting (e.g. Lampe 2011). If this strategic behavior tends to occur when in scenarios of high fragmentation of ownership rights and technological complexity the coefficients on the main explanatory variables are likely to be biased. This endogeneity associated with individual firm heterogeneity is accounted for in two ways. First, a control variable for the average number of back citations in a firm's portfolio is included. This captures the tendency for some firms to undercite in their patent applications. Second, a robustness check that includes individual firm effects is carried out. One option is to use *fixed* effects estimators. However, the use of *fixed* effects estimators causes the 'incidental parameters' problem (Greene 2007, Allison and Waterman 2002) which gives inconsistent results, particularly in short panels where the effect can be large. To avoid this, a random effects model can be used. A random effects model is considered to be most appropriate since it is more efficient and has the advantage of computing all time invariant effects[7].

A number of further robustness tests are carried out. First, in order to investigate whether sample selection associated with omitting missing values of fragmentation index and knowledge diversity measure is likely to be a concern, the analysis is repeated removing these observations. Second, a probabilistic model is run

[6] There is however, little evidence of this practice presumably because firms risk incurring serious ex-post penalties for failing cite relevant prior art.
[7] Note though that random effects models can be inconsistent if fixed effects are present, causing bias if there is correlation with explanatory variables. A Hausman test, which tests the hypothesis that the parameters from the fixed effects analysis are significantly different from the parameters from the random effects analysis, is typically carried out to test for possible inconsistency (Greene 2012). However, it is not possible to carry out a Hausman test in this case, since in a fixed effects analysis over 80% of the observations are lost through having all zero outcomes or only one observation per group.

where the dependent variable takes on the value of 1 if the firm is the subject of one or more lawsuits in a given year and 0 otherwise.

## 2.4 Results

Tables 2.1 and 2.2 display descriptive statistics and correlations respectively for each of the variables described in the previous section. The maximum number of new patent infringement cases for any one firm in any given year is 16. A review of the correlations between the independent variables indicates that multi-colinearity is generally not a cause for concern. The correlation of 0.31 between fragmentation and technological diversity is not excessively high and excluding either variable does not substantially change the results. Furthermore, likelihood ratio tests for hierarchical inclusion of each variable indicate that both significantly improve the fit of the model at the 5% significance level. The model is therefore able to discern the separate effects of both fragmentation and technological diversity despite the moderate correlation between the two variables.

**Table 2.1 Descriptive statistics**

| Variable | Mean | Std. Dev. | Median | Min | Max |
|---|---|---|---|---|---|
| Cases | 0.112 | 0.530 | 0 | 0 | 16 |
| FRAG | 0.835 | 0.194 | 0.828 | 0 | 1 |
| KNOW | 0.697 | 0.221 | 0.690 | 0 | 1 |
| Patents_ln | 2.820 | 2.134 | 2.484 | 0 | 10.6 |
| Employment_ln | 0.288 | 2.222 | -0.182 | -6.90 | 7.5 |
| Fwdcitations/patents | 21.24 | 27.07 | 13.40 | 0 | 807.2 |
| Bwdcitations/patents | 8.58 | 3.69 | 8.58 | 0.13 | 301.19 |
| Capintensity_ln | 4.612 | 1.046 | 4.349 | -.833 | 11.7 |
| Assets($Bn) | 5.984 | 35.48 | 0.342 | .00005 | 1566 |
| Earnings($Bn) | 0.657 | 2.721 | 0.019 | -6.311 | 59.2 |
| Revenue($Bn) | 3.948 | 15.50 | 0.171 | -0.023 | 328.2 |

**Table 2.2 Correlation matrix**

| | Cases | FRAG | KNOW | Patents_ln | Emp_ln | Fcitns/pts | Bcitns/pts | Capint_ln | Assets | Earnings | Revenue |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Cases | 1.0000 | | | | | | | | | | |
| FRAG | 0.0431 | 1.0000 | | | | | | | | | |
| KNOW | 0.0808 | 0.3130 | 1.0000 | | | | | | | | |
| Patents_ln | 0.1246 | 0.0330 | 0.1706 | 1.0000 | | | | | | | |
| Emp_ln | 0.0820 | 0.0336 | 0.1172 | 0.3879 | 1.0000 | | | | | | |
| Fcitns/pts | 0.0288 | 0.0688 | 0.0197 | -0.0347 | -0.0403 | 1.0000 | | | | | |
| Bcitns/pts | 0.0206 | 0.1518 | 0.0307 | -0.0181 | -0.0395 | 0.2159 | 1.0000 | | | | |
| Capint_ln | 0.0090 | 0.0307 | 0.0982 | 0.1133 | 0.0329 | -0.0973 | -0.0167 | 1.0000 | | | |
| Assets | 0.0496 | 0.0051 | 0.0808 | 0.3315 | 0.3932 | -0.0216 | -0.0224 | 0.1449 | 1.0000 | | |
| Earnings | 0.1173 | 0.0358 | 0.1201 | 0.4154 | 0.5495 | -0.0411 | -0.0245 | 0.2703 | 0.6942 | 1.0000 | |
| Revenue | 0.0959 | 0.0326 | 0.1359 | 0.4545 | 0.7028 | -0.0553 | -0.0312 | 0.2097 | 0.6138 | 0.8470 | 1.0000 |

Table 2.3 presents means of key variables by industry. Average rates of litigation vary greatly by industry. For example, firms in the computer industry have a mean litigation count of over five times that of firms in machinery and equipment manufacture. The computer industry is also characterized by the highest average number of patents per firm (1247.9 per firm) and relatively large firm sizes. The pharmaceutical industry, perhaps surprisingly, has a relatively low average number of annual cases per firm (0.072) suggesting that many pharmaceutical firms are the subject of little or no litigation or that a high number of the pharmaceutical firms that are sued are privately owned and thus do not appear in the sample. The average annual case rate for wholesale and retail is also worthy of note with a relatively high value of 0.198.

**Table 2.3 Means of key variables by industry**

| Industry | Cases | FRAG | KNOW | Patents | Employment (1000s) | Fwdcitations /patents |
|---|---|---|---|---|---|---|
| Pharmaceuticals | 0.072 | .806 | .633 | 187.9 | 3.2 | 12.8 |
| Machinery & equipment | 0.099 | .830 | .732 | 410.1 | 12.9 | 17.9 |
| Computers | 0.509 | .874 | .727 | 1247.9 | 14.3 | 30.2 |
| Software | 0.193 | .848 | .702 | 41.8 | 1.8 | 44.5 |
| Semiconductors/electronic components | 0.128 | .897 | .741 | 390.3 | 6.0 | 22.2 |
| Instruments | 0.104 | .847 | .697 | 152.9 | 2.9 | 24.1 |
| Electrical/electronic equipment | 0.117 | .860 | .708 | 440.5 | 6.6 | 18.4 |
| Other manufacturing | 0.064 | .810 | .689 | 170.2 | 12.0 | 12.3 |
| Wholesale & retail | 0.198 | .825 | .685 | 65.9 | 21.7 | 18.7 |
| Information | 0.151 | .841 | .697 | 153.4 | 12.2 | 33.7 |
| Other | 0.026 | .827 | .691 | 405.2 | 8.3 | 17.5 |
| Total | 0.082 | .832 | .694 | 333.8 | 9.2 | 20.3 |

The results of the main empirical analysis are shown in Table 2.4. Coefficients on control variables generally have high levels of significance and are of similar sign and magnitude to those found in prior research. For example, consistent with the findings of Bessen and Meurer (2005), the number of patents, firm size and the quality of a firm's patent portfolio (as measured by the average number of forward citations per patent) all have positive effects on the expected number of times a firm is sued for patent infringement.

**Table 2.4 ZINB regression estimates - Expected number of lawsuits for alleged patent infringement**

| VARIABLES | Controls & Industry FE (2.1) | With FRAG & KNOW (2.2) | Interactions (2.3) | Alt. knowledge Measure (2.4) | Interactions (alt. KNOW) (2.5) |
|---|---|---|---|---|---|
| FRAG | | 0.450** | 0.603** | 0.554*** | 0.733*** |
| | | (0.226) | (0.280) | (0.212) | (0.274) |
| KNOW | | 0.552*** | 0.570*** | 0.017*** | 0.018*** |
| | | (0.195) | (0.202) | (0.005) | (0.004) |
| KNOWXemp | | | -0.041 | | 0.003** |
| | | | (0.068) | | (0.002) |
| FRAGXemp | | | -0.164* | | -0.201** |
| | | | (0.094) | | (0.093) |
| Patents_ln | 0.118*** | 0.090** | 0.096** | 0.156 | 0.197*** |
| | (0.043) | (0.039) | (0.040) | (0.100) | (0.029) |
| Employment_ln | 0.302*** | 0.303*** | 0.470*** | 0.297*** | 0.411*** |
| | (0.039) | (0.036) | (0.095) | (0.067) | (0.083) |
| Fwdcitations/patents | 0.004* | 0.004* | 0.004** | 0.004 | 0.005*** |
| | (0.003) | (0.002) | (0.002) | (0.004) | (0.001) |
| Bwdcitations/patents | -0.001 | -0.002 | -0.002 | -0.004 | -0.003 |
| | (0.004) | (0.004) | (0.004) | (0.007) | (0.004) |
| Capintensity_ln | 0.215*** | 0.216*** | 0.215*** | 0.181 | 0.121** |
| | (0.075) | (0.067) | (0.069) | (0.192) | (0.059) |
| Assets | -0.011*** | -0.011*** | -0.011*** | -0.010** | -0.009*** |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.003) |
| Earnings | 0.105*** | 0.110*** | 0.112*** | 0.090 | 0.063*** |
| | (0.030) | (0.028) | (0.028) | (0.064) | (0.023) |
| Revenue | 0.000 | -0.000 | -0.000 | 0.001 | 0.004 |
| | (0.005) | (0.005) | (0.005) | (0.007) | (0.005) |
| MISS | -0.947*** | -0.994*** | -0.975*** | -0.889*** | -0.832*** |
| | (0.160) | (0.164) | (0.165) | (0.163) | (0.142) |
| Pharmaceutical | 0.165 | 0.226 | 0.244 | 0.239 | 0.326 |
| | (0.288) | (0.262) | (0.259) | (0.282) | (0.210) |
| Machinery | 0.241 | 0.246 | 0.259 | 0.305* | 0.318*** |
| | (0.247) | (0.218) | (0.211) | (0.178) | (0.122) |
| Computers | 1.222*** | 1.193*** | 1.202*** | 1.193*** | 1.169*** |
| | (0.231) | (0.211) | (0.205) | (0.167) | (0.158) |
| Software | 0.950*** | 0.897*** | 0.908*** | 0.942*** | 0.995*** |
| | (0.297) | (0.248) | (0.240) | (0.324) | (0.149) |
| Semicondctrs | -0.099 | -0.138 | -0.142 | -0.077 | -0.040 |
| | (0.264) | (0.229) | (0.225) | (0.269) | (0.157) |
| Instruments | 0.563** | 0.566*** | 0.572*** | 0.591*** | 0.541*** |
| | (0.232) | (0.216) | (0.212) | (0.191) | (0.188) |
| Electrical | 0.339 | 0.313 | 0.330 | 0.381 | 0.416*** |
| | (0.325) | (0.273) | (0.264) | (0.305) | (0.150) |
| Manufacturing | 0.308 | 0.367* | 0.377* | 0.375* | 0.362** |
| | (0.221) | (0.217) | (0.216) | (0.215) | (0.179) |
| Wholesaleretail | 1.365*** | 1.406*** | 1.398*** | 1.527*** | 1.617*** |
| | (0.391) | (0.320) | (0.307) | (0.520) | (0.153) |
| Constant | -3.819*** | -4.486*** | -4.662*** | -4.486*** | -4.599*** |
| | (0.360) | (0.384) | (0.416) | (0.308) | (0.327) |
| Observations | 15,385 | 15,385 | 15,385 | 15,385 | 15,385 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Model 2.1 is a baseline model which estimates the annual litigation count using the control variables, year fixed effects that account for time trends in litigation and industry fixed effects into the analysis. The coefficients on the industry group effects generally have high levels of significance demonstrating the importance of their inclusion and confirming the caution that should be applied when looking to infer general results from single industry studies.

The inclusion of the main explanatory variables in Model 2.2, ownership fragmentation (FRAG) and knowledge diversity (KNOW), enables the testing of Hypotheses 2.1 and 2.2. The coefficient on FRAG is 0.450 and is significant at the 5% significance level, providing support for Hypothesis 2.1. Since the interpretation of coefficients in zero inflated negative binomial models is complex, an assessment of the economic significance of FRAG can be made by reference to a standard negative binomial model (refer to Table 5, Model 2.9).The exponential of the coefficient on FRAG gives an incident rate ratio (IRR) of 1.939 (=exp0.662). Thus, the effect of the anticommons through the fragmentation of property rights increases the expected number of lawsuits against a firm by up to 94%.

The coefficient on KNOW (0.552), as shown in Model 2.2 (Table 2.4) is also statistically significant ($p<0.01$). The IRR of 1.59 (=exp0.464), as shown in Model 2.9 (Table 2.5), indicates that the knowledge diversity aspect of thickets results in an increase in litigation rate of up to 59%. Thus Hypothesis 2.2 is also supported.

Comparing the relative economic significance of fragmentation and knowledge diversity, a one standard deviation change in FRAG (a 23.2% change at the mean), changes the expected case count by 18.22% (93.9x0.194). A one standard deviation change in KNOW (a 31.7% change at the mean), changes the expected case count by 13.04% (59.0x0.221). This suggests that the economic significance of the fragmentation of ownership is greater than the economic significance of knowledge diversity. This conclusion is robust to the specification using the alternative measure of knowledge diversity.

Model 2.3 introduces the interactions of firm size with the main explanatory variables that provide tests of Hypotheses 2.3a and 2.3b. The sign of the coefficient on FRAGXemp is negative as predicted and is statistically significant at moderate significance levels. The level of statistical significance increases under the alternative specification (refer to Model 2.5) and therefore, the hypothesis (2.3a) that fragmentation disproportionately affects small firms is supported. However, although the sign on KNOWXemp is negative as the theory suggests, the hypothesis that this coefficient is different from zero is rejected at all reasonable significance levels. Furthermore, the alternative specification using the knowledge diversity measure based on the average number of claims per patent produces a positive coefficient suggesting that knowledge diversity may even disproportionately affect *large* firms more. Thus, Hypothesis 2.3b is rejected.

In order to ensure confidence in these results, a comprehensive set of further analyses were carried out using alternative specifications and measures. The results of these robustness analyses are presented in Table 2.5.

**Table 2.5 Robustness regression estimates**

| VARIABLES | Logit<br>(2.6) | ZINB<br>(2.7) | ZINB Restricted sample<br>(2.8) | Standard NB<br>(2.9) | Random Effects NB<br>(2.10) | Random Effects NB (Alt KNOW)<br>(2.11) |
|---|---|---|---|---|---|---|
| FRAG | 0.627** | 0.603** | 0.657** | 0.662** | 0.453** | 0.538* |
| | (0.258) | (0.280) | (0.281) | (0.289) | (0.229) | (0.287) |
| KNOW | 0.428** | 0.570*** | 0.490** | 0.464** | 0.392* | 0.015*** |
| | (0.182) | (0.202) | (0.218) | (0.202) | (0.203) | (0.005) |
| KNOWXemp | -0.098 | -0.041 | -0.031 | -0.091 | -0.042 | 0.002 |
| | (0.069) | (0.068) | (0.076) | (0.067) | (0.078) | (0.002) |
| FRAGXemp | -0.137 | -0.164* | -0.168* | -0.150 | -0.136 | -0.156** |
| | (0.096) | (0.094) | (0.093) | (0.093) | (0.097) | (0.073) |
| Patents_ln | 0.143*** | 0.096** | 0.109*** | 0.157*** | 0.161*** | 0.204*** |
| | (0.020) | (0.040) | (0.035) | (0.023) | (0.030) | (0.028) |
| Employment_ln | 0.419*** | 0.470*** | 0.448*** | 0.440*** | 0.388*** | 0.358*** |
| | (0.091) | (0.095) | (0.096) | (0.092) | (0.097) | (0.073) |
| Fwdcitations/patents | 0.006*** | 0.004** | 0.003** | 0.007*** | 0.007*** | 0.007*** |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| Bwdcitations/patents | 0.003 | -0.002 | -0.002 | 0.004 | 0.001 | -0.001 |
| | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) | (0.004) |
| Capintensity_ln | -0.049 | 0.215*** | 0.235*** | -0.011 | -0.020 | -0.028 |
| | (0.037) | (0.069) | (0.064) | (0.041) | (0.054) | (0.055) |
| Assets | -0.003* | -0.011*** | -0.011*** | -0.003** | -0.003 | -0.003 |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.003) | (0.005) |
| Earnings | 0.041* | 0.112*** | 0.120*** | 0.064*** | 0.022 | 0.017 |
| | (0.021) | (0.028) | (0.027) | (0.020) | (0.041) | (0.040) |
| Revenue | -0.011*** | -0.000 | -0.002 | -0.011*** | -0.005 | -0.005 |
| | (0.003) | (0.005) | (0.005) | (0.003) | (0.007) | (0.007) |
| MISS | -0.821*** | -0.975*** | | -0.794*** | -0.583*** | -0.528*** |
| | (0.124) | (0.165) | | (0.128) | (0.131) | (0.170) |
| Pharmaceutical | 0.301** | 0.244 | 0.165 | 0.333* | 0.225 | 0.186 |
| | (0.152) | (0.259) | (0.265) | (0.171) | (0.231) | (0.228) |
| Machinery | 0.396*** | 0.259 | 0.269 | 0.365*** | 0.287* | 0.302 |
| | (0.112) | (0.211) | (0.208) | (0.113) | (0.148) | (0.184) |
| Computers | 1.056*** | 1.202*** | 1.227*** | 1.183*** | 1.015*** | 0.969*** |
| | (0.148) | (0.205) | (0.210) | (0.156) | (0.283) | (0.242) |
| Software | 1.004*** | 0.908*** | 0.874*** | 1.045*** | 0.963*** | 0.926*** |
| | (0.142) | (0.240) | (0.219) | (0.144) | (0.205) | (0.221) |
| Semicondctrs | 0.106 | -0.142 | -0.140 | 0.049 | 0.087 | 0.073 |
| | (0.147) | (0.225) | (0.211) | (0.149) | (0.193) | (0.174) |
| Instruments | 0.491*** | 0.572*** | 0.501** | 0.413*** | 0.403** | 0.391** |
| | (0.153) | (0.212) | (0.216) | (0.157) | (0.187) | (0.181) |
| Electrical | 0.489*** | 0.330 | 0.230 | 0.437*** | 0.534** | 0.531** |
| | (0.144) | (0.264) | (0.240) | (0.145) | (0.221) | (0.218) |
| Manufacturing | 0.348** | 0.377* | 0.510** | 0.220 | 0.270 | 0.287 |
| | (0.135) | (0.216) | (0.237) | (0.142) | (0.229) | (0.205) |
| Wholesaleretail | 1.768*** | 1.398*** | 1.531*** | 1.773*** | 1.776*** | 1.800*** |
| | (0.147) | (0.307) | (0.259) | (0.146) | (0.183) | (0.219) |
| Constant | -4.030*** | -4.662*** | -4.766*** | -4.139*** | -1.012*** | -1.020** |
| | (0.304) | (0.416) | (0.453) | (0.342) | (0.368) | (0.417) |
| Observations | 15,385 | 15,385 | 11,541 | 15,385 | 15,385 | 15,385 |
| Number of groups | | | | | 3,408 | 3,408 |

Robust standard errors shown in parentheses for models 6-9.
Bootstrapped standard errors shown in parentheses for models 10-11
*** p<0.01, ** p<0.05, * p<0.1

The first model in the table (Model 2.6) is a logistic regression which predicts the probability that a firm will be the subject of at least one lawsuit in a given year. As can be seen, coefficients on the main explanatory variables remain significant under this alternative specification, though the significance of the interaction effects is reduced. The theoretical predictions presented in this chapter are therefore not overly sensitive to the annual lawsuit count and are not driven by outlying observations[8].

Model 2.7 repeats the results from the last model in Table 2.4 and serves as a basis for comparison for the next analysis (Model 2.8) which removes missing values of the explanatory variables. The baseline specification in Model 2.7 includes missing observations of the fragmentation index and a dummy variable MISS is used to identify them. Omitting these observations would generate a sample which might have a greater proportion of large firms that spend more on R&D and would consequently be more likely to be the subject of litigation (Ziedonis 2004). This restricted sample is analyzed in Model 2.8 and as can be seen from the results in Table 2.5, the general magnitude and statistical significance of the coefficients is substantively similar to the results from the complete sample, indicating that selection effects are not likely to be a significant source of bias.

The final collection of models (Models 2.9-2.11) incorporate individual firm random effects to account for unobserved firm heterogeneity. Model 2.9 is a standard Negative Binomial specification and is included for comparison purposes. Model 2.10 shows the inclusion of the firm effects using the principal measure of knowledge diversity and Model 2.11 shows the results using the alternative measure. Compared to baseline analysis in Model 2.9, the size of all coefficients on the explanatory variables reduce slightly (FRAG=0.453 compared to 0.662 and KNOW=0.392 compared to 0.464) with the inclusion of the firm effects, though moderate levels of statistical significance are maintained. Significance on the interaction effects is also reduced, in this case to the extent that they are no longer statistically significant. Thus, overall, it is concluded that the inclusion of the individual firm random effects produces results that are consistent with the initial findings, though the significance of the results associated with interaction effects is substantially reduced.

In summary, the empirical results show a significant and positive causal effect of fragmentation of intellectual property ownership on the likelihood that the firm is the subject of patent infringement

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[8] A further analysis was carried out which removed zero observations of the dependent variable. Regressing the log count of the positive values of the dependent variable using OLS against the same regressors in the main analysis resulted in a substantial weakening of the results. This is likely due to the loss of efficiency associated with a drastically smaller sample size or it may be because the regressors are better predictors of whether or not the firm is subject to at least one lawsuit than it is at predicting the number of lawsuits, though it is not theoretically clear why this may be the case.

litigation. There is also strong support for the hypothesis that knowledge diversity has a positive relationship with litigation risk. There is limited support for the prediction that the effect of knowledge diversity is greater for small firms.

## 2.5 Discussion

The shift of innovation paradigms and the consequent increases in ownership fragmentation and technology diversity[9] has resulted in growing opportunities to hold up innovators of multi-component products at the commercialization stage and in uncertainty over the boundaries of property rights. This situation is encouraging firms to engage in strategic patenting behavior through moves to acquire defensive patent portfolios and to maximize value extraction from intellectual properties by 'patent mining' (Shapiro 2001). Other strategic actions include the seeking of injunctions, particularly by large firms (Lanjouw and Lerner 2001), which can delay a competitor's product into the market even when infringement is not ultimately proved. These strategic actions compound the costs to firms arising from thickets. Indeed, as previously suggested, many of the most innovative companies are finding the assertion of their existing rights more lucrative than investing in innovation. These incentives are particularly strong when it is very difficult to predict the scope of competitors patents when they involve multiple technologies to which different standards are applied by the patent office and the courts.

This chapter contributes to the existing body of knowledge on thickets and litigation. The evidence that the fragmentation of ownership causes litigation is consistent with the theory that the anticommons problem can undermine innovation incentives (Heller and Eisenberg 1998). It also complements the empirical findings of other scholars that have demonstrated other potentially costly effects of ownership fragmentation (e.g. Huang and Murray's (2009) findings that fragmentation can have a negative effect on the production of public knowledge). They are also consistent with Ziedonis' (2004) findings that fragmentation causes increased levels of patenting since Bessen and Meurer (2005) have shown that the number of patents are positively associated with litigation risk. Moreover, the results provide generalizable support across industries for the study by Hall and Ziedonis (2007) which found an escalation in the occurrence of semiconductor firms being the target of litigation from outside the semiconductor industry. The findings are contrary to Lichtman's (2006) assertion that multiple

[9] The data shows increases in both the fragmentation and knowledge diversity measure over the sample period. Furthermore, Allison and Lemley (2002) provide further evidence of the increasing complexity of patents over time.

overlapping property rights lessen incentives to enforce intellectual property rights. The chapter also develops further the theoretical arguments that relate the emergence of patent thickets to increases in the complexity of innovations manifested in multiple knowledge components and the diversity of technologies they represent. The bounded search capacity of innovators to discover overlapping claims in other fields of technology and the emergence of intellectual property protection systems with increasingly differing industry specific application have increased the likelihood of unintentional infringement of patents, uncertainty about patent boundaries, and simultaneous independent inventing of overlapping technologies. The study found an economically and statistically significant impact of patent thickets on litigation and thus highlights an important potential source of disincentive to invest in innovation – especially exploratory innovation which cuts across technologies.

The increasing significance of litigation costs and the deleterious effect these costs may have on innovation in key sectors of the economy is presenting policy makers with a challenge. Prior literature has focused on co-operative solutions, such as cross-licenses and patent pools, that are being used to "clear" the thicket associated with the high numbers of patents and their overlapping claims (Shapiro 2001). However, there is evidence (Lemley and Shapiro 2007) that their effects are limited. Co-operative solutions not only become less likely as the number of intellectual property owners increases, they become less feasible when those owners are distributed across a wide range of industries. For example, in the previously noted case of computer manufacture which involves many inter-related technologies (processors, memory modules, etc.) all of these technologies are subject to their own patents. Whilst some patent pools have been formed, particularly where there is need to establish standards, cooperative agreements that cover the entirety of complex, components based products are rare. This was not the case with early patent pools which required the agreement of fewer parties who tended to be within the same industry. For example, the first patent pool in US history, the Sewing Machine Combination (1856-1877), had just 3 members and covered seven patents. The Manufacturer's Aircraft Association of 1917 also involved a relatively small number of inventors and manufacturers. In contrast, the proposed patent pool for 4G LTE cellular technology comprises 20 members and covers over 3000 patents and yet this just relates to a communications standard not the overall function of cell phones. Furthermore, this patent pool does not encompass all patents pertaining to the technology, a common feature of patent pools. Layne-Farrar and Lerner (2011) find in a survey of nine patent pools, that they license anywhere between 5% and 89% of relevant patents and that firm participation ranges from 1% to 58%. Consequently, even with the formation of patent pools, litigation risk remains high where there are overlapping claims in uncertain, knowledge diverse environments.

If private cooperative solutions are not likely to mitigate sufficiently the adverse influence on innovation of ownership fragmentation (and the “tragedy of the anticommons” it causes) and of knowledge diversity (and the uncertainty regarding claim boundaries and the existence of overlapping technologies it creates), it is plausible to consider other policy levers available to governments (and courts) to deal with this dual problem. The most pertinent levers available to governments (and courts) are the decisions concerning the requirements associated with patent issuing and the scope of patent claims granted. As noted previously, granting fewer patents with broader claims would reduce ownership fragmentation. No doubt, limiting the number of patents awarded would be particularly appropriate for marginal patent applications. The alternative of granting narrower patents would reduce the emergence of patent thickets and litigation that are generated as a result of technology diversity, but would aggravate the problems caused by ownership fragmentation.

To resolve this dilemma I propose a hybrid solution: governments could mandate compulsory patent pools within industries or technology fields (or at least resolve existing constraints on cooperation that result from anti-trust laws) to reduce the impact of ownership fragmentation whilst granting narrower patents to reduce the effect of knowledge diversity (i.e. limiting the number of technological fields that patents cover). Indeed granting narrower patents would encourage patent holders to join patent pools. Such solutions may be especially beneficial to smaller firms which are important sources of innovation. The results reported earlier in this chapter indicated that ownership fragmentation (but not knowledge diversity) has a significantly higher deleterious impact on these firms. A policy that provides opportunity to innovate in niche fields, which would be a consequence of issuing narrower patents, and provides better access to patent pools is likely to facilitate the founding of such firms and improve their survival prospects.

The study has clear implications for innovating firms. Since the occurrence of unintentional infringement and opportunities for hold up is high in the current state, building defensive patent portfolios, maintaining ‘deep pockets’ (or purchasing litigation insurance) and forming alliance relationships, such as cross-licensing agreements, are all important defensive activities. In addition, the employment of interdisciplinary teams of patent practitioners to ensure a more thorough search and accurate interpretation of all relevant legal standards that may be impinging will reduce unintentional patent infringement.

### 2.5.1 Limitations and future research agenda

Although it has been shown that the fragmentation of ownership rights increases litigation, some caution should be exercised before concluding that fragmentation has a net adverse effect on innovation incentives since fragmentation has been shown to lessen settlement times once litigation has been instigated (Galasso and Schankerman 2010). Thus although this chapter shows that fragmentation increases litigation hazard, costs per patent infringement case may be less due to their faster resolution. Future research on whether fragmentation has a net negative cost on innovation incentives is therefore required. One study that would further knowledge in this area would be to assess whether fragmentation causes an increase the proportion of cases that end in trial since litigation that ends in trial tends to be substantially more expensive. It should also be noted that the findings relating to technology diversity only capture part of the overlapping claims dimension of patent thickets. Within industry uncertainty is not captured in this study and hence the size of the effect of overlapping claims in patent thickets relative to ownership fragmentation may be underestimated.

In addition to these limitations it should be noted that patent citations are not exhaustive indicators of knowledge flows and that firms that are cited may not be potential licensees (Miller et al 2007). It is not uncommon to cite patents in order to demonstrate how an innovation differs from prior art, not just to illustrate how an innovation builds on existing intellectual property[10]. Thus, further studies that utilize alternate measures of knowledge flow and technological antecedent are warranted.

Finally, the results relate to the firm level and any policy implications associated with patent breadth decisions require an assumption that they translate at the level of the individual patent. A study at the patent level would provide greater confidence in policy recommendations. I also must caution that my policy recommendations assume that patent litigation reduces overall investment in research and development. This assumption holds in countries with highly litigious cultures and where the costs of litigation are substantial. Litigation, however, provides a signal to innovators that intellectual property rights can be enforced, thus encouraging innovators to patent and disclose information that can foster further innovation. A research agenda that explores the relationship between the frequency of patent litigation and innovation rates may reveal an optimal (i.e. welfare maximizing) level of litigation for the economy as a whole.

[10] However, although the measures based on citations may be somewhat imperfect, it is generally recognized (Jaffe 2000) that they do embody significant information about knowledge dependencies and innate characteristics.

# Chapter 3: Alliance Networks, Competition and Patent Enforcement

## 3.1 Background and synopsis

Whilst there are extensive law and economics literatures dealing with patenting and more generally intellectual property protection issues, the interest of strategy scholars in patents as an element of firm strategy is relatively recent (See Somaya 2012 for a comprehensive review of patent strategy in the management literature). Surprisingly, there are only a few studies that examine the strategic role that patent litigation plays. This is despite the growing recognition that patent litigation serves as a key strategic tool, particularly in high-technology industries. Aggressive enforcement can enhance the value of patents and can provide other strategic advantages. For example, the filing of patent lawsuits can establish a reputation for toughness that dissuades knowledge leakage through employee mobility (Agarwal et al 2009) and temporary preliminary injunctions can be sought to place financial distress on rival firms which can be particularly effective when those firms are capital constrained (Lanjouw and Lerner 2001).

Most patent infringement lawsuits are filed to support a "proprietary" patent strategy, whereby the aim of litigation is to force alleged infringers to stop using patented technology or to pay royalties: the enforcement of a patent's legal right to exclude. However, patent litigation can also be used defensively, to improve competitive positions, such as through the filing of patent invalidity claims or declaratory judgment suits (Graham and Somaya 2004). Whilst the extant literature provides some insight into how litigation is used as part of a firm's business and patent strategies, relatively little is known about how firm strategy affects litigation likelihood. Numerous scholars, particularly within the fields of economics and law, have presented theories as to why disputes occur but few of these examine the effects of value creating business strategies. It is important to understand how business strategy affects litigation hazard in order to design effective policy levers that minimize unnecessary litigation and bolster the incentives to innovate which the patent system provides, yet does not undermine firms' profit making opportunities.

In this chapter I answer the call for further research on "the effects of value creation strategies on patent strategies" and address some of the "important unanswered questions" in the management of intellectual property rights (Somaya 2012: p1105, p1107). I examine strategic alliances since they are an important source of value creation, providing access to complementary resources and new markets (Baum et al 2010, Kumar 2010); acquisition of new knowledge and capabilities (Mowery et al 1996); and the sharing of risks and costs (Harrigan 1988, Hagedoorn 1993). I focus on the implications of alliance participation for patent litigation hazard as there is need for further knowledge relating to patent enforcement in the management field (Somaya 2012).

Inter-firm alliances are a particularly appropriate context to examine the economic and competitive antecedents of patent litigation since one of the main reasons firms form alliances is to access technological know-how that facilitates innovation (Mowery et al 1996, Inkpen and Dinur 1998) and that cooperative alliances are often undertaken in the shadow of competition (Inkpen and Tsang 2007, Silverman and Baum 2002, Greve et al 2010). Potential gains, however, in the planned exchanges of knowledge resources which provide the information and learning benefits that lead to innovation and new product development, are accompanied by appropriation hazards whereby competitors may acquire the focal firms' knowledge assets and erode its competitive advantage (Kale et al 2000, Kumar 2010, Hennart 1988, Anand and Khanna 2000). Whether appropriation occurs depends on the characteristics of the relationship between partnering firms such as the intensity of competition between partners and the degree of complementarity between firms' resources and product offerings. However, incentives to appropriate not only depend on dyadic characteristics, but also depend on the relational and competitive landscape of the wider inter-firm network. For example, firms with opportunities to expropriate another's knowledge resources may refrain from such action due to the anticipated response from others in the network and the detrimental effect it may have on the firm's reputation. I therefore adopt a network perspective in this study in order to capture these relational effects that may be influencing decisions to imitate and litigate.

Thus, this chapter aims to understand when appropriation is likely to occur in a relational and competitive network and when firms are likely to seek redress in the courts. I show that, not only is the competitive environment between a firm and its alliance partner relevant, but that the competitive environment between all partners in an alliance portfolio also affects litigation hazard. I show that embeddedness within the network sometimes serves as an important check on litigious behavior but that its effect is nuanced and depends on the type and often the relative degree of embeddedness between potential litigants. Furthermore, I find that network embeddedness and competition are inter-related and that the effect of power imbalances caused by asymmetrical network positions depends on the intensity of competition within alliance portfolios.

I make several contributions to the management and strategy literatures. First, as mentioned, I contribute to the underdeveloped study of the effect of value creation strategies on patent strategy and second, I add to the relatively limited amount of current management research on patent litigation strategy. This is particularly significant considering the importance of strategic alliances for value creation in high technology industries, the growing recognition that litigation strategy is an essential component in patent strategy and the increasing rates of both alliance and litigation activity (Bessen and Meurer 2005).

The third contribution is to add to the literature on inter-organizational alliances and their implications for innovation. As noted, strategic alliances provide substantial benefits to firms and in some industries they are viewed as indispensable vehicles for acquiring new knowledge and capabilities (Mowery et al 1996). However, a number of scholars have highlighted drawbacks of alliances such the risk of knowledge appropriation by partner firms (e.g. Gulati and Singh 1998, Kale et al 2000). The recent emergence of the strategic network literature has provided a more fine grained understanding of the tradeoff between the advantages and disadvantages of alliances. From this network perspective, firms in favorable positions with respect to the network structure and the attributes of the constituents have been shown to have higher performance (Burt 1992, Rothaermal 2001, Rowley et al 2000, Zaheer and Bell 2005) and higher rates of innovation (Ahuja 2000, Powell et al 2005). Complementing this literature, several studies have examined partner selection and the evolution of networks (Gulati 1995, Powell et al 2005, Gulati and Westphal 1999, Baum et al 2003). Most recently, scholars have explored alliance dissolution which rests on the tension between the cohesive effect of network embeddedness (Granovetter 1985) and the corrosive effect of frictions that develop between partners (Polidoro et al 2011, Greve et al 2010, Kumar 2010). This study extends this recent work by examining the effect of these cohesive and corrosive forces to firm strategy beyond that of the alliance. Moreover, I demonstrate that the network perspective can be extended to a wider set of the firm's strategic decisions, not just those related to the network.

Finally, the fourth contribution is methodological. Utilizing a unique dyadic dataset, drawn from four separate sources, I use a quasi-experimental method that addresses selection effects.

## 3.2 Theory

Firm outcomes are arguably best understood by appreciating that organizations can be seen as systems of inter-related social behaviors between participants both inside and outside the firm (March and Simon 1958). Thus, economic decision making is made under the influence of social structures at both the individual levels within the organization and those formed by inter-organizational relationships (Gulati 1998). How a firm is embedded in social structures affects strategic choices since "a structure of relations affects the actions taken by the individual actors composing it….by constraining the set of actions available to the individual actors and by changing the dispositions of those actors toward the actions they may take" (Marsden 1981). In the context of inter-firm alliance networks, embeddedness provides cohesion to relationships, making them more stable and less likely to be terminated (Polidoro et al 2011, Greve et al 2010). It also affects decisions to form new alliances, such as which partners to ally with (Baum et al 2010).

An embeddedness perspective (Granoveter 1985) highlights the informational advantages social networks can confer on partners (Gulati 1998). One such advantage in the context of inter-organizational networks is that network connections facilitate the exchange of information that enables innovation. Information travels not just through direct ties but through the network itself, so not only are the firm's relationships with those it has direct contact with relevant, but so too are the relationships that those partners have with others. How a firm is embedded in this network determines its access to new knowledge and thus has a significant bearing on its ability to innovate. However, collaboration also has its risks. The knowledge exchange afforded by inter-firm alliances provides partners with the opportunity to appropriate proprietary knowledge from focal firms. When incentives for such opportunistic behavior exist (Williamson 1985), where the private benefits from appropriation outweigh the advantages of collaboration, then partners are likely to infringe on the intellectual property rights of focal firms. This is likely to prompt focal firms to enforce their rights in the court of law.

Relational embeddedness through prior direct ties and structural embeddedness associated with common partners can constrain opportunistic behavior (Greve et al 2010, Kale et al 2000, Ring and Van de Ven 1994). Cohesive relationships that discourage opportunism and aggressive strategic behavior can also result from relative positions in a network structure (Polidoro et al 2011, Greve et al 2010). Thus, these relational, structural and positional perspectives provide a framework that can explain when appropriation of knowledge resources is likely to occur and when these actions are likely to be met through legal recourse.

### 3.2.1 Relational embeddedness

Relational embeddedness can be defined as the strength of social attachment between partnering firms (Lavie 2012). It is characterized by repeated interactions that facilitate information sharing of a detailed nature (Uzzi 1996, 1997). Relational embeddedness increases opportunities for organizational learning through increased information flow, with the direct ties that constitute relational embeddedness providing relatively “fine grained” information compared to that received from indirect ties (Uzzi 1996, 1997). Moreover, relational embeddedness enables the transfer of tacit knowledge which is, by its definition, relatively difficult to articulate (Cowan et al 2000) in the formal documentation that is required in patent applications and claim boundaries of related technologies will tend to be relatively unclear. Thus, this information tends to be more difficult to protect using the intellectual protection provided by the patent system and the potential for misunderstanding concerning claim boundaries is increased.

For relational embeddedness to develop, mutual trust must form between parties. Trust in an inter-organizational context is “the expectation held by one firm that another will not exploit its vulnerabilities when faced with the opportunity to do so” (Krishnan et al 2006). Trust overcomes uncertainty in collaborative agreements by establishing goodwill and fairness of partner behavior (Krishnan et al 2006). This reduces conflict and allows for an open exchange of information (Zaheer et al 1998), which are important factors in determining alliance success (Dyer and Chu 2003, Krishnan et al 2006). Since trust generally reduces conflicts between parties, one might then expect trust to result in reduced potential for patent disputes[11]. However, the open exchange of information associated with trust provides the knowledge spillovers which enable firms to innovate in areas close to their partner’s area of expertise and prior research has found that this relational capital has no significant effect on preventing the appropriation of proprietary knowledge by alliance partners (Kale et al 2000). Thus, although trust has a number of benefits to alliance members, including the constraint of opportunism to extract alliance generated rents (Polidoro 2011, Krishnan and Martin 2006); these benefits do not extend to protecting the firm from knowledge leakage. Trusting partners tend to screen the information provided to each other for accuracy less carefully (McEvily et al 2003) and trust limits cognitive efforts (Krishnan et al 2006). This leads to a “dropping of the guard” vis-à-vis the risk of potential opportunistic behavior by partners and firms are more likely to divulge information about their proprietary knowledge assets. This blindness or naivety regarding potential appropriation risks is similar to the “strategic blindness” which McEvily et al (2003) describe in relation to the desensitizing effect of trust on the firm’s responsiveness to environmental uncertainty. Thus although trust associated with relational embeddedness establishes goodwill and norms of fairness it has the paradoxical effect of increasing the likelihood of the knowledge appropriation which leads to alleged intellectual property infringement[12].

[11] The role of trust is considered further in the discussion.
[12] This is consistent with the recognition of paradox in organizational theory (Poole and Van de Ven 1989). Evidence of firms litigating in conjunction with alliance collaboration would be further evidence of firms simultaneously competing and collaborating (Gnyawali 2011, Hamel 1991, Gnyawali and Madhavan 2001).

Hence due to the increased flow of information, the tacit aspect of this information and the paradoxical effects of trust that increase the likelihood of alleged infringement,

*Hypothesis 3.1: Firms with high relational embeddedness will have high probability of patent litigation.*

### 3.2.2 Structural embeddedness

Whilst relational embeddedness concerns the nature of direct ties between firms, structural embeddedness extends the sphere of influence to include the set of partners that are common to firms (Coleman 1988). Actors may not be tied with each other but may be tied to a similar set of others. Third party ties can act as referral agents, bringing firms together in the first instance (Ahuja 2000). Once formed, third party ties have a stabilizing influence on relations (Krackhardt 1998, 1999) and third parties can reduce conflict by acting as mediators (Greve et al 2010). Common partners help instill collaborative trust based norms, such as reciprocity and sharing (Uzzi 1997, Gulati 1995) which discourage opportunistic behavior. As Greve et al note, "(common partners) can thus enforce shared norms of behavior and serve as social constraints that lead members to act in accordance with each other's expectations and to expect the same from other members".

Common partners also ensure that opportunistic behavior is visible (Polidoro et al 2011) and provide outlets for notification of norm-breaking behavior to the wider network. Penalties for opportunism are potentially enhanced as not only direct partners may retaliate with uncooperative, protective or even aggressive behavior but it may also elicit similar responses from common partners. Punishment may not be limited to retaliatory actions in existing alliances but are also likely to affect the firm's attractiveness as a future alliance partner (Park and Ungson 1997). Hence, structural embeddedness provides social monitoring controls that encourage firms to consider the effects of opportunism on their reputations and on their wider alliance portfolio (Greve et al 2010, Walker et al 1997, Rowley et al 2000, Kreps 1990). Since consideration of the benefits of appropriating knowledge assets is undertaken in the "shadow of others" (Polidoro et al 2011), firms are pressured to refrain from such behavior.

*Hypothesis 3.2: Firms with high structural embeddedness will have a low probability of patent litigation*

### 3.2.3 Positional embeddedness

Positional embeddedness, an actor's position with respect to others in a network, has similarities with structural embeddedness (common partners) as it can also confer informational and reputational benefits. Positional embeddedness has two main dimensions, centrality within the network and structural holes, specifically the degree to which an actor spans structural holes (Burt 1992). Central positions in alliance networks provide the firm with a large catchment area for information. Relevant developments in different technologies come to the attention of the firm, which can be combined with existing knowledge resources and can result in valuable innovations (Kogut and Zander 1992, Ahuja 2000). Central firms also learn about potential infringing technologies through their contacts.

The presence of structural holes reduces information flow by eliminating the conduits that facilitate knowledge exchange. However, in dense local clusters with few structural holes, there is a high degree of redundancy in the information received. Therefore, *ceteris paribus* (maintaining the same number of ties), firms derive more benefit from central positions that span structural holes since this provides greater access to novel and distinctive information (Burt 1992, Ahuja 2000). Firms in such positions have a high degree of network status (Yang et al 2010) and are influential in inter-firm relationships (Podolny 1993, Brass and Burkhardt 1993, Washington and Zajac 2005). The control of information and the reliance of others on them as brokers of new knowledge resources provide them with power (Burt 1992). As *tertius gaudens* – one who is situated between others – a firm has control advantages (Gulati 1998) that affect the decision making of that firm and the others in the network. Relative centrality, the centrality of one firm with respect to another, in a network is therefore an indicator of power imbalance (Bonacich 1987) which has implications for strategic decision making such as whether to appropriate another's knowledge assets or whether to engage in litigation.

Power imbalance affects the incentives of firms to appropriate another firm's proprietary knowledge assets in a number of ways. First peripheral actors in scenarios of power imbalance are more likely to refrain from opportunistic behavior since, with access to multiple knowledge resources; central firms have a high detection capability. Second, firms in central positions reduce opportunistic behavior by peripheral actors by being able to relay information about such actions to a wide set of firms (Yang et al 2010), thus damaging the reputation of the peripheral firm and prompting sanctions against it. Third, there is the potential for retaliation where peripheral firms risk losing access to valuable knowledge flows that are routed through the central firm. Central firms are in a beneficial position to access resources and retaliate (Gnyawali and Madhava 2001) should peripheral firms appropriate proprietary knowledge assets.

Conversely, central firms with opportunities for knowledge appropriation are not constrained by these effects. Indeed, central firms have little or no reliance on peripheral firms for knowledge flows and the impact on the firm's reputation from appropriation is limited by the peripheral firm's isolation in the network, since the peripheral firm is constrained in its ability to disseminate information about the actions of the central firm. Moreover, centrally positioned firms are better able to leverage the benefits of the information that they receive (Polidoro et al 2011) since they have the opportunity to combine different sources of information from multiple sources, which can lead to valuable innovations (Kogut and Zander 1992). This increases their incentives to appropriate by increasing the potential benefits of appropriation.

Thus, due to the threat of retaliation, the potential for damage to reputation, implications for detection capability and opportunities for combinative innovation, relatively peripheral firms have reduced incentives for appropriation and relatively central firms have increased incentives for appropriation.

*Hypothesis 3.3: Relative positional embeddedness causes a decreased probability of litigation between firms*[13].

### 3.2.4 Competition within alliance portfolios

Collaboration between firms in alliance networks takes place under the "shadow of competition" and one of the advantages of the network perspective is that it allows a joint analysis of competitive and cooperative relations (Inkpen and Tsang 2007). Firms often ally with competitors (Hamel at al 1989) and the benefits to such relationships can be significant. However, alliances between competitors tend to have high levels of friction which leads to instability and high dissolution rates (Kogut 1989, Park and Russo 1996, Greve et al 2010). Friction arises due to enhanced incentives for opportunism to gain advantages in market competition (Park and Ungson 2001). In these circumstances private benefits are more likely to outweigh the collective benefits of the alliance (Khanna et al 1998). There are also increased incentives to appropriate knowledge and capabilities from partner firms that are competitors (Gimeno 2004).

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[13] Positive relative positional embeddedness occurs when the patentee has a greater centrality than the alleged infringer and this causes a decreased likelihood of litigation since more peripheral firms are less likely to infringe on the intellectual property rights of more central firms. Similarly, negative relative positional embeddedness (where the potential infringer is more central than the patentee) causes an increased likelihood of litigation between firms since more central firms are more likely to infringe on the intellectual property of peripheral firms. The expected coefficient on the test of this hypothesis will therefore be negative.

In addition to the competitive forces between firms within an alliance, previous research has shown that the competitive structure of the alliance *network* can also have implications for individual alliances and the firms that comprise them. For example, Silverman and Baum (2002) show that the alliances of a firm's rivals influence the competitive environment of the focal firm. Greve et al (2010) show that multi-market contact with partners across the network results in mutual forbearance which promotes cohesion and stability in relationships and that market overlap within the network, a measure of competitive pressure, is a source of instability that can lead to the dissolution of alliances.

The level of bilateral network competition, defined as "the extent to which partners can be considered competitors of the focal firm" affects the degree to which firms engage in cooperative and opportunistic behavior. High bilateral competition presses firms to seek new sources of information that can lead to innovation and competitive advantage. Firms in competitive multi-alliance environments are more likely to be tuned into the potential benefits of appropriating knowledge in order to improve their competitive position (Hamel 1991). In contrast, firms in less competitive environments are subject to less pressure to acquire new knowledge resources from others.

*Hypothesis 3.4: High network competition*[14] *causes an increased probability of litigation.*

### 3.2.5 Moderating effects on relative positional embeddedness

The theory relating to network competition has described how the competitive environment of the firm affects its incentives to engage in opportunistic behavior: firms subject to high levels of competition within their alliance portfolios are more likely to attempt to appropriate the knowledge resources of their partners. Yet the question remains as to whom they are likely to choose to infringe upon, if given the opportunity. As we have seen, firms occupying peripheral positions in the network tend to be discouraged from opportunistic behavior against central firms who control access to information as brokers. These central firms are able to relay information about alleged infringements to a broad set of firms (Yang et al 2010) leading to widespread sanctions, and they are also able to withdraw valuable sources of new, non-redundant knowledge. In competitive environments, these repercussions against firms that engage in opportunism are heightened since the termination of collaboration agreements and the loss of knowledge sources can have detrimental effect on competitive positions.

[14] In the network of the potential infringer.

Thus, a firm with high bilateral competition will have increased incentives to engage in the appropriation of partner resources; however, that firm is likely to avoid targeting firms in powerful positions.

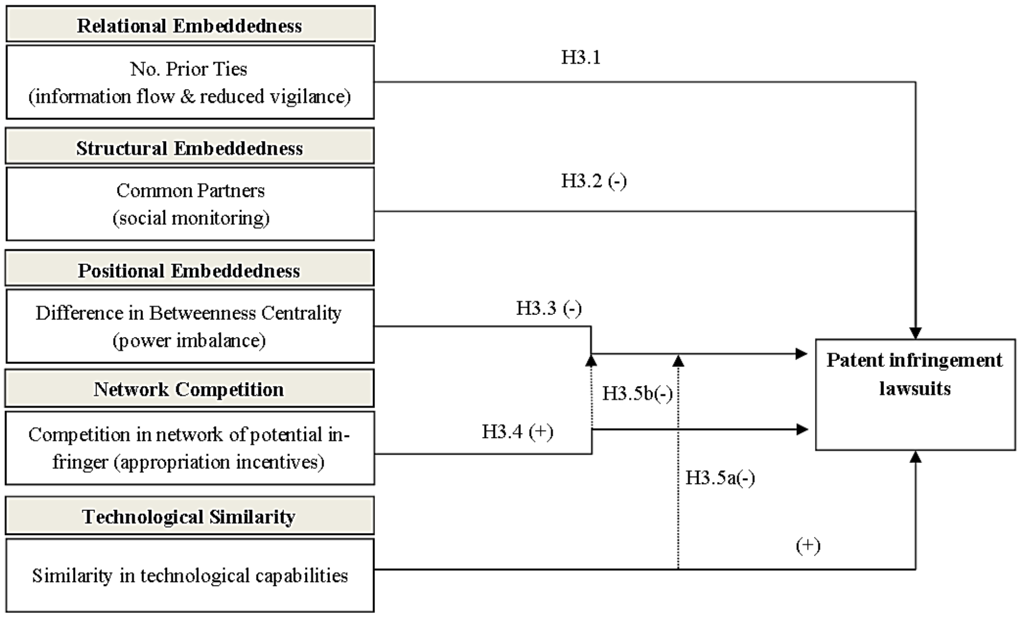
*Hypothesis 3.5a: The level of network competition will have a moderating effect on relative positional embeddedness such that increased levels of bilateral competition will increase the negative effect that relative positional embeddedness has on probability of firms to be engaged in litigation*[15].

The theory that results in the prediction of Hypothesis 3.3 (relative positional embeddedness decreases litigation probability) identifies detection capability, reputation effects and the potential loss of knowledge sources as factors that influence the incentives of firms to appropriate knowledge assets. These factors are dependent on how similar firms are in terms of their technological capabilities. Firms operating in different technological areas are less likely to detect infringement and the loss of potential knowledge sources is likely to be less critical. Moreover, reputation effects will be less damaging away from a firm's technological community. Conversely, firms in close technological proximity will be more sensitive to power imbalances from relative positional embeddedness. Detection capabilities are enhanced and there is a large effect of appropriation on reputation since firms which are closely related, and with whom the firm may rely upon, will be informed of such action. Furthermore, the impact of the retaliation threat is increased, since firms risk losing access to valuable information that is particularly closely related to their areas of technological expertise.

*Hypothesis 3.5b: The level of technological similarity will have a moderating effect on relative positional embeddedness such that increased levels of technological similarity will increase the negative effect that relative positional embeddedness has on probability of firms to be engaged in litigation*[16]

[15] Since the coefficient on network competition is predicted to be positive and since the predicted coefficient on relative positional embeddedness is negative, the predicted sign of the coefficient of the interaction is negative.
[16] Since the coefficient on technological similarity is predicted to be positive and since the predicted coefficient on relative positional embeddedness is negative, the predicted sign of the coefficient of the interaction is negative.

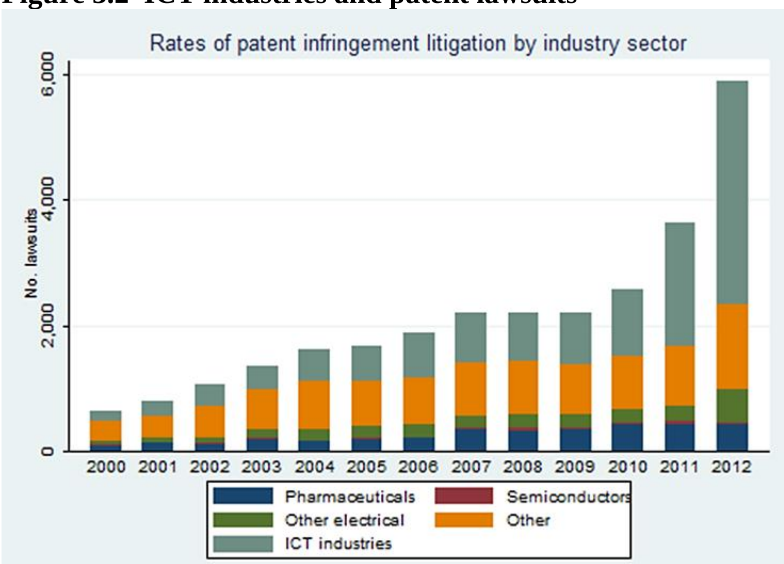
**Figure 3.1 The Effects of Network Embeddedness, Competition and Technological Similarity on the Likelihood of Patent Litigation**




## 3.3 Empirical methodology

The empirical analysis which tests the hypotheses is carried out within the setting of the ICT (Information Communications Technologies) sector. Appendix B lists the 6 digit NAICS codes included in the sample. This group of industries is particularly relevant for at least three main reasons. First, firms operating in this high technology environment are particularly reliant on alliances for gaining access to complementary resources and capabilities as firms are often highly specialized. Technologies tend to span multiple knowledge domains and inter-firm collaboration provides access to the expertise required to produce complex products. Furthermore, alliance participation within high technology industries has been shown to be an important source of new knowledge and skills that lead to innovation (Vonortas 1997, Hagedoorn 1993, Stuart 2000). Second, a large proportion of the increase in alliance activity over the past few decades has occurred in high technology industries (Hagedoorn 1993) and alliances within ICT industries currently account for a large proportion of all alliance activity. Alliance networks in ICT are therefore becoming increasingly prevalent and their effects on strategic behavior are likely to be becoming increasingly relevant. Third, because I use patent lawsuit filings as my dependent variable, it is important to select industries where lawsuits are common. The recent rise in patent litigation in the U.S. is largely attributable to the growth in lawsuit filings within the ICT sector (see Figure 3.2). Thus due to the importance of inter-firm knowledge exchange and the growth in both alliance activity and litigation, ICT industries provide a rich setting to explore the relationship between alliance networks and litigation outcomes.

**Figure 3.2  ICT industries and patent lawsuits**




Following Inkpen (2001) and Yang et al (2010), I adopt a relatively broad definition of alliances which includes equity and non-equity joint ventures; shared product development projects; shared purchasing, marketing and manufacturing arrangements; and research and development projects. Since most lawsuits are the result of dyadic interactions between two firms and since the theory is based on relational characteristics, I take a dyadic firm approach rather than a focal firm approach (Yang et al 2011). In order to address potential reverse causality[17], I construct a panel dataset that allows the lagging of independent

[17] It is possible that litigation will affect a firm's alliance activity. For example, firms that enforce their property rights may become reluctant to engage in future alliances, especially with competitors, for fear of further appropriation efforts. The use of lagged variables as instruments is designed to avoid this possibility. I tested for potential autocorrelation in the lagged specification using a Durbin Watson (1971) type test which tests whether the dependent variable can be predicted from the lagged value. i.e. A test of the null hypothesis that $\rho=0$ in the regression $Y_{it} = \alpha + \rho Y_{it-1} + \beta X_{it} + \varepsilon_{it}$. I found no evidence of significant autocorrelation in this and a number of alternative specifications.

variables. The panel dataset also allows individual firm heterogeneity to accounted for through the inclusion of fixed effects. The unit of analysis is therefore the dyad (firm pair) year[18].

### 3.3.1 Selection effects

Selection effects are common in studies of firm strategy and organizational behavior. In the context of this study, selection effects are likely to occur through at least three mechanisms: (1) Selection bias would occur if say, firms selected more innovative firms for alliance collaboration with the ex ante intention of appropriating their knowledge resources[19]. (2) Selection bias would also occur if there was a preference for larger firms as alliance partners since they provide greater resources, status and legitimacy (Stuart 2000). As larger firms may have a greater propensity to enforce their property rights[20], preference for large, well connected actors in the alliance network will lead to bias in the coefficients of the explanatory variables. (3) Competitive considerations are likely to affect alliance decisions and, as discussed, often have an impact on the strategic decision of whether to engage in litigation. For example, firms, if given the choice, may choose non-competitors in lieu of competitors as alliance partners and non-competitiors will have less incentive to aggressively enforce their intellectual property rights.

Matching methods can account for selection bias which arises from choice based sampling (Heckman and Navarro 2004). I adopt a case matching technique that "seeks to equate individual cases from different populations prior to treatment in the expectation of thereby unconfounding treatment and selection effects" (Cook and Steiner 2010). Starting with the list of lawsuits for the data period, I construct a pseudo (control) group of non-litigants by matching the plaintiff in the lawsuit to other closely related firms and keeping the defendant unchanged. Thus for each lawsuit, a number of non-lawsuits are created whereby for each pair of plaintiff and defendant a number of matched non-litigant pairings are formed. This approach is similar to the one employed by Bena and Li (2013) in their study of technological overlap in mergers and acquisitions.

This matching technique has several advantages over traditional Heckman (1979) two stage selection correction methodologies. First, by ensuring that all actual litigation cases are included in the analysis and by retaining privately owned defendants, the number of observations in the analysis is maintained at a high level. This is important since not all firms engaged in litigation participate in inter-firm alliances.

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[18] Rather than, say, the alliance dyad level.
[19] One effect of this would be to increase the number of common partners between firms
[20] Bessen and Meurer (2005). However, per patent, smaller firms are more likely to sue for patent infringement.

Second, with correct covariate selection (see following discussion) and significant correlations, Zhao (2004) shows using Monte Carlo simulations that matching methods can be highly effective in estimating treatment effects. Third, matching methods are well suited to dyadic analysis, particularly when relative measures between firms are of interest. Fourth, matching techniques are not dependent on functional form assumptions (Rubin 1977).

As noted by Stuart (2010), in terms of matching criteria, priority should be given to variables believed to be related to the outcome, as there is a higher cost in terms of increased variance of including variables unrelated to the outcome but highly related to treatment assignment (Brookhart et al., 2006). She also states "that to avoid allegations of variable selection based on estimated effects, it is best if the variable selection process is done without using the observed outcomes, and instead is based on previous research and scientific understanding" (Rubin, 2001). Consequently this is the approach adopted. I use industry categorization, quality weighted pre-sample patent stock and firm size as selection criteria, all of which have been shown to be strong indicators of alliance activity and all of which are the primary source of selection effects. A number of prior studies have found competitive considerations to be important in the selection of alliance partners (e.g. Oxley 1997). Since Blundell et al (1995) find that the main source of heterogeneity in innovation models lies in the different knowledge stocks, it follows that the main source of heterogeneity in patent litigation is intellectual property stocks. The value of patent stocks are an even more precise source of heterogeneity since firms with more valuable intellectual property are more likely to be infringed upon and they are more likely to have to enforce their intellectual property. All of these predictors are strong predictors of the assignment mechanism[21] and have high levels of reliability.

### 3.3.2 Data and sample construction

To form the sample of litigants, I take all patent infringement cases filed in U.S. District Courts, as contained in the Lex Machina IPLC legal database[22] between January 1, 2000 and December 31, 2006[23]. The Plaintiffs (patentees) are then matched to the NBER patent data project database which includes patent information on public firms for the data period. Financial and general company information is then

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[21] Preliminary estimation of the selection equation confirmed each criterion to be a highly significant predictor of alliance participation.

[22] Prior litigation studies have tended to use datasets that rely on self registration with the Commissioner of the United States Patent and Trademark Office (USPTO).. Since only approx. 60% of lawsuits are registered at the USPTO (Bessen and Meurer 2005) there is a potential for sample selection bias in prior research. The Lex Machina database includes all patent lawsuits within the data period, eliminating any potential for sample selection bias.

[23] The chosen sample period begins in 2000 since legal data from Lex Machina starts in 2000. The sample ends in 2006 (with lagged regressors for 2005) since beyond 2005 information contained in the NBER patent data project is incomplete or unavailable.

incorporated from Compustat. The sample of litigants comprises all cases where the Plaintiff is a publically listed firm in an ICT industry and where patent and Compustat data is available for at least 3 years within the sample period. This produces 1544 firm pairings who have at least one lawsuit between them.

This sample of litigants is appended to a matched pseudo sample, formed by taking each case in the litigants sample and finding up to five matching firms (if they exist) for the Plaintiff (patentee) in the case. Closest matches are found from the pool of (publically listed) Compustat firms during the sample period. Firms are matched on the following criteria: 1) they are they are in the same industry (6 digit NAICS code) as the actual Plaintiff 2) the closest match to quality weighted[24] pre-sample patent stock and to firm size (employment) according to the shortest Mahalonobis distance (Leuven and Sianesi 2012) and 3) there is a minimum of three years of data available on Compustat and the NBER patent data project within the sample period. Using Mahalonobis distance has the advantage of taking into account correlations in the data set and is scale invariant (Mahalonobis 1936). Thus it has a multi-variate effect size and is more suited to gauging similarity of an unknown sample set to a known one. Mahalanobis distance, rather than using coarsened exact matching, works well when there are relatively few covariates (Rubin, 1979; Zhao, 2004) as is this case in this analysis. This results in 6818 firm pairings for the pseudo sample and 8362 firm pairings overall.

The final step in the sample construction process involved the generation of the alliance network. Since the termination dates of alliances are often not publicized in alliance data, a five year moving window was used following previous studies (e.g. Yang et al 2010) [25]. Therefore for each year in the sample period (2000-2006), the alliance network was formed for activity in the five years prior. For example, for the year 2000, alliances that were formed between 1995 through 1999 were included. Data was drawn from the Thompson SDC Platinum database and verified using Lexis-Nexis. The alliance networks for each five year period varied in size from 14440 to 18856 nodes with the number of edges ranging from 38,082 to 48,982. Analysis of the networks indicated a relatively sparse, fragmented structure with many areas local clustering as is common in social and inter-organizational collaboration networks (Newman 2010).

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[24] Weighted by forward citations, a common indicator of patent quality.

[25] A number of previous studies (e.g. Yang et al 2011) have assumed alliances without termination dates to last 5 years, hence the 5 year moving window. This assumption is considered particularly appropriate in this instance since beyond this period there is a reduced amount of new knowledge spillovers from partner firms and appropriation opportunity is likely to be substantially diminished.

Network analysis to calculate the independent variables was carried out using Pajek software which is well suited for analyzing large scale networks[26].

### 3.3.3 Dependent variable

The dependent variable in the analysis takes the value of 1 if there is at least one lawsuit within the year between the firms in the Dyad where the Plaintiff (or pseudo Plaintiff) sues the Defendant (or pseudo Defendant) for patent infringement and 0 otherwise.

### 3.3.4 Independent variables

#### 3.3.4.1 Relational embeddedness

Following prior literature, relational embeddedness is defined as the number of prior ties between firm pairs. Thus, *relational embeddedness* is the number of alliance partnerships between the two firms in the alliance network.

#### 3.3.4.2 Structural embeddedness

In order to measure the extent to which two actors share the same partners (*structural embeddedness*), the Euclidean distance between the vectors associated with each firm's alliance portfolio is calculated (Batageli and Bern 1992).

Let $Q = [q_{uv}]$ be the adjacency matrix of the network, which is of dimension n x n. Then the dissimilarity (distance) between two firms is the Euclidian distance between the two vectors of Q which represent the two firms, $X_i$ and $X_j$:

[26] The number of nodes in the networks generated for each 5 year window varied between 14440 and 18856 which is beyond the capacity of most network software packages.

$$d_E(X_{it}, X_{jt}) = \sqrt{\sum_{\substack{s \neq i,j \\ s=1}}^{n} (q_{ist} - q_{jst})^2}$$

Thus, the Euclidean distance between two the alliance network vectors of two firms is equal to the square root of the sum of the squared differences between them. That is, the strength of actor *i*'s tie to *s* is subtracted from the strength of actor *j*'s tie to *s*, and the difference is squared. This is then repeated across all the other actors (up to *n*, the total number of actors in the network) and summed. The square root of the sum is then taken and the result is normalized such that it varies between 0 and 1. One minus this value is taken to obtain a measure of similarity rather than dissimilarity.

#### 3.3.4.3 Positional embeddedness

I operationalize *positional embeddedness* using Freeman's (1979) measure of "betweenness centrality", since this captures both the centrality and the spanning of structural holes, core concepts in the theoretical development leading to Hypothesis 3.3. Betweenness centrality calculates the extent to which a firm is located on the shortest path (i.e. geodesic) between any two actors in its alliance network.

Therefore, for firm *i* in year *t*:

$$Betweenness\ Centrality_{it} = \sum_{j<k} g_{jkt}(n_{it})/g_{jkt}$$

where $g_{jk}(n_i)$ refers to the number (*n)* of geodesics (i.e., shortest paths) linking firms *j* and *k* that contain focal firm *i*. The term $g_{jk}(n_i)/g_{jk}$ captures the extent to which firm *i* is involved in the shortest path between all others in the network.

The relative betweenness centrality between two firms, *a* and *b*, is the difference between the relative centrality values for each firm:

$$Relative\ Betweenness\ Centrality_{abt} = \sum_{j<k} \frac{g_{jkt}(n_{at})}{g_{jkt}} - \sum_{j<k} \frac{g_{jkt}(n_{bt})}{g_{jkt}}$$

### 3.3.4.4 Network competition (bilateral competition)

Following Lavie (2007), I calculate the level of competition between the firm and its alliance partners as the percentage of matches between the firm's primary industry segment (four-digit SIC) and the primary industry segments of its partners:

$$Network\ competition_{it} = \sum_{j=1}^{K} m_{ijt}/K_{it}$$

where $m_{ijt}$ is a dummy with the value of 1 when the SIC of firm *i* matches that of partner *j* in year *t*.

### 3.3.4.5 Controls

As discussed, the sample construction methodology enables a substantial amount of individual firm heterogeneity to be accounted for; however, additional control variables are included in the analysis to further reduce any possibility of omitted variable bias. Focus is placed on including controls that are potentially correlated with the main explanatory variables since it is these that may cause bias to coefficients.

Previous studies have shown that alliances between competitors are characterized by high levels of friction (Kogut 1989, Park and Russo 1996, Greve et al 2010) and that there are incentives for firms to engage in opportunistic behavior to gain advantages in market competition (Park and Ungson 2001). Thus, although the matching methodology should remove competition effects, I further control for *competition* between firms in dyads by including a variable that takes the value of 1 if both firms are in the same 4 digit industry SIC code and 0 otherwise, following a number of prior studies (e.g. Oxley 1997).

Since firms who use similar technologies are more likely to infringe each other's intellectual rights, I control for *Technological Similarity* using Jaffe's (1986) technological proximity measure. For each pair of firms, the following correlation coefficient is computed:

$$Technological\ Similarity_{abt} = \frac{\mathrm{S_{at}\,S'_{bt}}}{\sqrt{\mathrm{S_{at}\,S'_{at}}}\sqrt{\mathrm{S_{bt}\,S'_{bt}}}}$$

where the vector $S_{at}$ = ($S_{at}$,*1*, ..., $S_{at}$,*K*) captures the scope of innovation activity for the first firm in the dyad (the patentee), the vector $S_{bt}$ = ($S_{bt}$,*1*, ..., $S_{bt}$,*K*) captures the scope of innovation activity for the second firm in the dyad (the alleged infringer) firm, and *k*∈*(1,K)* is the patent technology class index. $S_{at}$,*k* ($S_{bt}$,*k*) is the ratio of the number of awarded patents to the patentee (the alleged infringer) in technology class *k* with granted years from *yr-5* to *yr-1* to the total number of awarded patents to the patentee (the alleged infringer) in all technology classes applied over the same five-year period.

Anecdotal reports of firms responding in kind to patent infringements litigation are common; indeed the existence of such cases would seem to be behind the emergence of the expression "patent wars". High profile examples between mobile communications handset producers and large computer software firms suggest that firms do retaliate to a patent lawsuit not just by filing an invalidity motion but also with a lawsuit that alleges infringement of the defendant's intellectual property by the plaintiff. I control for this response by including a variable *Retaliation* that takes the value of 1 if the alleged infringer (defendant) has previously sued the patentee (plaintiff) for patent infringement within the year prior to the observation. Moreover, I control for general litigation propensities for both patentees and alleged infringers, since prior research (e.g. Eisienberg and Farber 1997) suggests that some firms may be litigious plaintiffs and others may be serial infringers. Variables that measure the total number of lawsuits in the year for each firm in the dyad, *Total no. lawsuits where plaintiff sues* and *Total no. of lawsuits where alleged infringer is sued,* are therefore included in the analysis

In order to ensure that the explanatory variables are not just acting as proxies for general levels of alliance activity, I control for the total number of alliances (*No. alliances)* within the five year window used to calculate the network measures. I include controls for both the alleged infringer (AI) and patentee (P). I also control for the general level of *information flow* between the two firms in the dyad by including the maximum flow, defined as the number of independent paths between nodes (Newman 2010), in the analysis[27]. This variable captures the extent to which technological information flows through the alliance network between the firm pairs and which may increase the likelihood of detection of patent infringement or may provide opportunities for appropriation. Since multi-partner alliances can entail more complex management (Lavie 2007) I also control for the average number of partners *(Ave. no. partners)* in the portfolios of each of the firms in the dyad.

[27] An alternative measure of information flow, geodesic path (the shortest path between nodes), was used as a robustness check for this measure. Results are similar using this alternative measure.

Alliances which have principal objectives to exchange existing technology or to develop new technology are likely to be associated with high levels of patenting and intellectual property litigation. The requirement to share knowledge resources results in close interaction (Rowley et al 2000) and new jointly created knowledge tends to be hard to observe, value and protect (Krishnan 2006). Therefore, following Schilling and Phelps (2007), I include a variable, *%Technology alliances,* that controls for the proportion of R&D and cross-technology transfer alliances in each firm's alliance portfolio. Conversely, alliances with exploitative (March 1991) purposes, such as those with the purpose of establishing joint marketing initiatives, or those to form supply partnerships, have relatively low levels of knowledge spillovers (Lavie and Rosenkopf 2006). I therefore include a variable, *%Marketing alliances,* which controls for the proportion of marketing and supply agreements in each firm's portfolio.

## 3.4 Analysis and results

The hypotheses predict how the probability of litigation between firms is affected by the characteristics of alliance networks and hence a probabilistic model is used in the empirical analysis. Estimation is by Maximum Likelihood and a Logit specification is used:

$$\text{Prob}(\mathbf{Y}=1|\mathbf{X}) = \exp(\mathbf{X}'\beta) / 1+\exp(\mathbf{X}'\beta)$$

Table 3.1 shows the descriptive statistics for both the litigants (firms involved in actual cases) and the matched sample. Patentees in the first group tend to be involved in more alliances and have a higher proportion of technology alliances, thus controlling for these factors is an important requirement in the analysis. Moreover, the mean value of technological similarity for the litigants is more than twice the value for the matched group confirming the need to control for this effect. Mean values of Relational Positional Embeddedness are close to zero for both litigants and the matched group indicating the unlikeliness of any systemic bias in this relative measure from the matching process. Although there is little difference in the descriptive statistics between litigants and the matched group with respect to the general propensity of firms to be the subject of lawsuits (*Total no. of lawsuits where the defendant is sued*), there is a noticeable difference in the average number of lawsuits instigated by firms in the litigants sample (Mean=1.52, SD=3.21) compared to those in the matched sample (Mean=0.43, SD=1.89).

**Table 3.1 Descriptive statistics**

| Variable | Mean | Std. Dev. | Median | Min | Max |
|---|---|---|---|---|---|
| **Litigants sample** | | | | | |
| Lawsuits | 0.13 | 0.33 | 0 | 0 | 1 |
| Relational embeddedness | 0.08 | 0.33 | 0 | 0 | 4 |
| Structural embeddedness | 0.50 | 0.23 | 0.52 | 0 | 0.94 |
| Relative positional embeddedness | 0.05 | 0.20 | 0 | -1 | 1 |
| Network competition(AI) | 0.18 | 0.26 | 0.06 | 0 | 1 |
| Technological similarity | 0.22 | 0.30 | 0.01 | 0 | 1 |
| Network competition(P) | 0.20 | 0.24 | 0.10 | 0 | 1 |
| No. alliances(AI) | 17.72 | 45.7 | 3 | 0 | 482 |
| No. alliances(P) | 46.36 | 95.6 | 7 | 0 | 482 |
| Competition | 0.22 | 0.42 | 0 | 0 | 1 |
| Retaliation | 0.07 | 0.25 | 0 | 0 | 1 |
| Total no. lawsuits where plaintiff sues | 1.52 | 3.21 | 0 | 0 | 26 |
| Total no. lawsuits where defendant is sued | 0.91 | 0.13 | 0 | 0 | 20 |
| Information flow | 5.90 | 15.4 | 2 | 0 | 170 |
| Ave no. partners(P) | 2.01 | 0.67 | 2.12 | 0 | 7.60 |
| %Technology alliances(P) | 0.27 | 0.28 | 0.20 | 0 | 1 |
| %Marketing alliances(P) | 0.15 | 0.19 | 0.13 | 0 | 1 |
| Multilateral competition(P) | 0.17 | 0.18 | 0.13 | 0 | 1 |
| Ave no. partners(AI) | 1.73 | 1.14 | 2.00 | 0 | 7.60 |
| %Technology alliances(AI) | 0.25 | 0.32 | 0.10 | 0 | 1 |
| %Marketing alliances(AI) | 0.17 | 0.25 | 0.07 | 0 | 1 |
| Multilateral competition(AI) | 0.15 | 0.20 | 0.11 | 0 | 1 |
| **Matching sample** | | | | | |
| Lawsuits | 0.00 | 0.04 | 0 | 0 | 1 |
| Relational embeddedness | 0.01 | 0.09 | 0 | 0 | 2 |
| Structural embeddedness | 0.44 | 0.22 | 0.47 | 0 | 0.9 |
| Relative positional embeddedness | -0.02 | 0.09 | 0 | -1 | 0.16 |
| Network competition(AI) | 0.18 | 0.27 | 0.05 | 0 | 1 |
| Technological similarity | 0.10 | 0.19 | 0 | 0 | 0.98 |
| Network competition(P) | 0.17 | 0.24 | 0.05 | 0 | 1 |
| No. alliances(AI) | 19.34 | 48.1 | 3 | 0 | 482 |
| No. alliances(P) | 9.46 | 18.1 | 4 | 0 | 136 |
| Competition | 0.20 | 0.40 | 0 | 0 | 1 |
| Retaliation | 0.00 | 0.04 | 0 | 0 | 1 |
| Total no. lawsuits where plaintiff sues | 0.43 | 1.89 | 0 | 0 | 26 |
| Total no. lawsuits where defendant is sued | 0.96 | 2.16 | 0 | 0 | 20 |
| Information flow | 3.12 | 5.18 | 2 | 0 | 76 |
| Ave no. partners(P) | 1.70 | 0.93 | 2 | 0 | 4.75 |
| %Technology alliances(P) | 0.22 | 0.29 | 0.11 | 0 | 1 |
| %Marketing alliances(P) | 0.20 | 0.27 | 0.11 | 0 | 1 |
| Multilateral competition(P) | 0.15 | 0.21 | 0.09 | 0 | 1 |
| Ave no. partners(AI) | 1.74 | 1.11 | 2.00 | 0 | 7.60 |
| %Technology alliances(AI) | 0.27 | 0.32 | 0.14 | 0 | 1 |
| %Marketing alliances(AI) | 0.16 | 0.24 | 0.03 | 0 | 1 |
| Multilateral competition(AI) | 0.15 | 0.20 | 0.11 | 0 | 1 |

P=Patentee, AI=Alleged Infringer

Table 3.2 presents a correlation matrix for the main variables and controls used in the analysis. A number of moderately high correlations can be seen, particularly with respect to the number of alliances for alleged infringer and patentee. These variables are equivalent to degree centrality in network theory and high correlations between network measures are common in network-based research. Testing for potential multicolinearity, Variation Inflation Factors (VIFs) for the number of alliance partners (VIF=6.37 and 8.85 for alleged infringer and plaintiff respectively) were found to be below the commonly cited maximum threshold of 10 associated with potential multicolinearity. Furthermore, the Condition Index (=16.237) was well below the value of 30 suggested by Belsley et al (1980) as indicating serious multicolinearity.

## Table 3.2 Correlation Matrix

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Lawsuit | 1.00 | | | | | | | | | | | | | | | | | | | | | |
| 2. Relational embeddedness | 0.07 | 1.00 | | | | | | | | | | | | | | | | | | | | |
| 3. Structural embeddedness | 0.02 | 0.20 | 1.00 | | | | | | | | | | | | | | | | | | | |
| 4. Relative positional embeddedness | 0.04 | 0.20 | 0.04 | 1.00 | | | | | | | | | | | | | | | | | | |
| 5. Network competition(P) | 0.04 | -0.01 | 0.02 | 0.03 | 1.00 | | | | | | | | | | | | | | | | | |
| 6. Technological similarity | 0.12 | 0.08 | 0.14 | -0.02 | 0.04 | 1.00 | | | | | | | | | | | | | | | | |
| 7. Network competition(AI) | 0.00 | -0.02 | -0.04 | -0.01 | 0.02 | 0.04 | 1.00 | | | | | | | | | | | | | | | |
| 8. No. alliances(AI) | -0.01 | 0.10 | 0.24 | -0.60 | -0.06 | 0.08 | -0.04 | 1.00 | | | | | | | | | | | | | | |
| 9. No. alliances(P) | 0.06 | 0.34 | 0.27 | 0.74 | -0.01 | 0.03 | -0.05 | 0.01 | 1.00 | | | | | | | | | | | | | |
| 10. Competition | 0.03 | -0.03 | -0.10 | -0.05 | 0.23 | 0.16 | 0.21 | -0.03 | -0.09 | 1.00 | | | | | | | | | | | | |
| 11. Retaliation | 0.39 | 0.06 | 0.03 | 0.03 | 0.01 | 0.13 | 0.00 | 0.00 | 0.04 | 0.00 | 1.00 | | | | | | | | | | | |
| 12. Total no. lawsuits (plaintiff sues) | 0.04 | 0.13 | 0.09 | 0.13 | 0.01 | 0.08 | -0.02 | -0.02 | 0.16 | 0.00 | 0.07 | 1.00 | | | | | | | | | | |
| 13. Total no. lawsuits (defendant sued) | 0.00 | 0.11 | 0.17 | -0.26 | -0.03 | 0.04 | -0.01 | 0.49 | 0.04 | -0.03 | 0.00 | 0.06 | 1.00 | | | | | | | | | |
| 14. Information flow | 0.03 | 0.30 | 0.48 | 0.21 | -0.01 | 0.07 | -0.03 | 0.21 | 0.45 | -0.09 | 0.00 | 0.08 | 0.14 | 1.00 | | | | | | | | |
| 15. Ave no. partners(P) | 0.06 | 0.07 | 0.27 | 0.14 | 0.01 | 0.08 | 0.03 | -0.04 | 0.19 | 0.01 | 0.07 | 0.13 | 0.01 | 0.14 | 1.00 | | | | | | | |
| 16. %Technology alliances(P) | 0.04 | -0.02 | -0.01 | 0.01 | 0.03 | 0.12 | 0.00 | -0.07 | -0.02 | 0.12 | 0.03 | 0.06 | -0.08 | -0.01 | 0.06 | 1.00 | | | | | | |
| 17. %Marketing alliances(P) | -0.04 | 0.01 | -0.08 | -0.01 | 0.00 | 0.03 | -0.05 | -0.01 | -0.02 | -0.01 | -0.03 | 0.01 | 0.03 | -0.03 | 0.02 | 0.00 | 1.00 | | | | | |
| 18. Multilateral competition(P) | 0.02 | 0.01 | 0.07 | 0.04 | 0.04 | -0.01 | 0.55 | -0.04 | 0.02 | 0.07 | 0.02 | 0.07 | 0.00 | 0.02 | 0.06 | -0.09 | -0.11 | 1.00 | | | | |
| 19. Ave no. partners(AI) | 0.00 | 0.04 | 0.27 | -0.06 | 0.05 | 0.12 | 0.01 | 0.21 | 0.01 | -0.01 | 0.03 | 0.02 | 0.20 | 0.10 | 0.05 | -0.07 | -0.01 | 0.03 | 1.00 | | | |
| 20. %Technology alliances(AI) | 0.05 | -0.01 | 0.04 | 0.00 | 0.17 | 0.10 | 0.01 | 0.01 | -0.01 | 0.07 | 0.03 | 0.01 | 0.02 | 0.03 | -0.05 | 0.14 | -0.01 | 0.02 | 0.10 | 1.00 | | |
| 21. %Marketing alliances(AI) | -0.01 | 0.01 | -0.01 | 0.00 | -0.06 | -0.02 | -0.01 | 0.02 | -0.01 | -0.05 | -0.01 | 0.01 | 0.02 | 0.01 | 0.00 | 0.01 | -0.03 | 0.00 | -0.04 | 0.05 | 1.00 | |
| 22. Multilateral competition(AI) | -0.01 | 0.01 | 0.11 | 0.01 | 0.58 | 0.02 | 0.02 | 0.00 | 0.01 | 0.14 | 0.00 | 0.01 | -0.01 | 0.03 | 0.03 | 0.00 | -0.03 | 0.06 | 0.02 | 0.04 | 0.04 | 1.00 |

Table 3.3 presents the results of the regression analysis. As expected (refer to Model 3.1), technological similarity is a highly significant predictor of litigation between firms ($\beta$=1.556, p<0.001): firms engaged in activities within similar technological areas are more likely to infringe on each other's intellectual rights. Converting the coefficient to an odds ratio, a one standard deviation increase in the technological proximity measure increase litigation hazard by 18% (=exp(1.556)(0.1074)=1.182). Firms are also more likely to instigate litigation if they have a high amount of alliance activity as demonstrated by the results associated with the variable *No. alliances(P)* ($\beta$=0.003, p<0.001). This is consistent with prior research that has found alliance participation to involve appropriation hazards (e.g. Oxley 1997, Kale et al 2000) and to enable valuable knowledge flows which lead to innovation (Mowery et al 1996, Inkpen and Dinur 1998). The coefficient on retaliation is large and highly significant ($\beta$=3.606, p<0.001) confirming that firms do indeed respond in kind to being sued for infringement by asserting their own patent portfolios. Firms are over 30 times more likely to engage in litigation if there is a prior lawsuit where the alleged infringer has sued the patentee within the last year.

**Table 3.3 The determinants of patent infringement litigation (Logit regression results)**

| VARIABLES | (3.1) Controls only | (3.2) Main effects | (3.3) Interaction (H5a) | (3.4) Interaction (H5b) | (3.5) Conditional on patent match | (3.6) Random Effects |
|---|---|---|---|---|---|---|
| H3.1: Relational embeddedness | | 0.530*** | 0.510** | 0.543*** | 0.626*** | 0.568** |
| | | (0.205) | (0.208) | (0.205) | (0.230) | (0.224) |
| H3.2: Structural embeddedness | | -0.370 | -0.345 | -0.356 | -0.900* | -0.416 |
| | | (0.415) | (0.415) | (0.416) | (0.477) | (0.412) |
| H3.3: Relative positional embeddedness | | -3.755*** | -3.188** | -2.827** | -3.650** | -4.101** |
| | | (1.253) | (1.298) | (1.416) | (1.423) | (1.682) |
| H3.4: Network competition(AI) | | 1.040*** | 1.137*** | 1.056*** | 1.320*** | 1.077*** |
| | | (0.249) | (0.257) | (0.249) | (0.279) | (0.313) |
| H3.5a: Network competition and positional embeddedness | | | -3.754** | | | |
| | | | (1.822) | | | |
| H3.5b: Technological similarity and positional embeddedness | | | | -4.167** | | |
| | | | | (1.906) | | |
| Technological similarity | 1.556*** | 1.630*** | 1.648*** | 1.643*** | 1.903*** | 1.656*** |
| | (0.287) | (0.297) | (0.296) | (0.295) | (0.309) | (0.280) |
| Network competition(P) | -0.458 | -0.427 | -0.441 | -0.458 | -0.049 | -0.404 |
| | (0.425) | (0.423) | (0.425) | (0.429) | (0.510) | (0.402) |
| No. alliances(AI) | -0.004 | -0.009** | -0.009** | -0.009*** | -0.007** | -0.009** |
| | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) | (0.004) |
| No. alliances(P) | 0.003*** | 0.009*** | 0.009*** | 0.008*** | 0.009*** | 0.010*** |
| | (0.001) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Competition | 0.229 | 0.129 | 0.126 | 0.109 | 0.047 | 0.139 |
| | (0.179) | (0.182) | (0.183) | (0.184) | (0.219) | (0.230) |
| Retaliation | 3.606*** | 3.586*** | 3.586*** | 3.601*** | 3.933*** | 3.785*** |
| | (0.204) | (0.206) | (0.207) | (0.208) | (0.247) | (0.261) |
| Total no. lawsuits where plaintiff sues in year | 0.021 | 0.015 | 0.017 | 0.017 | -0.003 | 0.011 |
| | (0.022) | (0.023) | (0.023) | (0.022) | (0.036) | (0.022) |
| Total no. lawsuits where defendant is sued in year | 0.045 | 0.034 | 0.030 | 0.030 | 0.043 | 0.027 |
| | (0.037) | (0.036) | (0.037) | (0.037) | (0.045) | (0.040) |
| Information flow | 0.005 | 0.006 | 0.006 | 0.010* | 0.006 | 0.006 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.009) |
| Ave no. partners(P) | 0.282*** | 0.285*** | 0.286*** | 0.280*** | 0.228** | 0.306** |
| | (0.092) | (0.098) | (0.098) | (0.098) | (0.113) | (0.124) |
| %Technology alliances(P) | 0.311 | 0.305 | 0.294 | 0.289 | -0.107 | 0.277 |
| | (0.247) | (0.249) | (0.250) | (0.251) | (0.287) | (0.261) |
| %Marketing alliances(P) | -1.308*** | -1.389*** | -1.387*** | -1.380*** | -1.397*** | -1.394*** |
| | (0.375) | (0.385) | (0.384) | (0.384) | (0.435) | (0.363) |
| Multilateral competition(P) | 0.352 | 0.419 | 0.415 | 0.423 | 0.596 | 0.449 |
| | (0.411) | (0.411) | (0.411) | (0.414) | (0.530) | (0.410) |
| Ave no. partners(AI) | -0.098 | -0.083 | -0.077 | -0.080 | -0.067 | -0.083 |
| | (0.066) | (0.070) | (0.070) | (0.070) | (0.079) | (0.076) |
| %Technology alliances(AI) | 0.635*** | 0.504** | 0.524*** | 0.529*** | 0.429* | 0.475** |
| | (0.228) | (0.201) | (0.202) | (0.200) | (0.242) | (0.235) |
| %Marketing alliances(AI) | -0.414 | -0.239 | -0.230 | -0.234 | 0.065 | -0.226 |
| | (0.354) | (0.329) | (0.330) | (0.328) | (0.389) | (0.480) |
| Multilateral competition(AI) | -0.664 | -1.304*** | -1.333*** | -1.305*** | -1.088* | -1.307** |
| | (0.481) | (0.496) | (0.492) | (0.495) | (0.604) | (0.581) |
| Missing patent data dummy | 0.073 | 0.112 | 0.113 | 0.085 | | 0.102 |
| | (0.183) | (0.184) | (0.183) | (0.184) | | (0.200) |
| Constant | -4.615*** | -4.605*** | -4.647*** | -4.592*** | -4.748*** | -4.823*** |
| | (0.326) | (0.338) | (0.343) | (0.339) | (0.399) | (0.354) |
| Observations | 8,931 | 8,931 | 8,931 | 8,931 | 5,890 | 8,931 |

Robust standard errors in parentheses (Models 3.1-3.5), Bootstrapped standard errors for Model 3.6
Year fixed effects included, *** p<0.01, ** p<0.05, * p<0.1 P=Patentee, AI=Alleged Infringer

The coefficients on *Total no. lawsuits where plaintiff sues* and *Total no. lawsuits where defendant is sued* are not statistically significant. This suggests that the matching process has, as intended, removed sources of heterogeneity beyond that of matching criteria. Since smaller firms have been found to be more litigious per patent (Lanjouw and Schankerman 2004), matching on firm size is likely to match firms with similar propensities to litigate. Similarly, firms with more patents, who tend to be more innovative, are more likely to be serial infringers and matching on patents will remove effects associated with serial infringement. The lack of significant results for *Competition* are also likely due to the matching process since one of the matching criteria is to match to the same NAICS industry category.

The last set of control variables, those associated with the network portfolio characteristics of the patentees and alleged infringers are generally in line with expectations. Firms engaged in a large number of marketing alliances are less likely to sue for patent infringement, consistent with the idea that exploitation based alliances provide fewer opportunities for the knowledge transfer that leads to innovation and imitation ($\beta = -1.308$, $p<0.01$). Similarly, firms engaged in a greater proportion of technology alliances are more likely to accused of patent infringement ($\beta = 0.635$, $p<0.01$).

Also of interest is the result for *Average no. partners(P)* ($\beta = 0.282$, $p<0.001$) indicating that firms which tend to be involved in alliances with more than one other partner will have a greater likelihood of litigating within the dyad. This may because multi-partner alliances are complex with greater scope for uncertainty. Alternatively, alliances with multiple partners may be characterized by competing interests and high incentives for appropriation – a “den of thieves”.

Model 3.2 of Table 3.3 introduces the main effects corresponding to Hypotheses 3.1 to 3.4. The coefficient on Relational Embeddedness is positive and statistically significant ($\beta = 0.530$, $p<0.01$) supporting Hypothesis 3.1. Firms entering into alliances with another firm risk appropriation of their knowledge resources by that firm. This effect increases as the number of interactions with the firm increases since repeated interaction enables greater understanding of the other’s knowledge base. In contrast, Model 3.2 does not provide support for Hypothesis 3.2 since although the sign of the coefficient is as predicted, it is not statistically significant. It is therefore possible that the social monitoring effects of common partners do not have a major effect on the decision to appropriate or litigate or that other factors such as potential economic gain and the protection of existing rents take precedence over such considerations. Supporting Hypothesis 3.3, relative positional embeddedness has a negative effect on the likelihood that firms will be involved in a lawsuit. This is consistent with prior studies which have found that brokerage positions within collaborative networks confer informational advantages and provides evidence that relative positions in a network can impact strategic decision making. Hypothesis 3.4 predicts that firms in networks which are characterized by high levels of competition between the firm and the network members will have greater incentive to appropriate knowledge resources and hence will be more likely to be the subject of litigation. This hypothesis is supported given the results for *Network Competition(AI)* in Model 2 ($\beta$= 1.040, $p<0.01$)

Models 3.3 and 3.4 introduce the interaction effects. The coefficient on the interaction of network competition on relative positional embeddedness in Model 3.3 ($\beta$= -3.754, $p<0.05$) is of the predicted sign and is significant, lending support for the hypothesis that highly competitive environments increase the effects of power imbalances and informational (dis)advantages in the network. There is also support for Hypothesis 3.5b as demonstrated by the results in Model 3.4 (Coefficient on interaction= -4.167, $p<0.05$) indicating that technological similarity between firms increases the effect of relative positional embeddedness. This suggests that central firms are even more likely to detect infringement by peripheral firms when firms are in close technological proximity, thus deterring infringement in the first place. Moreover, this is also consistent with Hall and Ziedonis' (2001) findings within the semiconductor industry that smaller, more peripheral firms tend to be more exclusionary in their management of intellectual property and are thus more likely to litigate[28].

### 3.4.1 Robustness

The penultimate model in Table 3.3 presents results for a restricted sample that is conditional on a successful match to patent data. Restricting the analysis to dyads where both firms have a positive match to the patent data reduces the number of observations by 34%. Since the success rate of potential correct matches is high (checks found the rate to be the same as the 93% found by Bessen and Meurer 2005), the majority of firms with no match are those without patents registered at the USPTO. Excluding these firms in the analysis would have created potential sample selection bias as the restricted sample would likely be composed of fewer smaller firms with less propensity for alliance activity. The results in Model 3.5 for the restricted sample indicate that the main effects are broadly consistent but that the size of the effects tends to strengthen.  Thus, for the sub-sample of firm pairs where both firms have patent portfolios, the

[28] Negative values of relative positional embeddedness indicate that the alleged infringer is less central than the patentee. The negative variable value and the negative coefficient on the main effect of relative positional embeddedness result in a positive value (an increased likelihood of litigation). This positive effect is increased with increasing technological similarity.

size of all causal effects predicted by Hypotheses 3.1, 3.3 and 3.4 are increased. Even the effect of Structural Embeddedness (Hypothesis 3.2) becomes significant, albeit only marginally.

The findings are also robust to the specification of different lag structures. The use of a 3 year window for the occurrence of litigation provides broadly consistent results though the significance of relative positional embeddedness diminishes. This suggests that the positional (dis)advantages associated with relative network position may have a low degree of inertia and that power imbalances are sensitive to changes in network structures. The interaction effect of relative positional embeddedness with technological similarity (Hypothesis 3.5b) increases significantly under the 3 year litigation window whereas in contrast, the size of the interaction effect of positional embeddedness with network competition is reduced. This may indicate that the persistence of relative positional embeddedness is nuanced, that this network characteristic only has an enduring effect on firms when they share similar technological space. Indeed, this may be an example of "organizational forgetting" whereby knowledge that is extraneous to core activities or that conflicts with more appropriate knowledge is forgotten (Holan and Phillips 2004). Extensions to this study to examine temporal and dynamic effects in greater detail are raised in the discussion.

An additional regression analysis was carried out using an alternative measure of relative betweenness centrality. Although betweenness centrality is an established measure of positional embeddedness, other measures such as the Burt (1992) measure of structural holes have been used in prior studies. Using relative structural holes as an alternative relative positional embeddedness measure gives very similar results to the main analysis with generally increased levels of significance throughout. The results for relative positional embeddedness using relative structural holes ($\beta$= -0.506, $p<0.001$), and the interaction effects of positional embeddedness X network competition and positional embeddedness X technological similarity ($\beta$= -4.937, $p<0.05$ and $\beta$= -5.126, $p<0.01$ respectively), demonstrate the largest increase in statistical significance Thus the analysis is robust to the alternative specification of the positional embeddedness variable. A number of other alternative measures such as weighted values of relational embeddedness (past alliances being discounted according to how many years previously they had been formed) were tried which generally gave consistent results with lower statistical power.

The findings are also robust to the inclusion of dyad random effects which accounts for residual unobserved heterogeneity from the matching process[29]. These results are presented in the final model in Table 3.3.

### 3.5 Discussion

Although strategic alliance networks provide firms with access to information and resources that facilitate innovation and value creation, until now little has been known about how and when knowledge leakage in these networks may impact on the likelihood that firms infringe upon each other's intellectual property rights. This chapter demonstrates how participation in alliance networks increases knowledge transfer between firms, causing patent disputes, and shows that certain network characteristics affect incentives to engage in knowledge appropriation. Through this study I explain some of the key mechanisms by which a principal value creation strategy, collaboration in inter-organizational alliances, impacts on an increasingly important aspect of patent strategy: patent enforcement.

I find that relational embeddedness accruing from alliances with partner firms increases the likelihood of future litigation between focal and partner firms. I also find that position within the network, which determines access to information resources, plays a key role in whether infringement is detected and whether firms refrain from knowledge appropriation and litigious activity to avoid jeopardizing access to valuable knowledge flows. In addition to relational and positional embeddedness, network competition also affects litigation likelihood: the competitive landscape of the network affects incentives to appropriate, with more competitive network environments encouraging firms to appropriate the proprietary knowledge resources of partner firms. These effects all have considerable economic significance. One additional alliance increases the odds of litigation by 70% between firms (exp0.530=1.70), a one standard deviation increase in network competition increases the chances of a lawsuit by 32% (exp0.267*1.04=1.32) and a one standard deviation increase in relative positional embeddedness decreases the odds by 51% (exp0.189*-3.755=0.49). The interaction effects were also

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[29] In this case a random effects model was chosen over a fixed effects model since the maximum likelihood estimator (MLE) in nonlinear panel data models (such as a Logit) with fixed effects is widely understood to be biased and inconsistent when the length of the panel is small and fixed (Greene 2004). Furthermore, since within unit changes must be observed over time for effects to be estimated (Agarwal et al 2009), the use of a fixed effects model in this instance, with the relatively large number of zeros in the dependent variable, causes a large reduction in the number of observations and a large drop in efficiency. It should be noted though that a random effects model can be inconsistent if fixed effects are present, causing bias if there is correlation with explanatory variables.

found to be significant, with network competition and technological similarity increasing the effect of relative positional embeddedness. This demonstrates that competitive and technological factors play an important role in moderating the informational (dis)advantages of network position.

Perhaps surprisingly, the social monitoring effect of structural embeddedness was not found to limit opportunism and litigious action. This may be due to the institutionalization of inter-organizational alliances and patent disputes within ICT industries. High rates of alliance participation (over 50% of the focal firms in this sample were found to engage in alliance activity during the sample period) and high numbers of patent disputes may be an indication that appropriation of other firms' proprietary knowledge is common among all firms and that third party responses to such action may be minimal. In this environment, firms must collaborate in inter-organizational alliances to access new knowledge resources despite the inherent risks of appropriation by partners. Reputation and social constraint effects associated with common third party ties are likely to be dwarfed by competitive pressures to keep abreast of technological developments in these fast moving environments. However, this may not be the case in other industry environments and further work is required to extend the scope of the study to other industries.

One of the key findings in this chapter is that repeated interaction through multiple alliances increases the likelihood that firms will engage in patent infringement litigation since increased relational embeddedness provides detailed and tacit information which facilitates imitation and joint activity increases technological overlap of firms' capabilities. However, the question remains as why trust associated with relational embeddedness does not appear to limit patent conflicts through forbearance. Since trust encourages goodwill and fairness of partner behavior (Krishnan et al 2006), trust may be expected to add to the value of the alliance, discouraging opportunistic behavior by increasing the returns of collaboration compared to the pursuit of private benefits. Firms tempted by opportunism risk not only losing the benefits of their existing relationships but they also undermine their attractiveness as future alliance partners. Opportunities for the appropriation of knowledge resources from partner firms are thus made under "the shadow of the future" (Heide and Mine 1992, Kale et al 2000) and thus, trust should, under certain circumstances, be expected to reduce litigation likelihood between partnering firms through forbearance. Although this study is consistent with Kale et al (2000) whose survey-based empirical analysis found that relational capital had no significant impact on firms' ability to protect their proprietary knowledge assets, more work is needed to separate the different effects of trust – potential forbearance, reduced vigilance and increased knowledge flows.

One further area for future study is to analyze more closely the effect of alliance characteristics on litigation hazard. For example, more exploratory R&D alliances with high levels of uncertainty and incomplete contracts may be expected to have higher levels of patent disputes. However, if effective governance measures are employed to manage uncertainty and hold up (Oxley 1997), such as joint equity arrangements, these alliances may result in a sufficient level of trust whereby forbearance outweighs the other forces that make patent disputes more likely. Governance choice will also influence firms' appropriation opportunities of new jointly pioneered innovations. It is also likely to affect the allocation of intellectual property ownership rights of these joint technologies and the perceptions of ownership rights of associated technologies in parent firms. Thus, research that combines environmental uncertainty, alliance governance structure and tie strength may provide further insights into when disputes are likely to occur.

Closer examination of alliance types may also provide information on how the degree of complementarity between partnering firms affects the likelihood of patent lawsuits. Whereas this and other studies (e.g. Mowery et al 1996) have shown that technological overlap increases knowledge flow between firms, the exact role of different complementarities, such as technology, products and resources complementarity, on patent strategy is still not fully known. Since a principal reason for firms to form alliances is to access complementary resources (Baum et al 2010, Kumar 2010) and to develop complementary products, the joint value created by these arrangements should dissuade opportunistic behavior. Examination of the degree of complementarity of alliance relationships may provide insights into the precise reasons for patent disputes, particularly whether they occur intentionally through expropriation or unintentionally through increased activity in similar technological areas. In the latter case patent lawsuits may be a necessary means of clarifying property boundaries. Closer examination of alliances would also enable the effects of patent pooling and essential standards licensing on litigation strategy, which is beyond the scope of this study.

# Chapter 4: Small Firms, Patent Enforcement and the Market for Innovation

## 4.1 Background and synopsis

Entrepreneurial enterprises and small firms provide an important contribution to innovation, economic productivity and growth (Acs and Audretsch 1990, van Praag and Versloot 2007). The purpose of the patent system is to encourage innovation by ensuring that the economic value created by invention can be appropriated by the inventor. This institution should be of essential value to individuals and small firms since these innovators are particularly vulnerable to imitation by large firms who have the development capabilities and resources to establish dominant market positions. However, whilst many government regulations are often more lenient to small business (Nooteboom 1994), there is evidence that small firms are at a disadvantage when protecting their intellectual property through the patent system (Lanjouw and Schankerman 2004).

These concerns are reflected in the discussions surrounding recently enacted and proposed policy changes to the US patent system. For example, the America Invents Act[30] has divided opinion by scholars and practitioners on how key aspects of the legislation, particularly the new misjoinder rules and the ‘First to File’ provision, will impact small firms[31]. Several recent reforms such as the Federal Circuit Advisory Council’s position on ‘e-discovery’ requirements and the proposed SHIELD Act[32] suggest that the concerns of small firms are increasingly being considered in patent policy. Despite the contention regarding small firms and the patent system there have only been a limited number of empirical studies. These studies have tended to be conducted on pre- 2000 samples, before the recent “explosion” in patent litigation (Bessen and Meurer 2004), and have yet to provide evidence for the various theories that have been presented to explain differences between firms in litigation rates and lawsuit outcomes[33]. Moreover, there have been few attempts to estimate the overall cost to small firms associated with patent enforcement compared to large firms. There has also been little work to investigate whether there are ways that small firms overcome potential disadvantages in the patent system.

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[30] Leahy-Smith America Invents Act, H.R. 1249, 122th Cong.

[31] For example, Chien (2014) has found that following the AIA the number of lawsuits by Patent Assertion Entities increased, however the number of small companies among unique defendants decreased, likely due to the new misjoinder rules. Other commentators have suggested that the change to ‘First to File’ from ‘First to invent’ favors large firms with the resources to patent liberally even when the commercial value of innovations is highly uncertain.

[32] SHIELD Act, H.R. 6245, 112$^{th}$ Cong. This proposed legislation includes provisions which would require Patent Assertion Entities (PAE’s) or patent “trolls” to pay the legal costs of the defendant in the event of an unsuccessful prosecution, with the aim of reducing costs for small technology firms.

[33] Somaya (2003) is a notable exception.

The purpose of this chapter is to fill these gaps in the empirical literature. First, building on the seminal work by Lanjouw and Schankerman (2004), I evaluate whether there is a level playing field for small firms in the patent system, using a contemporaneous dataset to provide a timely examination that can inform current policy debate. To assess overall costs of participation in the patent system for small firms compared to larger firms, I determine whether the higher costs associated with the higher rates of litigation per patent for small firms (Lanjouw and Schankerman 2004) are mitigated by reduced costs from shorter lawsuit durations and a higher rate of favorable outcomes. Second, I extend previous studies by Galasso and Schankerman (2010) and Galasso et al (2013) to examine the role of patent trading by small firms to large firms. If patent trades are associated with increased propensity of litigation then efficient markets for innovation may reduce any disadvantages that small firms are subject to in the patent system. Finally, the empirical analysis offers a number of methodological contributions to empirical work in this area, overcoming many of the limitations of prior studies. For example, by comparing a sample of renewed patents to the wider population of patents, I am able to make inferences regarding the extent of selection effects: are small firms still more likely to litigate their patents even when accounting for different levels of patent utilization?[34]

Thus, the chapter comprises two parts. Combining information on patent renewals with highly complete legal data from Lex Machina IPLC, I begin by examining how small firms fare in the patent system, assessing the extent to which they are more likely to enforce their patents, despite potential capital constraints; whether they are more likely to settle lawsuits quicker; and whether trial outcomes are different from those of larger firms. I find that small firms do litigate their patents more than large firms but that, contrary to previous findings, their lawsuits have shorter durations. Since the duration of a lawsuit is directly related to the costs of the lawsuit, this implies that the overall cost to small firms associated with their high litigation rate is mitigated by a reduced average cost per lawsuit. However, small firms have a lower likelihood of achieving a favorable outcome in a lawsuit, especially when these cases go to bench[35] trials.

The second part investigates how the market for innovation is related to patent enforcement. Making use of inferences from the change in patent owner size on patent renewal data, I test whether patents

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[34] Findings by Weinburg (1990) suggest that small firms may apply their patents more than large firms. See following section.
[35] Bench trials, in contrast to jury trials, are those in which a judge determines the outcome. Trials are particularly expensive undertakings for those involved, costing on average $6.25 million in legal counsel fees for cases with at least $25million at stake (AIPLA 2011).

originally owned by small firms and then transferred to large firms are more likely to be litigated. I find that these traded patents have a hazard rate of litigation almost *twice* that of the underlying hazard rate, suggesting that patent enforcement is an important component of the strategy behind patent trades.

## 4.2 Literature review and theory

### 4.2.1 Existing economic theory on patent enforcement

Scholars have presented at least three inter-related theories as to why legal disputes occur rather than be settled ex-ante before a lawsuit filing. First, the parties in a dispute may have divergent expectations (DE) as what constitutes a fair ex-ante settlement and what the outcome of lawsuit would be, should a lawsuit be instigated. Different expectations may result simply from uncertainty (Priest and Klein 1984) or also through self-serving biases (Lowenstein et al 1993, Babcock et al 1995, Somaya 2003). In DE theory, the determinants of litigation and settlement include "the expected costs to parties of favorable or adverse decisions, the information that the parties possess about the likelihood of success at trial, and the direct costs of litigation and settlement (Priest and Klein 1984). In the earlier stages of patent disputes, before the filing of a lawsuit or immediately following a filing when settlement terms are often discussed, non-settlement occurs when different expectations of outcomes are drawn from error distributions[36]. Thus, in some cases, due to the 'probabilistic' nature of patents (Lemley and Shapiro 2004), parties are unable to agree on settlement terms and lawsuits proceed to trial. The Priest and Klein DE model predicts that, when this happens and when gains and losses from litigation are equal to the parties, the maximizing decisions of the parties will result in a success rate for plaintiff at the resultant trial of 50%.

DE theory is closely related to the second of the theoretical perspectives, asymmetrical information (AI), whereby one party is better informed as to the merits of a case and the likelihood of a successful prosecution (P'ng 1983, Bebchuk 1984, Schweizer 1989, Spier and Spulber 1993). AI theory suggests that firm size may have a role in determining likelihood of litigation. If large firms with in-house legal departments and R&D centers have more detailed knowledge of claim boundaries and more experience of litigating similar patents compared to small firms, this can provide them with superior knowledge as to the likely outcome of legal recourse. Alternatively, small firms in specialist niche markets may have very accurate knowledge of the intellectual property in their technological area and could have a high level of

[36] Errors from the actual likely outcome.

information regarding expected outcomes. Both scenarios would suggest that small firm patentees have a higher likelihood of litigating their patents, since the existence of information asymmetry makes settlement less likely, but the former situation implies that small firms would have a lower win-rate than larger firms and the latter would imply the opposite. This empirical study can help to reveal which scenario is likely to be the case.

The last of the theoretical perspectives, the strategic stakes (SS) hypothesis (Somaya 2003, Waldfogel 1995), is also closely associated with DE theory. It simply predicts that legal disputes are likely to occur if one party has more to lose than the other. SS theory shows that if firms have higher strategic stakes in their IP then they have higher incentives for protection and are more likely to litigate their patents. It also predicts that patentees with high strategic stakes are less likely to settle lawsuits (Somaya 2003). SS theory also has implications for lawsuit win likelihood when combined with DE theory, as in the Priest and Klein (1984) model. The authors show that when stakes are greater for plaintiffs than defendants, there is divergence away from the 50% win rate. In these situations plaintiffs are likely to win greater than 50%, with defendants winning less than 50%.

### 4.2.2 Implications of prior empirical studies

Empirical studies of patent litigation have found that although small firms may be financially constrained, they are more likely, per patent, to assert their patents in the courts (Allison et al 2001, Lanjouw and Schankerman 2004, Bessen and Meurer 2005).  A number of propositions have been made to explain this observation. First, each patent owned by small firms may be, on average, more valuable than a patent owned by large firms. (Bessen and Meurer 2004, Allison et al 2003, van Praag and Versloot 2007). Without the financial constraints of small firms, large firms may be more likely to file patent applications for 'marginal' innovations, those with uncertain or relatively low commercial value. Since more valuable patents have a greater patent premium, valuable patents are more likely to be litigated as the greater benefits of enforcement are more likely to outweigh the costs of litigation.

Second, patents owned by small firms may be more critical to the overall profit making ability of the firm. SS theory predicts that if smaller firms have higher strategic stakes in their IP then they have higher incentives for protection and are more likely to litigate their patents. Larger firms who tend to have larger patent portfolios may be less likely to be reliant on individual patents for their success. This is consistent with the findings of Brouwer and Kleinknecht (1996) who show that when small firms have sales from innovative products, they derive a higher fraction of sales from these products compared to larger firms. In essence, the patent premium may be larger for small firms (Hall 2004). Further evidence for higher strategic stakes or patent value in small firms has been found in a study by the Patent Foundation of George Washington University (Weinburg 1990) who found that small firms below $100 million in sales or whom owned less than 100 patents applied 71% of their patents compared to larger firms who applied only 51% of their patents. The effect of patent quality and higher strategic stakes on the likelihood of litigation has been found to be moderated by the size of the firm's patent portfolio. Lanjouw and Schankerman (2004) show that small firms with small patent portfolios are even more likely to assert a patent than small firms with relatively large portfolios. The authors posit that this may be because larger patent portfolios facilitate co-operative agreements such as cross licensing which avoids litigation (Lanjouw and Schankerman 2004).

Third, market structure in some industries may explain relatively high litigation rates amongst small firms or low litigation rates among large firms. In concentrated industries, repeated interaction between large firms may reduce incentives for firms to engage in litigation. For example, Hall and Ziedonis (2001) have found that in the semi-conductor business, large vertically integrated firms cross-license whilst smaller design firms outsource manufacture and are litigious and exclusionary towards others.

Fourth, firms with relatively high litigation costs, such as small firm patentees who are potentially less able to enforce their IP, pose less of a deterrence threat against potential infringement (Lerner 1995). With a questionable capacity to enforce patents, potential injurers take less care to avoid disputes. IP litigation is often used as a reputation building strategy (Agarwal et al 2009) and the threat associated with patent litigation is less credible for small firms with limited resources to prosecute lawsuits. The credibility of enforcement threat is also likely to be affected by patent portfolio effects. Small firms with small patent portfolios have even less to gain from building a reputation for toughness since the benefits accruing from aggressive litigation from individual patents are not applied to a large number of other patents in the portfolio.

In summary, these empirical finding suggest that small firm patentees may tend to have greater strategic stakes in their IP than large firms and that there may be factors relating to resource constraints and market structure which explain higher patent litigation rates for small firm patentees. Assuming that small firms tend to have higher strategic stakes in their intellectual property, then SS combined with DE theory predicts a win rate of greater than 50% for small firm litigants for cases that are not resolved through settlement.

### 4.2.3 Firm size and the market for innovation

Strong intellectual property (IP) rights are important to small firms, such as those in the semiconductor business studied by Hall and Ziedonis (2001), who lack in-house complementary assets to appropriate their innovations (Teece 1986). For these firms, markets for innovation in the form of intellectual property trading and licensing, are an important mechanism for commercializing innovation. The development of in-house downstream capabilities in such areas as manufacturing, marketing and distribution is often difficult and they take time to acquire (Arora and Ceccagnoli 2006). This often makes the development of downstream capabilities unfeasible and small firms will look to form partnerships with other firms, offering a stake in their innovation in return for access to complementary assets. Thus small firms often rely on the market for innovation to appropriate their IP and an efficient market maintains the incentives for small firms to innovate.

Large firms tend to be attractive partners for small firms since they often have the necessary complementary assets to successfully enter product markets. Thus, the market reallocation of patent rights from small firms to large firms is an important component of the market for innovation. However, IP reallocation has implications beyond increasing the profit from innovation, particularly for patent trades which transfer enforcement rights. Firms may have incentives for strategically acquiring patents and enforcing them to improve competitive positions. Consider, for example, a situation where a small firm without complementary assets owns a technology and licenses it to two other large firms who both commercialize the technology and compete in the same product market. Assuming that the downstream firms have the same costs and that products are undifferentiated, both firms have an incentive to obtain sole use of the technology since the monopoly profits are greater than the sum of the duopoly profits (Cournot 1838, Gans and Stern 2000). If either of the downstream firms purchases the technology from the upstream supplier, that firm will be able to enforce the IP against the other. If substitutes to the technology are not available or if the other firm has significant sunk costs in the technology, then the buyer of the technology will be able to obtain a dominant market position by extracting a high level of rents from their competitor. This suggests that there are instances when patent trades will subsequently result in the enforcement of IP.

Beyond strategic motivation for acquisition and subsequent enforcement of patents, there are other reasons to expect greater litigation risk from traded patents. As noted earlier, the transfer of IP from firms without complementary assets to those which possess them has the effect of increasing the value of the innovation. Since the higher patent premium associated with the now commercialized innovation is more likely to outweigh the costs of enforcement, more valuable innovations are more likely to be litigated. The additional value generated from the reallocation therefore increases litigation risk.

Moreover, the transfer of ownership from small firms to large firms is also likely to alleviate any resource constraints which may have impeded effective enforcement. As previously discussed, without effective enforcement threat, potential infringers face little incentive to refrain from appropriating IP. Trade of patents to large firms, with the financial resources to enforce them, forces imitators to pay royalties for the use of technology they may have previously been infringing on. The filing of a patent infringement lawsuit signals an intention to collect rents due and hence these traded patents are likely to have a higher rate of litigation.

In summary, due to 1) the strategic motivations of buyers; 2) the increased value obtained through access to complementary assets; and 3) the increased financial capacity of the buyers to enforce IP; patents transferred from small firms to large firms are expected to have a greater likelihood of litigation[37].

## 4.3 Empirical analysis

### 4.3.1 Data

The data used in the empirical analysis is drawn from a number of different sources. I start by taking the population of patents issued by the USPTO since 1993 and I identify those that have been renewed. Patents applied for after December 12, 1980 need to be renewed after years 4, 8 and 12 from their grant date and failure to renew results in the patent expiring. Thus, the identification of renewed patents enables only “relevant” patents to be examined – those with current or expected commercial value, whose owners have enforcement incentives. This renewals data has a number of useful characteristics. As well as providing basic information such as patent number, application and grant dates, etc, it identifies whether the patent owner is classified as a “small entity” and subject to reduced renewal fees[38]. Small entities represent 20.0% of patents issued between 1993 and 2010 which are subsequently renewed. Moreover,

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[37] There are also a number of reasons why in some cases, traded patents may be associated with a lower likelihood of litigation, such as when they are bought to establish defensive portfolios. This empirical study aims to establish whether, on aggregate, traded patents are more or less likely to be litigated.

[38] Since November 6$^{th}$ 1986, firms defined as small under the US Small Business Administration’s definition of a small firm are subject to a 50% reduction in fees payable to the USPTO for renewal. The criteria for meeting “small firm” status varies by industry but typically has limits on annual revenue and often limits employee numbers to 500.

the data identifies patents that change status from small entity ownership to large entity ownership, enabling patent reallocation to be observed.

This renewals data is combined with litigation data provided by Lex Machina IPLC. The Lex Machina dataset has information on all patent lawsuits since 2000 and includes data on various aspects of the cases, including which patents are asserted, the identities of the parties involved, filing and termination dates, as well as information on outcomes. The data distinguishes between patent infringement lawsuits where the patent holder is the plaintiff (claimant) and declaratory lawsuits, whereby the patent holder is the defendant in a claim of invalidity, infringement or unenforceability. Furthermore, the Lex Machina dataset includes detailed information on how each lawsuit is resolved, enabling an in depth analysis of the effect of explanatory variables on case outcomes to be undertaken. The Lex Machina dataset contains 32,078 patent cases filed during the period 2000 to 2013.

In addition to the litigation data, further patent data is added to the renewals dataset, providing controls for the empirical analysis and enabling industry categorization. In order to examine patent portfolio effects and to provide an alternative measure of size, a measure of the total number of patents held by the patent owner is developed. Using entity identifiers from USPTO assignee references, the size of patent portfolios is compiled for patent owners. 65.2% of patent owners are identified. Analysis of this subset of the data provides robustness and allows any moderating effect of patent portfolio size to be estimated. The sample period extends from January 1st, 1993 to January 1st 2013[39]. Patent data is compiled for 1993 through 2010[40] and the Lex Machina legal data covers the period 2000 through 2012. The final dataset comprises 1329999 observations (patents).

The data enables a number of limitations of previous studies to be overcome. First, prior research has tended to use datasets of publically listed firms with limits of employee numbers to establish small firms (e.g. Bessen and Meurer 2005) or has assumed that all unlisted firms are small (Lanjouw and Schankerman 2004). Patent owners in this study are classified as small if they meet the criteria set out by the US Small Business Association (SBA) which takes into account relative size differences across industries. Furthermore, this classification criteria enables both private as well as public firms to be used

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[39] Left and right truncation of the data is accounted for in the Cox proportional hazard-rate models (see following section) by specifying an "observation window" (entry and exit dates) in the Stata coding that was used for the analysis.
[40] The author is grateful to Lai et al (2013) for the patent data made available through the Patent Network Dataverse. The Lai et al data covers all patents issued up to the end of 2010. Although the renewals data has information on patents through to 2012 in order to incorporate the full set of controls provided by the Lai et al data, the patent data used in this study is for patent grants between 1993 and 2010.

in the analysis (most small firms are privately owned) and does not require the assumption that all privately owned firms are small (many privately owned firms are large[41]).

Second, as previously noted, this analysis includes consideration of only relevant patents – those considered worthwhile enough to maintain. Studies based on samples that include expired patents may provide misleading results if selection effects are present. For example, large firms may be patenting more “extravagantly”, applying for more patents with relatively high uncertainty over commercial value, but letting more patents expire. Higher litigation rates per patent amongst small firms may therefore be simply because they are using more of their patents. By including only maintained patents in the analysis, comparisons of the commercially valuable patents held by both small and large firms can be made. This can provide insights into the differing incentives and strategic motivations behind patent enforcement.

Third, the data also allow previous limitations relating to potential sample selection effects to be addressed. Most previous litigation studies have been based on the Derwent Lit Alert dataset which relies on self reporting to the Commissioner of the United States Patent and Trademark Office (USPTO). Approximately 60% of cases are registered leaving a substantial number of lawsuits unreported and missing from empirical analysis. Since small firms tend to have fewer managerial resources than larger firms it is likely that a high proportion of unreported lawsuits are from small firms. Thus, previous studies that aim to establish whether small firms are litigate their patents more than large firms may underestimate the size of effects. The Lex Machina data used in this study is fully complete, containing all cases filed at US District Courts during the sample period. Any sample selection bias is therefore eliminated.

A further advantage of the Lex Machina data is that it includes all patents asserted in a case. The Lit Alert dataset only includes the “main” patent in a case, a significant limitation since patent cases have become increasingly complex[42] with multiple patents commonly asserted in a lawsuit. Between 2000 and 2012, 49.2% of patent infringement cases involved claims concerning more than 1 patent. Often it is not clear which patent constitutes the “main” patent and subjective decisions are required to select one.

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[41] For example, until its IPO in 2012 when it was valued at over $100bn, Facebook was a privately held company.
[42] However, some of the recent reforms associated with the America Invents Act have had the effect of reducing the complexity of lawsuits, particularly the new misjoinder rules which has reduced the average number of defendants in cases (Chien 2012).

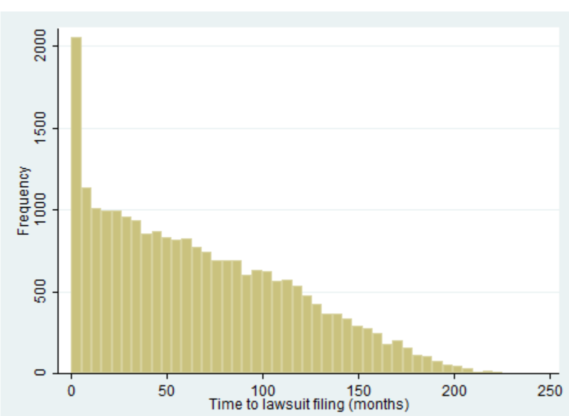
### 4.3.2 Measures and descriptive statistics

#### 4.3.2.1 Dependent variables

The empirical analysis comprises three parts to match the different stages of patent litigation disputes (Galasso and Schankerman 2010). First, I examine the likelihood of a lawsuit occurring, taking into account the time elapsed from patent grant. The inclusion of this duration variable in the initial model is important since litigation likelihood varies substantially over the life of a patent. Moreover, since the litigation data covers the period 2000-2012, not the entire life of each patent in the sample[43], there is truncation in the data which would create bias in simple probabilistic models which estimated the probability of a patent being litigated. Hazard rate models are therefore used, which estimate the probability of litigation, conditional on the duration. The empirical specifications are discussed more in following sections.

In this first part of the analysis, the data is analysed to assess how key variables, namely whether patents are owned by small firms and whether those patents are traded to large firms, affect the likelihood that a patent will be litigated and how this probability varies over time. The dependent variables used in this stage of the analysis include *infringement lawsuit* , a dummy variable that takes the value of 1 if the patent is asserted in a patent infringement lawsuit; and *lawsuit lag*, which is defined as the time between the patent grant date and the patent lawsuit filing date at the District Court. Figure 4.1 illustrates the distribution of *lawsuit lag*. It can be seen that a large number of lawsuits occur around the time of the patent grant.

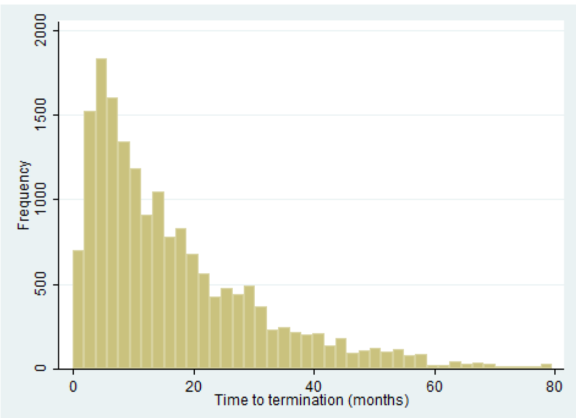
**Figure 4.1 Distribution of time between patent grant and lawsuit filing for litigated patents**




[43] For example, patent litigation "histories" are not known for patents beyond the date of writing of this paper.

Second, I examine the next stage in the litigation process by evaluating the role of the key independent variables in relation to post lawsuit filing outcomes, specifically the probability of an ex post settlement occurring and the probability of a settlement or termination of a lawsuit, conditional of the time elapsed since the lawsuit filing date. This enables conclusions to be drawn regarding whether small firms are subject to shorter lawsuit durations and have different settlement propensities, which has implications for the cost of patent enforcement for small firms, compared to large firms. Conditional on a lawsuit occurring, dependent variables include *settlement*, a dummy for whether a case results in a settlement or likely settlement and *case duration,* which is defined as the time between the case filing date and the case termination date as recorded in the Lex Machina data. Figure 4.2 illustrates the distribution of *case duration*. The variable *settlement* includes "likely settlements" which constitute instances where plaintiffs voluntarily dismiss cases where they hold positions of relative strength.

**Figure 4.2 Distribution of lawsuit duration**




The third part of the analysis investigates outcomes for those cases that go to trial. Dependent variables for this stage of the analysis include *plaintiff win*, a dummy that takes the value 1 if the party instigating the lawsuit wins the case at trial[44].

Table 4.1 reports variable definitions and summary statistics for all variables used in the analysis.

[44] *plaintiff win* includes summary judgements and trial wins for some supplementary specifications which investigate pre-trail as well as trial outcomes..

**Table 4.1 List of variables and descriptive statistics**

| Variable | Description | Mean | Standard deviation |
|---|---|---|---|
| *infringement lawsuit* | Dummy = 1 if patent asserted in infringement lawsuit | 0.01 | 0.09 |
| *lawsuit lag* | Time between patent grant and first instance of lawsuit filing | 118.9 | 61.9 |
| *small* | Dummy = 1 if small entity status | 0.22 | 0.41 |
| *trade* | Dummy = 1 if patent traded (status change small to large) | 0.004 | 0.059 |
| *claims* | Number of claims on patent | 16.62 | 13.53 |
| *backward citations* | Number of backward citations on patent | 11.08 | 22.64 |
| *application time* | Time between patent filing and grant (months) | 30.82 | 15.87 |
| *tech classes* | Number of 4 digit IPC technology classes on patent | 1.72 | 0.91 |
| *forward citations (ln)* | Log of forward citations to patent (adj truncation) | 2.35 | 1.03 |
| *self citations* | Number of self citations / Total number of back citations | 0.076 | 0.182 |
| *foreign* | Dummy = 1 if patentee is foreign owned firm | 0.356 | 0.479 |
| *portfolio size (ln)* | Number of patents in portfolio at time of patent grant | 3.95 | 3.81 |
| Industry fixed effects: | | | |
| *chemical* | Dummy = 1 if firm in chemical industry | 0.137 | 0.343 |
| *comp&comms* | Dummy = 1 if firm in computers or telecommunications | 0.219 | 0.413 |
| *pharma&med* | Dummy = 1 if firm in pharmaceutical or medical | 0.101 | 0.302 |
| *electrical&electronic* | Dummy = 1 if firm in electrical or electronics | 0.207 | 0.405 |
| *mechanical* | Dummy = 1 if firm in mechanical | 0.165 | 0.371 |
| Conditional on lawsuit: | | | |
| *settlement* | Dummy = 1 if case settled | 0.545 | 0.498 |
| *case duration* | Time between case filing date and case termination date | 17.44 | 15.57 |
| *plaintiff win* | Dummy = 1 if plaintiff 'win' by settlement, summary judgment or trial win | 0.94 | 0.23 |
| *number of cases* | Number of lawsuits where patent is asserted 2000-2012 | 1.925 | 3.377 |
| *number of patents* | Number of patents asserted in lawsuit | 6.170 | 6.847 |

#### 4.3.2.2 Independent variables

The central focus of the empirical analysis is on small firms and the patents that they trade. As noted earlier, small firms are categorized on the basis of the criteria stipulated by the US Small Business Association (SBA). For each patent, the dummy variable *small*, indicates whether the patent owner meets this criteria. The development of a variable that includes whether that patent has been traded is less straightforward. Although the renewals data identifies whether a patent owner no longer claims small entity status, it is not known whether the change in status occurs either through 1) firm growth (the firm no longer meets the SBA criteria); 2) a patent trade (and the new owner no longer meets the SBA criteria) or 3) a merger or acquisition (and the merged entity no longer meets the criteria). I distinguish between patent trades and other changes in status (due to firm growth or mergers and acquisitions) by examining the characteristics of subsequent patent awards to the firm. If the firm is awarded small entity status on future patents then it is concluded that the firm has remained small through this period and the change in status from small to large on the earlier patent must be due to a sale of a patent. Using this basis for distinction, 81.0% of the patents which changed status from small entity ownership to large entity ownership were traded. In the analysis, the variable *trade* identifies patents that were traded to large firms. In order to address potential endogeneity, specifically the concern that patent lawsuits may have a causal effect on whether a patent is traded, the time series nature of the data is utilized. Only lawsuits that occur after the confirmed date of the patent trade are retained in the analyses in which the variable *trade* is included.

#### 4.3.2.3 Control variables

As shown in Table 4.1, the data includes a number of control variables. Following previous work on small firms and patent litigation (Lanjouw and Schankerman 2004), I control for the number of claims in the patent (*claims*) and the number of backward citations (*backward citations*). The number of claims in a patent has been argued to reflect the complexity of the underlying technology (Allison 2002). Since complex technologies are more likely to have unclear property boundaries (Shapiro 2001), controlling for complexity is potentially an important requirement in the analysis. In addition to *claims*, I therefore include *application time*, defined as the length of time between a patent application filing and the patent grant award as a further proxy for uncertainty; the rationale being that in general, long application times are likely to be associated with more complex technologies where more care is required to attempt to delineate boundaries[45]. The number of technology classes recorded on the patent is also included (*tech classes*)

I also include proxies for 1) the quality of the patent, *forward citations(ln),* defined as the natural log of the number of forward citations to the patent, adjusted for truncation and 2) the strategic importance of the patent, the proportion of backward citations whereby the patent owner cites itself (*self citations*). Somaya (2003) argues that this measure captures a firm`s strategic stake in a patented technology and shows that it effects litigation outcomes, particularly whether a firm is inclined to settle. As well as these patent characteristics, I also incorporate the firm characteristics *portfolio size(ln)*, defined as the natural log of the number of patents held by the firm at the time of the patent award and *foreign*, a dummy variable for whether the patent owner is foreign owned, since foreign firms have been found to enforce their patents less than domestic firms (Lanjouw and Schankerman 2004). In order to account for the general increase in litigation over the sample period, I include year dummies associated with the patent grant year. I also construct industry dummies from the patent technology class following the classification system adopted by Hall et al (2001), since there are large differences across industries in litigation

[45] Despite these attempts to establish non-overlapping claims, litigation hazard of these patents is likely to be higher.

behavior (Burk and Lemley 2002, Bessen and Meurer 2005). This enables industry fixed effects to be incorporated into the analysis, facilitates stratified hazard rate models and allows comparison of the main effects across industries. Table 4.2 shows the means of key variables across industries.

**Table 4.2 Means of key variables by industry**

| Variable | Chemical | Pharma/ Medical | Computers/ Telecomms | Electrical/ Electronic | Mechanical | Other |
|---|---|---|---|---|---|---|
| *infringement lawsuit* | 0.005 | 0.011 | 0.011 | 0.005 | 0.006 | 0.009 |
| *lawsuit lag* | 137.3 | 108.7 | 130.4 | 118.4 | 131.5 | 103.7 |
| *small* | 0.179 | 0.097 | 0.327 | 0.142 | 0.271 | 0.325 |
| *trade* | 0.004 | 0.002 | 0.007 | 0.003 | 0.004 | 0.004 |
| *claims* | 15.72 | 19.01 | 17.90 | 16.14 | 14.80 | 15.86 |
| *backward citations* | 10.72 | 11.93 | 14.42 | 10.22 | 10.92 | 9.88 |
| *application time* | 28.58 | 37.34 | 33.21 | 27.69 | 25.80 | 31.35 |
| *tech classes* | 1.893 | 1.725 | 1.859 | 1.623 | 1.616 | 1.725 |
| *forward citations (ln)* | 2.096 | 2.710 | 2.419 | 2.423 | 2.132 | 2.224 |
| *self citations* | 0.098 | 0.085 | 0.068 | 0.081 | 0.075 | 0.048 |
| *foreign* | 0.416 | 0.371 | 0.267 | 0.444 | 0.428 | 0.211 |
| *portfolio size (ln)* | 3.202 | 5.665 | 2.601 | 4.923 | 3.395 | 2.345 |

With respect to the analysis on post lawsuit filing outcomes, a number of additional controls are added. To ensure that it is not just a few highly litigated patents that are driving results, a control for the total number of litigation events for each patent is constructed (*number of cases*). To allow for the likelihood that complex cases involving multiple patents may have different outcomes than other cases, a variable that counts the number of patents asserted in the case is included[46] (*number of patents*).

### 4.3.3 Specification

The empirical analysis has several objectives. First, I aim to establish the extent to which small firm patentees differ in the likelihood that their patents are litigated. Another objective is to assess whether patent trades are associated with a greater probability of patent litigation. I also investigate whether small firms have shorter lawsuit durations. As discussed, since these objectives require estimation of the probability of an event occurring, taking account of the time occurring between treatment and the event, a hazard rate model is used due its advantages over maximum likelihood probabilistic models in censored samples. A semi-parametric Cox proportional hazard-rate is used since the distribution of the underlying

[46] If small or large firms are disproportionately involved in these types of cases, bias to regression coefficients and hazard rates would result.

hazard rate is not accurately known due to the censoring. Parametric alternatives require the distribution of the underlying hazard to be precisely specified. Indeed, the underlying distribution of the hazard-rate is not of primary interest and the Cox proportional hazard-rate model eliminates risk of mis-specification[47].

As noted by Gans et al (2008), the Cox proportional hazard-rate model is specified as a continuous time based hazard-rate function, incorporating a non-parametric baseline hazard rate and a multiplicative term whereby regressors have a proportional impact relative to the baseline. Thus, the model takes the following form:

$$h_{LAWSUIT}(t, X_i, SMALL_i, TRADE_i) = h(t)\exp(\beta_0 + \beta_X X_i + \beta_{SMALL} SMALL_i + \beta_{TRADE} TRADE_i + \varepsilon_i) \tag{1}$$

Where $h_{LAWSUIT}$ is the hazard rate of lawsuit changing from zero to one (the probability of the event occurring at time t, conditional on time t; $X_i$ are the patent controls, firm controls and fixed effects. $\beta_{SMALL}$ and $\beta_{TRADE}$ are interpreted as the effect of small firm status and patent trade on the patent litigation hazard.

For robustness, I also test an industry stratified Cox proportional hazard-rate model, whereby the underlying hazard rate is allowed to vary by industry sector, *k*. Equation (1) thus becomes:

$$h_{LAWSUIT}(t, X_i, SMALL_i, TRADE_i, k) = h^k(t)\exp(\beta_0 + \beta_X X_i + \beta_{SMALL} SMALL_i + \beta_{TRADE} TRADE_i + \varepsilon_i) \tag{2}$$

The second and third parts of the empirical analysis involve investigation of post-suit outcomes and consideration of the length of time to reach those outcomes. A Cox proportional hazard-rate model is again used for the same reasons discussed earlier in this section:

$$\begin{aligned} h_{SETTLEMENT}(t, X_i, SMALL_i, TRADE_i) \\ = h(t)\exp(\beta_0 + \beta_X X_i + \beta_Z Z_i + \beta_{SMALL} SMALL_i + \beta_{TRADE} TRADE_i + \varepsilon_i) \end{aligned} \tag{3}$$

[47] A number of robustness checks using parametric specifications are undertaken (see subsequent sections). These models tend to have higher Log Likelihood values than the baseline Cox proportional hazard-rate models, however, the sizes of the coefficients and statistical significance levels are very similar to the baseline Cox model, indicating that the results are not sensitive to choice of semi-parametric or parametric model specification.

Where $Z_i$ refers to the case level controls, *number of cases* and *number of patents*.

The analysis of post-suit outcomes also includes a number of probabilistic analyses to test whether small firms are more or less likely to settle or win their lawsuits, without reference to time elapsed. This enables a useful comparison with the Cox Proportional Hazard models. In these models, estimation is by Maximum Likelihood and a Logit specification is used:

$$\text{Prob}(\mathbf{Y}=1|\mathbf{X}) = \exp(\mathbf{X}'\beta) / 1+\exp(\mathbf{X}'\beta) \tag{4}$$

## 4.4 Results

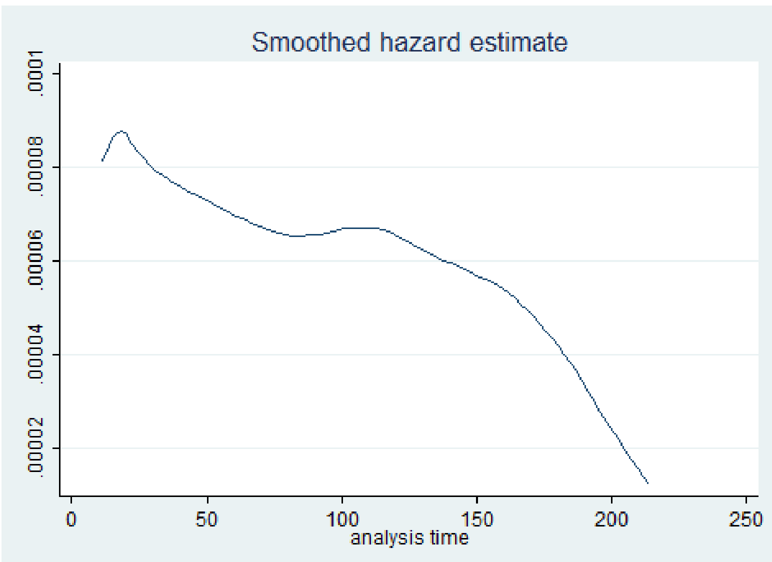
Table 4.3 presents the first set of results from the semi-parametric Cox proportional hazard-rate models. In each of the five models in Table 4.3, the “failure” event is the occurrence of a filed patent infringement lawsuit and the time variable is the difference in months between the date of the lawsuit filing and the patent grant date. Model 4.1 comprises the inclusion of the control variables only and Model 4.2 introduces the explanatory variables, *small* and *trade*.

**Table 4.3 Main results – Cox Proportional HR models (failure event - filing of lawsuit)**

| VARIABLES | (4.1) Controls only | (4.2) Main effects | (4.3) Renewed patents only | (4.4) Industry interactions | (4.5) Industry interactions |
|---|---|---|---|---|---|
| *small* | | 1.353*** | 1.539*** | 1.539*** | 1.538*** |
| | | (0.025) | (0.028) | (0.051) | (0.028) |
| *trade* | | 2.059*** | 1.871*** | 1.818*** | 1.761*** |
| | | (0.141) | (0.128) | (0.124) | (0.249) |
| *claims* | 1.007*** | 1.007*** | 1.007*** | 1.007*** | 1.007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *tech classes* | 0.990 | 0.991 | 0.991 | 0.990 | 0.991 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| *self citations* | 0.255*** | 0.309*** | 0.294*** | 0.304*** | 0.294*** |
| | (0.017) | (0.020) | (0.020) | (0.020) | (0.020) |
| *forward citations (ln)* | 1.699*** | 1.724*** | 1.680*** | 1.677*** | 1.680*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| *backward citations* | 1.003*** | 1.004*** | 1.004*** | 1.004*** | 1.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *application time* | 1.000 | 1.001 | 1.001 | 1.001 | 1.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *foreign* | 0.396*** | 0.424*** | 0.423*** | 0.430*** | 0.423*** |
| | (0.009) | (0.009) | (0.009) | (0.010) | (0.009) |
| *chemical* | 0.534*** | 0.564*** | 0.535*** | 0.507*** | 0.536*** |
| | (0.018) | (0.019) | (0.018) | (0.021) | (0.018) |
| *comp&comms* | 0.886*** | 0.947* | 0.906*** | 0.871*** | 0.902*** |
| | (0.020) | (0.021) | (0.021) | (0.024) | (0.021) |
| *pharma&med* | 0.864*** | 0.873*** | 0.819*** | 1.058 | 0.821*** |
| | (0.023) | (0.023) | (0.022) | (0.035) | (0.022) |
| *electrical&electronic* | 0.515*** | 0.545*** | 0.521*** | 0.495*** | 0.521*** |
| | (0.014) | (0.015) | (0.014) | (0.017) | (0.014) |
| *mechanical* | 0.696*** | 0.712*** | 0.700*** | 0.642*** | 0.700*** |
| | (0.019) | (0.019) | (0.019) | (0.024) | (0.019) |
| *smallXchemical* | | | | 1.184* | |
| | | | | (0.083) | |
| *smallXcomp&comms* | | | | 1.251*** | |
| | | | | (0.061) | |
| *smallXpharma&med* | | | | 0.453*** | |
| | | | | (0.027) | |
| *smallXelectrical&electronic* | | | | 1.226*** | |
| | | | | (0.072) | |
| *smallXmechanical* | | | | 1.236*** | |
| | | | | (0.069) | |
| *tradeXchemical* | | | | | 0.754 |
| | | | | | (0.243) |
| *tradeXcomp&comms* | | | | | 1.408 |
| | | | | | (0.264) |
| *tradeXpharma&med* | | | | | 0.938 |
| | | | | | (0.190) |
| *tradeXelectrical&electronic* | | | | | 1.109 |
| | | | | | (0.272) |
| *tradeXmechanical* | | | | | 0.949 |
| | | | | | (0.236) |
| Observations | 1,674,303 | 1,674,303 | 1,462,034 | 1,462,034 | 1,462,034 |
| Log Likelihood | -228088 | -227915 | -221375 | -221192 | -221371 |

The specification for Model 4.3 limits the analysis to only patents that have been renewed at least once in their lifetime. The hazard ratio of 1.539 in Model 4.3 implies that when considering the population of "relevant" patents, small firms are associated with a 54% increase in the underlying hazard rate. The estimate is significant at the 0.1% level. Figure 4.3 shows the smoothed hazard-rate estimate over time for Model 4.3. As expected, the hazard-rate is initially relatively high and then decreases at a decreasing rate. The rate is then approximately constant between 6 and 10 years after patent grant. The shape of the graph beyond 10 years shows a steep decline in hazard-rate.

**Figure 4.3 Graph of hazard rate of patent litigation over time (months) for Model 4.3**




The 54% increase in hazard rate for small firms using the sample of renewed patents contrasts with an increase of 35% when all patents are included. The increase in hazard-rate for small firms over the underlying hazard-rate for renewed patents shows that if we are interested only in the characteristics of "relevant" patents, those which are utilized to the extent that they are considered worthwhile to renew, then previous studies are likely to have underestimated the extent to which small firms litigate their patents more than large firms. The hazard-rate ratio for *trade* also has high economic and statistical significance. The results from Model 4.3 show that patents traded by small firms to large firms are associated with an increase in the probability of litigation of 87% ($\beta$= 1.871, $p<0.001$). This supports the theory that predicts patents traded to firms with complementary assets and greater financial resources are more likely to be litigated.

The hazard-rate ratios for the control variables are broadly consistent with prior research (Lanjouw and Schankerman 2004, Bessen and Meurer 2005). Patents with more claims, forward citations and backward citations are all more likely to be litigated. However, the number of technology classes assigned to the patent and the patent application time are not significant predictors of litigation. A number of variables reduce litigation probability. Patents owned by foreign firms are 58% less likely to be litigated. The hazard-rate ratio of 0.309 ($p<0.001$) indicates that firms that cite a high proportion of their own technology are much less likely to be involved in litigation. This may suggest that in many industries, firms are able to fence out an "acreage" with their intellectual property, laying claim to a specific technological area with relatively clear boundaries. Firms build on their expertise within a niche by patenting further refinements to existing technology and they patent closely related technological applications to ensure "freedom to operate".

The industry fixed effects in Model 4.3 are all significant at the 0.1% level, confirming large differences in litigation rates across industries. In Model 4.4, industry interactions with *small* are introduced to explore whether there are differences across industries in the propensity for patents owned by small firms to be litigated. Indeed, there are a number of important differences. In contrast to other industry sectors, small firms in the pharmaceutical and medical instruments industries are no more likely to litigate their patents[48]. The hazard-rate ratios on the other industry sectors indicate an 18-24% increase in the underlying rate over and above the 54% increase implied by the hazard-rate on *small*. For firms in these sectors, the net increase is therefore approximately 75%. In these four sectors, the industry fixed effects remain significant at the 0.1% level even with the introduction of the interaction effects. However, the fixed effect for the pharmaceutical and medical instruments sector loses all statistical significance, suggesting that a large proportion of the pharmaceutical and medical industry fixed effect is associated with differences in firm size.

Model 4.5 examines industry interaction effects with *trade*. In contrast to the findings in Model 4.4, the effect of *trade* does not vary by industry: none of the hazard-rate ratios on the interactions are significant.

[48] The hazard-rate ratio on *small* is 1.539, a 54% increase and the hazard-rate ratio on the interaction is 0.453, a 55% decrease on the underlying hazard rate, thus the net increase/decrease is zero.

### 4.4.1 Robustness and extended analysis

Tables 4.4 and 4.5 present the results from a number of alternative empirical specifications to ensure robustness of the findings. First, whilst I have categorized patent owners according to their size, as defined by the US Small Business Administration, this classification does not take into account the size of a firm's portfolio. Since patents are often used defensively to discourage litigation (Ziedonis 2004), higher litigation rates by small firms may be explained by the smaller patent portfolio sizes of small firms[49]. The results presented in Model 4.7, Table 4.4 show that the findings are robust to the inclusion of portfolio size. As expected, the hazard-rate ratio for portfolio size is less than 1 indicating that, per patent, firms with large portfolios are less likely to litigate their patents. The hazard-rate ratio for small drops to 1.231 yet it remains significant at the 0.1% level, indicating that regardless of portfolio effects, firm size is a significant predictor of litigation. Model 4.8 includes an interaction variable of *small* with portfolio size to ascertain whether portfolio effects are stronger for small firms. The lack of statistical significance on the interaction provides evidence that, in contrast to the findings by Lanjouw and Schankerman (2004), defensive portfolios have little effect in reducing litigation likelihood for small firms.

[49] Portfolio size is not included in the baseline analysis for two reasons. First, portfolio size can be considered a proxy for firm size, hence its inclusion would mean that the accurate estimate of the effect of small firm status would not be captured. Second, construction of firm portfolio size requires each patent to be matched to an ownership entity. The matching process used in this analysis makes use of USPTO assignee numbers. These references are provided for 70.0% of the observations and it is likely that they are provided less for small firms compared to large firms, giving rise to concerns over sample selection bias. Moreover, unlike earlier datasets such as those developed by the NBER Patent Data Project, the identifiers do not consolidate multiple subsidiaries into single entities. Therefore, due to these limitations and the requirement for accurate estimates, the number of patents is not included in the baseline analysis. It is however included as a robustness check and to evaluate portfolio effects on the main variables.

**Table 4.4 Robustness checks: Restricted samples**

| VARIABLES | (4.6)<br>Baseline | (4.7)<br>Conditional on firm match | (4.8)<br>Portfolio effects | (4.9)<br>Grant date post 2000 |
|---|---|---|---|---|
| *small* | 1.539*** | 1.231*** | 1.241*** | 1.688*** |
| | (0.028) | (0.029) | (0.033) | (0.040) |
| *trade* | 1.871*** | 1.861*** | 1.863*** | 7.032** |
| | (0.128) | (0.128) | (0.128) | (4.975) |
| *portfolio size (ln)* | | 0.803*** | 0.803*** | |
| | | (0.004) | (0.004) | |
| *smallXportfoliosize(ln)* | | | 0.987 | |
| | | | (0.017) | |
| *claims* | 1.007*** | 1.008*** | 1.008*** | 1.007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| *tech classes* | 0.991 | 0.984 | 0.984 | 0.988 |
| | (0.008) | (0.010) | (0.010) | (0.011) |
| *self citations* | 0.294*** | 0.784*** | 0.787*** | 0.230*** |
| | (0.020) | (0.050) | (0.050) | (0.021) |
| *forward citations (ln)* | 1.680*** | 1.691*** | 1.691*** | 1.529*** |
| | (0.013) | (0.015) | (0.015) | (0.016) |
| *backward citations* | 1.004*** | 1.003*** | 1.003*** | 1.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| *application time* | 1.001 | 1.002** | 1.002** | 1.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| *foreign* | 0.423*** | 0.455*** | 0.455*** | 0.420*** |
| | (0.009) | (0.012) | (0.012) | (0.012) |
| *chemical* | 0.535*** | 0.503*** | 0.504*** | 0.568*** |
| | (0.018) | (0.021) | (0.021) | (0.025) |
| *comp&comms* | 0.906*** | 0.986 | 0.986 | 0.858*** |
| | (0.021) | (0.027) | (0.027) | (0.025) |
| *pharma&med* | 0.819*** | 0.831*** | 0.832*** | 0.768*** |
| | (0.022) | (0.027) | (0.027) | (0.028) |
| *electrical&electronic* | 0.521*** | 0.555*** | 0.556*** | 0.510*** |
| | (0.014) | (0.019) | (0.019) | (0.018) |
| *mechanical* | 0.700*** | 0.711*** | 0.711*** | 0.666*** |
| | (0.019) | (0.024) | (0.024) | (0.024) |
| Observations | 1,462,034 | 1,172,633 | 1,172,633 | 824,130 |
| Log Likelihood | -221375 | -148308 | -148308 | -126921 |

The final specification in Table 4.4 uses a restricted sample of patents that were granted after January 1st, 2000, the date of commencement of the Lex Machina legal data. Whilst left and right truncation are accounted for through the specification of an observation window (see footnote under "Data" section), a robustness check of a subsample with no left truncation is undertaken[50]. The hazard-rate ratio for *small* remains high with this specification and significant (β= 1.688, p<0.001). *trade* continues to have

[50] Right truncation is unavoidable since we do not observe the litigation history of patents beyond 2013 i.e. until the end of the life of many patents

explanatory power at the 1%, however the large reduction in identification associated with the reduced sample size makes the interpretation of the size of the hazard-rate unreliable[51].

**Figure 4.4 Graph of –log(-log(survival probability)) for Model 4.3**

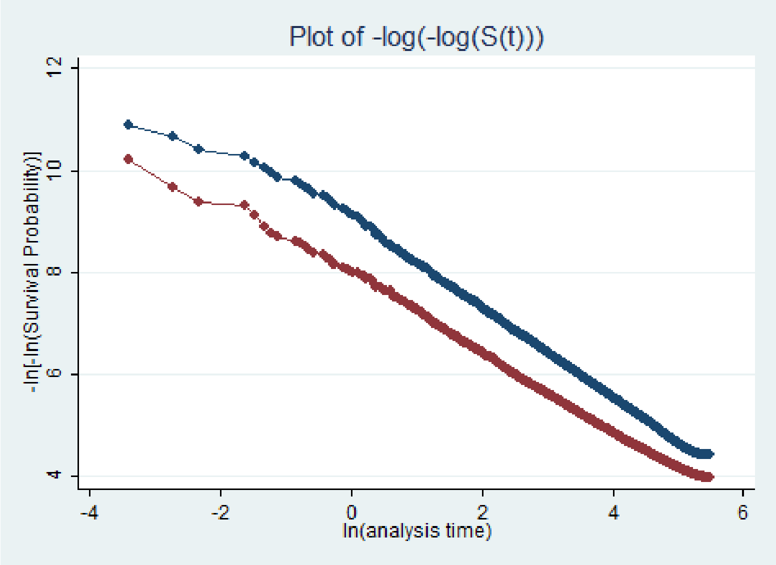



Figure 4.4 shows a log-log graph of the cumulative hazards estimated in Model 4.3 which can be used to check the proportionality assumption in Cox hazard-rate models. The two lines show the baseline cumulative hazard and hazard with the variable *small* added. As can be seen, the plots are approximately parallel indicating that the proportionality assumption is reasonable. Table 4.5 presents results from alternative specifications of the underlying hazard rate. Model 4.11 allows each industry to have its own baseline hazard function. Models 4.12-4.14 test several parametric specifications, assuming exponential, Weibull and Gompertz distributions respectively. The size of hazard ratios and the statistical significance display a high degree of similarity and it can be concluded that the findings are not dependent on a particular empirical specification.

[51] The construction of the variable *trade* requires data on renewals at 4 and 8 years. Limiting the sample to patent grants after 2000 thus reduces the number of observations where trade can be calculated substantially.

**Table 4.5 Robustness checks: Alternative specifications**

| VARIABLES | (4.10) Cox PH | (4.11) Cox PH Industry Stratified | (4.12) Parametric (exponential) | (4.13) Parametric (Weibull) | (4.14) Parametric (Gompertz) |
|---|---|---|---|---|---|
| *small* | 1.539*** | 1.545*** | 1.540*** | 1.539*** | 1.539*** |
| | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| *trade* | 1.871*** | 1.863*** | 1.871*** | 1.871*** | 1.871*** |
| | (0.128) | (0.127) | (0.128) | (0.128) | (0.128) |
| *claims* | 1.007*** | 1.007*** | 1.007*** | 1.007*** | 1.007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *tech classes* | 0.991 | 0.991 | 0.991 | 0.991 | 0.991 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| *self citations* | 0.294*** | 0.291*** | 0.294*** | 0.294*** | 0.294*** |
| | (0.020) | (0.019) | (0.020) | (0.020) | (0.020) |
| *forward citations (ln)* | 1.680*** | 1.672*** | 1.680*** | 1.680*** | 1.680*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| *backward citations* | 1.004*** | 1.004*** | 1.004*** | 1.004*** | 1.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *application time* | 1.001 | 1.001 | 1.001 | 1.001 | 1.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *foreign* | 0.423*** | 0.422*** | 0.423*** | 0.423*** | 0.423*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| *chemical* | 0.535*** | | 0.534*** | 0.534*** | 0.535*** |
| | (0.018) | | (0.018) | (0.018) | (0.018) |
| *comp&comms* | 0.906*** | | 0.907*** | 0.906*** | 0.906*** |
| | (0.021) | | (0.021) | (0.021) | (0.021) |
| *pharma&med* | 0.819*** | | 0.819*** | 0.819*** | 0.819*** |
| | (0.022) | | (0.022) | (0.022) | (0.022) |
| *electrical&electronic* | 0.521*** | | 0.521*** | 0.521*** | 0.521*** |
| | (0.014) | | (0.014) | (0.014) | (0.014) |
| *mechanical* | 0.700*** | | 0.700*** | 0.700*** | 0.700*** |
| | (0.019) | | (0.019) | (0.019) | (0.019) |
| Observations | 1,462,034 | 1,462,034 | 1,462,034 | 1,462,034 | 1,462,034 |
| Log likelihood | -221375 | -193473 | -97631 | -97556 | -97563 |

The next part of this results section examines the latter stages of patent disputes: post-filing lawsuit outcomes for small firms. Table 4.6 displays the results from a series of maximum likelihood Logit probability models, with Models 4.15-4.17 estimating the likelihood of a patentee settling a lawsuit and Models 4.18-4.21 estimating the probability that the firm instigating the lawsuit wins the lawsuit either through forcing a settlement or through a summary judgment or trial win. The results show that small firms are 10% less likely to settle lawsuits and contrasts with the assertions of Lanjouw and Schankerman (2004) that small firms (assumed in the study to be the all "domestic unlisted" firms) have no difference in settlement rates[52]. This result is robust to the inclusion of portfolio effects, as shown in Model 4.16. The number of patents in a patentee's portfolio does not have a significant on the likelihood of settlement. This suggests that 1) there are limited benefits to defensive portfolios when the focal firm is the subject of infringement by others and that defensive portfolios are most effective in avoiding litigation where the focal firm is an alleged infringer. Moreover, the result implies that 2) defensive portfolios are not effective in obtaining favorable post-suit outcomes.

[52] This is based on the authors finding of a 94.0% settlement rate for "domestic unlisted" firms and 94.1% settlement rate for "domestic listed".

**Table 4.6 Logit models: conditional on lawsuit occurring**

| VARIABLES | (4.15) Prob settlement | (4.16) Prob settlement | (4.17) Prob settlement (Industry Interactions) | (4.18) Prob plaintiff win | (4.19) Prob plaintiff win (Industry Interactions) | (4.20) Prob plaintiff win (Bench trials) | (4.21) Prob plaintiff win (Jury trials) |
|---|---|---|---|---|---|---|---|
| *small* | -0.104** | -0.109* | -0.156* | -0.368*** | -0.388** | -1.244*** | -0.344 |
| | (0.037) | (0.054) | (0.065) | (0.073) | (0.132) | (0.376) | (0.181) |
| *portfolio size (ln)* | | -0.016 | | | | | |
| | | (0.010) | | | | | |
| *smallXportfoliosize(ln)* | | 0.044 | | | | | |
| | | (0.036) | | | | | |
| *number of cases* | -0.020** | -0.020* | -0.020** | -0.006 | -0.007 | -0.223 | -0.064 |
| | (0.006) | (0.008) | (0.006) | (0.011) | (0.011) | (0.118) | (0.089) |
| *number of patents* | -0.017*** | -0.015*** | -0.018*** | 0.017** | 0.016** | -0.034 | -0.015 |
| | (0.002) | (0.003) | (0.002) | (0.006) | (0.006) | (0.019) | (0.009) |
| *claims* | -0.001 | -0.001 | -0.001 | -0.002 | -0.002 | -0.007 | -0.003 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.007) | (0.003) |
| *tech classes* | -0.043** | -0.040* | -0.042* | 0.073* | 0.075* | 0.033 | 0.088 |
| | (0.016) | (0.020) | (0.016) | (0.035) | (0.035) | (0.106) | (0.066) |
| *self citations* | 0.005 | 0.093 | 0.024 | 0.111 | 0.132 | -0.323 | 0.212 |
| | (0.125) | (0.132) | (0.124) | (0.280) | (0.279) | (0.786) | (0.438) |
| *forward citations (ln)* | -0.042** | -0.040* | -0.039* | -0.001 | 0.004 | 0.370** | 0.145* |
| | (0.015) | (0.018) | (0.015) | (0.034) | (0.034) | (0.130) | (0.070) |
| *backward citations* | 0.001** | 0.001* | 0.001** | 0.001 | 0.001 | -0.003 | 0.002 |
| | (0.000) | (0.001) | (0.000) | (0.001) | (0.001) | (0.002) | (0.002) |
| *application time* | -0.003** | -0.001 | -0.003** | -0.001 | -0.001 | 0.014* | -0.004 |
| | (0.001) | (0.001) | (0.001) | (0.003) | (0.003) | (0.007) | (0.005) |
| *foreign* | 0.019 | 0.038 | 0.026 | 0.044 | 0.058 | -0.026 | 0.107 |
| | (0.045) | (0.051) | (0.045) | (0.101) | (0.102) | (0.354) | (0.180) |
| *chemical* | -0.089 | -0.151 | -0.181* | -0.004 | -0.144 | 0.252 | 0.117 |
| | (0.066) | (0.082) | (0.082) | (0.137) | (0.176) | (0.442) | (0.282) |
| *comp&comms* | -0.120** | -0.134* | -0.095 | 0.024 | 0.092 | -1.395** | -0.717*** |
| | (0.046) | (0.056) | (0.055) | (0.100) | (0.128) | (0.432) | (0.195) |
| *pharma&med* | -0.321*** | -0.379*** | -0.400*** | -0.116 | -0.139 | -0.970* | -0.214 |
| | (0.054) | (0.065) | (0.065) | (0.109) | (0.142) | (0.389) | (0.219) |
| *electrical&electronic* | 0.056 | 0.081 | 0.005 | 0.517*** | 0.545** | -1.038* | -0.350 |
| | (0.055) | (0.068) | (0.067) | (0.135) | (0.177) | (0.511) | (0.245) |
| *mechanical* | 0.105 | 0.069 | 0.030 | -0.068 | -0.239 | -1.409 | -0.492 |
| | (0.055) | (0.069) | (0.074) | (0.108) | (0.151) | (0.735) | (0.258) |
| *smallXchemical* | | | 0.265 | | 0.374 | | |
| | | | (0.140) | | (0.285) | | |
| *smallXcomp&comms* | | | -0.194* | | -0.264 | | |
| | | | (0.096) | | (0.188) | | |
| *smallXpharma&med* | | | 0.283* | | 0.058 | | |
| | | | (0.118) | | (0.225) | | |
| *smallXelectrical&electronic* | | | 0.154 | | -0.089 | | |
| | | | (0.118) | | (0.274) | | |
| *smallXmechanical* | | | 0.170 | | 0.356 | | |
| | | | (0.111) | | (0.217) | | |
| Constant | 0.563 | 0.288 | 0.552 | 3.041** | 3.004** | -0.371 | -2.807** |
| | (0.393) | (0.498) | (0.393) | (1.051) | (1.055) | (0.795) | (1.076) |
| Observations | 17,205 | 11,788 | 17,205 | 17,205 | 17,205 | 438 | 1,102 |
| Log Likelihood | -11625 | -7976 | -11613 | -3709 | -3704 | -224.2 | -652.6 |

The coefficients on *number of cases* and *number of patents* are negative and statistically significant throughout Models 4.15-4.17 indicating that that the more patents that are asserted in any one case and the more cases that a patent is asserted in, the less likely that there will be an agreement that settles the case. The result that it is more difficult to resolve the differences between parties in complex cases with multiple patents is consistent with divergent expectations theory since increased complexity gives rise to increased uncertainty over outcomes. The result that patents involved in multiple lawsuits are less likely to be settled is consistent with transaction cost theory, particularly where global settlements are sought with multiple defendants.

There are a number of industry fixed effects that are of interest. In particular, it can be seen that lawsuits in the pharmaceutical and medical instruments industries are much less likely to be settled ($\beta_{PHARMA\&MED}$= -0.321, $p<0.001$) possibly reflecting the high stakes associated with high research and development costs. Model 4.17 introduces industry interactions with small firm status. Small firms in the computers and communications are much less likely to settle lawsuits than small firms in other industries (the probability is over 2 times greater that no settlement will be reached[53]). The interaction between *small* and *pharma&med* ($\beta$ = 0.283, $p<0.05$) is positive, significant and of similar magnitude to the coefficient on *small* ($\beta$ = -0.156, $p<0.05$) indicating that there is little difference in settlement rates for small and large firms in the pharmaceutical and medical instruments industries.

Models 4.18-4.21 estimate the likelihood of a favorable outcome for patentees in infringement lawsuits. The coefficient on *small* in Model 4.18 ($\beta$ = -0.368, $p<0.001$) indicates that small firm patentees are significantly less likely to force a settlement or gain a favorable judgment in a patent infringement lawsuit. There is no evidence for differences in the size of this effect across industries, given the lack of significance on the interaction coefficients in Model 4.19. The final two models in Table 4.6, Models 4.20 and 21, estimate the probability of a patentee win when cases go to trial. Contrary to anecdotal suggestions[54] that jurors favor small firms over large corporation, there is no evidence that small firms are more likely to win jury trails. However, they are significantly less likely to win bench trials (Model 4.20: $\beta$ = -1.244, $p<0.001$). One possible explanation for these results is that there is bias in favor of small firms but that there are also selection effects. Consistent with information asymmetry theory[55], small firms may

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[53] $\beta_{smallXcomp}$= -0.194, $\beta_{small}$= -0.156 therefore the ratio of the coefficients of small firms in computers and communication to small firms in other industries can be estimated as (-0.194-0.156) /-0.156 = 2.24

[54] See for example the ALM Newsletter (Volume 7, Number 8, January 200 available at http://www.milbank.com/images/content/1/0/1079/Jan07-Patent-Strategy-Newsletter.pdf

[55] See earlier discussion regarding the possibility that small firms have less information regarding the likelihood of successful litigation outcomes.

select cases for trial with relatively low probabilities of success compared to large firms. In bench trials, we observe the consequences of this selection effect in lower probabilities of trial wins for small firms. However, in jury trials the selection effect is counter-balanced by bias in favor of small firms resulting in a zero overall effect. It should be noted though that, since patentees choose whether to have a trial heard by either a judge or a jury, there is another potential selection effect which could explain these results. Since jury trials are considerably more expensive than bench trials, small firm patentees may only select jury trials when they believe that they have a relatively high chance of success. Thus, small firms may have lower likelihoods of success in jury trials due to information symmetry, but they only select jury trials when they believe that they have a high probability of success. These two effects may therefore cancel each other out.

Finally, Table 4.7 presents Cox Proportional hazard-rates for the probability of a lawsuit terminating, given the time elapsed since filing. High hazard rates are associated with shorter lawsuit durations. As shown in Models 4.22 and 4.23, small firms have a 7% higher hazard rate for all cases and a 10% hazard rate for cases that end in settlements, providing evidence for small firms having shorter lawsuit durations. This finding is robust to the inclusion of portfolio size (Model 4.24). The portfolio effect, the interaction of *small* and *portfolio size(ln)*, was not found to be significant (Model 4.25). Hazard–rates on the industry interactions with *small* (Model 4.26) were also found to be insignificant, with the exception of the chemical industry: small firms in the chemical industry have substantially shorter durations of lawsuits compared to large firms.

**Table 4.7 Cox proportional HR models: conditional on lawsuit occurring (failure event-termination of lawsuit)**

| VARIABLES | (4.22) All cases | (4.23) Settled cases | (4.24) Conditional on firm match | (4.25) Portfolio effects | (4.26) Industry interactions |
|---|---|---|---|---|---|
| *small* | 1.076*** | 1.109*** | 1.081** | 1.074* | 1.049 |
| | (0.022) | (0.027) | (0.029) | (0.032) | (0.039) |
| *trade* | 0.990 | 0.987 | | | |
| | (0.073) | (0.092) | | | |
| *portfolio size (ln)* | | | 0.983** | 0.983** | |
| | | | (0.006) | (0.006) | |
| *smallXportfoliosize(ln)* | | | | 1.009 | |
| | | | | (0.021) | |
| *number of cases* | 1.014*** | 1.015*** | 1.010** | 1.010** | 1.014*** |
| | (0.003) | (0.003) | (0.004) | (0.004) | (0.003) |
| *number of patents* | 0.969*** | 0.975*** | 0.971*** | 0.971*** | 0.969*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *claims* | 0.999** | 0.999** | 0.998** | 0.998** | 0.999** |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) |
| *tech classes* | 0.977* | 1.009 | 0.983 | 0.983 | 0.978* |
| | (0.009) | (0.011) | (0.011) | (0.011) | (0.009) |
| *self citations* | 0.927 | 0.950 | 1.001 | 0.996 | 0.941 |
| | (0.065) | (0.073) | (0.074) | (0.074) | (0.066) |
| *forward citations (ln)* | 0.945*** | 0.968*** | 0.947*** | 0.946*** | 0.947*** |
| | (0.008) | (0.009) | (0.010) | (0.010) | (0.008) |
| *backward citations* | 1.000 | 0.999*** | 1.000 | 1.000 | 1.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *application time* | 0.998** | 1.000 | 1.000 | 1.000 | 0.998** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *foreign* | 0.984 | 0.999 | 1.003 | 1.003 | 0.990 |
| | (0.025) | (0.027) | (0.029) | (0.029) | (0.025) |
| *chemical* | 0.829*** | 0.892** | 0.814*** | 0.814*** | 0.751*** |
| | (0.031) | (0.037) | (0.039) | (0.039) | (0.035) |
| *comp&comms* | 0.891*** | 0.962 | 0.893*** | 0.893*** | 0.902*** |
| | (0.023) | (0.028) | (0.028) | (0.028) | (0.028) |
| *pharma&med* | 0.817*** | 0.843*** | 0.811*** | 0.811*** | 0.796*** |
| | (0.024) | (0.029) | (0.029) | (0.029) | (0.029) |
| *electrical&electronic* | 0.888*** | 0.900** | 0.902** | 0.902** | 0.887** |
| | (0.028) | (0.032) | (0.035) | (0.035) | (0.033) |
| *mechanical* | 0.979 | 0.941 | 0.974 | 0.975 | 0.934 |
| | (0.030) | (0.032) | (0.036) | (0.036) | (0.037) |
| *smallXchemical* | | | | | 1.364*** |
| | | | | | (0.109) |
| *smallXcomp&comms* | | | | | 0.903 |
| | | | | | (0.050) |
| *smallXpharma&med* | | | | | 1.087 |
| | | | | | (0.070) |
| *smallXelectrical&electronic* | | | | | 0.985 |
| | | | | | (0.068) |
| *smallXmechanical* | | | | | 1.113 |
| | | | | | (0.069) |
| Observations | 17,204 | 10,868 | 11,787 | 11,787 | 17,204 |
| Log Likelihood | -119936 | -89646 | -78655 | -78655 | -119920 |

## 4.5 Discussion

This article considers small firm engagement in patent litigation and the effect that a key aspect of the market for innovation, the trade of patents from small to large firms, has on litigation likelihood. To the extent that litigation propensity and lawsuit duration reflect costs to firms from participation in the patent system, this study enables a comparison of the overall cost to small firms with respect to large firms. Analysis of the sample of renewed patents that were granted between 1993 and 2007[56] shows that small firms are considerably more likely to litigate their patents but that, contrary to previous findings (Lanjouw and Schankerman (2004), these additional costs are mitigated somewhat by reduced costs associated with shorter lawsuit durations. However, although costs may be reduced by shorter durations, small firms carry the additional burden of being less likely to achieve favorable outcomes from lawsuits.

Patents traded by small firms to large firms are found to be associated with a substantially higher likelihood of litigation, implying that the market for innovation, which facilitates the appropriation of innovation through access to complementary assets, is often closely tied to the enforcement of innovation. Since the higher likelihood of litigation for traded patents implies increased enforcement threat and since it is likely many traded patents are deployed strategically, this finding has implications for market failure in technology markets[57]. The degree to which firm size and patent trades affect litigation likelihood is found to vary significantly across industries.

This chapter provides insights into which of the theories discussed in previous sections are more consistently supported by the data. The finding that small firms are more likely to litigate their patents is consistent with information asymmetry (IA), strategic stakes (SS) and divergent expectations (DE) theory. As discussed, AI theory explains higher litigation rates among small firms if they are less knowledgeable than large firms who may have in-house legal departments and large R&D centres or if they are more knowledgeable through specialization. DE and SS theories explain higher litigation and settlement rates for disputes involving small firm patentees since smaller firms with higher stakes have greater settlement demands and hence agreements are harder to attain (Priest and Klein 1984, Somaya 2003). Similarly, these theories all predict the lower settlement rate of small firm patentees which is found in the results.

[56] The sample covers the period 1993-2012, however for a patent to be renewed at least once it needs to have been granted before 2007.

[57] Cockburn (2007) identifies lack of enforcement threat, search costs and hold-up in negotiations as sources of failure in licensing markets. Agrawal et al (2014) and Gans and Stern (2010) identify lack of ‘market thickness’, ‘non-congestion’ and ‘market safety’ as causing market failure. The filing of a lawsuit signals enforcement threat (i.e. the findings suggest that trade increases enforcement threat) implying a reduction in market failure. The likelihood that traded patents are used strategically in patent disputes implies an increase in market failure through reduced ‘market safety’.

However, the finding that small firms are also significantly less likely to win cases when they go to the latter stages of legal proceedings (i.e. in the absence of settlement) implies the presence of asymmetric information only, since in the case of divergent expectations with asymmetrical stakes, a *higher* win rate for small firm plaintiffs is predicted (Priest and Klein 1984)[58].

This chapter is not without limitations. Although the high rate of litigation and lower case win rate for small firms suggests that smaller firms have higher patent enforcement costs than large firms[59], information on the monetary size of settlements is not known[60]. If smaller firms, ceteris paribus, achieve a higher transfer of rents from the settlement of litigation then it cannot be concluded that smaller firms have higher overall costs of participation in the patent system[61]. Further research that provides a better understanding of any differences between small and large firms in rent reallocation from lawsuit determination is thus required. Not only is further work on litigation outcomes needed, but the analysis presented in this chapter should be extended beyond the decision to assert patent rights to explore instances where small firms are accused of patent infringement. This study focuses on patentees, those who potentially have the need to enforce their IP. Whether small firms disproportionately attract a large share of litigation *against* them has only received limited attention.

The second part of the essay explores the relationship between the trade of IP and patent enforcement. Since markets for innovation enable small firms to access the complementary assets and financial resources to appropriate their IP, an efficient market is a pivotal mechanism for levelling the playing field between small and large firms. However, a functioning market for innovation is not without cost. As noted earlier, strategic acquisition of patents can undermine competition and the reallocation of patent rights increases the costs associated with the patent system through increased litigation propensity. In the sample of patents traded by small firms to large firms studied in this chapter, I find that patents traded are almost twice as likely to be litigated. Though this finding is robust to a number of alternative specifications, further research should be carried out on other samples of traded patents using alternative means of identifying patent trades.

[58] See Table 3, p27, of Priest and Klein (1984)
[59] Notwithstanding the reduced costs of shorter case durations which are small in comparison to the increased costs associated with higher litigation rates and lower win rates. It should also be noted that although it is assumed that on aggregate longer lawsuits are associated with higher costs, delay is a common litigation strategy and thus longer lawsuits may not necessarily be indicative of higher costs.
[60] Damages awards are often published, however the details of settlements rarely are.
[61] There is no theoretical reason why smaller firms should achieve higher settlements. Theory by Priest and Klein (1984) actually predicts that settlement amounts for smaller firms, with larger strategic stakes than larger firms, will be lower. However, the possibility that settlements are higher cannot be discounted.

This analysis should also be extended to cover patents traded by large firms to other large firms and patents traded by small firms to other small firms. It is possible that a larger proportion of sales of patents from large firms to other large firms, compared to sales between small firms and large firms, are intended either for defensive purposes or to deploy in existing disputes. High litigation rates associated with trades from small firms to other small firms may be attributable to sales to Patent Assertion Entities (PAE's) (Chien 2014)[62]. Moreover, further work should be undertaken to explore the differences between patents traded by small firms and patents traded by individuals to understand the contrasting results of this study and the findings by Galasso et al (2011). In the paper by Galasso et al, the authors found that patents traded by individuals are *less* likely to be litigated, reasoning that buying firms have larger patent portfolios than individuals which facilitate ex-ante agreements. The results contrast with the results from this chapter which has found that patents traded by small firms to large firms are *more* likely to be litigated and that portfolio effects are not significant. Why trade by individuals should be different from trade by small firms is not clear. Reconciliation of these contrasting results and theoretical reasons for the differences is therefore required. Indeed, all of the findings of this empirical study present many opportunities for theoretical scholarship and it is hoped that the results and their implications can provide support for future theoretical work in this area.

[62] No evidence was found in this study that the high litigation rate of traded patents was because patents were traded to PAE's. I matched the plaintiff names to a list of 2414 known PAE's compiled from the NPE tracker list at IP Checkups and the list on PlainSite, finding that lawsuits following patent trades were not attributable to PAE activity. This is consistent with Chien (2012) who found that almost all PAE's operate through small subsidiaries and are thus classified as small entities under the SBA criteria.

# Chapter 5: Conclusion

Patent infringement lawsuits have become increasingly common and there is concern that the high level of litigation is undermining the patent system. These concerns are amplified if small firms are disproportionately involved in litigation since the costs associated with patent enforcement are relatively high for small firms. In this thesis I explore some of the technological, economic and relational causes of litigation, focusing in particular on the changing nature of innovation and on firm strategy in competitive environments.

In Chapter 2, I investigated how changing technological paradigms and the growth of 'patent' thickets affect the likelihood that firms will be involved in litigation. Both the fragmentation of ownership rights and the presence of unclear property boundaries associated with diverse technologies were found to cause an increase in the likelihood that firms will be the subject of litigation. With respect to the ownership fragmentation and the anticommons problem, transaction costs associated with licensing from multiple owners combined with royalty stacking effects cause a failure in the market for technology, making litigation more likely. Changes in the nature of technological innovation, particularly with respect to the diverse range of technologies that are often needed in the production of complex products, have also led to increased litigation. Knowledge diverse firms have higher litigation hazard due to the bounded rationality of innovators, different interpretations of legal standards across industries and the high rate of innovation in technologically diverse fields. Evidence was found that the effect of the fragmentation of ownership is higher for smaller firms.

The focus of Chapter 3 was on the collaborative alliances which enable valuable knowledge resources to be exchanged between innovating firms. I found that repeated alliance activity between partnering firms (relational embeddedness) increases the likelihood of litigation. The findings also show that position within the network (positional embeddedness) plays a key role in whether infringement is detected and whether firms refrain from knowledge appropriation and litigation. Moreover, I found that network competition affects litigation likelihood, with more competitive network environments encouraging firms to appropriate the proprietary knowledge resources of partner firms. Several moderation effects were found to be significant: network competition and technological similarity increase the effect of relative positional embeddedness, thus competitive and technological factors play an important role in moderating the informational advantages or disadvantages of network position.

In Chapter 4, I examined whether small firms have higher costs of patent enforcement and whether traded patents from small firms to large firms are associated with higher rates of litigation. I found that small firms do litigate their patents more than large firms but that, contrary to previous findings, their lawsuits have shorter durations. Since the duration of a lawsuit is directly related to the costs of the lawsuit, this implies that the overall cost to small firms associated with their high litigation rate is mitigated by a reduced average cost per lawsuit. However, small firms have a lower likelihood of achieving a favorable outcome in a lawsuit, especially when these cases go to bench trials. Thus, small firms are likely to have a higher overall cost of patent enforcement. In the second part of the chapter I investigated how the market for innovation is related to patent enforcement. Making use of inferences from the change in patent owner size on patent renewal data, I tested whether patents originally owned by small firms and then transferred to large firms are more likely to be litigated. I found that these traded patents have a hazard rate of litigation almost twice that of the underlying hazard rate, suggesting that patent enforcement is an important component of the strategy behind patent trades.

Since litigation represents a failure in markets for technological assets and since litigation has been shown to affect innovation incentives, this thesis contributes to the body of management and economics literature on incentives to innovate and the functioning of markets for technology. The theory and empirical findings in relation to patent strategy and firm behavior in collaborative alliance networks adds to extant literature in the strategic management field. The empirical analysis which forms part of Chapter 3 makes a methodological contribution to this literature.

The study contained in this thesis can be extended in a number of ways. First, examination of ex ante settlements (settlements made before the need for litigation) and the monetary amounts of patent dispute settlements would provide a more complete understanding of the topics investigated. Moreover, there is a need to extend this work beyond that of patent infringement filings to encompass other types of lawsuits. Second, although competition is a central theme in Chapter 3, further research into aspects of competition such as industry structure and the degree of complementarity of products would be valuable extensions. For example, how does the degree of product complementarity affect appropriation and litigation incentives in collaborative alliance networks? Does product complementarity lessen competition to the extent that firms refrain from certain strategic actions such as imitation and litigation? Third, whilst it is assumed in this thesis that the high amount of patent litigation is sub-optimal, a study which explores the relationship between innovation and litigation to determine the welfare maximizing level of litigation would provide guidance on whether legislative changes to the patent system are warranted. Finally, many of the findings have unexplored implications for patent policy. Whilst some of the implications are discussed in Chapter 2, further consideration of policy levers that may overcome some of the problems highlighted would be of benefit.

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# Appendices

## Appendix A

In Chapter 2, the zero inflation regression model is a combination of the following conditional probabilities:

Prob $(z_i = 0/W_i) = \mathrm{F}(W_i, \gamma)$ Regime 1: y will equal zero
Prob $(y_i = j/X_i, z_i = 1) = \mathrm{F}(X_i, \gamma)$ Regime 2: y will be a count outcome

In the analysis, the covariates $W_i$ are assumed to be the same as $X_i$.
For all of the zero inflation (Regime 2) and standard negative binomial regressions, the NB2 probability form (Cameron and Trivedi 1986) is used which assumes that the variance-mean ratio is linear in the mean,

$$Prob(Y = y_i/X_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(1 + y_{i+1})\Gamma(\theta)} r_i^{y_i}(1 - r_i)^{\theta},$$

Where $\lambda_i = \exp(X_i'\beta),\ r_i = \lambda_i/(\theta + \lambda_i)$, $\theta$ is the reciprocal of the dispersion parameter, and $\Gamma$ is a gamma function. Time subscripts are omitted for clarity. The conditional mean function is then,

$$E[y_i/X_i] = exp(X_i{}'\,\beta) = \lambda_i$$

Estimation is made by Maximum Likelihood method.

## Appendix B

**List of ICT industries used in sample (Chapter 3)**

| NAICS | NAICS Description |
|---|---|
| 333295 | Semiconductor Machinery Manufacturing |
| 334111 | Electronics & Computer Manufacturing |
| 334112 | Computer Storage Device Manufacturing |
| 334113 | Computer Terminal Manufacturing |
| 334119 | Other Computer Peripheral Equipment Manufacturing |
| 334220 | Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing |
| 334290 | Other Communications Equipment Manufacturing |
| 334413 | Semiconductor and Related Device Manufacturing |
| 334611 | Software Reproducing |
| 335921 | Fiber Optic Cable Manufacturing |
| 425110 | Business to Business Electronic Markets |
| 511210 | Software Publishers |
| 516110 | Internet Publishing and Broadcasting |
| 517110 | Wired Telecommunications Carriers |
| 517212 | Cellular and Other Wireless Telecommunications |
| 517410 | Satellite Telecommunications |
| 517910 | Other Telecommunications |
| 518111 | Internet Service Providers |
| 518210 | Data Processing, Hosting, and Related Services |
| 519190 | All Other Information Services |
| 541511 | Custom Computer Programming Services |
| 541512 | Computer Systems Design Services |
| 541513 | Computer Facilities Management Services |
| 541519 | Other Computer Related Services |