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Patent Thickets and the Market for Innovation: Evidence from Settlement of Patent Disputes

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Abstract
We study how fragmentation of patent rights ('patent thickets') and the formation of the Court of Appeal for the Federal Circuit (CAFC) affected the duration of patent disputes, and thus the speed of technology diffusion through licensing. We develop a model of patent litigation which predicts faster settlement agreements when patent rights are fragmented and when there is less uncertainty about court outcomes, as was associated with the 'pro-patent shift' of CAFC. The model also predicts that the impact of fragmentation on settlement duration should be smaller under CAFC. We confirm these predictions empirically using a dataset that covers nearly all patent suits in U.S. federal district courts during the period 1975-2000. Finally, we analyze how fragmentation affects total settlement delay, taking into account both reduction in duration per dispute and the increase in the number of required patent negotiations associated with patent thickets.

Keywords: patents, anti-commons, patent thickets, litigation, settlement
JEL Codes: K41, L24, O31, O34.

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1 Introduction

The licensing and sale of patents - the 'market for innovation' - are an important source of R&D incentives. Recent studies have shown that transactions in patent rights contribute to the diffusion of technology, and strongly affect the incentives for firms to undertake innovation in the first place (Arora, Fosfuri and Gambardella, 2001; Gambardella, Giuri and Luzzi, 2007; Serrano, 2008). Firms increasingly recognize and exploit the commercial potential of their patent portfolios through licensing (Rivette and Kline, 2000). To cite one high profile example, it is reported that IBM earns 958 million from its portfolio. But the market for innovation is not just important for large firms. For small firms patents are often their most important asset, and the ability to license or sell them effectively is critical to preserving their innovation incentives and access to venture capital finance (Mann and Sagel, 2007). Moreover, transactions in patent rights are important to the development of efficient market structures in high technology sectors. In biotechnology and other high technology areas, transactions in patent rights strongly shape the division of labor, and nature of competition, between small firms who specialize in radical innovation and larger firms whose comparative advantage is in the development, production and marketing of these innovations (Gans and Stern, 2002; Gans, Hsu and Stern, 2003).

One of the difficulties in studying transactions in patent rights is the lack of large scale data sets. As a result, existing studies are typically based on survey information. The only exception of which we are aware is Serrano (2008), who exploits patent office information on changes in the registered ownership to study the sale of patents.

In this paper we study the market for innovation through a new lens – the settlement of patent infringement disputes. It is common for patents to be licensed as part of settlement agreements that arise from patent disputes (Anand and Khanna, 2000). An effective market for innovation requires that such disputes are settled as quickly as possible. Delay and uncertainty in the settlement and licensing process mean slower diffusion of patented technology. Moreover, longer delays would typically be associated with higher transaction costs for the negotiating parties. We use comprehensive data on the timing of settlements in patent disputes filed in U.S. courts to study this issue. As a window on the market for innovation, studying the duration of patent disputes has both advantages and limitations. First, the speed with which disputes are resolved is itself important for innovation, and an indication of how well the market for innovation works. The second advantage is that we have much more extensive data on patent settlements than on licensing. In particular, this paper exploits information on essentially all patent cases filed in U.S. courts over the period 1978-2000. The main limitation of our empirical strategy is that we do not observe the terms of patent settlements, and thus do not know whether licensing actually occurred as part of the agreement (or court order).

Licensing negotiations are shaped by characteristics of the patent, the disputants, and the legal environment. Two key aspects of the patent environment, which have attracted attention by economists, legal scholars and policy-makers, are the fragmentation of patent rights (often referred to as 'patent thickets') and the establishment of the centralized appellate court for patents (CAFC) in 1982. Various scholars have claimed that the interplay of fragmentation and the perceived pro-patent regime under CAFC has increased the complexity of the bargaining framework and created impediments for innovation (Heller and Eisenberg, 1998; Eisenberg, 2001; Jaffe and Lerner, 2004). The argument is that greater ownership fragmentation generates higher transaction costs, longer bargaining delays and higher risk of bargaining failures. Despite the appeal of this argument, the evidence is not particularly supportive. Surveys from the biomedical industry indicate relatively few cases of substantial bargaining delays or failures in connection with licensing of research tools and material transfer agreements (Walsh, Arora and Cohen, 2004; Walsh, Cho and Cohen, 2005).

Recently, Lichtman (2006) challenged the anti-commons view, arguing that the proliferation of overlapping patent rights may facilitate negotiations and speed up technology diffusion. The idea is that when an innovator needs to secure the use of a variety of patented inputs which are owned by distinct patentees, the value at stake in each negotiation is lower so each of the potential licensors has a smaller incentive to litigate. If this happens, ownership fragmentation can have the effect of speeding up settlement of patent disputes, and promoting rather than retarding technology diffusion and the market for innovation. But even if fragmentation might have the effect of reducing the *settlement delay per dispute*, it still might be that the sheer numbers of patents (required negotiations) associated with patent thickets could cause *total settlement delay* to rise.

In this paper we investigate how the fragmentation of patent rights and the introduction in 1982 of the Court of Appeal for the Federal Circuit (CAFC) affected the length of (costly) patent infringement disputes. We develop a model that focuses on how the uncertainty of the enforcement regime and 'upstream' fragmentation affect 'downstream' bargaining behavior during patent litigation. Our model extends the settlement negotiation game of Bebchuk (1984) and Spier (1992) by considering features of patent ownership fragmentation similar to those described in Lerner and Tirole (2004). The model shows that settlement agreements will be reached more quickly when the patent rights needed by the infringer are more fragmented (ownership is more dispersed) and in the more 'certain' enforcement regime associated with CAFC.

We test the main predictions of the model using an extended version of the dataset originally compiled by Lanjouw and Schankerman (2001a, 2004). This dataset combines information about the timing of patent case settlements from U.S. district courts with detailed data on the litigated patents from the U.S. Patent and Trademark Office. We find strong support: controlling for other characteristics, patent disputes litigated in the U.S. district courts are settled more quickly when infringers require access to fragmented external rights. We also find that the creation of CAFC substantially reduced settlement delays and, in addition, reduced the impact of fragmentation on settlement delay (i.e. fragmentation matters less after CAFC). Moreover, we find that CAFC reduced settlement duration more strongly in lower courts that had the greatest uncertainty of outcomes in the pre-CAFC regime. Finally, we use the parameter estimates results to study whether fragmentation of patent rights reduced the total settlement delay, and find that this may have occurred in some technology fields but not in others. These findings have important implications for an assessment of the impact of 'patent thickets' on the functioning of the market for innovation and the speed of technology diffusion.

The paper is organized as follows. Section 2 presents the model and the predictions that we empirically test. Section 3 describes the data and variables used in the empirical work. In Section 4 we present and discuss the econometric results, with particular focus on how fragmentation of patent rights and CAFC affect the settlement delay per dispute. In Section 5 we use the parameter estimates to explore how the observed changes in fragmentation affect the total settlement delay, taking into account both the duration per dispute and the number of disputes. Brief concluding remarks follow.

2 Model

In this section we develop a model to analyze how intellectual property fragmentation affects settlement bargaining behavior during patent litigation. The model extends the pre-trial negotiation games of Bebchuk (1984) and Spier (1992) by introducing dispersion of intellectual property ownership, building on the study of patent pools by Lerner and Tirole (2004). To simplify the exposition, we focus on a simple two period model. In Appendix 1 we extend the model to longer time horizons and more general payoff functions.

2.1 Intellectual Property

Consider a technology that builds on a set of features of existing, patented technologies held by other firms. Following Lerner and Tirole (2004), we assume for simplicity that these features are covered by n patents symmetrical in importance and each owned by a different patentee. We refer to these as the 'constituent patents'. We assume that a licensee obtains a revenue of V if he uses all n constituent patents. Using only $m < n$ patents, he obtains a revenue equal to $\frac{m}{n}\theta V$. We interpret the parameter $\theta \in [0, n/m]$ as a measure of the complementarity among the n constituent patents. If these patents are perfect complements, $\theta = 0$; if they are perfect substitutes, $\theta = n/m$. The case $\theta = 1$ captures the setting in which the value of the technology is equally split among the n constituent patents. We interpret the number of required patents, n, as a measure of the degree of fragmentation of patent rights.

As we show shortly, the case in which a potential user already has access to $n-1$ patents will play a crucial role in our analysis. When $m = n-1$, the value at stake in the n^{th} negotiation is the difference between the value earned using all n patents and the value obtained using only $n-1$ of them. We call this this difference the 'negotiation value' and define it as

$$z(n, \theta, V) \equiv V - V\frac{(n-1)}{n}\theta. \tag{1}$$

Equation (1) allows us to study how the value at stake is affected by both the level of complementarity among patents and the degree of ownership fragmentation.[1] Specifically, an increase in the degree of complementarity (lower θ), for constant n, increases the negotiation

[1] We can also do comparative statics on how the total value of the technology, V, affects the negotiation value. We do not focus on this aspect because we do not have a satisfactory measure of V in the data.

value of the n^{th} patent. An increase in the degree of fragmentation, n, for constant θ, reduces the negotiation value. These effects will play a central role in the predictions of the model.

The expression for the value at stake in equation (1) is similar in spirit to the marginal willingness to pay for a patent used by Lerner and Tirole (2004) in the context of patent pools. For simplicity, and to bring out the economic intuition more sharply, we impose linearity of $z(n, \theta, V)$ in V and θ. In Appendix 1 we show that all our results hold in a more general framework as long as $z(n, \theta, V)$ is decreasing in n and θ.

2.2 Litigation Game

We study litigation between a patentee and infringer who are both risk neutral. We assume that the infringer has some private information about factual issues that is relevant to predicting the expected outcome of the trial. This assumption can be justified (and microfounded) in different ways. One approach is to assume that the infringer has more knowledge on how the validity of the patent can be challenged because of prior art not found by the patent office. Another possibility is to assume that the infringer knows better what proportion of his product is covered by the claims in the patent. Using this private information, the defendant estimates the likelihood that the patentee will prevail at trial, which we denote by p. We refer to such an infringer as being of type p. The patentee does not know the infringer's type, but knows that p is uniformly distributed over the interval $[0, 1]$.[2]

The settlement bargaining game proceeds as follows. At time $t = 0$, the plaintiff makes a take-it-or-leave it settlement offer to the infringer (i.e., the license payment the infringer pays to the patentee). If he accepts the offer, the game ends. If the offer is rejected, a trial takes place at $t = 1$. Litigation is costly – if a trial takes place, the patentee and infringer incur costs of L_p and L_i, respectively. If the infringer is found liable, the court awards the patentee damages equal to $z(n, \theta, V)$. This represents the amount the defendant would earn from successful infringement of this patent, given that he had secured licenses to use the other $n-1$ constituent patents. This assumption is consistent with the *Unjust Enrichment* doctrine, as described by Schankerman and Schotchmer (2001). Under this doctrine, the patent owner is entitled to recover the profits realized by the infringer, on the theory that the infringer should

[2] It is easy to show that Proposition 1 below holds for any distribution $F(p)$ with increasing hazard rate.

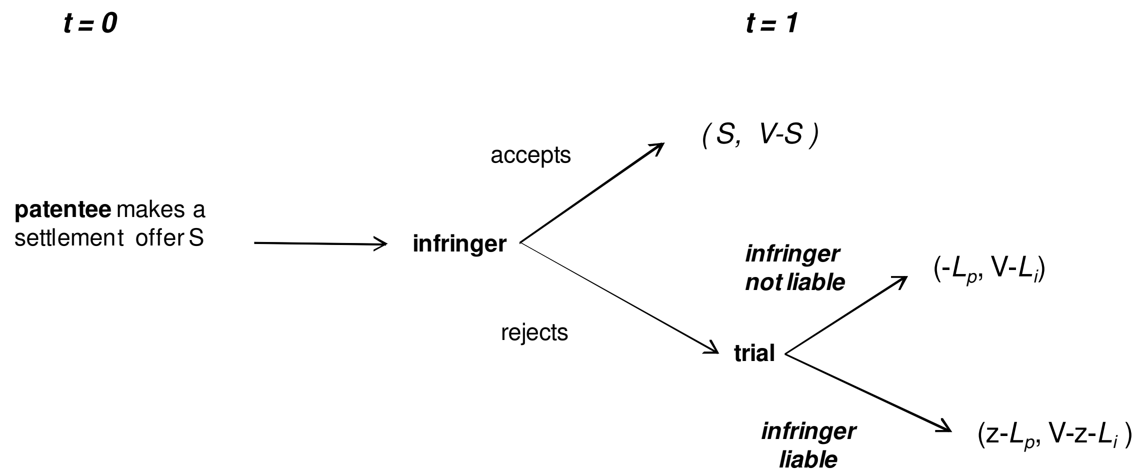

Figure 1: Settlement Bargaining Game

not profit from his wrongdoing.[3] Figure 1 summarizes the timing of the game.

2.3 The Impact of Fragmentation

Applying backward induction, we first compute the settlement offer that the patentee makes at $t = 0$. The settlement (license fee) must be no larger than the sum of his expected damages and legal costs. Thus, a defendant of type p will accept a settlement S only if $S \leq pz(n, \theta, V) + L_i$, i.e. $p \geq (S - L_i)/z(n, \theta, V)$. Knowing this, the patentee's optimization problem is to maximize his expected profit by choosing a cutoff type, p^*, such that infringers above this cutoff accept the offer and those below reject it. Formally,

$$\max_p \ \pi = \int_p^1 [pz(n, \theta, V) + L_i]dy + \int_0^p [yz(n, \theta, V) - L_p]dy$$

subject to the constraint $p \in [0, 1]$. The first integral is the expected settlement value, and the second is expected damages net of the patentee's litigation cost. Defining $L \equiv L_i + L_p$, the unconstrained first order condition yields the following optimal cutoff type:[4]

[3] *Lost Royalty* is the alternative liability rule used in the U.S.. Schankerman and Scotchmer (2001) point out that the lost royalty doctrine involves a "circularity" between damages and licensing fee. From a technical point of view, this circularity generates a large number of equilibria. If we compute the average level of damages across the set of possible equilibria, one can show that average damages increase linearly in θ and decrease in n. In this sense, our framework is consistent with the lost royalty doctrine as well.

[4] Because of the uniform distribution of p, the expected win rate is $p^*/2$ that for high litigation costs can be arbitrarily close to zero. In a more general model, the win rate will depend on z, L and the distribution of p and will be equal to the average probability among defendant types lower than p^*. In principle it possible to generate parameter values that match any empirical win rate.

$$p^* = 1 - \frac{L}{z(n, \theta, V)}.$$

In a two period model, because all types with $p < p^*$ reject the settlement, the uniform distribution over types implies that the expected length of a dispute is equal to the optimal cut-off:

$$E(t^*) = p^* = 1 - \frac{L}{z(n, \theta, V)}. \tag{2}$$

This allows us to summarize the relationship between fragmentation, complementarity and the expected settlement time in the following proposition:

Proposition 1 *The expected settlement time, $E(t^*)$, is non-increasing in n and θ.*

P roof. Using equations (1) and (2), it follows immediately that $\partial E(t^*)/\partial n \leq 0$ and $\partial E(t^*)/\partial \theta \leq 0$. ■

This proposition describes two properties of the expected settlement time in equilibrium. First, fragmentation (large n) tends to reduce bargaining delay in each dispute. The intuition is that, provided the n patents are not perfect complements ($\theta \neq 0$), fragmentation reduces the negotiation value and hence the patentee's marginal benefit of screening, making early agreement more likely. Second, stronger complementarity among the required patents increases the expected settlement time per dispute. When patents are highly complementary, the surplus that the patentee expects to extract by litigating and holding-up the alleged infringer is larger. This increases expected damages, making early agreement less attractive. Therefore, for a given θ, an increase in n tends to reduce delay; similarly, for a given n, an increase in θ tends to reduce the expected delay.[5]

To summarize, Proposition 1 delivers two testable predictions about the relationship between the settlement delay per dispute and the degree of fragmentation and complementarity:

H1: Settlement negotiations will be shorter when the infringer requires access to more fragmented patent rights.

[5]It is easy to show that the results in this Section also hold under the following extensions: 1) allowing parties to incur settlement costs in period zero, and 2) allowing the patentee and/or infringer's litigation costs to increase with the negotiation value (potential damages) – $L_p(z)$ and $L_i(z)$ – provided that the elasticity of total litigation costs with respect z is less than one.

H2: Settlement negotiations will be longer for patents that have fewer substitutes (i.e., greater complementarity).

2.4 The Impact of CAFC

The Court of Appeal for the Federal Circuit (CAFC) was established in 1982 to unify patent doctrine and to bring greater uniformity and predictability to patent decisions.[6] Many scholars have argued that CAFC generated a distinct 'pro-patent' shift (Hall and Ziedonis, 2001; Jaffe and Lerner, 2004). This took the form of tougher evidentiary standards to invalidate patents (Allison and Lemley, 1998; Henry and Turner, 2006), and increased likelihood of large damage awards (Merges, 1997). We study the impact of CAFC's on *district court decisions.* We would expect the pro-patent shift at the appellate court level to affect lower court decisions, since there is a reputational cost to lower court judges if they are reversed on appeal (Songer, Segal and Cameron, 1994; Klein and Hume, 2003).

In this section we examine how this pro-patent shift altered the bargaining framework for disputes litigated after 1982. A natural way to introduce this pro-patent shift is to assume that CAFC induced a stochastically dominant shift in the distribution of damages for the patentee. But this is not adequate because it does not capture the widely held view that patent decisions became more predictable after CAFC (first order stochastic dominance does not imply a reduction in variance). For ease of exposition, in this section we present an extremely simple specification that embodies stochastic dominance and a reduction in variance in outcomes. In Appendix 2 we show that our results are robust to more complex specifications.

We assume that there are two types of district courts. A proportion of them (α) are 'biased' in the sense that they always award full damages, $z(n, \theta, V)$, to the patentee independently of infringer's type p. The remaining fraction $(1-\alpha)$ are 'unbiased' in the sense that they correctly assess whether the infringement took place, i.e., the probability p. We also assume that the parties to the dispute know which type of district court is adjudicating their dispute.

In this simple setting, it is straightforward to compute the expected settlement delay (averaged across courts). If the court is not biased, the bargaining game is identical to the

[6] Gallini (2002) documents how proponents of CAFC stressed the importance of predictability in enforcing patent rights in promoting R&D investment.

one studied in the previous section and the expected settlement time is $E(t^*)$. If the court is biased, there is no asymmetric information and the two parties settle immediately. Thus the expected settlement time, averaged across courts, is

$$E(t^B) = (1 - \alpha)E(t^*). \tag{3}$$

Proposition 2 *The expected settlement time in the presence of court bias, $E(t^B)$, is decreasing in α. In addition* $\dfrac{\partial^2 E(t^B)}{\partial n \partial \alpha} \geq 0.$

P roof. It follows immediately from (3) and the fact that $\partial E(t^*)/\partial n \leq 0$. ■

The fact that $E(t^B)$ is decreasing in α suggests that the pro-patent bias associated with the introduction of CAFC facilitated early settlement agreements. The intuition is that pro-patent bias reduces the uncertainty about damage awards and thus diminishes the impact of asymmetric information on the bargaining process. It is interesting to note that it is not the *direction* of bias that affects settlement delay in our model, but the reduced uncertainty that bias entails. Any bias would reduce settlement delay as long as it reduces the variance of the distribution of damages.[7] What the direction of the bias (pro-patent, in our model) does is to affect the *terms of the settlement agreement,* increasing the patentee's expected payoff.[8] In the context of cumulative innovation, the settlement terms are important because they determine the structure of innovation incentives for initial and follow-on invention, as Green and Scotchmer (1995) and Scotchmer (1996) have shown. In this paper we do not take a normative position on court bias (either pro- or anti-patent). We study only how such bias affects bargaining delay and thus technology diffusion.

The second part of Proposition 2 says that when there is less uncertainty about the outcome of the trial, the impact of the negotiation value (fragmentation reduces this value) on the likelihood of reaching a settlement agreement is reduced. To highlight intuition, consider the extreme case in which courts always award the patentee damages. In this case, all disputes will be settled immediately, independently of the level of fragmentation.

[7] Consider the case of 'anti-patent bias' where a fraction α of courts always award zero damages, independently of infringer type. Again there is no asymmetric information for biased courts, so parties settle immediately, and average settlement time is again $E(t^B) = (1 - \alpha)E(t^*)$.

[8] To see this, define $\pi(p^*) \equiv (1-p^*)\,(p^*z + L_i) + \frac{(p^*)^2}{2} z - p^* L_p$. It is straightforward to show that the patentee's equilibrium payoff is $(1-\alpha)\pi(p^*) + \alpha z$ when there is pro-patent bias, and $(1-\alpha)\pi(p^*)$ with anti-patent bias.

Proposition 2 provides two additional testable predictions about settlement delay:

H3: Settlement negotiations will be shorter for cases filed after the introduction of CAFC;

H4: The impact of fragmented external rights will be lower after the introduction of CAFC.

2.5 Heterogeneity in Uncertainty across Circuit Courts

Before the establishment of CAFC, there were sharp differences across circuit court jurisdictions in their enforcement of patent rights. Henry and Turner (2006) document substantial heterogeneity in the frequency of validity and infringement findings, both across circuit courts of appeal and across district courts within any given circuit. These differences suggest that the impact of CAFC may have varied across circuit court jurisdictions, depending on the level of pre-CAFC uncertainty.

To address this issue, we extend our model by assuming that in each circuit the likelihood that the patentee will prevail at trial is uniformly distributed over the interval $\left[\frac{1}{2}(1-\lambda), \frac{1}{2}(1+\lambda)\right]$ with $\lambda \in [0,1]$. An increase in λ enlarges the variance of the distribution while preserving its mean.[9] We interpret the parameter λ as a measure of the level of pre-CAFC uncertainty in court outcomes (including appeals), and we conduct comparative statics in λ to study the differential impact of CAFC across circuits.

In this setting the optimal cutoff type becomes

$$p^*(\lambda) = \frac{1}{2} + \frac{\lambda}{2} - \frac{L}{z}$$

which implies an expected settlement time equal to

$$E(t^*(\lambda)) = 1 - \frac{L}{z\lambda}. \tag{4}$$

After CAFC the expected settlement time is

$$E(t^B) = (1-\alpha)E(t^*(\lambda)). \tag{5}$$

[9] Bebchuk (1984) shows that the results in this section are valid for more general (non-uniform) mean-preserving shifts.

Proposition 3 *The expected settlement time is increasing in λ. In addition* $\frac{\partial^2 E(t^B)}{\partial\lambda\partial\alpha} < 0$.

P roof. It follows immediately from formulas (4) and (5). ■

As first pointed out by Bebchuk (1984), "spreading out" the distribution of types increases the expected settlement time because it amplifies the differences among types in the expected outcome of a trial. Moreover, the proposition implies that the impact of CAFC is larger in circuits where the variance of p is greater and suggests the following testable prediction.

H5: The impact of CAFC is stronger in circuits where there is larger uncertainty in court outcomes in the pre-CAFC regime.

3 Description of Data

The empirical work is based on two data sets: patent litigation data from the U.S. federal district courts, and the NBER patent dataset. The patent litigation dataset was compiled by Lanjouw and Schankerman (2001a, 2004). This dataset matches litigated patents identified from the Lit-Alert database with information on the progress or resolution of suits from the court database organized by the Federal Judicial Center. The dataset contains 9,219 patent infringement cases filed during the period 1975-2000 and terminated before 2001. For each of these case filings, the dataset reports detailed information on the main patent litigated (although there may be other patents listed), the patentee, the infringer and the court dealing with the case. Following Lanjouw and Schankerman, we focus on the main patent in dispute (when multiple patents are listed).

We extended the Lanjouw and Schankerman dataset by collecting information on the identity of the infringers. We manually matched infringer names listed in the court data with assignee names in the NBER patent dataset. We were able to match the infringer to a patent assignee for 5,131 infringement cases. In most cases where matching was not possible, the names of the infringers suggest they were individuals or small firms. This matching procedure allows us to identify the patents owned by the infringing parties, and thus to construct the size of their patent portfolios and other information at the time of litigation. In this respect, our data is more comprehensive than those used in earlier studies, where information on infringers was not present (Lanjouw and Schankerman, 2001a, 2004; Simcoe *et al.*, 2008) or was limited to specific industries (e.g. semiconductors in Hall and Ziedonis, 2007; drugs and computers in Somaya, 2003).

The main variables used in the empirical analysis are described below.

Dispute Duration: This is the endogenous variable in the analysis. It is defined as the number of months elapsed between the original case filing date and the case termination date, as reported in the district court data. This variable indicates the time period required to reach the settlement agreement or, in its absence, the court judgment. On average, it takes 18 months and 18 days to settle a patent litigation case. However, the distribution of length is sharply skewed (Figure 1): 25 percent of cases settle within 5 months, but 25 percent last more than 24 months.

We use the following control variables to capture the main ingredients of our bargaining model.

Fragmentation1: Let $p_{\tau T}$ denote a patent in technology class τ which is litigated at time T, and let j denote the infringer (we use the 36 two digits categories as defined in Hall, Jaffe and Trajtenberg, 2001). We identify the set of the infringer's patents in class τ with application year within five years in either direction of the suit, say $\{p_{j\tau t}\}_{T-5\leq t\leq T+5}$. We then identify the share of citations of these patents in each of the 417 classes defined by the USPTO, and compute the fraction of citations to patents belonging to class n, w_{jnT}. For each class we compute the share of patents accounted for by the top four patentees in the same 10-year window, $C4_{nT}$. Using this information we construct the following fragmentation measure:

$$Fragmentation1_{j\tau T} = 1 - \sum_{n} w_{jnT} C4_{nT}. \tag{6}$$

For 25 percent of the infringers in the sample, we do not observe any patent in the technology class of the litigated patent with application year in a ten year window around the suit (this is because they are very small, not missing information). For these infringers, following Lanjouw and Schankerman (2004), we calculate a concentration index using the citations of the *litigated* patent as weights for the fragmentation measure. A dummy variable, **Missing**, is set equal to one for observations for which this correction was performed.

As a robustness check we construct an alternative measure:

Fragmentation2: As in the previous measure, we construct the set $\{p_{j\tau t}\}_{T-5\leq t\leq T+5}$. We then identify the citations of these patents that refer to other (distinct) assignees. Let C_{kj} denote the number of these citations that refers to assignee k. Following Ziedonis (2004), we construct the following fragmentation measure:

$$Fragmentation2_{j\tau T} = \left[1 - \sum_{k\neq j}\left(\frac{C_{kj}}{C_j}\right)^2\right]\frac{C_j}{C_j - 1} \tag{7}$$

where C_j indicates the total number of non-self, backward citations.[10]

Both fragmentation measures attempt to capture the degree of concentration of patent rights. The idea is that when a firm's patents are related to technology areas with few patentees, that firm is more likely to be involved in a smaller number of negotiations and disputes (Ziedonis, 2004; Noel and Schankerman, 2006). The two measures differ in the way they identify the technology areas in which the firms obtain their patented inputs. Fragmentation1 uses the infringer's backward citations to identify these technology classes. Fragmentation2 uses the patentees actually cited as a proxy for the number of required negotiations.[11],[12]

Our data contains a substantial minority of infringers with very small patent portfolios (e.g., 50 percent have fewer than four patents in the technology area in a ten year window). For these cases we considered it more sensible to infer the degree of fragmentation from the entities operating in their technology area rather than from the entities cited. For this reason, we use Fragmentation1 as primary measure of ownership dispersion, and Fragmentation2 as a robustness check on the results.

Complementarity: Let $p_{\tau t}$ denote a litigated patent with application year t and belonging to the technology class τ (we use the 36 two digits categories as defined in Hall, Jaffe and Trajtenberg, 2001). Our complementarity measure is the ratio between the non-self ci-

[10] As recommended by Hall (2002), we use the term $C_j/(C_j - 1)$ to remove the downward bias of the Herfindahl index.

[11] To see the difference, consider the case in which all backward citations of a firm go to a single patentee that operates in a technology area in which ownership is very fragmented. In this case *Fragmentation1* will indicate the infringer as operating in a very fragmented area, whereas *Fragmentation2* will show that the infringer deals with only one patentee

[12] We also constructed a third measure of fragmentation using the distribution of the infringer's patents across classes, rather than the infringer's patent citations, to identify the technology areas in which the firm obtains its inputs. This measure is highly correlated with Fragmentation1 and the econometric results are very similar with this measure.

tations that $p_{\tau t}$ has received up to the year 2002 from patents in technology class τ and the non-self citations received by all patents in τ that have application dates in a 10 year window from the application of the litigated patent. Formally, let $C^{\tau}_{p_{\tau t}}$ denote the number of non-self citations received by $p_{\tau t}$ from other patents belonging to τ. Our measure is:

$$Complementarity_{\tau t} = \frac{C^{\tau}_{p_{\tau t}}}{\sum\limits_{\substack{b \in \tau \\ t-5 \leq T < t+5}} C^{\tau}_{b_{\tau T}}}. \tag{8}$$

In the analysis that follows, we multiply this index by 1000. With this normalization, *Complementarity*$=\alpha$ means that the citations received by the litigated patent account for α percent of the citations received by patents in a *one-year* window in the technology field.

This measure is indirect and imperfect. Ideally, we would like to measure complementarity more directly, but this would require detailed information about the actual set of patented inputs used by each firm in the sample. The number of citations received by a patent has been widely used as a indicator of 'importance' of a patent. Our complementarity measure reflects the importance of the litigated patent *relative to* other patents in the same technology field. This measure is based on the idea that the greater is the relative importance of the patent, the more difficult is for the infringer to find a substitute patented input in that technology field. Thus we associate a higher value of the measure with a lower value of the parameter θ in the model.

Patent value: We use the number of total (self and non-self) citations received by the litigated patent from patents in all technology fields (up to the year 2002) as a measure of the value of the litigated patent. This measure is conceptually and empirically distinct from the complementarity index, which measures the relative importance of the patent in its own technology field. The sample correlation between our measures of patent value and complementarity is only 0.16.

CAFC: We construct a dummy variable for patent suits filed after the creation of the specialized patent appellate court, which was introduced in 1982. The dummy takes value of one for cases filed from 1982 onwards. We experimented with alternative timings (to reflect lags in the effects of CAFC) but the empirical results were very similar.

High-Variance Circuits: We use information on district court decisions and circuit court appeals for the period 1953-1981 (Henry and Turner, 2006) to construct a dummy variable for cases litigated in the top three (alternatively, four) circuits with greatest uncertainty about court outcomes. We treat the court decision as a Bernoulli process. Let p denote the probability that the patentee 'wins' in a given district court. Then the variance on outcomes for that court is given by $p(1-p)$. We use two alternative definitions of a 'win': i) the fraction of cases where the district court finds the patent "valid and infringed" and ii) this fraction adjusted by the observed rates of appeal and circuit court affirmation of the pro-patent decision.[13] Both approaches identify the same top four circuits in terms of variance: the 4th, 5th, 7th and 10th circuits.

Duplicate cases: In the data we observe distinct patent suits that involve the same patentee, the same infringer and the same patent and which are recorded in the same year. Sometimes these cases have been re-entered with the same docket number, sometimes with a different one. Part of this re-entry appears to be associated with a change in the litigation venue. We generated a dummy variable to control for these "duplicate" cases.

Technology field dummies: Following Lanjouw and Schankerman (2004), we control for the technology field of the litigated patents. We use eight broad technology areas (percent of sample): Pharmaceuticals (3.8%), Other Health (8.8%), Chemicals (14.4%), Electronics excluding computers (21.3%), Mechanical (30.9%), Computers (1.0%), Biotechnology (0.7%), and Miscellaneous (19.1%).

District court dummies: We use a complete set of dummy variables to control for the district of the court in which the patent is litigated. There are 89 district courts in the 50 states and all of them are represented in our sample.

Table 1 presents descriptive statistics for the main variables.

In Table 2 we examine the key predictions of the bargaining model using the raw data. The top panel shows that the dispute duration is negatively related to fragmentation. For the entire sample period, the mean dispute duration for patents with fragmentation index above the median is about 10 percent lower than for those below the median. The difference is larger for

[13] Specifically, let q denote the probability that the patent is held "valid and infringed," r be the probability the decision is appealed, and ω denote the probability the lower court decision is affirmed. Under the second method, the patentee win rate is given by $p = q(1-r) + qr\omega + (1-q)r(1-\omega)$.

cases filed before the formation of CAFC, consistent with the prediction that fragmentation is less important when there is less uncertainty over court outcomes. The lower panel of the table shows that dispute duration is positively related to complementarity. For the whole sample period, the mean dispute duration for patents with complementarity index above the median is about 40 percent longer than for those below the median.[14] This table also shows that there is a sharp drop in the mean dispute duration for cases filed in district courts after the formation of CAFC.

These simple mean comparisons are confirmed by the sample distributions of dispute durations (survival curves) in Figure 2. The distribution for patents with below-median fragmentation stochastically dominates the one for above-median fragmentation (the reverse holds for complementarity; figures omitted for brevity). In addition, the distribution of dispute duration for cases filed before CAFC stochastically dominates the one for cases after CAFC.

In Table 3 we show that the reduction in dispute duration is associated with a *decline* in the fraction of cases reaching final adjudication at trial. Prior to the introduction of CAFC, 17.2 percent of all patent suits reached final adjudication, as compared to only 5.9 percent afterwards. As the table shows, this reduction occurred in all technology fields. This is exactly what we would expect since CAFC increased the likelihood of the patentee prevailing on appeal, and thus reduced the incentive for the alleged infringer to hold out (at great cost) for a lower court decision.[15] At the same time, the number of patent suits per year increased dramatically as well – from about 185 before CAFC to 550 in the period 1983-94. These facts suggest that the observed reduction in dispute duration is due to earlier settlements and not to an increase in the rapidity of court decisions.

In the next section we examine whether these conclusions are confirmed by formal econometric analysis.

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[14] We also find that dispute duration is longer for more valuable patents (not shown in the table). The mean duration for cases in the fourth quartile of the distribution of patent citations is about 30 percent longer than for those in the first quartile.

[15] We also find that there was a substantial increase in the number of cases settled very early, before the pre-trial hearing is reached.

4 Empirical Specification and Results

4.1 Econometric Specification

To study the data on the duration of disputes, we adopt a proportional hazard model with an exponential specification:

$$\begin{aligned} \ln h_{ijct} &= \alpha_0 + \alpha_1 Fragmentation_{ijt} + \alpha_2 Complementarity_{it} + \\ &\quad \alpha_3 CAFC_t + \alpha_4 CAFC_t * Fragmentation_{ijt} + \alpha_5 X_{it} + \omega_c + \eta_t + \varepsilon_{ijct} \end{aligned} \tag{9}$$

where h denotes the (age-constant) hazard rate, i, j, c and t represent the patent being sued, the infringing firm, the district court hearing the case, and the year the suit is filed, respectively, X is a vector of control variables for other factors that affect bargaining delay (including patent value), ω_c represents a full set of court dummy variables, η_t is a partial set of year dummies (explained below), and ε_{ijct} is a mean zero random error. For the baseline results, we assume that ε_{ijct} is independent over i, j, c and t. However, we also discuss how standard errors change when we allow for clustering across patents and patent owners.[16] A *negative* coefficient on a regressor in the hazard rate model means that the variable makes it less likely that negotiations end, which corresponds to a *longer expected settlement delay.* The model implies the following predictions in this specification: fragmentation reduces bargaining delay ($\alpha_1 > 0$), complementarity increases delay ($\alpha_2 < 0$), CAFC reduces delay ($\alpha_3 > 0$) and also reduces the impact of fragmentation on delay in absolute value ($\alpha_4 < 0$). The exponential specification imposes a constant (baseline) hazard rate, but the results are nearly identical for the more flexible Weibull specification which allows for an age-dependent hazard rate (Kiefer, 1988).[17]

The baseline specification embodies two sets of restrictions that should be noted. First,

[16] Such correlation can arise from two sources. First, there are instances in the data of multiple cases involving the same patent, so any unobserved heterogeneity at the patent level would induce correlation. Second, there are instances of the same plaintiff (patentee) involved in multiple suits over different patents, so unobserved heterogeneity at the patentee level can also induce correlation across patents (e.g. some firms are more aggressive than others in enforcing their patent rights). Thus we also compute robust standard errors with clustering at the patent, or patentee (plaintiff), level.

[17] The Weibull is a two-parameter distribution with the (baseline) hazard function $h(t) = \lambda\gamma t^{\gamma-1}$.The exponential case arises when $\gamma = 1$. In the baseline econometric specification, the point estimate of γ is 1.28 (s.e. = 0.013), so we formally reject the exponential restriction in favor of the Weibull with an increasing hazard rate.

most of the variation over time in settlement delays is captured through the CAFC dummy variable (equal to one for $t \geq 1982$). This is a constrained version of a more general specification which allows for an unrestricted set of year dummies for 1976-2000, say $\{\eta_t\}$, and their interactions with the fragmentation measure, $Fragmentation * \{\eta_t\}$. We began by estimating this unrestricted specification – Figure 3 plots the estimated year effects (normalized to zero in 1975). They show no trend during 1976-81, a sharp drop in 1982, which was when CAFC was established. We do not reject the joint hypothesis that the coefficients on the dummies are zero for 1976-1981 and equal to each other for 1982-1991 (*p-value*$= 0.08$). We therefore introduced the additive CAFC dummy and allowed year dummies only for 1992-2000.[18] We then tested, and do not reject, the hypothesis that the coefficients on the interaction terms $Fragmentation * \{\eta_t\}$ are zero for 1976-1981 and equal to each other for 1982-2000 (*p-value*$= 0.08$). This provides support for our baseline specification, where year dummies η_t are included only for 1992-2000.

Second, the baseline specification assumes that the coefficients on the fragmentation measure and its interaction with the CAFC dummy are the same across technology fields. We tested these restrictions using six broad technology categories and do not reject them (*p-value*$= 0.17$).

Before turning to results, two additional points should be noted. First, the key determinants of bargaining delay in our model – fragmentation and complementarity – are difficult to measure, and the constructs we use are likely to contain random measurement error. The associated attenuation bias will cause us to underestimate the impact of fragmentation and complementarity on expected settlement duration, so our estimates are conservative in this sense.

The final point involves sample selection. We observe disputes if a suit is filed but not if they are settled before that stage. Since negotiations occur in the shadow of litigation, the pro-patent bias of CAFC should have facilitated greater pre-suit settlement of the 'easier' cases. This selection implies that the cases we observe after the introduction of CAFC will tend to be those with longer dispute duration. On this account our estimates will underestimate the

[18] These free dummies are needed because there is a distinct decline in average settlement delay after 1997), which is partly due to truncation in the data (we only observe cases that have been settled by 2000). We decisively reject the hypothesis that these free dummies are jointly zero.

true (negative) impact of CAFC on settlement delay.

4.2 Empirical Results

Table 4 reports the baseline parameter estimates for the hazard model, together with the implied marginal effects of each control variable on the expected dispute duration.[19] In column (1) we include only the three key variables – Fragmentation, Complementarity and CAFC – and the year dummies for 1992-2000. The results are consistent with the predictions of the model. First, the estimated coefficient on fragmentation (α_1) is positive and significant, confirming hypothesis H1: when infringers require access to more fragmented patent rights, disputes are settled faster (higher hazard rate). A one standard deviation increase in the fragmentation index reduces dispute duration by 22 days. Second, stronger complementarity among patents increases the duration of disputes (reduces hazard rate), supporting hypothesis H2. The point estimate of α_2 is negative and significant, and implies that a one standard deviation increase in the complementarity index increases duration by 23 days. Third, the duration of disputes was sharply reduced by the establishment of the specialized appellate court, CAFC. The positive and significant point estimate of α_3 implies that CAFC reduced the average settlement delay by 6 months. This finding supports the hypothesis that the pro-patent bias associated with CAFC reduced the uncertainty over litigation outcomes and damages, thereby facilitating settlement.

In columns (2)-(4) we incrementally add control variables. Column 2 includes technology field and district court fixed effects. In this specification the estimated impact of fragmentation is 30 percent larger than without fixed effects. There is almost no change in the estimates for complementarity and CAFC. Not surprisingly, the court fixed effects are highly significant (we reject the null that they are zero, *p-value* < 0.01). This is consistent with studies by legal scholars which show that there is substantial variation in the degree to which federal district courts seem to favor patent holders (Moore, 2001).[20]

[19] Two points should be noted. First, for all these regressions we present heteroskedaticity-robust standard errors. We also allowed for clustering at the patentee level and at the patent level (for cases where there are multiple suits on the same patent). The clustered standard errors are very similar, and statistical significance is unaffected.

Second, we obtain very similar estimated marginal effects and significance levels if we use a simple linear specification estimated by ordinary least squares.

[20] Given this variation, there is the possibility that the disputants may 'venue-shop' for courts sympathetic to

Column (3) adds a control for patent value (citations count) and dummy variables to account for cases where there are duplicate disputes and for (small) infringers for whom we were unable to compute the fragmentation index. The estimated coefficients on Fragmentation, Complementarity and CAFC are robust to the inclusion of these additional controls. As expected, we find that negotiations over more valuable patents take longer to settle. A one standard deviation increase in the citations count extends dispute duration by 0.78 months. However, as we show in the next Section, this estimate corresponds to patents of an 'average' age. Taken together with the finding by Lanjouw and Schankerman (2001a, 2004) that more valuable patents are much more likely to be involved in litigation in the first place, we conclude that patent enforcement and licensing are most problematic precisely for the patents that matter most. Moreover, our finding that both patent value and complementarity independently affect dispute duration suggests that our measure of complementarity is not just a proxy for value. Finally, the estimated coefficients on the dummy variables for duplicate and missing cases (involving very small infringers) are statistically significant. Duplicate cases take much longer to settle (13 months), which is not surprising since they are likely to be more complex. Interestingly, the Missing dummy indicates that cases that involve very small infringers (who have no patents in the same technology subclass as the infringed patent) settle faster, by about 1.1 months.

The model predicts that the reduction of uncertainty associated with the 'pro-patent bias' of the centralized appellate court should reduce the impact of fragmentation on dispute duration. In column (4) we introduce the interaction between Fragmentation and the CAFC dummy to test this prediction. We treat this as the baseline specification. The estimated coefficient on the interaction term is statistically significant and strongly confirms this prediction. The marginal effect of fragmentation prior to CAFC is -55.4, but after CAFC it drops to -7.2, and we reject that it is equal to zero (*p-value* = 0.03). Allowing for the interaction increases our estimate of the impact of CAFC on dispute duration. The net effect of CAFC, evaluated

their position, to the extent this is allowed by law. If this occurs and both parties are aware of court 'bias', this should facilitate earlier settlement. However, there is no reason to believe that venue shopping should be correlated with our measures of fragmentation or complementarity, and thus it should not introduce any bias in the estimated coefficients on these variables. If the extent of venue-shopping changed at all after CAFC, we would expect it to have declined since there is less uncertainty about the outcome on appeal. Thus our estimate of the impact of CAFC on dispute duration should be conservative.

at the mean value of fragmentation, is to reduce dispute duration by 7.8 months. This is larger than the estimate for column (3) where we do not allow for the interaction (reduction of 5.3 months). Interestingly, in our baseline regression, we find no strong evidence that settlement delay varies across technology fields (we do not reject at 5-percent that the technology fixed effects are zero, *p-value*= 0.09).[21]

As discussed earlier, there was substantial heterogeneity across circuits in the uncertainty of court outcomes before CAFC. The model predicts that the effect of introducing CAFC should be stronger for district courts located in circuits where the uncertainty over damages was larger. To test this prediction, in column (5) we introduce an interaction between the dummy variable for CAFC and a dummy variable for the top 3 circuit courts with the highest variance in outcomes. This is exactly what we find: the estimated impact of CAFC is almost twice as large for the high-variance district courts. This finding gives us additional confidence that the CAFC effect is not simply due to some unobserved factor that reduced settlement duration, since we find that the reduction is systematically related to the degree of pre-CAFC variance in court outcomes.

All of the preceding specifications include a full set of (additive) district court dummies. There are many reasons district courts might differ in their average settlement durations, including case loads and fiscal constraints. But the model predicts one factor that should play a role is the degree of uncertainty over court outcomes. This should not only interact with the impact of CAFC, as discussed above, but also should affect settlement duration in the pre-CAFC regime. To examine this hypothesis, in column (6) we replace the district court dummies with a single dummy variable for the high-variance circuit courts. We expect the estimated marginal effect of this dummy variable to be positive, and that is what we find. The point estimate implies that settlement negotiations in these high variance circuits lasted four months longer than in other circuits. At the same time, we reject the restrictions imposed by this more parsimonious specification (*p-value*<0.001). This is not surprising, and simply confirms that there are other factors accounting for variation across district courts. But it is

[21] Bulow (2004) points out peculiar settlement agreements that are sometimes observed in pharmaceutical patent infringements. As a robustness check, we dropped cases involving pharmaceutical patents and found that the estimated parameters were similar to the baseline results.

interesting to note that the estimated coefficients on the other variables are very similar in the more restricted specification (compare columns (5) and (6)), which indicates that these other factors are evidently not correlated with the variables of interest in the model.

4.3 Extensions and Robustness

In this section we examine extensions and robustness of the baseline specification (Table 5).

The first experiment involves a generalization of the way in which patent value affects dispute duration. We have controlled for the value of the patent using a citations measure. However, the stakes in the negotiation (potential licensing value), and thus the expected dispute duration, should also depend on the age of the patent for two reasons: first, there is age-related depreciation in the private returns from patented innovations (Schankerman, 1998) and, second, there is less time remaining until statutory expiration of the patent. To capture both effects, we write patent value at age a as $V_a = Ve^{-\delta a} \simeq V(1-\delta a)$. Assuming the true specification of the model involves V_a, if we include both V (citations) and an interaction term $V * a$ in the regression, the coefficient on the interaction term should be negative and the ratio between the coefficients yields an estimate of δ. The results in column (1), Table 5 confirm that the dispute duration is smaller for older patents, controlling for their citations count. Moreover, the point estimates show that, for young patents, the impact of value is about two times larger than when we do not incorporate the age effect (column (4), Table 4). For new patents ($a = 0$), marginal effect of value is 0.056, and a one standard deviation increase in value raises dispute duration by 1.4 months. Moreover, the implied estimate of δ is 0.054, implying the impact of value on dispute duration disappears after about 20 years.

Second, there is a concern that our results might be driven by serial litigants, either patentees or infringers involved in multiple disputes. In our sample there are 2,931 distinct patentees, with a mean number of disputes per patentee of 1.53 (median=1, maximum=19). The distribution is highly skewed - the top 1 percent of patentees account for 5.63 percent of disputes. The numbers are almost identical for the distribution of infringers. We take two approaches to address this concern. First, we include dummy variables for serial patentees and infringers (the top 1 percent) and re-estimate the baseline specification (column (2) in

Table 5).[22] Second, we simply drop cases involving the serial patentees or infringers (reducing the sample size by 8 percent). In both approaches the estimated parameters are similar to the baseline results. The coefficient on the dummy variables are significant at the 10 percent level and, interestingly, suggest that the disputes take longer to settle (nearly 4 months) when brought by a serial patentee, but are settled more quickly (3.5 months) when a serial infringer is involved. This finding is consistent with the idea that serial patentees are those who aggressively enforce their intellectual property, and serial infringers are those who only engage in licensing negotiations when forced to do so by patent suits.

Third, we examined whether the size of the litigants' patent portfolios affected their ability to settle disputes. Lanjouw and Schankerman (2004) show that firms with larger patent portfolios are much less likely to be involved in patent suits, indicating that portfolios provide bargaining chits and facilitate tacit cooperation in settling disputes without recourse to courts. One might think that a similar mechanism operates for settling disputes after suits are filed. To study this, and to check robustness of our key findings to this extension, we included measures of the patent portfolios (cumulated patents over the preceding 20 years) held by the patentee and infringer, as well as the relative portfolio size. We found no significant impact for these portfolio measures (not reported). However, we do find evidence that symmetry in portfolio sizes matter at the extremes of the size distribution (column (3), Table 5). Disputes are significantly shorter when both litigants have either very large patent portfolios ($\geq$1000 patents) or very small portfolios ($\leq$ 5 patents). For large firm pairings, the dispute duration is shorter by 4.4 months; for small firm pairings, by 1.3 months. The finding for large firms is consistent with the interpretation of Lanjouw and Schankerman, while the small firm finding suggests a role for cash constraints in the settlement process. However, we leave a more careful study of this topic for future research.

Fourth, as we discussed in Section 3, there is a potential truncation problem for cases not terminated before 2000. To address this concern we re-estimate our baseline regression using only cases filed before 1994 (fewer than 4 percent of cases last more than 5 years). This reduces the sample by 24.2 percent. Nonetheless, the results from this restricted sample (column (4),

[22] We also tried including a dummy for cases involving both serial patentee and infringers but the coefficient was not statistically significant ($p - value = 0.11$).

Table 5) are very similar to those for the full sample.

Fifth, the measure we use for patent value is the total citation count (including self-cites) received by the litigated patent. Unfortunately, for 29 percent off the litigated patents the NBER database does not allow us to distinguish between self-and non-self citations received. As a robustness check, we re-estimate the baseline specification using only non-self citations when available and total cites for the other 29 percent, and introducing an additive dummy for the latter. The parameter estimates are nearly identical to the baseline results (not reported, for brevity).[23]

Sixth, column (5) presents the baseline specification using the alternative, $Fragmentation2$, measure. The qualitative findings are the same, but the impacts of fragmentation and CAFC are somewhat smaller. The point estimates imply that a one standard deviation increase in $Fragmentation2$ reduces dispute duration before CAFC by 1.8 months, as compared to about 3.9 in the baseline specification. There is no statistically significant impact post-CAFC (*p-value* = 0.34), whereas in the baseline specification there was a small, but statistically significant, negative impact. Finally, the estimated impact of CAFC, evaluated at the mean fragmentation, is -7 months, very similar to the estimate in column (4) of Table 4.

Lastly, we consider the potential endogeneity of the fragmentation measure which might partially account for the negative relationship between fragmentation and settlement duration which we observe. There may be unobserved factors – in particular, transactional and technological complexity – that affect both the ability of firms to negotiate technology transfer agreements and the concentration of ownership of patent rights. When these factors are important, firms may choose to integrate into complementary technology areas in order to internalize these difficult transactions. In this case, fields with more concentrated ownership would exhibit longer settlement durations. It is difficult to think of suitable instrumental variables for fragmentation, so we address this concern in a different way. If fragmentation is simply a re-

[23] As explained in Section 3, for about 25 percent of cases the infringer has no patents in the technology sub-class of the litigated patent (within a 5 year window). For these cases, to construct the fragmentation measure we use the citations of the *litigated patent.* In the baseline estimation, we included a dummy variable (**Missing**) to identify observations with this correction. But probit regressions (not reported) indicate that these observations are not random – they are more likely to involve patents with low value and in areas where ownership is not concentrated. As additional robustness check, we restricted the sample to non-missing observations and re-estimate the baseline specification. The results are very similar to those reported in the text.

flection of transactional complexity that varies across technology fields, we would expect the coefficient on fragmentation to be smaller (in absolute value) when we conduct the analysis at a more detailed level of technology fields. We check this in column (6), where we replace the eight technology field dummies with the 36 two-digit categories defined by Hall, Jaffe and Trajtenberg (2001). The results are nearly identical to those in our baseline regression.

5 Fragmentation and Total Settlement Delay

We have shown that fragmentation of patent rights reduces the settlement delay per dispute. In this section we study how fragmentation affects total negotiation delay for a technology user litigating with n different patentees. In our set-up patents are symmetrical in importance and each court focuses on one infringement only. In addition, because damages are independently distributed and determined according to the unjust enrichment doctrine, court decisions will not be affected by the outcome of previous litigations or by the expected outcome of future disputes. These assumptions imply that each settlement negotiation will have an expected length equal to $E(t^*)$ and allow us to simplify the exposition avoiding problems of sequential common-agency.[24]

To compute total negotiation time, denoted by T, we need assumptions on the timing of negotiations. If all n negotiations are conducted simultaneously, the expected total bargaining delay is $E(t^*)$. At the other extreme, the upper bound in total negotiation time is reached when the downstream user negotiates sequentially with each patentee, in which case the expected total duration is $T = nE(t^*)$.[25] We focus on this case, which represents the maximum delay in technology diffusion predicted by our model.

The impact of fragmentation on total negotiation time is

$$\frac{\partial E(T)}{\partial n} = E(t^*) + \frac{\partial E(t^*)}{\partial n} n \tag{10}$$

[24] A possible way to extend the model is to introduce preliminary injunctions as in Lanjouw and Lerner (2001). This would change the outside options of our bargaining model and potentially impact on the symmetry of the outcomes. Another interesting theoretical extension would consider correlated damages.

[25] This is an upper bound because, following Lerner and Tirole (2004), we assumed that each patent is owned by a different patentee. An intermediate setting would be the case in which the n patents are equally split among k patentees. In this case if the alleged infringer approaches sequentially the k patentees but negotiates simultaneously (and independently) for each subset of patents, the expected delay will be equal to $kE(t^*)$.

This equation points to a trade-off that has been overlooked by previous literature on patent thickets. Ownership fragmentation affects total negotiation time through two channels. The first (positive) term of (10) is the *thicket effect.* Fragmentation extends total negotiation time because it increases the number of negotiations in which the infringer has to engage. The second (negative) term of (10) is the *negotiation value effect.* Fragmentation reduces the value at stake in each negotiation and thus the settlement delay per dispute.

These two effects help reconcile the two opposing views on patent thickets in the recent economic and legal literature – the pro-diffusion view of Licthman (2006) and the anti-commons view of Heller and Eiseberg (1998) and Shapiro (2001). Consider the case where θ is arbitrarily close to zero, so the required patents are almost perfect complements. In this setting the reduction in negotiation time per dispute due to fragmentation, $\partial E(t^*)/\partial n$, is close to zero and the thicket effect dominates the value effect. This result is consistent with the 'anti-commons' view: thickets powerfully increase transaction costs and reduce the speed of technology diffusion. Conversely, Licthman's conjecture holds when θ is arbitrarily close to $n/(n-1)$, so patents are almost perfect substitutes. In this case, the negotiation value per dispute, and thus the settlement time $E(t^*)$, are arbitrarily small. Then the value effect dominates the thicket effect, and total delay is reduced.

Formula (10) implies that fragmentation reduces total negotiation time if $|\varepsilon_{tn}| \equiv \left| \frac{\partial E(t^*)}{\partial n} \frac{n}{E(t^*)} \right| > 1$. Unfortunately, we cannot estimate this elasticity because we do not directly observe n. In the empirical work we used an infringer-specific index of fragmentation, which depends on the total number of patents across different technology classes. Thus we need to translate the elasticity condition in terms of the fragmentation index.

To simplify the analysis we assume that the user obtains all his inputs from a representative technology class. Then the *Fragmentation1* index is simply $f(N) = 1 - \frac{k(N)}{N} = 1 - C4$ where $k(N)$ denotes the number of patents held by the top four patentees in the class and N the total number of patents in the class. Let ε_{tf} be the elasticity of per-dispute litigation time respect to $f(N)$ and ε_{kN} denote the elasticity of $k(N)$ with respect to N. Using the fact that total negotiation time is $E(T) = nE(t^*(f(N)))$, after some manipulation, we can show that the condition under which an increase in fragmentation will reduce total negotiation time (under sequential negotiations) is

$$|\varepsilon_{tn}| \equiv |\varepsilon_{tf}| \frac{C4}{1-C4}(1-\varepsilon_{kN})\frac{1}{\varepsilon_{nN}} > 1 \tag{11}$$

where ε_{nN} is the elasticity of the number of negotiations, n, with respect to N.[26] Condition (11) requires that the (negative) impact of fragmentation on dispute duration is large enough and that ε_{nN} and ε_{kN} are not too large.[27]

We use our estimates of ε_{tf} for the pre- and post-CAFC sub-periods (-1.7 and -0.4, respectively) and the observed value of $C4$ to evaluate whether condition (11) holds. Since we found no significant differences in the fragmentation coefficient across technology areas (Section 4.2), we use a single value for ε_{tf}. To do this computation, we need to measure the impact of an increase in the number of patents on the portfolios of the top four patentees, ε_{kN}, and on the number of infringer negotiations, ε_{nN}. We compute ε_{kN} as the growth rate of the stock of patents held by the top four patentees divided by the growth rate of the total stock of patents, averaged over the entire sample period for a given technology field. We compute ε_{nN} as the average growth rate of the number of patent suits per assignee divided by the growth rate of the patent stock.[28] In doing this, we use the full NBER data set on patenting (not only patents in our litigated sample).

Table 6 summarizes the input and results of the calculations.[29] For a regime without CAFC, the condition is satisfied for two technology areas, Other Health and Chemicals. Here the pro-diffusion effect of fragmentation dominates the anti-diffusion effect of the increase in disputes, so total negotiation time declines. In the other technology areas, however, fragmenta-

[26] In this derivation we think of n, the number of patent holders with whom a technology user needs to bargain, as a (monotonic) function of the total number of patents, N.

[27] The condition is valid provided that $\varepsilon_{kN} \leq 1$. If $\varepsilon_{kN} > 1$, an increase in patenting is associated with an increase in the share of the top four patentees, and thus a reduction in our measure of fragmentation. In this case, settlement delay per dispute would rise, so the increase in patenting would necessarily raise total negotiation delay, $T = nE(t^*)$.

[28] We adjust for the substantial under-reporting of patent suits in the court data, using the estimates provided by Lanjouw and Schankerman (2001b), Appendix 1.

[29] It should be noted that over the sample period we observe a decline in the C4 measure – hence a rise in fragmentation – in four of the six technology areas: Biotechnology (0.12 to 0.07), Electronics (0.11 to 0.09), Chemicals (0.07 to 0.06), Pharmaceuticals (0.14 to 0.08) and Other Health (from 0.10 to 0.06). In the other two fields – Mechanical and Miscellaneous – fragmentation as we measure it actually declined, so there is no scope for changes in fragmentation to have reduced settlement delay. Thus we do not include these two areas in the table.

tion is associated with a rise in total negotiation time. The key factor that makes the difference is the extent to which the number of disputes per assignee increased as patenting rose (ε_{nN}). By contrast, in a regime with CAFC the anti-diffusion effect of fragmentation dominates in all technology areas, reflecting the fact that CAFC substantially reduced the pro-diffusion effect of fragmentation.

These calculations are only illustrative and should not be over-interpreted. Still, they suggest that the anti-commons view of Heller and Eisenberg (2001) may be too pessimistic, at least for some technology areas. Moreover, we emphasize that this analysis has focused on the case of sequential negotiations. At the other extreme, when negotiations are conducted simultaneously, total negotiation time is simply $E(t^*(n))$ and it immediately follows that fragmentation reduces *total negotiation time* because it reduces delay per dispute. Thus the impact of patent thickets depends crucially on the timing of licensing negotiations.

6 Conclusion

This paper investigates how fragmentation of patent rights ('patent thickets') and the formation of the Court of Appeal for the Federal Circuit (CAFC) affected the duration of patent disputes, and thus the speed of technology diffusion through licensing. We develop a model of patent litigation which predicts that settlement agreements are reached more quickly in the presence of fragmented patent rights and when there is less uncertainty about court outcomes as was the case after the introduction of the 'pro-patent' CAFC. The model helps to reconcile two opposite views of patent thickets in recent economic and legal literature: the pro-diffusion view of Licthman (2006) and the anti-commons view of Heller and Eiseberg (1998) and Shapiro (2001). We test the predictions of the model using a dataset that covers nearly all patent suits in U.S. federal district courts during the period 1975-2000.

There are two main empirical findings. First, patent disputes in U.S. district courts are settled more quickly when infringers require access to fragmented external rights, but this effect is much weaker after the introduction of CAFC. Second, the introduction of CAFC is associated with a direct and large reduction on the duration of disputes, which the model attributes to less uncertainty about the outcome if the dispute goes to trial. In addition, our calculations suggest that fragmentation may have reduced total negotiation delay, and thus sped up rather than retarded technology diffusion, in some technology areas during the period before CAFC.

There are several useful directions for further research. The first is to extend the bargaining framework to multiple players to study externalities in the litigation process and the determinants of settlement with multi-lateral bargaining. Second, it would be worthwhile to investigate more fully how firm characteristics, including the size and liquidity position of disputants, affects the duration of disputes. Finally, survey evidence on the actual timing and structure of negotiations between downstream users and upstream patent-holders would be extremely useful in assessing the impact of patent thickets on technology diffusion.

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Appendix 1. Generalization of the Bargaining Game

In this Appendix we introduce both a longer time horizon to the bargaining game and a richer class of payoff functions. Following Spier (1992) we assume that there are T periods of bargaining prior to the court judgment which takes place in period $T+1$. In each period t the patentee makes a settlement offer to the infringer which either accepts or rejects it. If the infringer rejects, the bargaining game continues with the patentee making another settlement offer in the following period. The case proceeds to trial if the litigants cannot agree before time T. If the infringer is found liable, the court will award a judgement $z(n, \theta, V)$ to the patentee. We allow now for a general damage function $z(n, \theta, V)$ that satisfies $\partial z/\partial n \leq 0$ and $\partial z/\partial \theta \leq 0$. As in Spier (1992), we assume a discount factor equal to δ and impose the following technical assumption:

Assumption A1: The defendants' strategies are such that if type p' accepts settlement offer S_t with positive probability, then all types $p'' > p'$ accept S_t with probability 1.

Under Assumption A1, the distribution of infringer types that remains in each period is a truncation of the original uniform distribution. Exploiting these truncated distribution, it is straightforward to compute the probability of settlement for each $t = 1, \ldots, T+1$ and the corresponding expected settlement time $E(t^*)$. Proposition A1 shows that the results of Proposition 1 can be generalized to this new setting.

Proposition A1 *The expected settlement time $E(t^*)$ is weakly decreasing in n and θ.*

P roof. From Spier (1992) we know that the distribution of types remaining at the beginning of period t is uniform on $[0, p_t]$ where $p_1 = 1$ in our model. In addition:

$$
\begin{aligned}
p_t &= p_1 - \delta^{-T} \sum_{i=1}^{t-1} \delta^i \frac{L}{z(n, \theta, V)} \qquad\qquad t = 2, ..., T \\
p_{T+1} &= p_T - \frac{L}{z(n, \theta, V)}.
\end{aligned}
$$

Given these cutoffs, we can express the expected agreement time as:

$$\begin{aligned} E(t^*) &= \sum_{t=1}^{T} t\frac{(p_t - p_{t+1})}{p_1} + (T+1)\frac{p_{T+1}}{p_1} \\ &= \sum_{t=1}^{T+1} \frac{p_t}{p_1} = (T+1) - \frac{L}{z(n,\theta,V)} \sum_{t=1}^{T} \frac{t}{\delta^{t-1}}. \end{aligned}$$

It follows immediately that $\dfrac{\partial z}{\partial n} \leq 0$ implies $\dfrac{\partial E(t^*)}{\partial n} \leq 0$, and $\dfrac{\partial z}{\partial \theta} \leq 0$ implies $\dfrac{\partial E(t^*)}{\partial \theta} \leq 0$. ■

Appendix 2. Generalization of the CAFC Effect

In this section, we extend the two period model adopting a more general family of distribution functions $G(p,m) = p^m$ with $m \geq 1$ and $0 \leq p \leq 1$. For each m the mean of $G(p,m)$ is $m(m+1)^{-1}$ and the variance is $m(m+2)^{-1}(m+1)^{-2}$. Following Rothschild and Stiglitz (1970) we use this family of distribution functions to investigate the impact of a first order stochastic dominance shift in the distribution of the probability of the patentee prevailing at trial. In fact, distributions with larger values of m have higher mean and lower variance, and first-order stochastically dominate those with lower values of m.

As in the case with uniform distribution, fragmentation (large n) tends to reduce bargaining delay whereas complementarity (low θ) increases the expected settlement time per dispute.[30]

Proposition A2 *The expected settlement time, $E(t^*)$, is non-increasing in n and θ.*

P roof. The first order condition becomes:

$$\frac{mp^{m-1}}{1-p^m} = \frac{z(n,\theta,V)}{L}. \tag{12}$$

For each m (12) has a unique solution that we denote $p(m)$ with corresponding expected settlement time $E(t^*) = G(p(m),m)$. Because the left hand side of the first order condition is increasing in p we have that $\dfrac{dp}{dz} > 0$. In addition, because $\dfrac{dz}{dn} \leq 0$ it is easy to see that

$$\frac{dE(t^*)}{dn} = \frac{dG}{dp}\frac{dp}{dz}\frac{dz}{dn} \leq 0.$$

[30] The comparative statics in fragmentation and complementarity are valid for all distribution functions, $G(p)$, having strictly increasing hazard rate.

Similarly because $\frac{dz}{d\theta} \leq 0$ it follows that $E(t^*)$ is non-increasing in θ. ■

Thus far, the impact of CAFC has been modeled as a shift in the distribution of p with a fraction of courts awarding damages with probability one. Exploiting the class of distribution functions $G(p, m)$ we can study the impact of the Centralized Appellate Court considering more general first order stochastic dominance shifts. Specifically, we model CAFC as an increase in m leading to a new distribution with higher mean (pro-patent bias) and lower variance (greater predictability). The next proposition shows that if legal costs are not too large an increase in m reduces expected settlement time.

Proposition A3 *If* $\frac{z}{L} > \frac{1}{1-e^{-1}} \simeq 1.582$ *an increase in* m *leads to a reduction in expected settlement time.*

P roof. Notice that $\frac{dE(t^*)}{dm} = \frac{\partial G}{\partial m} + \frac{\partial G}{\partial p}\frac{dp}{dm}$. By totally differentiating the first order condition we derive

$$\frac{dp}{dm} = -\frac{p^{m-1} + mp^{m-1}\log p + \frac{z}{L}p^m \log p}{m(m-1)p^{m-2} + \frac{z}{L}mp^{m-1}}$$

which implies

$$\frac{dE(t^*)}{dm} = -\frac{p^{m-1}(1+\log p)}{\Delta} \tag{13}$$

where $\Delta = \frac{m-1}{p} + \frac{z}{L}$. Notice that (13) is negative as long as $\log p > -1$ that requires $p(m) > 1/e$. We will now show that $p(m) \geq 1/e$ implies $p(m') \geq 1/e$ for each $m' \geq m$. To see this notice that the left hand side of the first order condition is increasing in p. Therefore $p(m) \geq 1/e$ implies that:

$$\phi(m) \equiv \frac{m(\frac{1}{e})^{m-1}}{1-\left(\frac{1}{e}\right)^m} \leq \frac{z}{L}.$$

Because $\phi'(m) < 0$ it follows that $\phi(m') < z/L$ and $p(m') \geq 1/e$. This result implies that whenever $p(1) \geq 1/e$ then $p(m) \geq 1/e$ for all $m > 1$. Finally notice that $p(1) = 1 - \frac{L}{z}$. Therefore if $\frac{z}{L} \geq \frac{1}{1-e^{-1}}$ then $p(1) \geq 1/e$, $p(m) \geq 1/e$ for all $m > 1$ and $\frac{dE(t^*)}{dm} < 0$. ■

The previous proposition shows that CAFC reduces settlement time if the ratio between legal fees and size of the case is not too large. The threshold on the ratio z/L is consistent with previous theoretical work on patent litigation (e.g., Lanjouw and Lerner, 1998). This generalization points out that CAFC has two opposite effects on litigants' incentive to settle. On one hand, it reduces uncertainty (variance) of outcomes and this facilitates settlement agreement. On the other hand, it increases the expected damages which increasing the appeal of litigation. Thus disputes that were too expensive to litigate before CAFC may become profitable to do so after CAFC and this explains why a condition on z/L is required. The same proposition also shows that the reduction in settlement time is larger for circuits where court decisions have larger variance. It is these circuits for which CAFC represents a larger increase in m.

Finally, the following proposition shows that in this generalized setting the interplay of CAFC and fragmentation is ambiguous, without further restrictions.

Proposition A4 $\dfrac{d^2E(t^*)}{dndm}$ *can be positive or negative.*

P roof. $E(t^*) = G(p(m), m)$ implies that:

$$\frac{d^2E(t^*)}{dzdm} = \frac{dg(p)}{dm}\frac{dp}{dz} + \frac{dg(p)}{dp}\frac{dp}{dz}\frac{dp}{dm} + g(p)\frac{d^2p}{dzdm}.$$

Using

$$\frac{dp}{dz} = \frac{1}{z\Delta} > 0$$

$$\frac{dp}{dm} = -\frac{1 + \log p\left(m + \frac{z}{L}p\right)}{m\Delta} \lessgtr 0$$

and

$$\frac{dg(p)}{dm} = p^{m-1}\left(1 + m\log(p)\right) \lessgtr 0$$

it is easy to see that the sign of the cross-derivative $\dfrac{d^2E(t^*)}{dndm}$ is ambiguous without further restrictions. ■

Figure 1. Distribution of Dispute Duration (in Months)

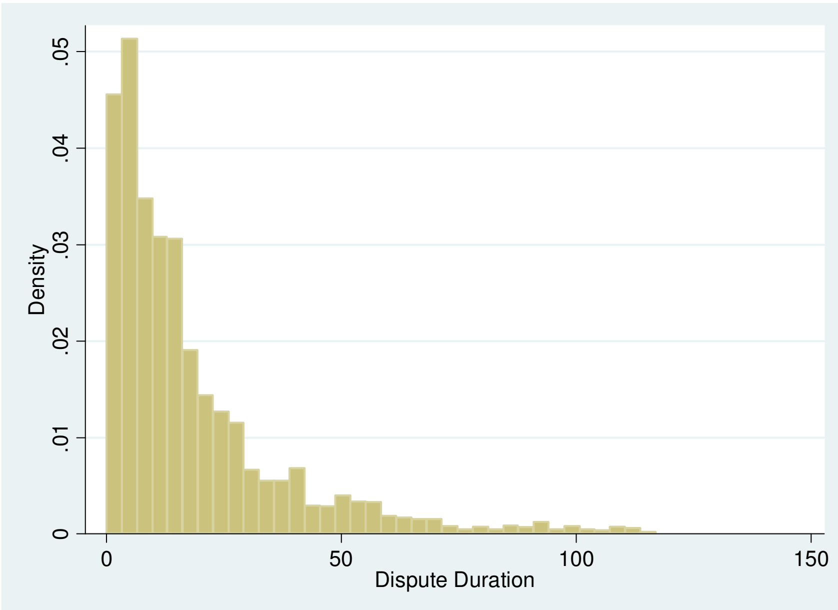

Figure 2. Distribution of Dispute Duration: Impact of CAFC and Fragmentation

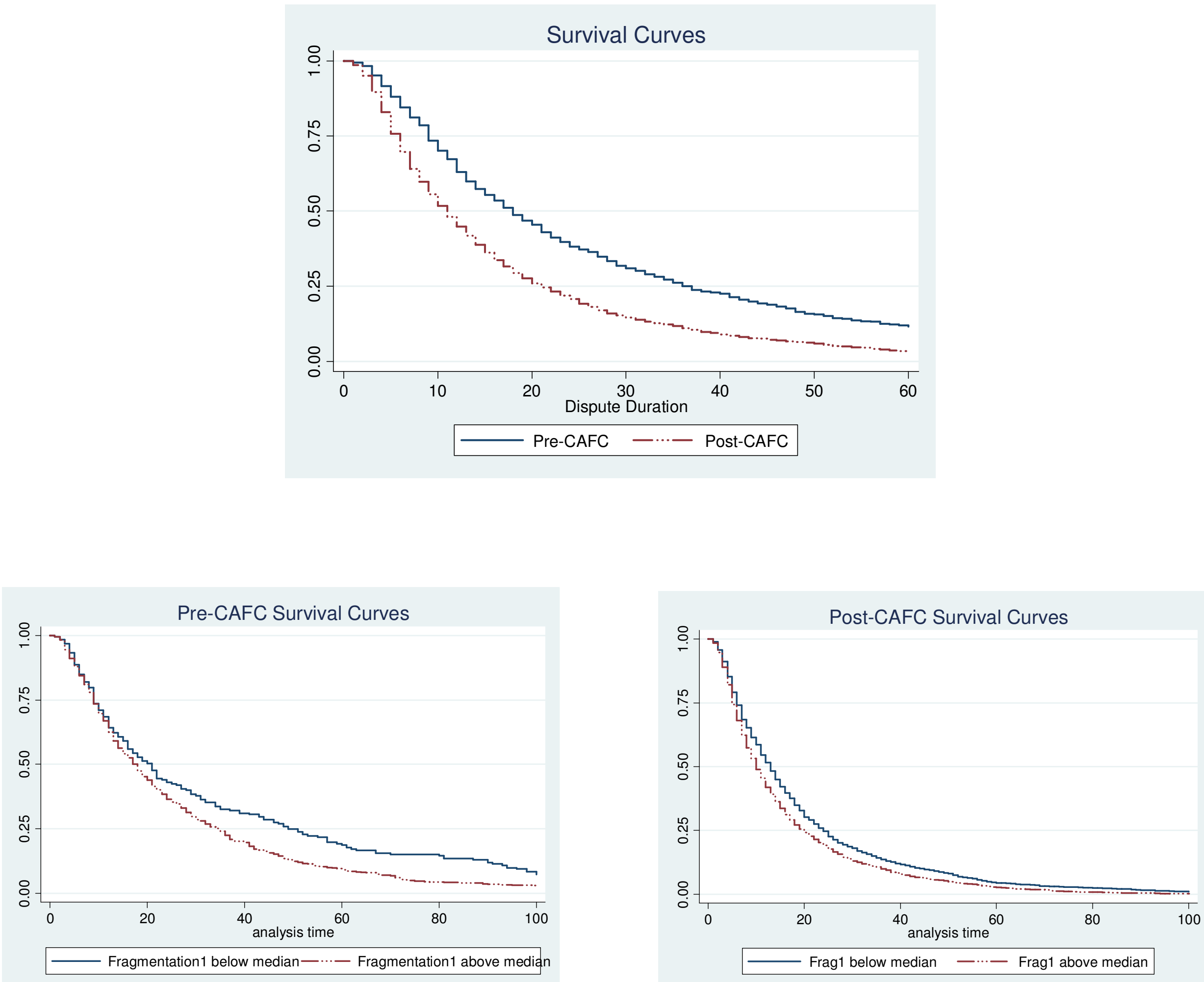

Figure 3. Estimates of Year Effects from Hazard Model of Dispute Duration

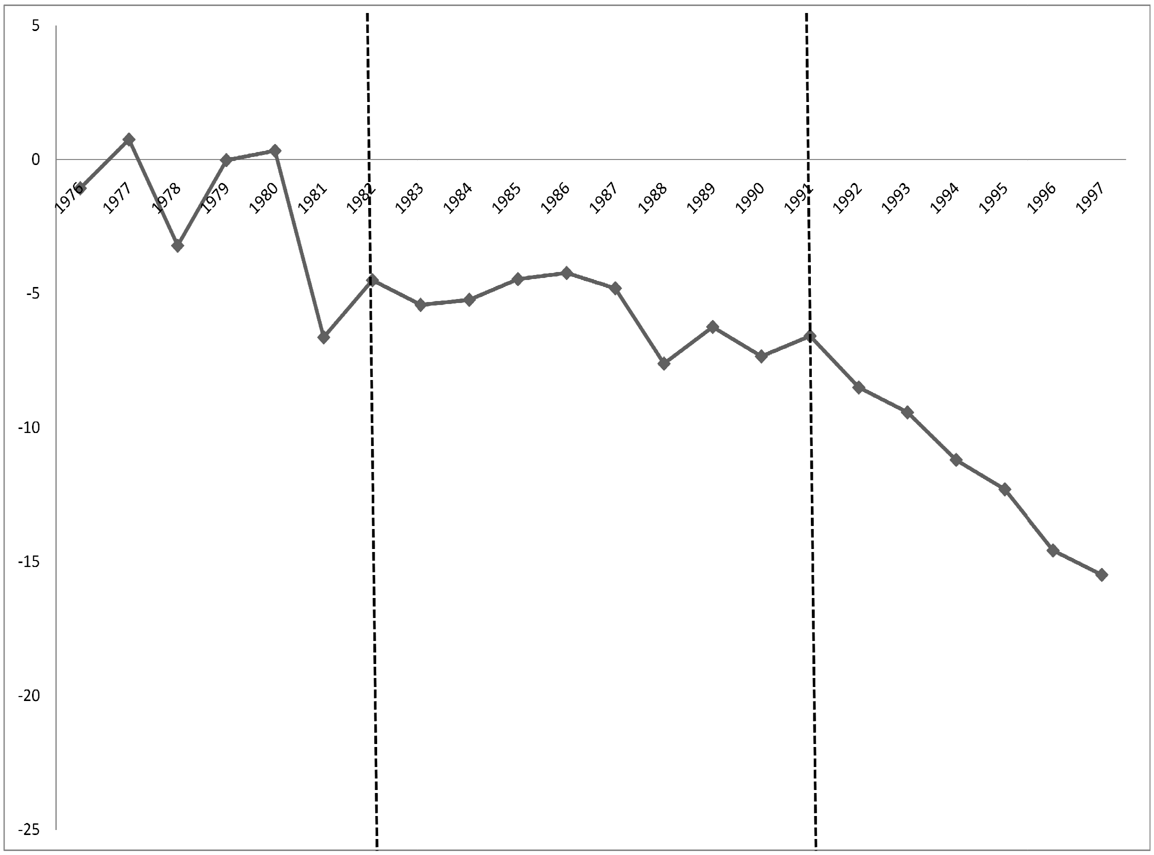

Table 1. Descriptive Statistics

	Mean	Median	Std. Dev.	Min	Max
Dispute Duration (Months)	18.60	12	20.48	0	172
Fragmentation1	0.89	0.91	0.07	0.45	0.99
Fragmentation2	0.95	0.98	0.11	0	1
Complementarity $x10^3$	0.27	0.01	3.52	0	110.32
Value	18.80	11	25.29	0	327
Age of Patent	7.76	6	5.37	0	20

Table 2. Fragmentation, Complementarity and Dispute Duration

	Fragmentation1 < 50th Percentile	Fragmentation1 > 50th Percentile
Dispute Duration	**Mean**	**Mean**
Entire Period (1975-2000)	19.6	17.6
Before CAFC (1975-81)	33.0	27.7
After CAFC (1982-2000)	18.3	16.4
	Complementarity < 50th Percentile	**Complementarity > 50th Percentile**
Dispute Duration	**Mean**	**Mean**
Entire Period (1975-2000)	15.9	23.1
Before CAFC (1975-81)	26.0	32.2
After CAFC (1982-2000)	15.2	21.2

Table 3. Impact of CAFC on Frequency of District Court Adjudications

	Percent Cases with District Court Decision		
	1975-2000	Before CAFC	After CAFC
Entire Sample	7.06	17.19	5.95
Drugs	6.47	22.22	5.59
Other Health	11.39	25.93	10.33
Chemicals	7.61	19.54	5.75
Electronics	4.38	13.10	3.55
Computers	0.00	0.00	0.00
Mechanical	7.80	20.53	6.24
Biotech	6.90	33.33	3.85
Others	6.73	6.33	6.77

Table 4. Baseline Specification - Dependent Variable: Dispute Duration

	(1)		(2)		(3)		(4)		(5)		(6)	
	Coefficient	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**
Fragmentation1	0.556***	-10.336	0.719***	-13.366	0.567***	-10.601	1.845***	-55.368	1.606***	-48.196	1.460**	-43.815
	(0.179)		(0.181)		(0.192)		(0.628)		(0.598)		(0.607)	
Complementarity x 10^5	-1.161***	21.582	-1.050***	19.519	-0.922***	17.140	-0.887***	16.489	-0.904***	16.805	-0.934***	17.363
	(0.102)		(0.127)		(0.114)		(0.108)		(0.115)		(0.098)	
CAFC	0.293***	-6.008	0.297***	-6.001	0.268***	-5.293	1.563***	-50.714	1.281**	-43.150	1.278**	-41.266
	(0.051)		(0.049)		(0.049)		(0.588)		(0.564)		(0.572)	
CAFC x Fragmentation1							-1.432**	48.207	-1.199*	41.139	-1.188*	39.099
							(0.647)		(0.619)		(0.628)	
High Variance											-0.169*	3.771
											(0.096)	
CAFC x High Variance									0.223**	-4.716	0.175*	-3.825
									(0.101)		(0.101)	
Value x 10^2					-0.165***	3.067	-0.174***	3.235	-0.177***	3.291	-0.172***	3.197
					(0.047)		(0.047)		(0.047)		(0.048)	
Duplicates					-0.556***	12.910	-0.557***	12.933	-0.563***	13.105	-0.586***	14.006
					(0.078)		(0.078)		(0.077)		(0.069)	
Missing					0.062**	-1.093	0.064**	-1.125	0.064**	-1.141	0.060**	-1.081
					(0.028)		(0.028)		(0.028)		(0.029)	
Tech Field Dummies			YES***		YES*		YES*		YES*	YES*	YES*	
District Court Dummies			YES***		YES***		YES***		YES***	YES***	NO	
Year Dummies (1992-2000)	YES***		YES***		YES***		YES***		YES***	YES***	YES***	
Observations	4489		4489		4489		4489		4489	4489	4489	

*NOTES: Robust standard errors are reported in parentheses. Statistical significance: *10%, **5%, ***1%. Coefficients, standard errors and marginal effects for complementarity and value are multiplied by 100. Coefficients are from proportional hazard regressions.*

Table 5. Extensions and Robustness - Dependent Variable: Dispute Duration

	(1)		(2)		(3)		(4)		(5)		(6)	
	Coefficient	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**	**Coefficient**	**Marg. Effect**
Fragmentation1	1.900*** (0.628)	-57.019	1.814*** (0.630)	-54.438	1.791*** (0.625)	-53.748	1.831*** (0.623)	-54.948			1.746*** (0.613)	-52.397
Fragmentation2									0.539** (0.251)	-16.715		
Complementarity x 10^5	-1.181*** (0.199)	21.955	-0.885*** (0.109)	16.452	-1.136*** (0.157)	21.119	-0.808*** (0.119)	15.021	-0.917*** (0.109)	17.047	-0.861*** (0.162)	16.006
CAFC	1.603*** (0.587)	-52.159	1.544*** (0.590)	-50.021	1.530*** (0.585)	-49.656	1.516** (0.594)	-55.941	0.882*** (0.263)	-25.501	1.494*** (0.570)	-47.223
CAFC x Fragmentation1	-1.491** (0.647)	49.927	-1.411** (0.649)	47.450	-1.399** (0.644)	46.951	-1.375** (0.654)	47.041			-1.340** (0.629)	45.397
CAFC x Fragmentation2									-0.649** (0.275)	18.622		
Value x 10^2	-0.294*** (0.084)	5.645	-0.175*** (0.049)	3.253	-0.168*** (0.047)	3.123	-0.220*** (0.053)	4.090	-0.169*** (0.047)	3.141	-0.195*** (0.048)	3. 625
Value*Age x 10^2	0.015** (0.009)	-0.309										
Serial Patentees			-0.200* (0.119)	3.856								
Serial Infringers			0.214* (0.122)	-3.459								
Large Portfolios					0.289** (0.139)	-4.451						
Small Portfolios					0.076** (0.033)	-1.329						
Detailed Field dummies	NO		NO		NO		NO		NO		YES***	
Observations	4489		4489		4489		3402		4489		4489	

*NOTES: Robust standard errors are reported in parentheses. Additional controls (not reported) are: missing, duplicates, tech field dummies, court dummies and year dummies for the period 92-00. Statistical significance: *10%, **5%, *** 1%. Cases litigated after 1993 are dropped in column (4). Coefficients, standard errors and marginal effects for complementarity and value are multiplied by 100.*

Table 6. Impact of Fragmentation on Total Negotiation Time

	e_{nN}	e_{kN}	C4	e_{tn}	
				Without CAFC	With CAFC
DRUGS	0.29	0.30	0.10	-0.46	-0.11
OTHER HEALTH	0.05	0.45	0.07	-1.41	-0.33
CHEMICALS	0.05	0.15	0.06	-1.84	-0.43
BIOTECH	0.13	0.28	0.08	-0.82	-0.19
ELECTRONICS	0.26	0.14	0.10	-0.53	-0.14

Notation: e_{nN} = elasticity of negotiations respect to patents granted, e_{kN} = elasticity of the size of four largest portfolios respect to patents granted, C4 = average share of top patentees in the period, e_{tn} = elasticity of negotiation time respect to number of negotiations.

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