

The Value of Certainty in Intellectual Property Rights:
Stock Market Reactions to Patent Litigation

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Abstract

Using a sample of patents litigated between 1977 and 1997, I estimate stock market reactions to patent litigation decisions and to patent grants. I find that the resolution of uncertainty over validity and infringement is worth as much to the firm as the initial patent right. Each is worth about 1 to 1.5% excess returns. Additionally, I find that there are significant differences pre and post-1982 with the establishment of the Court of Appeals for the Federal Circuit. I also find that there are significant differences in reactions for plaintiff patent-holders and defendant patent-holders. Interestingly, there is no similar effect for appellate court decisions relative to the district court. To my knowledge, this is the first study that measures the stock market reactions to legal outcomes of patent cases.

Keywords: patents, uncertainty, litigation, innovation, event study

JEL codes: L19, L29, O32, O34, K41

1 Introduction

Legal uncertainty is inevitable in a patent rights system. And since patents are fundamentally property rights, the legal environment can potentially significantly affect the value of patent protection (Lanjouw 1994, Lemley and Shapiro 2005). Uncertainty over whether a “title” to property can be enforced will undermine its market value: the title is only as good as the ability to enforce it.¹ Legal uncertainty is especially pervasive in emerging technology areas (or emerging *patenting* areas, like business methods and software patents). Where uncertainty is prevalent, the effects on appropriation and firm behavior can be dramatic.² Since the purpose of a patent system is to provide incentives for research, innovation, and diffusion by creating rewards, an inability to appropriate those rewards diminishes the very incentives for which the system was designed.

Intellectual property managers face decisions about whether to patent innovations (Lerner 1995, Grindley and Teece 1997, Hall and Ziedonis 2001), and how to manage market transactions in intellectual property. Different legal or institutional environments may affect the incentives for firms to license and do R&D (Reinganum 1989), to enter (Choi 1998), and to litigate (Meurer 1989). If property rights are well-defined, firms may organize transactions through arms length negotiations. In uncertain legal environments, we expect to see more integrated transactions ranging from cross-

¹Illustrative examples of the importance of property rights enforcement can be found in television portrayals of the “Old West.” In 1859, a title to land in Virginia was more valuable than one in Nevada, in part because of the “underlying value of the land,”—closer to transportation and markets, more fertile, etc. However, Virginia land was also more valuable because better enforcement mechanisms were in place there. On the TV series *Bonanza*, the value of the Ponderosa ranch was due in part to the quality of the land for grazing cattle, and in part to the ability of the Cartwrights to enforce their title—whether through formal institutions (the local constabulary) or self-help (the number of able-bodied Cartwrights available during the episode). See Ellickson (1991) for an excellent discussion of formal versus informal dispute resolution.

²The value of property rights is also affected by other institutional and technological factors, including standard-setting and the availability of alternative mechanisms such as lead time, marketing, and trade secret. Uncertainty in any of these areas will have impacts on appropriability.

licensing to strategic alliances to consolidation. To the extent that uncertainty affects or drives these decisions, it is of great strategic importance to firms. And, to the extent that policy makers have some control over the amount of legal uncertainty, or legal “quality” as coined by Merges (1999), it is an important and understudied policy instrument. Simulation estimates (Lanjouw 1994, Lanjouw 1998) find that changes in patent law or the legal environment can significantly change the value of patent protection, not just for litigated patents, but for all patents even if none are ever litigated.³

Uncertainty is introduced into a patent system by both the administrative agency (the Patent and Trademark Office (PTO) in the US) and the legal institutions. Because of the importance of enforcement on the value of intellectual property, many researchers in the US have pointed to the establishment of the Court of Appeals for the Federal Circuit (CAFC) in 1982 as a watershed in the rights of patent holders. The CAFC established—among other things—a single court that would hear the appeals of patent cases from all federal district courts (state courts do not hear patent cases). It is claimed that the CAFC strengthened the rights of patent holders—that the court is more “pro-patent” than its district peers (Lerner 1994, Lanjouw 1994, Lanjouw and Shankerman 1997, Kortum and Lerner 1999, Henry and Turner 2006 (forthcoming)), so that we can expect a shift in the legal standard in the early 1980s, perhaps increasing beliefs that a patent will be held valid and infringed.

The changes in the institutions governing patents can increase or decrease the uncertainty over the scope and validity of patents, and we must recognize that this uncertainty will have effects on firms’ incentives to litigate, license, do R&D, and to patent in certain areas. Lerner (1994) finds that the “shadow” of litigation may change the patenting behavior of firms; in particular, high-litigation-cost firms may target “less crowded” technology areas in order to avoid disputes. These effects may be large, and may be an important part of the patent system. For this reason, it is important to have an understanding of the quantitative impact of uncertainty on the value of patent rights.

The current political attention on tort reform in the US is evidence that policy-makers recognize

³For example, Lanjouw estimates that if the underlying probability of success for a plaintiff fell from 75% to 50%, and legal fees doubled, then the average patent value would be halved in her simulation, even if no cases were litigated.

the policy dimension of legal uncertainty on a broad scale. Since it is expensive for the administrative agency to authenticate every patent, it may want to depend on individual firms to enforce their own patents: it need not investigate each patent in depth. It may be more cost effective to introduce some degree of uncertainty into the system as to the validity and scope of patents. In this way, expenditure on each granted patent will be reduced, and only those which are in dispute will be investigated (in court) at further cost. One can therefore expect the socially optimal amount of uncertainty to be positive.

This paper presents an empirical investigation into the degree of uncertainty in granted US patents. I make use of stock market reactions to court decisions and to patent grants in order to estimate the magnitude of changes in beliefs about patent validity. It is from litigating that market participants “learn” about the validity of patents from the court, and update their beliefs accordingly. To my knowledge, this is the only study that measures stock market reactions to legal outcomes of patent cases.

In this paper, I use an event study analysis for several reasons. First, litigation events are well identified and there is little (if any) leakage about what the actual decision will be. Second, litigation events can be directly associated with changes over a patent’s uncertainty. If a patent is ruled to be valid, nothing about this decision affects the value of the underlying technology, so the change in value reflects changes in beliefs about the uncertainty over property rights.

The primary result is that I find that market response to patent litigation tends to on par with the market response to the patent grant itself. That is, the resolution of uncertainty about validity or infringement is worth as much as the initial patent right on average, indicating the presence of significant legal uncertainty. Secondly, I find there to be significant differences in market reactions based on when the patent was adjudicated (before or after the establishment of the Court of Appeals for the Federal Circuit in 1982) and whether the patent was owned by the plaintiff or defendant in the suit. The intuition for the first result comes from option pricing theory. The fundamental value

of a patent right is the right to exclude others from using the technology. Since enforcement is imperfect and costly (Lemley and Shapiro 2005), the right to exclude becomes the right to sue with some probability of success (Marco 2005 forthcoming). Thus, in the property rights context, the patent is an option to bring a lawsuit against an alleged infringer. Just like financial options, the option to sue need not be exercised in order for it to have value, and the exercise of an option can very well be worth more than the initial option value. Interestingly, I find no significant difference between appeals and district court decisions.

Section 2 lays out the econometric specification, and Section 3 describes the patent data, litigation data, and the event study results. In Section 4 I estimate several models that explain the size of the market reactions, and that compare the effects of infringement suits (where the patent holder brings the suit) to defensive suits (where the patent holder is the defendant). Section 5 concludes.

2 Empirical Model

Patent litigation is an especially useful area of law in which to examine market responses. First, the question of validity is primarily a binary decision.⁴ The issue of infringement is not as straightforward, but the court’s decision still generally fits into a binary classification. Second, there is little or no leakage prior to the announcement of the decision. Third, all the new information about the patent pertains to changes in beliefs about the property right as opposed to the patented technology.

For patent i born at time 0, I assume that the value at time t can be approximated by

$$v_{it} = p_{it}^V \cdot p_{it}^I \cdot z_{it}$$

where V is the value of the patent, p^V is the probability of winning on validity, p^I is the probability of winning on infringement, and z is some underlying private value of the technology were it to be perfectly enforceable.

⁴There are a handful of decisions where a patent is found valid in part and not valid in part. Those cases are excluded from my sample.

If the patent is litigated at time τ , the change in patent value is given by

$$\Delta v_{i\tau} = \Delta p_{i\tau}^V \cdot p_{i\tau}^I \cdot z_{i\tau} + \Delta p_{i\tau}^I \cdot p_{i\tau}^V \cdot z_{i\tau} + \Delta p_{i\tau}^V \cdot \Delta p_{i\tau}^I \cdot z_{i\tau} \quad (1)$$

where Δ represents the change in the variable as a result of the court's decision. Note that it may be that $\Delta p_{i\tau}^V = 0$ or $\Delta p_{i\tau}^I = 0$ if there is no decision on validity or infringement, respectively. Importantly, I assume that the actual technological value, z , does not change as the result of the court's decision. Put another way, the court makes decisions only about the property right, and not about the technology.

The econometric specification becomes

$$\Delta v_{i\tau} = \beta_0 + X_{i\tau}^V \beta_1 + X_{i\tau}^I \beta_2 + X_{i\tau}^{VI} \beta_3 + \varepsilon_{i\tau} \quad (2)$$

where $X_{i\tau}^V$ is a vector of variables that affect the market response to validity or invalidity decisions, $X_{i\tau}^I$ is a vector of variables that affect the market response to infringement or non-infringement decisions, and $X_{i\tau}^{VI}$ is a vector of interaction terms between $X_{i\tau}^V$ and $X_{i\tau}^I$. In a simple specification, I define $X_{i\tau}^V = [D_{i\tau}^V \ D_{i\tau}^{NV}]$ and $X_{i\tau}^I = [D_{i\tau}^I \ D_{i\tau}^{NI}]$ where the D s are indicator variables for different kinds of decisions: valid, not valid, infringed, not infringed. Note that I keep all the indicator variables in the equation because $D_{i\tau}^V + D_{i\tau}^{NV}$ may be equal to zero if there is no decision on validity at date τ ; similarly with infringement. $X_{i\tau}^{VI}$ then becomes

$$X_{i\tau}^{VI} = [D_{i\tau}^V \cdot D_{i\tau}^I, D_{i\tau}^V \cdot D_{i\tau}^{NI}, D_{i\tau}^{NV} \cdot D_{i\tau}^I, D_{i\tau}^{NV} \cdot D_{i\tau}^{NI}].$$

Note that the third term in equation 1, $\Delta p_{i\tau}^V \cdot \Delta p_{i\tau}^I \cdot z_{i\tau}$, has only a second order effect. If this effect is negligible, the estimation equation becomes

$$\Delta v_{i\tau} = \beta_0 + X_{i\tau}^V \beta_1 + X_{i\tau}^I \beta_2 + X_{i\tau}^{VI} \beta_3 + \varepsilon_{i\tau}. \quad (3)$$

It is clear from equation 1 that the change in the value of the patent will be a function of both the marginal change in the expected probability of winning on validity and infringement and the

private value of the underlying technology. In a companion paper, I estimate a structural model that attempts to disentangle these effects. For the current paper, I aim only to characterize the distributions of stock market reactions to litigation decisions and to patent grants in order to infer something about the value of resolution of legal uncertainty relative to the initial property right.

2.1 Multiple Patents-in-Suit

Before discussing the data and the calculation of excess returns and the probability of validity, one econometric problem must be dealt with. I am not able to observe changes in patent value, but rather changes in the value of a firm. So, if there are multiple “patents-in-suit” I observe only the aggregate market reaction. Table 2 shows that of 295 adjudications, 209 involved a single patent. the remaining 76 adjudications account for decisions on 266 patents. If there are N patents-in-suit that are adjudicated simultaneously,

$$\Delta f_{i\tau} = \Delta v_{i\tau 1} + \Delta v_{i\tau 2} + \dots + \Delta v_{i\tau N} \quad (4)$$

where $\Delta v_{i\tau n}$ represents the change in the value of patent n of firm i at time τ . So, while we observe $\Delta f_{i\tau}$, what we seek is the expectation of $\Delta v_{i\tau n}$ given $\Delta f_{i\tau}$, or $E(\Delta v_{i\tau n} | \Delta f_{i\tau})$. In cases where $N = 1$ there is no difficulty in the estimation. Removing cases where $N > 1$ leaves information from multiple patents-in-suit unexploited (and possibly biases the results). Instead, I use an application of the Expectation-Maximization (EM) Algorithm to make use of the data when there are “missing” $\Delta v_{i\tau n}$ ’s.⁵ The EM Algorithm in this application is described in detail in Appendix A. The intuition is that I estimate Equation (2) to predict values of $\Delta v_{i\tau n}$ for multiple patents-in-suit. These predicted values are used in a new iteration of the estimation, and the process is repeated until the parameter estimates converge.

⁵For a good overview of the EM Algorithm with applications to economics, see Ruud (1991); McLachlan and Krishnan (1997) provide an extensive treatment of the subject.

3 Data

My data begin with a database compiled by researchers at the National Bureau of Economic Research (NBER) and Case Western Reserve University (CWRU) (Hall, Jaffe and Trajtenberg 2000).⁶ The sample consists of over 417,000 patents owned by publicly traded US manufacturing firms. The patents are assigned Cusip identifiers using the 1989 ownership structure of the patent holder.

Litigation data were hand-collected from the United States Patents Quarterly (USPQ) 1977-1997.⁷ The USPQ publishes annual indices containing patents on which adjudications were made in that year. USPQ contains only “published” adjudications, which is a subset of all adjudications. However, the advantage of the USPQ is that it contains clear information on the disposition of the case with regard to validity and infringement. The USPQ data were merged with the NBER/CWRU data to obtain a list of litigated patents owned by publicly traded firms.

The merged data contain 701 case citations involving 670 patents. I entered the disposition data for each adjudication containing decisions relevant to validity or infringement.⁸ Adjudications involving preliminary motions about discovery, jurisdiction, etc. were discarded. Also, PTO interference proceedings and examination proceedings were not used. When a USPQ citation made explicit reference to an earlier related decision, I incorporated that case into the database.

The final adjudication data consist of 390 decisions involving 413 patents owned by 158 publicly traded firms. An observation in my data is a “patent-decision.” For example, a single case may involve four patents. When a decision is made, I record four patent-decisions. In total, I have 610 patent-decisions. About half of the cases involve only one patent-decision. The implied litigation rates are given in table 1, where case filing data was calculated using data obtained from LitAlert.⁹

In order to be able to analyze the adjudications using my methodology, I obtained CRSP data

⁶My thanks to Bronwyn Hall for permitting access to the data.

⁷See Allison and Lemley (1998) and Henry and Turner (2006 (forthcoming)).

⁸The opinions themselves were obtained electronically from Lexis, to whom I am grateful for access to the USPQ file.

⁹It is likely that both filing data and adjudication data are under-reported.

on daily stock returns from the Wharton Research Data Service (WRDS). Of the 390 adjudications, ownership and returns data were available for 295. These 295 adjudications represent 325 patents and 475 patent-decisions. Of those 325 patents, returns data were available for 287 patent application dates and 309 issuance dates; for 283 patents, I have returns data for both dates.

Table 2 shows the break down of the 475 decisions into various subsamples. The first important subsample is whether the case was decided in a lower court or a an appellate court. In my sample, 277 individual decisions were at the district court level. Note that my sample is subject to both right-hand and left-hand truncation. That is, for a 1977 appellate decision, I would not have in my sample the original lower court decision; for a 1997 lower court decision, I would not have in my sample the subsequent appeal. In any case, one might expect appellate decisions to be weighted differently by the market than district court decisions.

The next subsample shows that 125 cases occurred prior to 1982, when the Court of Appeals for the Federal Circuit (CAFC) was established. This distinction is important for two reasons. First, the CAFC is a centralized appellate court for patent cases. So, all appeals heard after that time were heard in the same court. Second, the centralization may have led to a harmonization among circuits in terms of precedent. Either of these may cause stock market reactions to differ pre- and post-CAFC.

In most cases, the plaintiff is the patent holder. Only 48 decisions involve a defendant patent holder. Market reactions between these two subsamples are likely to differ because of different selection effects. Plaintiff patent holders engage in the typical patent infringement case. A patent holder becomes a defendant in one of two instances: either it has been preemptively sued for a declaratory judgment that the patent is invalid, or it has been sued for patent infringement, and it counter-sues for infringement. In either case, defendant patent holders may have different incentives to settle than plaintiff patent holders (Priest and Klein 1984, Waldfoegel 1995). These different selection effects may lead to different market responses.

As stated above, 209 observations obtain from single-patent adjudications, whereas 266 arise from multiple-patent adjudications. Again, this problem leads to the use of the EM Algorithm to disentangle the effects of contrasting decisions on the same date.

The last two rows of table 2 shows the breakdown by type of adjudication. 326 out of 475 patent decisions involved validity, and 298 involved infringement. Two important things should be noted here. First, not every adjudication involves both infringement and validity. In many trials, the issue of validity is determined separately from that of infringement. Frequently the trial is bifurcated (or trifurcated): validity is determined first, and then infringement (and finally damages). Settlement may occur at any phase of the trial. In my sample that case would show up as first a validity adjudication, and some time later another adjudication on infringement. One trial, two adjudications, unless settlement occurs. Further, in some trials, validity may not be questioned as a defense. So, the court rules only on infringement. Thus, in my regression analysis, I code four dummy variables to represent a ruling of validity (V), invalidity (NV), infringement (I), and non-infringement (NI).¹⁰ Since any given adjudication can rule a patent valid, invalid, or can refrain from ruling on validity (and similarly for infringement), I include all four dummy variables and a constant in the estimation equation.

Another important piece of information is the relative frequency of validity rulings (326) relative to infringement rulings (298). While the vast majority of suits are brought by the patent holder, there are more validity rulings than infringement rulings. Clearly the validity of a patent is a common defense. And, a patent holder should expect to face a decision on validity when it brings an infringement suit. Among validity rulings, the win rate for the patent holder is 59%; for infringement it is 64%. Additionally, the correlation coefficient between positive validity rulings and positive

¹⁰Technically, since validity is presumed, the court will rule that the patent is either invalid or not invalid. I refer to valid and invalid patents for the sake of parsimony.

infringement rulings is 0.63. Defining the following variables as good news:

$$g_V = V - NV$$

$$g_I = I - NI,$$

I find that the correlation between g_V and g_I is 0.50.¹¹

3.1 Event studies

As an estimate of the value to a patent holder of news about a patent, I rely on the event study methodology. In particular I investigate two pieces of news: (1) news about the patent grant (at the time of application and the time of issuance); and, (2) news about a court's decision about the validity or infringement of a patent. Event studies measure the change in the value of the firm using cumulative abnormal returns, or excess returns. The methodology is the accepted way to tie stock market valuations to particular events, but there are two caveats that should be mentioned.

First, if information about the event leaks into the market prior to the event date, then the excess returns will measure only a portion of the total reaction. This problem is likely to be more important for patent grants than for patent adjudications. The announcement effect of a patent application or patent grant cannot be readily interpreted as representing the full value of the patent because announcement effects only reflect changes in value with respect to news about the patent. It is more likely that news about noteworthy patents may be known ahead of time. However, news about a court's decision is likely to be unknown prior to the decision.

Second, excess returns are notoriously noisy, since multiple factors can influence a stock price on any given day. So long as those other factors are not systematically correlated with news about patents, then they will add noise but will not bias the results.

¹¹The correlation coefficients are based on individual patent decisions. Thus, they do not account for earlier decisions by the same court on that patent.

Previous work on patent litigation and value has not explicitly made use of the information contained in market responses to patent litigation decisions, or on the outcomes of court decisions. Some renewal models use the incidence of litigation as well as renewal rates to estimate the parameters of the model (Lanjouw 1998). But these papers do not look at legal outcomes. Allison and Lemley (1998) investigate patent cases published in the US Patents Quarterly.¹² The authors do investigate the dispositions of these cases, but their focus is on the legal character of the cases more than the economic implications.¹³

I use cumulative abnormal returns as measured by event studies to measure the stock market reactions to patent decisions. Event studies are appropriate for several reasons. First, changes in value are precisely what event studies are designed to measure. Second, while event studies have been used by researchers to investigate the effects of other types of litigation (Bhagat, Brickley and Coles 1994), no study has concentrated on patent litigation.¹⁴ Market reactions provide information that has not been previously incorporated into the analysis of patent value. Third, litigation events are well identified: court records for published decisions identify the date of the decision. Last, litigation events can be directly associated with changes over beliefs about the legal patent right. If a patent is ruled to be valid, nothing about the decision affects the value of the underlying technology, so the change in value reflects changes in beliefs about the uncertainty over property rights.

In order to estimate equation 2, I need to calculate a measure for the market reaction to the litigation event. The market model is the model most frequently used in event studies (Campbell, Lo and MacKinlay 1997). The estimation equation is

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

¹²I am grateful to Mark Lemley for alerting me to this source.

¹³For instance, the incidence of certain legal defenses to infringement.

¹⁴Austin (1993) uses event studies to examine market reactions to patent issuance.

where

R_{it} = proportionate return on the stock of firm i from time $t - 1$ to time t .

R_{mt} = proportionate return on the overall market from time $t - 1$ to time t .

Abnormal returns are calculated by estimating the parameters of the market model in some pre-event equilibrium. Essentially, the abnormal return is the forecast error. The cumulative abnormal returns are given by

$$CAR_{it} = \sum_{t=-\tau_1}^{\tau_2} u_{it}$$

That is, cumulative abnormal returns are the summation of abnormal returns over the event window $-\tau_1$ to τ_2 , where the event occurs on day 0. For the analysis below the pre-event equilibrium is $[-300, -20]$, measured in trading days. For the adjudication events, the abnormal returns are calculated for symmetric event windows of 1, 3, 5, 7, 9, and 11 trading days around the event date, and an asymmetric window of two days (day 0 and day +1). For patent grants, I drop the one day window. The Equal Weighted Market Return is used for R_m , as defined by CRSP.

4 Analysis

4.1 Excess returns

Tables 3 and 4 summarize the results of the event studies. The first column lists the event window used to calculate the excess returns, 2 to 11. Additionally, I calculate a bootstrap sample. For a single bootstrap replication, a sample of patents (with replacement) is drawn from my sample. For each patent a single event window is randomly chosen. The distribution given in the table represents the distribution of 500 bootstrap replications. The random event window is admittedly arbitrary. However, it is less arbitrary than choosing a single event window for all application and issuance

dates.¹⁵

It is evident from table 3 that the application date produces a significant positive reaction from the market, in contrast to both the issuance date and the sum of the returns at the application and issuance dates. This may seem strange in light of US patent laws: applications are not made public, whereas patents themselves are. However leakage is important in this context, because important patents may have more information leaked near the application date than near the issuance date. Austin (1993) performs event studies on a sample of biotechnology patents and determines that the patent grant date is more appropriate.

For all windows greater than two days, the 90% confidence interval shows positive excess returns around the patent application date. For nine- and 11-day windows, the sum of the application and issuance date returns is also significantly positive. The 11-day returns show a response of 1.4% to 2% for the application date, and 1.2% to 3.3% for the sum of application and issuance returns. The bootstrap estimates show a smaller confidence interval of 0.14% to 1.0% at the date of application. Finally, bootstrap estimates show a dollar value (calculated from excess returns and market capitalization) of \$28.1 million at the mean, and a 90% confidence interval of \$0.7 million to \$55.4 million.

To put this in context, compare these reactions to the excess returns estimates of patent issuance done by Austin (1993). He finds that excess returns range from a mean of about \$500,000 for the full sample, to a mean of \$33 million for those patents mentioned in the Wall Street Journal. If litigated patents comprise a sample of the most valuable patents (Allison, Lemley, Moore and Trunkey 2003), the comparison to “Wall Street Journal” patents is apt.

Table 4 and figures 1 and 2 present excess returns at application date by the patent’s later

¹⁵It is unlikely that a single event window would represent all firms equally well. In the absence of a prior as to which window would work better for different types of firms or patents, I rely on the more robust bootstrapping estimator of the mean.

infringement or validity status,¹⁶ as determined by the court. Do patents that are later found to be valid or infringed show higher excess returns at the time of birth? The short answer is no. In fact, the histograms in figures 1 and 2 show that excess returns at the date of application are likely to be slightly higher for invalidated or not infringed patents than for valid or infringed patents, although the difference is not statistically significant. Patents that are later found valid have mean excess returns of 0.46% compared to 0.59% for patents that are later found invalid. Similarly, infringed patents have mean excess returns at the date of application of 0.53% compared to 0.99% for non-infringed patents. Only the non-infringed result is significantly different from zero at the 10% level. The lower returns for subsequently valid and infringed patents is not completely surprising and is almost certainly due to a selection effect. There may be some uncertainty over the strength of the original property right for patents that are later litigated. If a patent holder has private information about a patent’s validity (Meurer 1989), it will be more likely to pursue litigation if the market’s perception of the patent is particularly low relative to the patent holder. Thus, the low returns to later validated patents may be a signal of the market’s perception of value, rather than the patent holders.

Table 4 and figure 3 present the excess returns by type of disposition at the time of adjudication. The results of the response at adjudication is meaningless in the aggregate because they contain information for both good news and bad news events, as well as “mixed” events (e.g., a valid but not infringed patent). We expect the market returns to be somewhat noisy despite the precision of the event date. First, firms differ in size, so reactions to good or bad news about patents will vary not only according to revision in beliefs, but also according to the firm’s market capitalization. Large firms will have smaller responses, *ceteris paribus*. Additionally, there will be individual heterogeneity at the patent level because of the heterogeneity in the underlying technological value. I control for this heterogeneity by using the log of the dollar returns as the dependent variable, and by using a random effects model.

¹⁶For the current tables and figures, and those that follow, the bootstrap estimates of the distribution are presented.

It is evident that the mean reaction to infringement is positive and the mean reaction to non-infringement is negative. Validity leads to a positive response, but invalidity leads to an even higher positive response. In fact, of the four types of dispositions, only invalidity is significantly different from zero (at the 10% level). The market reactions to adjudications are confounded by two factors. First, multiple-patent decisions mistate the market reaction to any individual patent that is a part of the decision. If two patents are adjudicated simultaneously, and the decision is that one patent is valid and infringed, and one patent is not valid, then the market reaction will be a combination of the response to each patent.¹⁷ Secondly, the decision on an individual patent may be a mix of good news and bad news, e.g., valid and not infringed or invalid and infringed.¹⁸

Because of the confounding influences affecting market reactions to adjudication, it is appropriate to turn to regression analysis to disentangle the effects of multiple patents and mixed decisions.

4.2 Regression results

Table 5 presents the results of estimating a variation of equation 3

$$CAR_{it} = \beta_0 + V_{it}\beta_1 + NV_{it}\beta_2 + I_{it}\beta_3 + NI_{it}\beta + \varepsilon_{it}. \quad (5)$$

where CAR indicates the cumulative abnormal return at the time of adjudication from the event studies. All estimations use the EM Algorithm described in appendix A, and all standard errors are bootstrapped (1000 replications). Since the bias in the estimates relative to the bootstrap replications tended to be large (usually greater than 0.25 of the standard error), bias corrected

¹⁷Cases in the sample contain as many as 12 patents.

¹⁸Oddly enough, the latter decision is not unheard of. Six observations in my data are valid and not infringed. District courts began the practice in recognition that their decision on validity might be overturned on appeal. This is the consequence of anticipated appeals on the part of district courts. If an invalidity decision is overturned by the Court of Appeals for the Federal Circuit, then it can expedite proceedings to decide both issues at the time of the original trial, rather than have a separate trial on remand. In that instance, the court would save time to rule on both matters simultaneously. See, for example, *Datascope Corp. v. SMEC, Inc.* (224 USPQ 694 [1984]) N.J.

coefficients are reported and significance levels are determined from the bias-corrected confidence intervals rather than from the bootstrapped standard errors (Efron and Tibshirani 1993, Briggs, Wonderling and Mooney 1997).

The first model uses the two-day excess returns as the independent variable. The second model uses another application of the bootstrap, similar to that used in examining the means of the excess returns in section 4.1. Each replication consists of a sample of 475 observations drawn from the sample (with replacement). The event window is then chosen randomly for each observation from the set $\{1, 2, 3, 5, 7, 9, 11\}$ as above. The rationale is the same as with the means: there is no justification for choosing any particular event window since the appropriate window is likely to differ on the basis of the individual patent, company, and decision. Thus, I choose a random window for each observation. The bootstrapping procedure yields consistent estimates.

The third model in table 5 estimates a random effects version of equation 5

$$CAR_{it} = \beta_0 + V_{it}\beta_1 + NV_{it}\beta_2 + I_{it}\beta_3 + NI_{it}\beta + u_i + \varepsilon_{it}, \quad (6)$$

where u_i is a patent specific disturbance term and ε_{it} is the standard disturbance term. In addition to the ordinary parameter estimates, the random effects model estimates parameters σ_u and ρ , the proportion of the overall variance associated with σ_u as opposed to σ_ε . Lastly, the fourth model estimates a random effects model with the log of the dollar value of the excess returns as the dependent variable. The remaining regressions all use the bootstrapped random effects model with the EM Algorithm.

Model 1 (using the two-day window) shows a significant value for *NV* (not valid) decisions only. The estimated market reaction is -1.25% . Model 2 yields no significant results. However the random effects model estimates the parameters with much more precision. Again, from equation 1, the market response will depend on the value of z (the underlying technological value). The heterogeneity embedded in z is approximated by the random effects model.

The coefficients show a 1.6% excess return due to validity, -1.4% return from invalidity, a

−1.8% response to a non-infringement ruling, and a 0.8% response in the constant term; reaction to infringement is not measured precisely. Note that the constant term reflects a positive market reaction to the conclusion of a case. This is not unexpected since the resolution of uncertainty tends to be favored by the market. Additionally, providing certainty about validity, invalidity or infringement is worth about 1.5% to the firm. That is, more certain property rights are worth as much to the firm as the estimates of patent value at the time the patent is born (around 1%).

The estimate of ρ is quite high, indicating that much of the unobserved heterogeneity is patent specific (as opposed to observation specific), which is consistent with the idea that the random effects model captures the heterogeneity embedded in z_i . The log dollars equation confirms only the negative coefficient on invalidity. It is interesting that the dollars equation does not more accurately measure the coefficients, since some of the noise in excess returns arises from differences in firm size. However, it is standard in the event study literature to use excess returns rather than dollar values, and in this instance it does not appear to harm the precision of the estimates (as long as the random effects model is used).

Table 6 compares the simple random effects model (model 3 of table 5) to an estimation that includes the interaction terms according to equation 2. The interaction terms are mostly insignificant, and most of the coefficients on the primary disposition variables also become insignificant (including the constant term). The exceptions are the validity coefficient of 3.4% (significant at the 99% level) and the valid and not infringed interaction term of −4.9% (significant at the 95% level). These coefficients are much larger than without the interaction terms. Several of the other coefficients are large in magnitude but imprecisely measured, probably due to the presence of multicollinearity among the regressors. For the remaining regressions, I rely on the non-interacted model for the sake of simplifying the interpretation. That restriction does affect the results on the subsample regressions below.

In table 2, I described several different subsamples that might affect the size of market reactions

to patent adjudications and the resolution of uncertainty in patents. The next section investigates those subsamples in more detail.

4.3 Subsamples

Table 2 listed three ways to divide the sample:

1. appeals versus district court decisions,
2. pre- and post-1982 decisions, and
3. plaintiff patent holders and defendant patent holders.

For each pair of complementary subsamples, I use a Chow test to determine whether the coefficients of each subsample are different from one another (using the random effects model on excess returns in table 5). Based on non-bias-corrected coefficients, none of the subsamples have a significant effect; the largest Chi-squared statistic (five degrees of freedom) is 8.1, with a p-value of only 0.15.

Two of the three Chow tests using the bias-corrected coefficients were significant. Comparing the pre- and post-1982 decisions led to a statistic of 16.7 (p-value < 0.01). Reactions to plaintiff patent holders were significantly different from defendant patent holders, with a statistic of 13.0 (p-value < 0.05). It is very interesting that the appellate decisions did not lead to larger market responses than lower court decisions, on average (chi-squared statistic of 3.2, p-value = 0.67). One would think that the higher courts would have final say on validity and infringement (since very few patent cases go to the Supreme Court), and that markets would respect this greater power. While this may be true, the effect is not large enough to show in the data. However, the pre- and post-CAFC era does seem to make a difference, whether at the appellate level or the district level.

Tables 7 and 8 compare the results of estimating equation 5 for the pre- and post-CAFC era, and for plaintiff and defendant patent holders, respectively. Interestingly, the post-CAFC era is charac-

terized by smaller excess returns in response to validity and larger (negative) responses to invalidity. Pre-CAFC reactions to infringement decisions were much larger than post-CAFC responses (and both infringement and non-infringement led to negative responses). Taken together, a valid and infringed patent had a negligible market reaction prior to the establishment of CAFC, and the loss on infringement was a significant negative. This indicates that only very strong patents (patents that were believed to be likely to win) were being litigated because the response to the upside was small, and the response to the downside was large.

There is an intriguing results with regard to plaintiff and defendant patent-holders. Market reactions tend to be larger with validity decisions for plaintiffs and for infringement decisions with defendants. On the surface this may seem strange, since plaintiff cases are usually straight infringement cases, and defendant cases usually deal with validity (declaratory judgments for invalidity). However, this result has to do with selection, expectations, and uncertainty. Since plaintiff cases are brought with regard to infringement, it may be that the markets well predict the infringement outcome relative to the validity outcome. Similarly, since defendant cases are usually brought with respect to validity, the markets may well predict the validity outcome in comparison to the infringement outcome. Additionally, the constant term is significant (1.8%) for defendant cases. Because defendant cases are—in a sense—involuntary on the part of the defendant, their existence signals greater risk to the company than a lawsuit deemed necessary for the protection of the firm's property. Thus, the conclusion of such a case is likely to be more valuable to defendant patent-holders.

Separating the subsamples leads to one surprising result: that appellate courts do not generate more significant market responses than lower courts. Additionally, the comparison of pre- and post-1982 and plaintiff and defendant patent-holders highlights the impacts of selection on the returns to litigation.

5 Conclusion

By investigating the size of the market reactions—and how they differ systematically among cases—I am able to make some inferences about the value of certainty in patent rights. This paper is the first to estimate market reactions to patent litigation events, and to compare them to market reactions at patent birth. The primary result is that the resolution of uncertainty is as valuable to the firm as the initial patent grant (which is subject to uncertainty). If the sample is at all representative, then this result is an indication that there may be a significant amount of legal uncertainty created by the patent system. For some models, merely the conclusion of a case is worth a 1% return, similar in magnitude to the original patent grant.

Additionally, I find that firms can expect validity rulings whether the patent is owned by the plaintiff or defendant. This result is important because patent validity is one source of asymmetry of stakes, which is very important in the selection literature (Priest and Klein 1984, Waldfoegel 1995, Marco 2004). If a patent-holder expects to face a decision on validity, then the opportunity cost of an invalid patent (that affects negotiations with *all* potential licensees) becomes a significant litigation cost (near -1.5% return in my estimates). On the other hand, a win on validity has a similarly asymmetric upside. However, since returns to validity decisions are similar to returns on infringement decisions, it may be that a ruling on infringement can lead to similar asymmetry.

One very important caveat should be mentioned about the results. They are conditional on litigation. This is, of course, obvious because the sample consists entirely of litigated patents. However, because selection effects are well-known this sample does not represent in any way a random sample of patents.

On the other hand, to the extent that litigated patents represent a sample of valuable patents (Allison et al. 2003), then the results are important. If valuable patents are subject to uncertainty about validity and infringement, then resolving that uncertainty is important to patent holders. Leaving the uncertainty unresolved reduces patent value and the rewards to innovation (Lemley

and Shapiro 2005). Perhaps this is warranted: it may be that the patenting authorities wish to accommodate some uncertainty in the system (Cockburn, Kortum, and Stern, 2002). However, to the extent that uncertainty in the patent system is unintentional, then the reduction in patent value is certain to be suboptimal.

Legal uncertainty in patent policy may actually be an unexploited policy tool (Marco 2005 forthcoming). Uncertainty is likely to be high in emerging technology (or emerging patenting areas, such as business method patents). This may be exactly those areas where policy makers wish uncertainty to be high (or rather, for rewards to be low). As cases are litigated, and precedent becomes clearer, the uncertainty is reduced and rewards are increased (or decreased) appropriately. Treating uncertainty as a policy tool is predicated on the recognition that the current patent system creates uncertainty. This paper takes a step towards measuring the degree to which that uncertainty is economically meaningful.

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A EM Algorithm

The EM Algorithm enables me to estimate the change in the value of a particular patent given that I know the change in the value of the firm, and the disposition of the patent in question and other simultaneously adjudicated patents. That is, the EM Algorithm enables me to estimate values for Δv conditional on Δf for the special case where the Δv 's are missing. Since multiple patents may be adjudicated simultaneously, the excess returns for the firm's stock price must be apportioned across the Δv 's. To do so, we require $E(\Delta v_{i\tau n} | \Delta f_{i\tau}, X_{i\tau n})$ where $X_{i\tau n}$ is a vector of characteristics of the disposition of the case. Let

$$\Delta v_{i\tau n} = X_{i\tau n}\beta + \varepsilon_{i\tau n}$$

where

$$\varepsilon_{i\tau n} \sim N(0, \sigma^2)$$

so that the error term is normal and the $\varepsilon_{i\tau n}$'s are independently and identically distributed. The assumption of independence is convenient but not innocuous. We can imagine that patents that are litigated together may not be independent, but instead be part of a larger system. The validity of any component may rise and fall by the validity of the system. The potential dependence of component patents warrants investigation; however, for simplicity I will assume independence in this paper.

Since I assume that $\Delta f_{i\tau} = \sum_N \Delta v_{i\tau n}$, I can write

$$\Delta f_{i\tau} \sim N\left(\sum_N X_{i\tau n}, N\sigma^2\right)$$

and

$$\text{Var}(\Delta v_{i\tau n}) = \sigma^2$$

$$\text{Var}(\Delta f_{i\tau}) = N\sigma^2$$

$$\text{Cov}(\Delta v_{i\tau n}, \Delta f_{i\tau}) = \sigma^2.$$

Generally if two random variables A and B are correlated, the expectation of A given B can be written as $E(A|B) = E(A) + \frac{Cov(A,B)}{Var(B)}(B - E(B))$. Applying this formula to the case at hand yields

$$\begin{aligned} E(\Delta v_{i\tau n} | \Delta f_{i\tau}) &= E(\Delta v_{i\tau n}) + \frac{Cov(\Delta v_{i\tau n}, \Delta f_{i\tau})}{Var(\Delta f_{i\tau})} (\Delta f_{i\tau} - E(\Delta f_{i\tau})) \\ &= E(\Delta v_{i\tau n}) + \frac{1}{N} (\Delta f_{i\tau} - E(\Delta f_{i\tau})). \end{aligned}$$

Using predicted values this can be approximated by

$$E(\Delta v_{i\tau n} | \Delta f_{i\tau}) = \widehat{\Delta v_{i\tau n}} + \frac{1}{N} \left(\Delta f_{i\tau} - \sum_N \widehat{\Delta v_{i\tau n}} \right) \quad (7)$$

Implementing the EM Algorithm involves using a predicted value of the vector Δv to obtain a parameter estimate, which is used to get a better prediction for Δv :

$$\Delta v^{(0)} \rightarrow \beta^{(0)} \rightarrow \widehat{\Delta v}^{(1)}$$

In this case $\Delta v^{(0)}$ is the starting value. In my application $\Delta v^{(0)}$ consists of only single-patent cases from which we obtain a parameter vector $\beta^{(0)}$ (this is the maximization step because the EM algorithm is a maximum likelihood technique). I use $\beta^{(0)}$ to predict $\widehat{\Delta v}^{(1)}$. This prediction does not incorporate any information from Δf . In particular, for multi-patent cases, the sum of $\sum_N \widehat{\Delta v_{i\tau n}}^{(1)}$ is likely to be a poor predictor of $f_{i\tau}$. Instead a new value $\Delta v_{i\tau n}^{(1)}$ can be given by

$$\Delta v_{i\tau n}^{(1)} = E(\Delta v_{i\tau n} | \Delta f_{i\tau}) = \widehat{\Delta v_{i\tau n}}^{(1)} + \frac{1}{N} \left(\Delta f_{i\tau} - \sum_N \widehat{\Delta v_{i\tau n}}^{(1)} \right)$$

(this is the expectation step). $\Delta v^{(1)}$ is regressed on the explanatory variables to determine $\beta^{(1)}$ and the process is iterated until the sequence $\beta^{(0)}, \beta^{(1)}, \dots$ converges to a fixed point, β^{EM} .

B Figures

Figure 1: Cumulative abnormal returns at time of patent application, by subsequent validity status

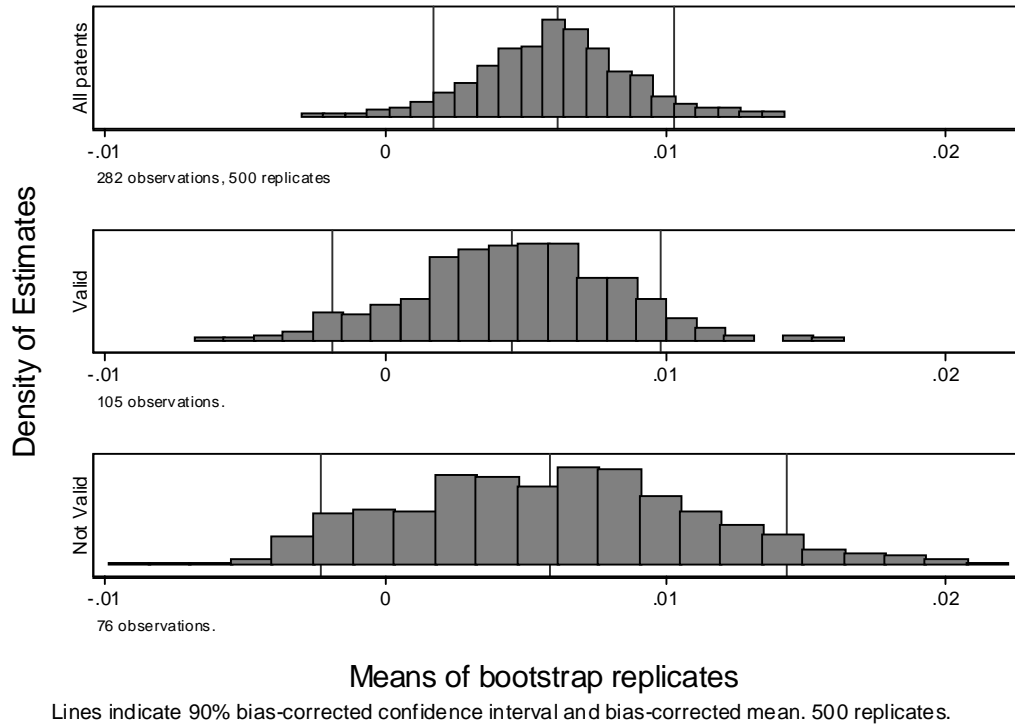
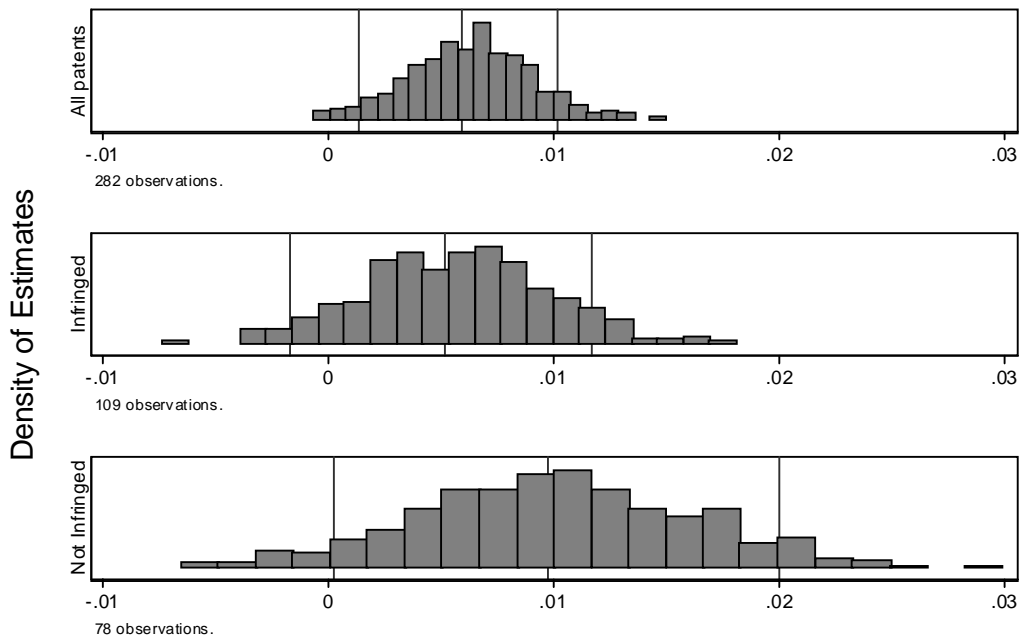


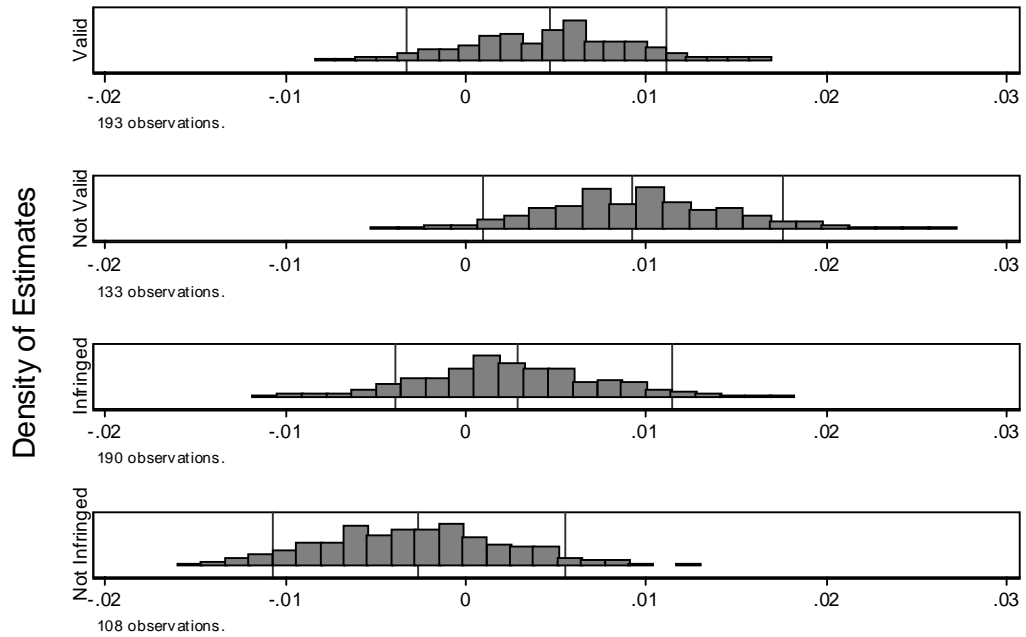
Figure 2: Cumulative abnormal returns at time of patent application, by subsequent infringement status



Means of bootstrap replicates

Lines indicate 90% bias-corrected confidence interval and bias-corrected mean. 500 replicates.

Figure 3: Cumulative abnormal returns at time of adjudication, by disposition



Means of bootstrap replicates

Lines indicate 90% bias-corrected confidence interval and bias-corrected mean. 500 replicates.

C Tables

Table 1: Frequency of litigation for patents and firms

	Total	Filed		Decided	
Firms	2,699	568	21.0%	158	5.9%
Patents	417,735	1,252	0.3%	413	0.1%
Cases				390	
Patent-decisions		2,252		610	

Table 2: Comparison of subsamples

District Court	277	198	Appellate Court
1982 and before	125	350	After 1982
Plaintiff patentee	427	48	Defendant patentee
Single patent decisions	209	266	Multiple patent decisions
Valid	193	133	Not Valid
Infringed	190	108	Not Infringed

475 observations total.

Table 3: Excess returns at time of patent grant, mean and confidence interval

Event Window (days)	Obs	Application Date			Issue Date			Sum		
		mean	10%	90%	mean	10%	90%	mean	10%	90%
(in percentage terms)										
2	283	0.01	-0.26	0.28	-0.36	-0.64	-0.07	-0.35	-0.73	0.04
3	282	0.19	0.19	0.52	0.05	-0.34	0.44	0.23	-0.27	0.74
5	282	0.61	0.18	1.03	0.03	-0.52	0.59	0.64	-0.10	1.38
7	282	0.46	0.02	0.90	-0.04	-0.85	0.76	0.42	-0.56	1.39
9	282	0.95	0.41	1.50	0.33	-0.56	1.22	1.29	0.16	2.41
11	282	1.44	0.88	2.01	0.79	-0.06	1.65	2.24	1.17	3.31
bootstrap	282	0.59	0.14	1.00	0.08	-0.41	0.89	0.76	-0.13	1.59
(in thousands of dollars)										
bootstrap	282	28119	746	55444	1499	-17068	23255	30158	-1501	58861

Observations restricted to those with both application date and issuance date data.
 2 day window is day zero and day +1. All other windows are centered on day zero.
 Bootstrap estimates are bias-corrected; replicates draw from all windows.

Table 4: Excess returns at time of patent grant, mean and confidence interval, by disposition

Sample	Application Date				Adjudication Date			
	obs	mean	10%	90%	obs	mean	10%	90%
(in percentage terms)								
All	282	0.62	0.19	1.08	--	--	--	--
Valid	105	0.46	-0.17	1.06	193	0.44	-0.21	1.23
Not Valid	76	0.59	-0.10	1.56	133	0.95	0.11	1.98
Infringed	109	0.53	0.11	0.91	190	0.28	-0.54	1.05
Not Infringed	78	0.99	-0.01	1.96	108	-0.28	-0.99	0.55

Bootstrap estimates are bias-corrected; replicates draw from all windows.

Table 5: Effects of case disposition on firm value

Variable	[1] CAR2 EM			[2] CAR EM/bootstrap			[3] CAR EM/RE/bootstrap			[4] ln(dollars) EM/RE/bootstrap			
	Coef.	90% conf. int.		Coef.	90% conf. int.		Coef.	90% conf. int.		Coef.	90% conf. int.		
Valid	0.63 (0.49)	-0.08	1.54	0.44 (0.53)	-0.40	1.33	1.59 (0.80)	**	0.28	3.06	1.28 (1.39)	-0.91	3.77
Not Valid	0.59 (0.35)	* -1.25	-0.08	-0.52 (0.46)	-1.29	0.23	-1.43 (0.68)	**	-2.99	-0.40	-3.29 (1.28)	***	-5.72 -1.20
Infringed	0.53 (0.50)	-1.54	0.10	-0.31 (0.53)	-1.23	0.52	-0.78 (0.73)		-1.97	0.37	0.01 (1.39)	-2.24	2.47
Not Infringed	0.15 (0.36)	-0.76	0.40	0.09 (0.48)	-0.67	0.90	-1.79 (0.62)	***	-2.60	-0.78	-0.92 (1.42)	-3.34	1.30
Constant	0.27 (0.34)	-0.29	0.83	0.23 (0.42)	-0.45	0.90	0.83 (0.52)	*	0.01	1.83	0.80 (1.05)	-0.86	2.60
Sigma e	--			--			1.35				2.78		
Sigma u	--			--			2.83				4.75		
Rho	--			--			0.82				0.74		
Chi2	--			--			280				133		
F	2.21			9.69			--				--		
R2 overall	0.010			0.010			0.012				0.019		
Observations	475			475			475				475		
Replications	1000			1000			1000				1000		

Bootstrapped SE in paranthesis. Bias-corrected confidence intervals used to calculate significance level.

* indicates $p < 0.1$, ** indicates $p < 0.05$, *** indicates $p < 0.01$.

All coefficients and confidence intervals are bias-corrected.

Table 6: Excess returns to adjudication: interaction terms

Variable	[1] CAR				[2] CAR			
	EM/RE/Bootstrap				EM/RE/Bootstrap			
	Coef.		90% conf. int.		Coef.		90% conf. int.	
Valid	1.59 **		0.28	3.06	3.44 ***		1.31	5.79
	(0.80)				(1.23)			
Not Valid	-1.43 **		-2.99	-0.40	-0.60		-2.43	0.92
	(0.68)				(0.96)			
Infringed	-0.78		-1.97	0.37	0.34		-1.68	2.76
	(0.73)				(1.34)			
Not Infringed	-1.79 ***		-2.60	-0.78	-0.57		-2.28	0.95
	(0.62)				(0.99)			
V/I	--				-2.13		-5.90	0.51
					(1.66)			
V/NI	--				-4.93 **		-8.70	-1.83
					(1.90)			
NV/I	--				-3.45		-8.12	1.80
					(3.44)			
NV/NI	--				-0.18		-2.64	2.16
					(1.47)			
Constant	0.83 *		0.01	1.83	-0.05		-1.23	1.14
	(0.52)				(0.74)			
Sigma e	1.35				1.33			
Sigma u	2.83				2.83			
Rho	0.82				0.82			
Chi2	280				530			
R2 overall	0.012				0.021			
Observations	475				475			
Replications	1000				1000			

Bootstrapped SE in paranthesis. Confidence intervals used to calculate significance.

* indicates $p < 0.1$, ** indicates $p < 0.05$, *** indicates $p < 0.01$.

All coefficients and confidence intervals are bias-corrected.

Table 7: Adjudications pre- and post-1982

Variable	[1] Pre-1982			[2] Post-1982		
	Coef.	90% conf. int.		Coef.	90% conf. int.	
Valid	3.31 *	0.01	6.51	2.21 ***	0.90	3.90
	(2.01)			(0.85)		
Not Valid	-0.93	-4.22	2.45	-1.32 *	-3.89	-0.12
	(2.01)			(0.88)		
Infringed	-4.09 **	-6.95	-1.54	-0.60	-2.04	0.80
	(1.57)			(0.88)		
Not Infringed	-5.40 ***	-7.96	-3.40	-1.18 *	-2.96	-0.02
	(1.27)			(0.79)		
Constant	1.50	-1.99	4.32	0.41	-0.52	1.55
	(1.88)			(0.61)		
Sigma e	0.80			1.28		
Sigma u	3.13			2.84		
Rho	0.94			0.83		
Chi2	716			293		
R2 overall	0.009			0.028		
Observations	125			350		
Replications	1000			1000		

Bootstrapped SE in paranthesis. Confidence intervals used to calculate significance.

* indicates $p < 0.1$, ** indicates $p < 0.05$, *** indicates $p < 0.01$.

All coefficients and confidence intervals are bias-corrected.

Table 8: Defendant and plaintiff patentees

Variable	[1]			[2]		
	Plaintiff patentee			Defendant patentee		
	Coef.	90% conf. int.		Coef.	90% conf. int.	
Valid	1.67 ** (0.92)	0.32	3.85	-0.34 (1.14)	-2.23	1.45
Not Valid	-1.47 * (0.81)	-3.84	-0.16	-2.67 (1.65)	-5.37	0.12
Infringed	-0.93 (0.94)	-2.72	0.47	1.22 * (0.67)	0.15	2.31
Not Infringed	-1.31 * (0.78)	-3.32	-0.15	-1.70 ** (1.02)	-3.81	-0.29
Constant	0.72 (0.68)	-0.37	2.29	1.77 ** (0.94)	0.35	3.45
Sigma e	1.36			0.76		
Sigma u	2.51			4.34		
Rho	0.77			0.97		
Chi2	243			95		
R2 overall	0.026			0.001		
Observations	427			48		
Replications	1000			1000		

Bootstrapped SE in paranthesis. Confidence intervals used to calculate significance.

* indicates $p < 0.1$, ** indicates $p < 0.05$, *** indicates $p < 0.01$.

All coefficients and confidence intervals are bias-corrected.