Learning by Suing: Structural Estimates of Court Errors in Patent Litigation

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Abstract

This paper presents structural estimates of the probability of validity, and the probability of Type I and Type II errors by courts in patent litigation. Patents are modeled as uncertain property rights, and implications of the model are tested using stock market reactions to patent litigation decisions. While court errors are inherently unobservable, the estimation quantifies beliefs about patent validity and court errors in a Bayesian context by relying on observable win rates and stock market reactions.

I estimate that the underlying beliefs about validity average from 0.55 to 0.70 for litigated patents. For a number of different specifications, I show that Type I errors (finding a valid patent invalid) occur with an estimated probability of 0.20 to 0.25. The range for Type II errors (finding an invalid patent valid) varies more broadly, from near zero probability to as high as 0.40. Additional implications of the model address patent value.

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

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

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"The prophecies of what the courts will do in fact, and nothing more pretentious, are what I mean by the law."

—Oliver Wendell Holmes, Jr. The Path of the Law, Part I.

1 Introduction

Courts make mistakes. That is a fact. It is plainly accepted by legal scholars and laymen alike; so much so that it is pointless to argue it. Appellate courts would not even exist if it were not so. Furthermore, the theoretical consequences of court errors have been well known at least since Priest and Klein (1984). For instance, uncertain legal standards or awards can lead to changes in observed selection rates and win rates (Waldfogel 1995, Rasmusen 1995). An uncertain legal standard can lead to over-precaution on the part of an injurer. At their worst, severely error-prone courts can diminish or eliminate any intended incentives from the justice system (Landes and Posner 2001); if violators and non-violators are equally likely to be found in violation, the deterrence mechanism fails completely and courts become deadweight. Less egregious errors will soften deterrence effects.

Empirically, the incidence of litigation is well studied (Stanley and Coursey 1990, Waldfogel 1995, Eisenberg and Farber 1997, Siegelman and Waldfogel 1999), including several studies relating to patent law in particular (Lanjouw and Lerner 1998, Lanjouw and Schankerman 2001, Allison, Lemley, Moore, and Trunkey 2004, Lanjouw and Schankerman 2004, Marco 2005). Scholars in the patent literature have also studied the outcomes of patent trials (Allison and Lemley 1998, Marco 2004, Sherry and Teece 2004, Henry and Turner 2006).

On the other hand, the *frequency* with which courts err is another matter entirely. There is little or no evidence on actual error rates because they are inherently unobservable (were it otherwise, courts would presumably correct their mistakes immediately). Thus, the extent to which courts err is an empirical question heretofore unanswered in the literature. This paper attempts to remedy that by investigating court errors in the context of patent litigation, by relying on observable features of patent litigation that are influenced by court error: namely, trial win rates and stock market reactions to trial outcomes.

Legal uncertainty is inevitable in a patent rights system (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. 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, and how to manage market transactions in intellectual property (Lerner 1995, Hall and Ziedonis 2001, Grindley and Teece 1997). If property rights are well-defined, firms may organize transactions through arm's length negotiations. In uncertain legal environments, we expect to see more integrated transactions ranging from cross-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 (Lemley 2001). 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.[2] Additionally, one can expect the value of patent rights to evolve as information about the validity and scope of a patent evolve (Sherry and Teece 2004), especially through court decisions.

Legal uncertainty is introduced into a patent system by the administrative agency (the Patent and Trademark Office—PTO—in the US, Lemley (2001), Cockburn, Kortum, and Stern (2002))

[1] Illustrative 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.

[2] For 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.

and by 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, Lanjouw and Schankerman 2001, Henry and Turner 2006), 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, and perhaps decreasing the rate at which mistakes were made with regard to validity and infringement suits.

It is these two sources of uncertainty—the PTO and the courts—that I will examine in the model and the estimation below. The PTO alters beliefs about the validity of patents. Courts are believed to err with some frequency, which alters beliefs about whether the patent will *win* a case on validity. When courts err at all, the probability of winning a validity ruling is not generally equal to the probability that the patent is valid.

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 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 (Lemley 2001). 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 structural estimates of market participants' beliefs about court errors and patent validity in the US. I make use of stock market reactions to court decisions 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.

The results are very provocative. Using a number of different specifications, I find that litigated patents are believed to be valid approximately 55% to 70% of the time. Further, I find that the win rate for valid patents is believed to be 75 to 80%; the win rate for invalid patents is ranges more broadly from near zero to over 40%. I make use of these estimates to compare the value of patent grants to the value of patent litigation. I find that litigated patents are worth over $20 million dollars at birth, and that patent litigation is worth $3 million to $5 million on average.

In the next section, I present a simple model of patent litigation and uncertainty that yields an estimable structural equation. The model enables me to interpret market reactions to news about patent issuance and patent litigation. By examining the differential impacts of market reactions to wins and losses, I can infer the market's implicit beliefs about patent validity, patent value, and court errors. Section 3 lays out the econometric specification based on the model, and Section 4 describes the patent data, litigation data, and event study results. In Section 5, I estimate several different specifications and compare the results. Section 6 concludes.

2 Model

The model assumes that the patent office and the courts may err. Both forms of uncertainty will be embedded in the market value of patents—and, thus, the market value of firms. I assume that the market has belief α that a given patent is valid. Courts err with a probability known to market participants, so that when a patent is litigated parties will update their beliefs about α according to Bayes' Rule (by which they incorporate the error rates of the courts).

More formally, let the prior belief about validity be α_0. Further, let $w_1 = \Pr(win|valid)$ be the probability that a valid patent is found valid and $w_2 = \Pr(win|invalid)$ be the probability that an invalid patent is found valid. Thus, the court makes a Type I error with probability $1 - w_1$ and a Type II error with probability w_2. I assume throughout that $w_1 > w_2$ so that the signal by the court is meaningful; however, this assumption is not enforced in the empirical specification.

The initial belief that the patent will win in court is given by

$$p_0 = w_1\alpha_0 + w_2(1-\alpha_0) = w_2 + \alpha_0\left(w_1 - w_2\right). \tag{1}$$

If a patent is litigated to trial, the court will announce a binary decision: either the patent "wins" or "loses," according to whether the patent is found valid (technically: not invalid) or invalid. Thus, the model treats validity independent from infringement. There are several justifications for doing so. First, validity decisions are clearly defined, whereas infringement decisions contain more noise. That is, infringement decisions depend not only upon the patent itself, but also the technology used by the infringer. In contrast, validity decisions are a function only of patent characteristics. Further, research has shown that patent litigation can be viewed as a unilateral decision on the part of the patent holder (Marco 2005), and that validity is a common defense raised by infringers (Allison and Lemley 1998, Marco 2004). So, a patent holder knows that it will risk invalidity when it litigates a patent, and it should expect a decision on validity.

Beliefs about validity are updated based on the court's known propensity to err. The updated belief, α_1, can take on one of two values, depending on whether the patent wins or loses on validity. According to Bayes' Rule, market participants expect:

$$\alpha_1 = \begin{cases} \frac{w_1}{p_0}\alpha_0 & \text{with probability} \quad p_0 \\ \frac{1-w_1}{1-p_0}\alpha_0 & \text{with probability} \quad 1-p_0 \end{cases} \tag{2}$$

The updated belief about validity generates two possible values for the updated belief about winning:

$$p_1 = \begin{cases} w_2 + \frac{w_1}{p_0}\alpha_0\left(w_1 - w_2\right) & \text{with probability} \quad p_0 \\ w_2 + \frac{(1-w_1)}{1-p_0}\alpha_0\left(w_1 - w_2\right) & \text{with probability} \quad 1-p_0 \end{cases}. \tag{3}$$

Note that prior to the ruling, $E\alpha_1 = \alpha_0$ and $Ep_1 = p_0$. This is important when considering the empirical results below. The day before a decision, beliefs are α_0, which reflect the expected updated beliefs about validity. The initial values α_0 and p_0 should be interpreted as those that exist just prior to a decision. Clearly beliefs about α and p may change over the life of the patent. The model restricts attention only to information that is revealed by the verdict. Thus, when a decision is made by the court, beliefs change discretely—unless someone has rigged the jury or bribed a judge.

The change in the belief about winning can be written as

$$\Delta p_{win} = p_1 - p_0 = w_2 + \frac{w_1}{p_0}\left(w_1 - w_2\right)\alpha_0 - p_0 \tag{4}$$

if the patent holder wins, and

$$\Delta p_{loss} = p_1 - p_0 = w_2 + \frac{1-w_1}{1-p_0}\left(w_1 - w_2\right)\alpha_0 - p_0 \tag{5}$$

if the patent holder loses. These probabilities reduce to

$$\Delta p = \begin{cases} \left(\frac{w_1}{p_0} - 1\right)(p_0 - w_2) & \text{after a win} \\ \left(\frac{1-w_1}{1-p_0} - 1\right)(p_0 - w_2) & \text{after a loss} \end{cases}. \tag{6}$$

In this specification, Δp is not explicitly a function of α_0, although α_0 enters through p_0. This fact is exploited in order to form an empirical specification.

To investigate changes in patent value based on market responses, I assume that the value of the patent at time t is

$$v_t = p_t z_t \tag{7}$$

where p is defined above, and z is the scope of the patent, measured as the discounted stream of profits accruing to the patent holder assuming the patent is known with certainty to be valid. The value pz represents a straightforward valuation of the property right to the patent holder. If p and z are common knowledge, then the Nash bargaining solution of the license negotiation game is pz. This specification assumes away signaling, litigation costs, and imperfect enforcement. Other valuation methods may represent the value as a non-linear function of p and z (see Marco (2005) for a more sophisticated analysis of patent value in a real options setting).[3]

At the time of a court decision on validity, only p will change. That is, the underlying value of the technology is unlikely to change overnight, and any change in value must be attributed to updated beliefs about validity. Thus, for a validity decision at time τ

$$\Delta v_\tau = \Delta p \cdot z_\tau. \tag{8}$$

3 Empirical Specification

I use equation 8 to interpret changes in firm value on the day of a court decision. Patent litigation is an especially useful area of law in which to examine market responses. First—as mentioned earlier—

[3] While this formulation is greatly simplified relative to a world with imperfect enforcement, the purpose is to develop a model with which to interpret revelations by the court about validity. For litigated patents, parties may be assumed to have already updated beliefs about the ability of the patent holder to enforce its patent rights.

validity is a binary decision.[4] 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 validity as opposed to the patented technology.

For patent i born at time 0 and adjudicated at time τ, the formal econometric specification becomes

$$\Delta f_{\tau,i} = \Delta p_{\tau,i} \cdot z_{\tau,i} + \varepsilon_{\tau,i} \tag{9}$$

where the change in the probability of winning is given by equation 6,

$$\Delta p_{\tau,i} = \left(\frac{w_1}{p_0} - 1\right)(p_0 - w_2)\, D_V + \left(\frac{1-w_1}{1-p_0} - 1\right)(p_0 - w_2) D_{NV}, \tag{10}$$

and the patent value is estimated as

$$z_{\tau,i} = \beta_0 + \beta_1 \cdot \Delta f_{-1,i} + \beta_1 \cdot \Delta f_{0,i} + \beta_3 \cdot forward + \beta_4 \cdot age + \beta_5 \cdot age^2. \tag{11}$$

The Ds are indicator variables for the court decision: valid and not valid. The patent underlying patent value—or scope—is measured as a linear function of several covariates. $\Delta f_{-1,i}$ and $\Delta f_{0,i}$ are estimates of the excess returns (unanticipated change in the value of the value of the firm) to the patent holder on the day of patent application and issuance, respectively. These variables are included because they are likely to be correlated with the underlying patent value, but not perfectly so. News about patents may be revealed to the market before or after patent application. And, while applications are not public information in the U.S., there is likely to be some leakage of information. Further, applications are not guaranteed to result in patents; the information contained near patent issuance may have to do with updating beliefs about issuance, or it may have to do with information about the innovation itself, as contained in the public documents. Equation 11 also includes the number of forward citations received by the patent at the time of adjudication, and the age of the patent at the time of adjudication. Greater forward citations are likely to indicate increased patent value, but age is likely to decrease it due to obsolescence (depreciation) or anticipated patent expiration. I include a squared term on age to allow for an inflection point in its impact on value. Equation 11 presents a linear approximation for value. However, I also estimate an alternative specification:

[4] There 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.

The patent value at the patent's birth is estimated to be a linear function of the change in the value of the firm on the day of patent grant, with unknown parameters β_0 and β_1. This specification acknowledges that some information about the patent may leak into the market prior to patent issuance and that market valuations reflect only *changes* in expectations about the value of the patent. Thus, I estimate the initial value of the patent as a linear function of the size of the response on the date of issuance, $z_0 = \beta_0 + \beta_1 \Delta f_0$. The scope at time τ is depreciated by $e^{-r\tau}$ to account for changes in the value of the patent right because of either an aging patent right or obsolescence.

$$z_{\tau,i} = (\beta_0 + \beta_1 \cdot \Delta f_{-1,i} + \beta_1 \cdot \Delta f_{0,i} + \beta_3 \cdot forward)\, e^{-r \cdot age}. \qquad (12)$$

The specification is identical to that above, except that it allows the patent to literally depreciate (or appreciate) as a function of age.[5]

Estimating the model requires several pieces of information:

1. The change in patent value at time τ (Δf_τ). I measure this below using an event study methodology to calculate the excess returns to patent decisions. This is the dependent variable.

2. An estimate of the value of the patent prior to litigation. I estimate this by calculating the excess returns at the time of application and at issuance. I also utilize forward citations and age.

3. An estimate of the probability of winning in court (p_0). This is estimated in section 4 using a simple probit.

The estimation routine utilized is non-linear least squares, where the parameters to be estimated are w_1, w_2, the β's and in some specifications, r. The win rates, w_1 and w_2 are modeled with several different specifications. The simplest specifications treat them as simple constants. However, I also allow them to vary on the basis of whether the court is an appellate court, and whether the decision

[5] The depreciation rate r is not constrained to be positive. A negative estimated value for r would indicate that the patent has appreciated, perhaps because new uses have been discovered for the technology. While this is possible, or even probable, while the technology is young, the value of the *patent right* (as opposed to the patented technology) will certainly decline at some point prior to expiration.

is made before or after the establishment of the Federal Circuit:

$$w_1 = w_{10} + w_{11} \cdot appeal + w_{12} \cdot preCAFC \tag{13}$$

$$w_2 = w_{20} + w_{21} \cdot appeal + w_{22} \cdot preCAFC \tag{14}$$

A more complicated specification constrains the win rates to be between zero and one by utilizing a logit-like formulation:

$$w_1 = 1/(1 + \exp(-(w_{10} + w_{11} \cdot appeal + w_{12} \cdot preCAFC))) \tag{15}$$

$$w_2 = 1/(1 + \exp(-(w_{20} + w_{21} \cdot appeal + w_{22} \cdot preCAFC))) \tag{16}$$

The specification is agnostic as to whether beliefs about validity. The notation implies that beliefs about validity and the win rate the day before the decision are equal to the beliefs at time 0 (as indicated by the subscript 0). However, the observed win rate is measured empirically as of the day before the decision ($\tau - 1$), so that I measure only the change in beliefs due to the court's decision.

The estimated probability of winning, p_0, can vary significantly from one case to the next. If court error rates are constant, so that w_1 and w_2 are constant across the estimation, then different p_0's imply different α_0's across the model. Because α_0 does not explicitly enter the estimation equation, I am able to impute the distribution of α_0 using observed p_0's and the estimated w_1 and w_2. Put another way, I estimate the equation with the constrain that $\alpha_0 = \frac{p_0 - w_2}{w_1 - w_2}$.

4 Data

In the following subsections I describe the sample of litigated patents, the description of court decisions, the calculation of excess returns (on adjudications and patent grants), and the estimation of the probability of validity.

4.1 Adjudication 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] My

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

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) for decisions published 1977-1997.[7] The USPQ publishes annual indices containing patents on which adjudications were published 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 adjudicated patents owned by publicly traded firms.

The merged data contain 701 case citations involving 670 patents. The disposition data were entered for each adjudication containing decisions relevant to validity. 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 data.

The final adjudication data consist of 390 decisions involving 413 patents owned by 158 publicly traded firms. An observation in my data is a "decision-patent." For example, a single case may involve four patents. Of the decision-patents, 385 involved a distinguishable decision on validity. About half of the cases involve only one decision-patent. The implied litigation rates are given in Table 1, where case filing data was calculated using LitAlert.[8]

Unfortunately, stock market returns are available for only a portion of my sample. Returns for the date of adjudication are available for 475 decision-patents. Of those, 303 represent decisions on matters of validity. Returns data for patent issuance and application dates are available for 179 of the 303 decision-patents.

4.2 Excess returns

In order to be able to analyze the adjudications using my methodology, I require an estimate of stock market reactions to news about the patents. I obtained CRSP data on daily stock returns from the Wharton Research Data Service (WRDS). I use cumulative abnormal returns—or excess returns—as measured by event studies to measure the stock market reactions to patent decisions

[7] See Allison and Lemley (1998). I thank Mark Lemley for the reference to USPQ.

[8] It is likely that both filing data and adjudication data are under-reported.

and patent issuance.

Event studies are appropriate for several reasons. First, the model provides a way to interpret the probability that a patent is valid as a function of changes in patent value. 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.[9] Market reactions provide information that has not been previously incorporated into the patent value (and consequently, the value of the firm). 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 in 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 9, I need to calculate a measure for the market reaction to the litigation event, and to patent issuance. So, the output of the event studies forms the dependent variable and an independent variable for the estimation equation. Appendix A describes the empirical methodology for event studies in detail. The excess returns are summarized in Table (2) for two-day event windows (the day of the event and the day after) and for 11-day event windows (from five days prior to five days after the event).[10]

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*. In the estimation I use both excess returns and dollar amounts. The results are fairly consistent across specifications, but there are some differences that I describe in Section (5). However, it is useful here to get a bearing on the dollar amount of the excess returns.[11]

First, note that the 11-day returns make more sense with regard to sign than the two-day returns. That is, with 11-day returns invalidity decisions are unambiguous bad news, and validity decisions and patent grants are unambiguous good news. The implication is that both adjudication

[9] Austin (1993) uses event studies to examine market reactions to patent issuance.

[10] I calculate excess returns of litigation for 1, 2, 3, 5, 7, 9, and 11 day event windows. Patent issuance and application returns are estimated for the same windows, except that I leave out the 1-day returns.

[11] Dollar values are obtained by multiplying the abnormal return by the market value of the firm.

information and patent grant information take some time to filter into the markets. The mean 11-day return to a validity decision is \$61.5 million. Similarly, the mean 11-day return to a patent application is \$31.1 million. Issuance is similar.

To put this in context, compare these reactions to the CAR 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.

4.3 Probability of validity

To calculate the probability of validity, I run a simple probit on my sample in the spirit of Marco (2004) and Lanjouw and Schankerman (2001). Appendix (B) describes the estimation in detail. From the estimated probit, I predict the probability that a patent will win and use this as a dependent variable in the estimation.

Note that the estimated probability of validity is conditional upon having been litigated; it does not control for self-selection. Because my model estimates market reactions on a sample of patents that are known to be in court, the conditional probability is appropriate. This implies that the resulting estimation for the probability of validity will also need to be interpreted as conditional on selection. See the Appendix for more details.

5 Results

There are two econometric problems that arise in the estimations. The first is that are multiple measurements of the dependent variable and the independent variable, in the form of different event windows. Excess returns for adjudication are measured with one, two, three, five, seven, nine, and 11 day event windows. Excess returns for application date and issuance date use similar windows, but without one-day returns. It is difficult to form a prior about which window is appropriate. Larger event windows will contain more information, but at the expense of precision. Further, the appropriate window may vary on a case by case basis. The number of permutations for the three measurements of excess returns is over 250 ($7 \times 6 \times 6$).

For this reason, I implement a bootstrapping technique. For each estimation, I create 200 bootstrap replicates of size 179 (the sample size). For each replicate, I randomly choose event windows for of the three excess returns used in the estimation. Thus, the coefficients and standard errors of the estimates reflect the range of errors captured in the different event windows.

The second econometric problem deals with multiple "patents-in-suit." Where there are multiple patents litigated in one suit, the interpretation of excess returns is ambiguous. If one patent is ruled valid, and another ruled invalid, then the change in the firm's market valuation will reflect conflicting news. Alternatively, if both patents are ruled valid, then the change in the firm's market valuation will reflect compounded good news. There are (at least) two approaches for dealing with this problem. First, one could attempt to use a missing data technique such as the EM Algorithm to impute the share of the excess returns contributed by each patent-in-suit. However, because my estimation relies on bootstrapping, conditioning on other patents-in-suit becomes difficult. Instead, I rely on the bootstrapping to properly account for the standard error in the estimation. On any given day, there are multiple sources of new information about a firm's profitability. Any given piece of information may be good or bad news. To the extent that other information creates noise in the estimation, it affects only the precision of the estimates. However, the estimates remain unbiased. If the information is highly correlated with the known event, then the estimates may become biased. This is a concern in the case at hand, because the outcome of patents litigated jointly may be jointly determined. Nonetheless, in unreported regressions, I implement the EM Algorithm with specific event windows and I obtain similar results to those presented below.

5.1 Court error

The results of the estimations are presented in tables 5 to 7. Table 5 represents a linear specification for w_1 and w_2 (the win rate for valid and invalid patents, respectively) and a linear specification for patent scope. Columns 1 and 2 use excess returns as the dependent variable, and columns 3 and 4 use the dollar value of the excess returns as the dependent variable. Columns 1 and 3 use a simple constant to estimate w_1 and w_2, whereas columns 2 and 4 allow the win rates to vary based on equations 13 and 14. By using a linear specification, w_1 and w_2 are not constrained to be between zero and one. Thus, the magnitudes of these parameters serve as a test of the model.

Table 6 presents models similar to table 5, but with a logit specification for w_1 and w_2 as defined in equations 15 and 16. Table 7 presents an alternative specification for scope, according to equation 12.

The results from table 5 show highly significant results. The estimated probability that a valid patent will be found valid is approximately 0.70 to 0.77 in the simply models. In the more complete models, the probability increases to 0.8 to 1.0, for lower court decisions. The fact that these estimates fall within the zero to one range supports the theoretical model. Note that the appeals court is believed to err with greater frequency than the lower court, as evidenced by the negative estimates for w_{11} (only column 2 is significant).

The excess returns estimations show that courts are believed to rule invalid patents valid about 20% of the time, and that appeals and the pre-CAFC era do not appear to influence this figure. The dollar estimations show insignificant results overall for w_2, but a negative impact from appeals (meaning less error) and a positive impact of the pre-CAFC era.

The logit formulations for win rates in table 6 show consistent results across the specifications (for lower courts). A value for w_{11} of 0.95 to 1.4 implies a value for w_1 of 0.72 to 0.80,[12] consistent with table 5. The effects of appeals and the 1982 reforms are inconsistent across the specifications. The believed win rate of a valid patent at the appellate level ranges widely from 0.53 to 0.86.

The win rate for invalid patents is much lower than for valid patents, however the variance is much higher across specifications. For a lower court decision the estimates range from as low as 0.05 to as high as 0.57. On average, appellate courts are believed to err less on invalid patents than the lower courts.

Table 7 shows both linear and logit specifications for the alternative patent value model. The win rates are modeled with a constant only. Again, the constant in the linear specifications can be interpreted as a probability. The results show again very consistent results for the win rate for valid patents: approximately 0.75-0.82. The win rate for invalid patents again is inconsistently estimated, ranging from near zero to as high as 0.41.

As discussed in section 3, estimates for w_1 and w_2 imply a distribution for α_0 based on p_0, $\alpha_0 = \frac{p_0 - w_2}{w_1 - w_2}$. Figures 1 and 2 show this relationship. The distribution of the bootstrap replicates for the model parameters w_1 and w_2 are shown in figure 1, for model 1 (table 5, column 1). Recall

[12] w_{11} can vary over the reals and still obtain values for w_1 between zero and one.

$$\begin{aligned} 1/(1+\exp(-0.95)) &\simeq 0.72 \\ 1/(1+\exp(-1.4)) &\simeq 0.80 \end{aligned}$$

that the parameters are not constrained to be between zero and one. Nonetheless, the vast majority of the estimates fall within those bounds. Additionally, w_1 is visibly greater than w_2. Using the medians of those distributions ($w_1 = 0.74$, $w_2 = 0.34$), α_0 can be calculated for each observation. That distribution is shown in figure 2. Again, α_0 is not constrained to be between zero and one. The distribution is evidently wider than those for w_1 and w_2, however a 95% confidence interval for α is $(0.55, 0.70)$ with mean 0.62.It should be pointed out that this value is subject to selection bias. We cannot infer from this sample that the average patent has a "true" probability of validity of 0.62.

However, the court errors may be less subject to the selection bias. If the court has a certain propensity to err, regardless of the case, then the estimates are not subject to selection bias. However, if the court has a different rate of error for the cases it sees, relative to the population of patents, then the selection bias would be an issue.

5.2 Patent value

The structural estimation enables the separation of two components of patent value: beliefs about validity and court error; and, what I have been calling the patent scope. By separating these two components, it is possible to divine information about the value of the innovation, as opposed to the enforceable patent right. If scope is what the patent is worth if it is perfectly enforceable, this value should lie closer to the underlying technological value of the innovation. Because scope represents a perfectly enforceable patent right, it may still underestimate the social value of the innovation if there are any technological spillovers that are not appropriable even under perfect enforcement. However, it is a much closer representation than the actual patent right, which reflects uncertainty in validity and in legal protections.

Two parameters in the value specification have consistent effects throughout the 12 models in tables 5 to 7: returns at date of issuance and forward citations. Both parameters are positively correlated with patent scope, which is unsurprising. The other parameters have inconsistent signs throughout the models.

At the median values of the β's, it is possible to estimate the patent scope at the time of litigation for the sample patents. Based on the median β's in model 3 (table 5, column 3), the mean patent scope at the time of litigation is approximately \$130 million, with a 95% confidence interval of \$61 million to \$199 million.

Some simple calculations underscore the quantitative importance of uncertainty to patent holders. Taking the following values as approximations for the model parameter values, one can calculate the impact of litigation on the patent holder.

$$\begin{aligned} w_1 &= 0.75 \\ w_2 &= 0.20 \\ \alpha_0 &= 0.62 \\ z &= \$130 \end{aligned}$$

Based on these parameters, the believed probability of winning is $p_0 = \alpha_0 w_1 + (1 - \alpha_0) w_2 = 0.54$.[13] The value of the patent right is then \$70 million. If the patent holder wins the case, beliefs will be updated to $p_1 = 0.67$. This represents a return to the patent holder of \$16.9 million due to the resolution of uncertainty. If the patent holder loses, p falls to $p_1 = 0.38$, which represents a loss of \$20.8 million. If these calculations are at all accurate, the resolution of uncertainty is worth approximately 10-15% of the *technological value of the innovation,* and 20-30% of the value of the patent right. The resolution of uncertainty would clearly be worth more, if the courts erred less than 25% of the time.

6 Conclusion

That courts err is not news to anyone—legal scholars and laymen alike. However, to this point there has been no empirical estimates investigating the frequency with which courts err. The reason for this empirical omission is obvious: error rates are inherently unobservable. However, by utilizing information from stock market reactions to patent litigation decisions and to patent grants, I am able to structurally estimate court errors, as well as patent value. In interpreting the results it is important to remember that the results on patent validity and patent value are subject to self-selection. However the court error rates are not subject to the same self-selection in that they are treated as exogenous to the decision-making of the litigating parties.

Several specifications used the equivalent of a linear probability model to estimate court errors. The fact that the estimates were consistently and significantly between zero and one, and that the estimates lined up closely with constrained estimates, lends credibility to the model.

[13] Note that this value is very close to the Priest and Klein limiting win rate of 50%.

With regard to patents in particular, litigated patents appear to be self-selected from a pool of fairly "low α" patents, with the belief about validity being about 0.62 at the mean. Combined with the estimates of court errors, I find that the mean litigated patent has close to a 50% chance of winning in court, consistent with Priest and Klein (1984). Interestingly, the results on the appellate court are mixed; in some specifications the beliefs about the "pro-patent" appeals court suggest that the court favors patent holders less than lower courts do.

My estimates of Type I errors (false negatives) are very stable, around 20-25%. The estimates of Type II errors (false positives) vary widely, perhaps representing more uncertainty in the market's beliefs surrounding court error for invalid patents. These results are of import to anyone interested in legal reform, including policy makers interested in tort reform. Any positive error rates by courts will necessarily dampen—to a greater or lesser extent—the impacts of reforms.

The theoretical model enabled me to decompose patent value into the legal right and the value of the underlying technology. Resolving some uncertainty about validity through "learning by suing" is worth about 10%-15% of the value of the average innovation, or 20-30% of the average value of the patent right.

Extensions to the model presented in this paper could include the accounting for infringement decisions as a means to change the legal scope of the patent. Additionally, more is necessary to determine the exact effect of the Court of Appeals for the Federal Circuit, and whether there are jurisdictional differences. These extension would require a richer dataset than the one used in this paper. I leave that to future research.

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A Event studies

The market model is the model most frequently used in event studies. The estimation equation is

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

where

$$\begin{aligned} R_{i,t} &= \text{proportionate return on the stock of firm } i \text{ from time } t-1 \text{ to time } t. \\ R_{m,t} &= \text{proportionate return on the overall market from time } t-1 \text{ to time } t. \end{aligned}$$

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

$$CARi = \sum_{t=-\tau}^{\tau} u_{i,t}$$

That is, cumulative abnormal returns are the summation of abnormal returns over the event window. For the analysis below the pre-event equilibrium is (-300, -20), measured in trading days, and the abnormal returns are calculated for event windows of 1, 3, 5, and 11 trading days around the event date. I use the Equal Weighted Market Return for R_m, as defined by CRSP.

B Probability of Validity

The specification for estimating the probability of validity is based on Marco (2004) and Lanjouw and Schankerman (2001). I base the probability of validity on observable patent characteristics as well as observable case characteristics. Patent data for my sample were obtained from the NBER Patent Citations Data Files, described in Hall, Jaffe, and Trajtenberg (2001). The variables used are described in Table (3).

Forward citations are citations received by a patent from subsequently issued patents. Similarly, backward citations are those made by the patent to previously issued patents. Patent applicants are required to cite "prior art" including previously issued patents. Failure to do so is grounds for invalidity if the omission is later discovered (Allison and Lemley). Hall, Jaffe, and Trajtenberg describe the creation of several indices in the NBER data using patent citations, including *generality* and *originality* (Jaffe, Trajtenberg, and Henderson 1993).

Generality for patent i is defined as

$$1 - \sum_{j}^{n_i} s_{ij}^2$$

where s_{ij} refers to the proportion of forward citations to patent i from patents in technology class j. The higher the index, the more spread out are the patents that cite it, technologically speaking (Hall, Jaffe, and Trajtenberg). Originality is similarly defined, except that s refers to backward citations rather than forward citations. Higher originality indicates that a wider array of technologies were utilized in creating the innovation.

Both generality and originality are undefined if the number of citations is zero. In my sample, undefined values are replaced by zero. In the case of generality this assignment makes sense in that an uncited patent is not applicable to *any* patented technologies (yet), and therefore receives a low score for generality. Alternatively, the patent may just be very young. In the case of originality, one could imagine that highly original patents might cite *no* previous patents. However, from an empirical standpoint, Hall, Jaffe, and Trajtenberg observe that higher numbers of citations tend to be associated with higher originality and generality indices; thus, assigning zero to undefined values seems the logical choice.

Self-citations are another important measure in the patent literature. The NBER dataset defines two self-citation variables, reflecting the proportion of forward citations that are made by the patent holder itself. Since the identity of patent holders is subject to error, an upper bound and a lower bound are defined. Missing values for the self-citation variables will obtain whenever there are no forward citations. In these cases, I replace missing lower (upper) bound values with zero (one), since this is the theoretical lower (upper) bound.

Table (4) shows the results of a simple probit on the probability of validity. Since the cases are subject to selection, the predicted probability of validity must be interpreted as the probability of validity conditional on being litigated (Marco 2004). For the current application, the conditional probability is appropriate because I want to measure the probability the *day before* the court's decision. At that point in time it is known that the patent has been litigated. Thus, using a selection-corrected unconditional probability would cause a bias.

The estimates are used to construct a predicted probability of validity. That variable is used as a dependent variable in the structural estimations in Section (5).

Table 1: Adjudication data

Sample	Obs	Percent
Total patents	417,735	--
Litigated patents	1252	0.3%
Adjudicated patents	413	33.0%
Decision-patents	610	
Returns data (adjudication)	475	
Validity rulings	303	
Valid	177	58.4%
Not Valid	126	41.6%
Returns data (appl./issuance)	179	

Table 2: Excess returns

Event	Event Window	Obs	Mean	Std.Err.	[95% Conf. Interval]	
Adjudications						
Valid						
Returns (%)	2	55	-0.19	0.28	-0.76	0.38
	11	55	1.52	0.81	-0.11	3.15
Dollars ($millions)	2	55	-23.0	11.7	-46.4	0.3
	11	55	61.5	46.1	-30.8	153.8
Not Valid						
Returns (%)	2	45	-0.64	0.30	-1.23	-0.04
	11	45	-0.82	0.54	-1.92	0.28
Dollars ($millions)	2	45	10.2	28.2	-46.6	67.0
	11	45	-10.7	58.6	-128.9	107.4
Patent issuance						
Application date						
Returns (%)	2	181	-0.05	0.17	-0.38	0.28
	11	181	1.10	0.39	0.32	1.87
Dollars ($millions)	2	181	-14.1	11.8	-37.4	9.3
	11	181	31.1	22.2	-12.7	75.0
Issue date						
Returns (%)	2	198	-0.31	0.19	-0.69	0.07
	11	198	1.41	0.60	0.23	2.59
Dollars ($millions)	2	198	6.5	7.8	-9.0	22.0
	11	198	30.0	13.3	3.9	56.2

Notes:
Adjudication data excludes multiple patents-in-suit adjudications

Table 3: Variables used to calculate the probability of validity

Dependent indicator variables		
	V	Indicates a positive validity ruling
Independent		
Court indicator variables		
	DEFENSIVE	Indicates the patent holder is the defendant
	APPEAL	Indicates an appellate decision
	PRIORPOS	Indicates there was a prior positive decision on validity (infringement)
	PRIORNEG	Indicates there was a prior negative decision on validity (infringement)
	PRE82CASE	Indicates case filed prior to 1982
Citation		
	BACKWARD	Number of backward citations per claim
	FORWARD	Average number of forward citations per claim per year
	SELF	Proportion of forward citations that are self-citations
	GENERAL	NBER "Generality" index. Undefined values set to 0
	ORIGINAL	NBER "Originality" index. Undefined values set to 0
Scope		
	NUMIPC	Number of 4-digit International Patent Classes
	LOGCLAIM	Number of patent claims
Technology		
	CHEM	Chemicals. NBER technology category = 1
	COMP	Computers and communication. NBER technology category = 2
	MED	Drugs and medical. NBER technology category = 3
	ELEC	Electronics. NBER technology category = 4
	MECH	Mechanical. NBER technology category = 5
Other		
	PATDELAY	Time between patent application and patent grant
	FOREIGN	Indicates non-US patentee
	PRE82PAT	Indicates patent application dated prior to 1982
	AGE	Age of the patent from patent application to case filing

Table 4: Probability of validity

Variable	Coef.		Std. Err.
DEFENSIVE	-0.099		(0.287)
APPEAL	-0.535	**	(0.217)
PRIORPOS	1.244	***	(0.314)
PRIORNEG	-0.448		(0.273)
PRE82CASE	-0.483	*	(0.263)
BACKWARD	-0.481		(0.301)
$BACKWARD^2$	0.034		(0.038)
FORWARD	0.667		(1.879)
$FORWARD^2$	0.182		(2.492)
SELF	-0.455		(0.482)
GENERAL	-0.247		(0.350)
ORIGINAL	0.281		(0.452)
NUMIPC	0.161		(0.177)
LOGCLAIM	-0.189		(0.208)
CHEM	0.188		(0.267)
COMP	0.620	*	(0.372)
MED	-0.425		(0.290)
ELEC	0.004		(0.263)
MECH	-0.157		(0.256)
PATDELAY	0.045		(0.055)
FOREIGN	0.590		(0.680)
PRE82PAT	-0.446		(0.310)
AGE	0.143	**	(0.063)
AGE^2	-0.006	**	(0.003)
CONSTANT	0.827		(0.856)
Observations	303		
Pseudo R2	0.188		
LR chi2(24)	77.5		

Notes:
Standard errors in parentheses
* signif. at 10%; ** signif. at 5%; *** signif. at 1%

Table 5: Structural estimations

		Linear specification for court error			
		Excess Returns		Dollars	
Equation/Parameter		[1]	[2]	[3]	[4]
Win rate (Valid)					
w10	Constant	.77 ***	.83 ***	.70 ***	1.03 ***
		(.02)	(.03)	(.01)	(.25)
w11	Appeal	--	-.20 ***	--	-.10
			(.04)		(.14)
w12	Pre-1982	--	-2.56	--	-.10
			(2.66)		(.13)
Win rate (invalid)					
w20	Constant	.19 ***	.18 **	-1.08	.03
		(.07)	(.08)	(.85)	(.12)
w21	Appeal	--	-.13	--	-.50 ***
			(.08)		(.16)
w22	Pre-1982	--	-.92	--	.23 *
			(.97)		(.13)
Patent value					
b0	Constant	.16 ***	.16 ***	-264,194. ***	-147,469. ***
		(.01)	(.02)	(45,200.)	(45,373.)
b1	Appl. Returns	-.36 ***	-.19	2.00 ***	3.85 ***
		(.10)	(.13)	(.22)	(.65)
b2	Iss. Returns	.82 ***	.87 ***	3.36 ***	5.09 ***
		(.10)	(.10)	(.30)	(.45)
b3	Forward citations	.013 ***	.007 ***	45,559. ***	32,651. ***
		(.001)	(.001)	(6,432.)	(8,728.)
b4	Age	-.050 ***	-.041 ***	37,891. ***	13,190.
		(.004)	(.004)	(11,888.)	(11,977.)
b5	Age squared	.003 ***	.002 ***	1,530. **	1,764. ***
		(.000)	(.000)	(645.)	(655.)

Dependent variable: Excess Returns ([1] & [2]) or Dollars ([3] & [4]).
Bootstrapped standard errors in parantheses.
*** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.01 level.
Coefficients and standard errors based on mean and standard errors of 200 bootstrap replicates.

Figure 1: Distribution of bootstrapped estimates for valid win rate (w10) and invalid win rate (w20) (Model 1)

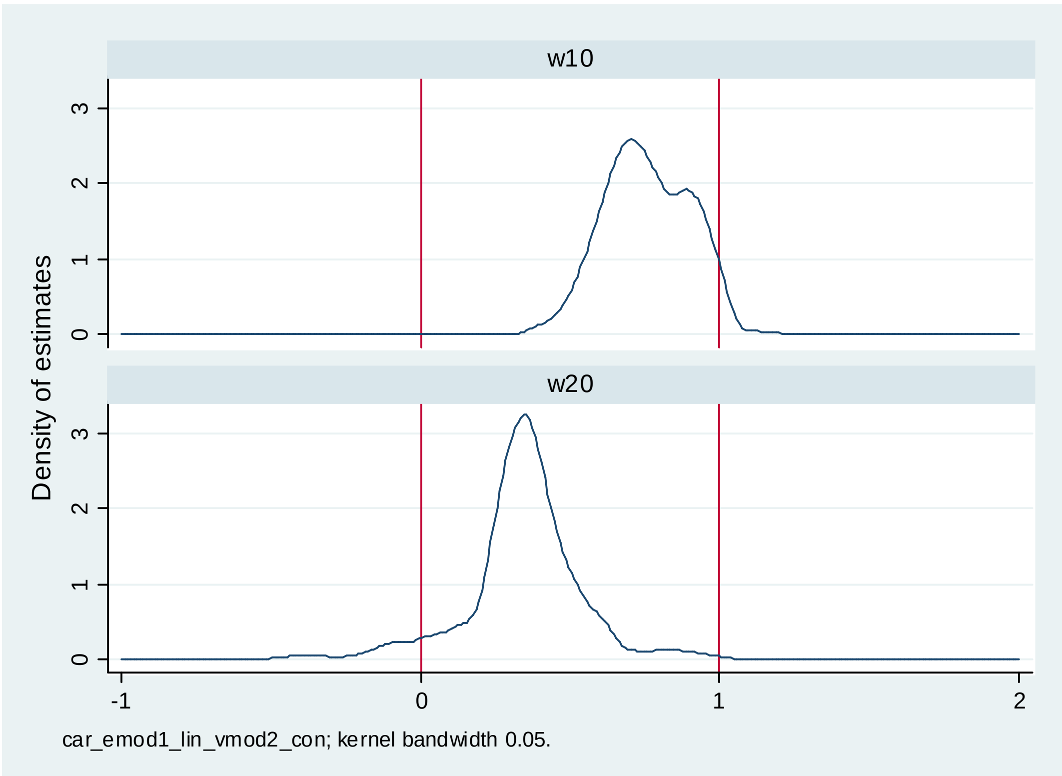

Figure 2: Implied distribution of the probability of validity (alpha) (Model 1)

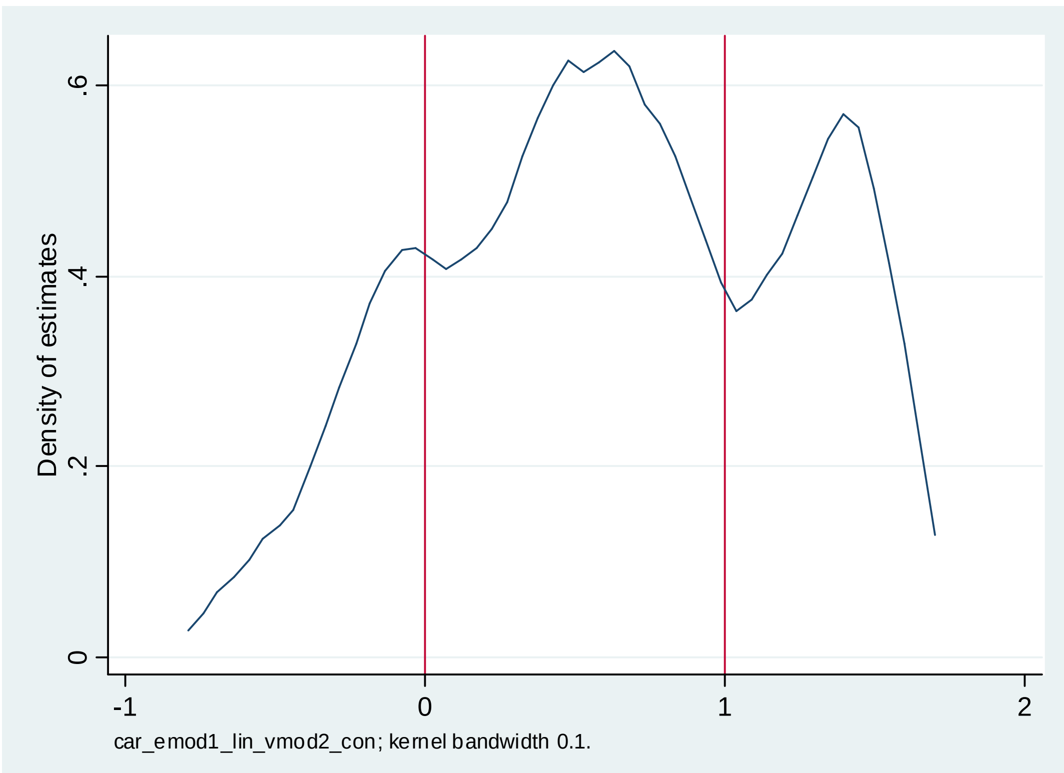

Table 6: Structural estimates

Equation/Parameter		Logit specification for court error: Excess Returns [5]		[6]		Dollars [7]		[8]	
Win rate (valid patents)									
w10	Constant	1.42	***	.96	***	.95	***	1.11	***
		(.08)		(.09)		(.18)		(.09)	
w11	Appeal	--		-.82	***	--		.70	***
				(.11)				(.16)	
w12	Pre-1982	--		.12		--		-.54	***
				(.13)				(.10)	
Win rate (invalid patents)									
w20	Constant	-.50	***	.28	***	-2.92	***	-1.38	
		(.06)		(.10)		(.42)		(1.07)	
w21	Appeal	--		-1.48	***	--		-1.81	***
				(.14)				(.31)	
w22	Pre-1982	--		.75	***	--		1.38	*
				(.14)				(.80)	
Patent value									
b0	Constant	.15	***	.32	***	-287,969.	***	-356,514.	***
		(.01)		(.02)		(56,954.)		(51,006.)	
b1	Appl. Returns	-.31	**	-.07		2.12	***	7.15	***
		(.12)		(.16)		(.27)		(.85)	
b2	Iss. Returns	.98	***	1.43	***	4.17	***	7.28	***
		(.09)		(.11)		(.29)		(.63)	
b3	Forward citations	.014	***	.006	***	59,854.	***	58,981.	***
		(.001)		(.001)		(6,385.)		(12,543.)	
b4	Age	-.048	***	-.078	***	38,205.	**	55,661.	***
		(.003)		(.004)		(14,949.)		(13,533.)	
b5	Age squared	.003	***	.004	***	2,073.	***	359.	
		(.000)		(.000)		(766.)		(757.)	

Dependent variable: Excess Returns ([5] & [6]) or Dollars ([7] & [8]).
Bootstrapped standard errors in parantheses.
*** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.01 level.
Coefficients and standard errors based on mean and standard errors of 200 bootstrap replicates.

Table 7: Structural estimates

		Alternative specification for patent value			
		Excess Returns		Dollars	
		Linear	Logit	Linear	Logit
Equation/Parameter		[9]	[10]	[11]	[12]
Win rate (valid)					
w10	Constant	.81 ***	1.18 ***	.75 ***	1.49 ***
		(.02)	(0.09)	(.02)	(0.19)
Win rate (invalid)					
w20	Constant	.22 *	-.33 ***	.045	-2.07 ***
		(.11)	(.08)	(.045)	(0.33)
Patent Value					
b0	Constant	.30	.03	-30,443.	30,149.
		(.22)	(.19)	(71,466.)	(32,432.)
b1	Appl. Returns	-.81	16.6	11.1 ***	8.74 ***
		(5.79)	(10.3)	(3.3)	(2.98)
b2	Iss. Returns	19.1 **	34.9	10.8 ***	6.88 ***
		(7.7)	(21.3)	(2.2)	(1.55)
b3	Forward citations	.051	.058	134,208. **	52,037. *
		(.094)	(.152)	(63,262.)	(31,306.)
r	Dep. rate	.26 ***	.27 ***	.074 ***	.017
		(.03)	(.03)	(.021)	(.020)

Dependent variable: Excess Returns ([9] & [10]) or Dollars ([11] & [12]).
Bootstrapped standard errors in parantheses.
*** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.01 level.
Coefficients and standard errors based on mean and standard errors of 200 bootstrap replicates.
Linear/logit specifications for court error.