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The Selection Hypothesis and the Relationship between Trial and Plaintiff Victory

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This paper develops implications of the selection hypothesis of Priest and Klein for the relationship between trial rates and plaintiff win rates. I find strong evidence for the selection hypothesis in estimated relationships between trial rates and plaintiff win rates at trial across case types and judges. I then structurally estimate the model on judge data, yielding estimates of the model's major parameters (the decision standard, the degree of stake asymmetry, and the uncertainty parameter) for each of three major case types, contracts, property rights, and torts.

I. Introduction

Priest and Klein (1984) have advanced a theory to explain the selection of cases for trial.[1] In their model, cases go to trial if the parties are overly optimistic about their prospects of success, that is, if the difference between plaintiff and defendant estimates of the plaintiff's expected judgment exceeds the difference between trial costs and settlement costs. The limiting implication of their model is that, with equal stakes to the parties, as the fraction of cases going to trial ap-

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[1] In this paper, the term "trial" refers to any case that is not settled. See n. 11 below.

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proaches zero (either because plaintiff or defendant uncertainty about trial outcomes declines or because trial costs increase), plaintiff win rates at trial will approach 50 percent. This effect is potentially important because it suggests that the sample of tried cases will be unrepresentative of the population of underlying disputes. As a consequence, it may be difficult to infer legal standards from the outcomes of tried cases.

Most existing evidence on the selection hypothesis is actually evidence on its limiting implication, the 50 percent rule.[2] Yet the Priest and Klein model can be used to generate a much richer set of predictions than the 50 percent rule alone. Using a few characteristics of cases (the decision standard, the parties' uncertainty about trial outcomes, and the degree of stake asymmetry), the model predicts both trial rates and plaintiff win rates, as well as the relationship between them. When stakes are symmetric, the model generally predicts that higher trial rates induce plaintiff win rates at trial to be farther from 50 percent.

In this paper I formally explore the implications of the Priest and Klein model for the relationship between trial rates and plaintiff win rates. I then test the selection hypothesis by directly analyzing the relationship between trial rates and plaintiff win rates across groups of cases.[3] I first examine the relationship between trial rates and plaintiff win rates across many different case types. I then use the natural experiment provided by random assignment of cases to judges to compare trial probabilities and plaintiff win rates across judges within each of three major case types: contracts, intellectual property (patent, trademark, and copyright), and torts. My evidence strongly supports the selection hypothesis. Finally, I structurally estimate the selection model using data on average trial rates and plaintiff win rates across judges. The structural parameter estimates allow me to go beyond previous research and draw inferences about the underlying population of filed cases from the sample of litigated cases and its relationship to the population of filed cases. In particular, I am able to infer the decision standard, the degree of stake asymmetry, and the level of uncertainty associated with the population of filed cases in the three case categories examined.

The approach developed in this study is relevant to current debates over the location of legal standards, for example, whether there is bias against minorities in criminal trials. This question would be diffi-

[2] One recent exception is the paper by Elder (1989), who estimates a simultaneous system with the probability of guilt in a criminal trial in one equation and the probability of accepting a plea bargain in the other.

[3] Eisenberg (1991) examines the relationship between plaintiff success at pretrial motion and trial across groups of cases.

cult to answer without such a model, given that a small and nonrandom sample of criminal cases go to trial. Tort reform provides another application for this approach. The current case for tort reform is based on the assertion that the United States is in the midst of a pro-plaintiff revolution in tort law that began in the 1960s.[4] According to this view, the tort decision standard—indicating the fraction of filed tort cases that would yield plaintiff victory if tried—favors plaintiffs. Legal system critics also charge that unpredictability of tort trial outcomes encourages trials. While Huber (1988) and others bemoan an increasingly pro-plaintiff tort system run amok, Henderson and Eisenberg (1990) and Eisenberg and Henderson (1992) argue that declining plaintiff win rates at trial since the mid-1980s signal reversal of the pro-plaintiff trend. They are careful to qualify their interpretations, but their analysis lacks a formal method for inferring the position of the decision standard. Resolution of this controversy would be aided by a method for inferring the decision standard and therefore the degree of pro-plaintiff bias in courts. Plaintiff win rates at trial are clearly inadequate for this purpose because of the possibility that tried cases are unrepresentative of filed cases. The selection model, when taken literally, allows inference of the position of the decision standard, the predictability of trial outcomes, and the degree of stake asymmetry for each case type from the observed relationship between trial rates and plaintiff win rates.[5] This paper advances a method for using the structure of the selection model to draw these inferences.

The paper proceeds in three steps. Section II explores the implications of the Priest and Klein model for the relationship between trial rates and plaintiff win rates. I model situations with both symmetric and asymmetric stakes to the parties, and I derive both testable implications of the selection hypothesis and a structural interpretation of plaintiff win rates and trial rates. Section III describes the data on trial rates and plaintiff win rates as well as how the assignment process creates a natural experiment for testing the selection effect across judges. Section IV examines the relationship between trial rates and

[4] See Huber (1988) for a discussion of the pro-plaintiff "legal revolution" in torts and Henderson and Eisenberg (1990) and Eisenberg and Henderson (1992) for studies arguing that the trend toward plaintiffs has reversed.

[5] The position of the decision standard indicates the fraction of filed cases that would result in plaintiff victory at trial. Shifts in the measure of the decision standard would reflect actual changes in the decision standard only if the relationship between filed cases and underlying disputes remains constant. The approach advanced in this paper takes the population of filed cases as given. Recent studies have examined possible changes over time on the relationship between filed cases and the underlying population of disputes (see Henderson and Eisenberg 1990; Eisenberg and Henderson 1992; Donohue and Siegelman 1991; Siegelman and Donohue 1993).

plaintiff win rates to test the selection hypothesis. Finally, Section V uses the data to estimate the structural parameters of the model.

II. The Model

A. *The Relationship between Trial Rates and Plaintiff Victory with Symmetric Stakes*

The Priest and Klein model describes selection of suits for trial and, given this selection, the probability of plaintiff victory at trial.[6] Filed cases lie along a case quality dimension that is divided at the decision standard into cases that would yield plaintiff and defendant victories if brought to trial. All cases to the right of the decision standard (D) would be plaintiff victories if tried. The distribution of filed cases' underlying quality is standard normal.[7]

Plaintiffs and defendants form unbiased estimates of case quality subject to error. The errors are drawn from independent normal distributions with equal variances (although the variances are generally not equal to the variance of filed case quality). If Y' is true case quality, then the plaintiff's estimate of case quality is $Y' + \epsilon_p^{Y'}$ and the defendant's estimate of case quality is $Y' + \epsilon_d^{Y'}$.[8] Plaintiff and defendant estimate case quality with an error that has standard deviation $\sigma^{Y'}$.

In this model, party error in estimating case quality is equivalent to error (which is independent across parties) in estimating the decision standard. That is, suppose that the plaintiff's estimate of the decision standard is $D_p = D + \epsilon_p^D$ (and that the defendant's estimate of the decision standard is defined analogously). The plaintiff's estimate of the probability of plaintiff victory, P_p, is then $F((Y' + \epsilon_p - D)/\sigma)$, where σ is the standard error of $\epsilon_i \equiv \epsilon_i^{Y'} - \epsilon_i^D$ ($i = p, d$), and $F(\,)$ is the cumulative normal; the defendant's estimate of the *plaintiff's* probability of victory P_d is $F((Y' + \epsilon_d - D)/\sigma)$. Thus all discussion of party uncertainty below refers to the composite of case quality and decision standard estimation error, and I refer to σ as the uncertainty parameter.

A case avoids litigation and is settled if the plaintiff's settlement demand is less than the defendant's offer. The plaintiff's demand is $P_pJ - C_p + S_p$, where J is the judgment the plaintiff would gain if he or she won at trial, and C_p and S_p are trial and settlement costs,

[6] For a complete description of the model, see Priest and Klein (1984).

[7] Some distributional assumption is required for this analysis. The main implications of the Priest and Klein model will follow from any one-humped distribution.

[8] I depart slightly from Priest and Klein's notation to allow uncertainty to stem from both errors estimating case quality and the position of the decision standard.

respectively, for the plaintiff. The defendant's offer is $P_dJ + C_d - S_d$ (the d subscript refers to the defendant). If the stakes and trial and settlement costs are equal for the plaintiff and defendant, then cases go to trial if the plaintiff's demand exceeds the defendant's offer, or if $P_p - P_d > (C - S)/J$.[9] If cases go to trial, they are decided without error. For example, if the true quality of the case Y' exceeds the decision standard D, then the case is a plaintiff victory if tried.

The settlement process acts as a filter on filed cases. Cases go to trial only if the parties disagree substantially over the probability of plaintiff victory. If the plaintiff and defendant have little uncertainty about case quality or the decision standard, then only cases with true quality near the decision standard will be tried (because cases with quality far from the decision standard will have clear outcomes and will therefore settle). This drives the plaintiff win rate at trial toward 50 percent regardless of the position of the decision standard. If parties have substantial uncertainty, the trial filter is less restrictive, and the sample of tried cases both is larger and is more nearly a random sample from the population of filed cases. The closer the sample of tried cases is to a random sample of filed cases, the nearer the plaintiff win rate at trial is to the fraction of plaintiff winners in the filed case population, rather than 50 percent.

Reductions in relative trial costs, or $(C - S)/J$, have an effect similar to the effect of an increase in the parties' uncertainty: An increase in σ or a decrease in $(C - S)/J$ will raise the fraction of cases litigated, and the farther the decision standard is above (below) the mean, the lower (higher) the fraction of plaintiff wins in litigated cases. Thus discussions below of varying party uncertainty may be interpreted as variation in relative trial costs. In the model below, $(C - S)/J$ is formally held constant at 0.33 whereas σ varies.

With symmetric stakes, the theory generates a relationship between trial rates and plaintiff win rates that depends on the location of the decision standard (D) and the uncertainty parameter (σ). Table 1 shows the trial rates and plaintiff win rates that result from simulations of the model assuming symmetric stakes and various decision standards and values of the uncertainty parameter.[10] Column 5 also shows the probability that a filed case has quality above the decision standard and would yield a plaintiff victory if tried. In all simulations

[9] As below, Priest and Klein (1984) set $(C - S)/J$ at 0.33 to close the model. They justify this assumption on the basis of lawyers' contingency fees. Total trial costs $C = C_p + C_d$ and total settlement costs $S = S_p + S_d$. This is, admittedly, a simple bargaining structure. However, one can view the offers and demands as reservation offers and demands.

[10] I simulate the model because, as is seen below, it has no closed-form expressions for the trial rate and plaintiff win rate at trial.

TABLE 1

SIMULATED TRIAL RATES AND PLAINTIFF WIN RATES WITH DIFFERENT DECISION STANDARDS AND CASE QUALITY ESTIMATION ERROR

DECISION STANDARD (D)	UNCERTAINTY PARAMETER (σ) .5 (1)	1.0 (2)	1.5 (3)	2.0 (4)	WIN RATE* (5)
−1.5:					
Trial rate	4.6	10.1	14.1	16.5	
Plaintiff win rate	76.1	86.0	88.7	91.9	93.3
−1.0:					
Trial rate	7.4	12.9	16.5	18.4	
Plaintiff win rate	68.4	76.6	79.8	81.9	84.1
−.5:					
Trial rate	9.5	15.4	18.1	19.8	
Plaintiff win rate	60.0	64.1	66.9	67.9	69.1
.0:					
Trial rate	10.8	16.4	18.7	20.4	
Plaintiff win rate	50.8	49.6	49.4	51.5	50.0
.5:					
Trial rate	9.4	15.4	18.2	20.1	
Plaintiff win rate	41.8	34.9	32.2	31.8	30.9
1.0:					
Trial rate	7.1	12.5	16.7	18.8	
Plaintiff win rate	28.1	21.1	17.7	17.5	15.9
1.5:					
Trial rate	4.6	9.6	13.9	17.1	
Plaintiff win rate	22.1	13.3	10.1	8.8	6.7

NOTE.—All simulations are based on 10,000 cases. The distribution of filed cases is standard normal. The ratio $(C - S)/J$ is set at 0.33.

* Fraction of filed cases with quality above the decision standard.

the distribution of filed case quality is standard normal, the ratio $(C - S)/J$ is 0.33, and stakes are symmetric. Each simulation is based on 10,000 cases. The assumed decision standards, which vary between −1.5 and 1.5, are "z-values" that correspond to a range of plaintiff victory probabilities (if tried) in the population of filed cases between 93.3 percent and 6.7 percent. The parties' uncertainty parameters vary between 0.5 and 2.0. For example, when σ is 0.5 and D is −1.5, 4.6 percent of filed cases are tried, and plaintiffs win 76.1 percent of cases that go to trial.

The table illustrates the operation of the model. When D is 0.0 and half of filed cases would therefore be plaintiff winners if tried, the simulated rate of plaintiff victory at trial is near 50 percent, whatever the degree of party uncertainty. When D is not equal to 0.0, increases in σ cause the sample of tried cases to become more random, and the probability of plaintiff victory at trial diverges from 50 percent and grows closer to the fraction of plaintiff wins among filed cases. The position of D also affects the trial rate. For a given level of

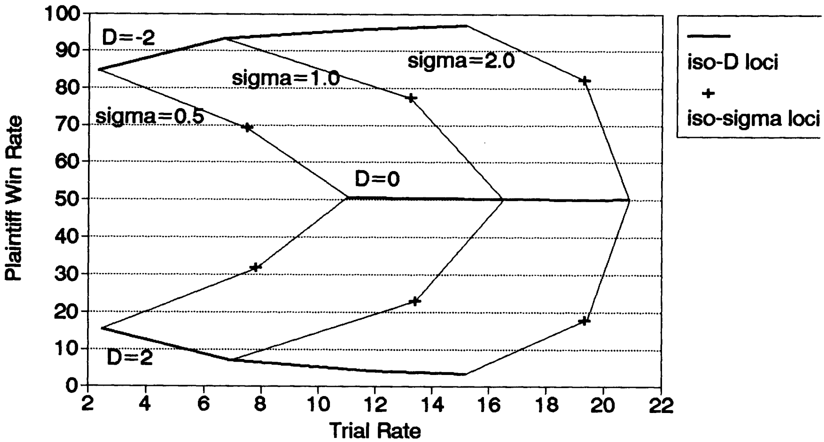

FIG. 1.—Trial and plaintiff win rates and iso-σ and iso-D loci

uncertainty, trials are more likely when true case quality is nearer to the decision standard. Hence, trials are more likely when the decision standard lies at the center of the distribution of filed cases ($D = 0.0$) and less likely when the decision standard lies in the tails. Thus the trial rate declines as D moves away from zero.

An alternative way of representing the model is in trial rate–plaintiff win rate at trial, or "T-P" space (see fig. 1). In T-P space, decision standards and party uncertainty are represented by iso-D and iso-σ loci. To trace the iso-D loci, vary the propensity of cases to go to trial without changing the decision standard. Because a decision standard of zero generates a plaintiff win rate of 50 percent whatever the level of the parties' uncertainty—and ensuing trial rate—the $D = 0.0$ locus is a horizontal line at $P = 50$ percent. With a decision standard above 0.0, the probability of plaintiff victory at trial is less than 50 percent. As the parties' uncertainty parameter increases, the fraction of cases tried increases, and the fraction of cases won by the plaintiff at trial declines toward the fraction of winning plaintiff cases among filed cases. Hence, the iso-D loci with $D > 0$ are downward sloping and always below the 50 percent plaintiff win rate. Analogously, the iso-D loci with $D < 0$ are positively sloped and above the 50 percent plaintiff win rate.

To trace out the iso-σ locus, imagine shifting the decision standard from above zero to below zero. The farther the decision standard is above zero, the fewer cases are tried *and* the lower the plaintiff win rate at trial. For $D > 0$, the iso-σ locus has a positive slope. If $D < 0$, the farther D is below zero, the lower the trial rate and the higher the plaintiff win rate. Hence, for $D < 0$, the iso-σ locus has a negative slope. Overall, the iso-σ loci are shaped like backward C's.

B. Asymmetric Stakes

Stake asymmetry can be incorporated into this model as different-sized judgments (J) for the plaintiff and defendant. Trial occurs if $P_pJ_p - P_dJ_d > C - S$ (with symmetric trial and settlement costs). Suppose that $J_p = \alpha J_d = \alpha J$. Then the trial condition is rewritten as $\alpha P_p - P_d > (C - S)/J = 1/3$. If plaintiff stakes are 25 percent higher, then $\alpha = 1.25$. Higher defendant stakes are similarly modeled with $\alpha < 1$. A change in relative stakes rotates the iso-D loci. While the $D = 0.0$ locus for equal stakes is horizontal at $P = 50$ percent, an increase in plaintiff stakes causes a clockwise rotation in the $D = 0.0$ locus: The intercept increases, and the slope becomes negative. When defendant stakes are higher, the intercept is below 50 percent, and the slope is positive.

C. Formal Description of the Model

Formally, the probability that a case goes to trial is the probability that

$$\alpha F\left(\frac{Y' + \epsilon_p - D}{\sigma}\right) - F\left(\frac{Y' + \epsilon_d - D}{\sigma}\right) > 1/3, \tag{1}$$

which is a triple integral of the joint density of $(Y', \epsilon_p, \epsilon_d)$ evaluated over the region defined by (1). The use of $1/3$ on the right-hand side of (1) is admittedly somewhat arbitrary. In principle the model could include another parameter rather than the assumption of the $1/3$ threshold. I do not include such a threshold parameter in the model for two reasons. First, adding another parameter complicates estimation because it adds another dimension to the simulations (described below). Second, while the threshold parameter is not linearly dependent on σ, it is closely related. Hence, the threshold parameter would be difficult to meaningfully identify independent of σ.

If the region described by (1) is defined as R, then the probability that a case goes to trial is

$$\Pr(\text{trial}) = \int\int\int_R f(Y', \epsilon_p, \epsilon_d)\, d\epsilon_p\, d\epsilon_d\, dY', \tag{2}$$

where $f(Y', \epsilon_p, \epsilon_d)$ is trivariate independent normal with a standard error of $Y' = 1$ and standard errors of ϵ_p and $\epsilon_d = \sigma$.

The probability of plaintiff victory, given trial, is the probability that ϵ_p and ϵ_d fall in R and that the true case quality Y' exceeds the decision standard D, divided by the trial probability. This is written as

$$\Pr(\text{plaintiff victory}\,|\,\text{trial}) = \frac{\int_D^{\infty}\int\int_R f(Y', \epsilon_p, \epsilon_d)\,d\epsilon_p\,d\epsilon_d\,dY'}{\Pr(\text{trial})}. \quad (3)$$

I cannot derive closed-form expressions for these probabilities—or compute them directly—because the regions of integration are defined only implicitly. These probability expressions are discussed further in the section on estimation.

D. *Testable Implications of the Model*

With symmetric stakes, the predicted relationship between P and T depends on two unobserved parameters, the decision standard and the level of party uncertainty. With asymmetric stakes, the relationship depends on three unobserved parameters. Theory alone will not predict the shape of the relationship between P and T. However, except in remote special cases, theory dictates *some* relationship between P and T. A minimal test of the theory is the test of whether T and P are related.

If one could identify the source of variation in T and P across groups of cases a priori, then more refined tests would be possible. To see this, index groups of cases by g. Then the model indicates that P and T are represented as $P_g(D_g, \sigma_g, \alpha_g)$ and $T_g(D_g, \sigma_g, \alpha_g)$. If stakes are symmetric, the relationship between P and T across groups of cases may be an iso-σ locus, an iso-D locus, or some combination of the two. For example, if we believe that few filed cases would yield plaintiff victory at trial ($D > 0$) and that the source of variation across groups of cases is σ, then if stakes are nearly symmetric, we can predict a negative relationship between P and T.

It is plausible to suppose that all three parameters of the model vary across case types. The position of the decision standard, the relative costs of trial and settlement, the parties' uncertainty, and the relative stakes all would seem, on a priori grounds, to vary across case types. It is thus difficult to predict the shape of the relationship between T and P across case types from theory alone. If D, α, and σ vary across case types, then we can predict only that if one varies "more," it will induce the relationship.

Because of random assignment of cases to judges, each judge has, on average, similar cases. Hence, we may assume that case characteristics, such as the degree of stake asymmetry, do not vary across judges within each case type. Given that D and σ may vary across judges, the assumption that α does not vary across judges does not generate any particular prediction about the relationship between P and T. The test of the selection hypothesis is simply whether P and T are related across judges. Subsequently, we use the assumption that α is constant across judges to infer how decision standards and uncertainty parameters vary across judges and how all three parameters vary across case types from structural estimates of the selection model in Section V.

III. Data: Sources and Interpretations

A. *Data*

The data for this study cover federal civil cases from the Southern District of New York (SDNY), filed 1984–87 and terminated by the end of 1989. The data come from two sources. All data on the cases except the judge identity come from the Inter-university Consortium for Political and Social Research (1989) (ICPSR) data set on federal court cases, 1970–89. This data set includes information obtained on all federal civil cases filed between 1970 and 1989. It includes information obtained at the time of filing, as well as information on the nature and size of judgments. Notably lacking from this publicly available data set are judge identifiers. These identities were collected from the SDNY civil index for all cases filed between 1984 and 1987. They are matched by docket number with ICPSR data on cases terminated by 1989. I was able to match 27,008 cases (for the 23 judges included below) filed between 1984 and 1987 with cases terminated by 1989 in the ICPSR data.

Relevant variables included in the ICPSR data set are (1) docket number; (2) filing date; (3) nature of the suit (a detailed list of suit types enumerated in table 2 below); (4) disposition: cases are disposed of (*a*) for procedural reasons (transfer to another district, remand to state court, or statistical closing), (*b*) because of case dismissal (for want of prosecution or because they are discontinued, settled, or withdrawn), and (*c*) because of a trial and judgment (either on default, consent, motion before trial, jury verdict, directed verdict, court trial, or other); and (5) judgment for: whether the judgment is for the plaintiff.

The crucial distinction for this paper is made between cases that do and do not go to trial. I use the disposition variable to distinguish the tried cases as follows. First, the 1,518 cases transferred or remanded are excluded. Second, any case that does not receive a judgment is assumed not to have gone to trial. This is reasonable because the parties must have come to some agreement in any dispute that does not require adjudication. Finally, any case that receives a judgment is assumed to have gone to trial.[11]

B. *Random Assignment and the Natural Experiment*

Random assignment of cases to judges guarantees that, over a large number of cases, each judge is assigned a similar caseload. As a result, differences across judges, for example in trial rates, stem ultimately from characteristics of the judge.[12] To justify the premise that each judge is assigned, on average, to similar cases, we need to explore the actual assignment process.

When a civil case is filed in SDNY, it is initially allocated to one of three "wheels" (A, B, or C) according to how long the case is expected to last. Cases expected to last up to 5 days are allocated to wheel A, cases expected to last between 6 and 20 days are allocated to wheel B, and cases expected to last over 20 days are allocated to wheel C. If the federal government is a party to the case, then the U.S. attorney determines the case's wheel. Otherwise, wheel determination depends on the nature of the suit (a classification recorded on the civil cover sheet at filing). Cases are then randomly assigned from these wheels to judges in the Manhattan courthouse of the SDNY. However, only nonsenior judges are obliged to receive cases from all wheels. While senior judges must receive a random sample of cases within each wheel, they do not necessarily receive a random sample of all cases.

The actual system of case assignment differs from simple random assignment in three ways. First, senior judges who elect not to receive cases from all wheels will not be assigned a representative sample of cases according to expected length. Second, because the U.S. attorney chooses its cases' wheels and not all wheels assign cases to all judges, the U.S. attorney can exert indirect control over whether cases are assigned to senior judges. For example, if the U.S. attorney prefers the senior judges and if the senior judges are more likely to receive cases from wheel A than from wheel B, then the U.S. attorney can

[11] I include default and consent judgments, as well as other sorts of judgments, because contrary to common belief, the plaintiff does not always prevail in these judgments. In these data, default judgments are in favor of the plaintiff 90.0 percent of the time and consent judgments 80.1 percent. Hence, "trials" in this study are not necessarily trials in the conventional legal sense of the term. Rather, trials are simply cases in which no settlement is reached by the parties. My "trial rate" is sometimes called the "litigation rate." Designation of consent judgments as trials does not materially affect the results. First, such judgments make up only 3.5 percent of the 25,490 cases in the data. Second, redefined T and P (with consent judgments coded as settlements) are highly correlated with the measures used. The correlations are .73 and .96, respectively.

[12] This was first observed by Gaudet, Harris, and St. John (1933) and has recently been exploited in Waldfogel (1991, 1994) and Ashenfelter and Waldfogel (1993).

TABLE 2

CASES, TRIAL RATES, AND PLAINTIFF WIN RATES BY NATURE OF SUIT: SDNY CASES FILED, 1984–87

Nature of Suit	Code	Cases Filed (N = 25,490)	Trial Probability (%)	Plaintiff Win Rate (%)
Contract:				
Insurance	110	404	18.8	38.2
Marine	120	4,076	10.3	76.9
Miller Act	130	30	13.3	100.0
Negotiable instrument	140	339	38.6	87.8
Recovery of overpayment	150	60	50.0	86.7
Medicare Act	151	13	46.2	16.7
Student loan	152	230	85.2	94.4
Veteran's	153	112	67.0	90.7
Stockholder	160	91	33.0	33.3
Other	190	4,989	27.3	75.5
Product liability	195	47	31.9	46.7
Real property:				
Land condemnation	210	8	50.0	75.0
Foreclosure	220	45	33.3	73.3
Rent, lease, ejection	230	39	28.2	63.6
Torts to land	240	7	.0	
Tort product liability	245	3	.0	
Other	290	57	28.1	31.3
Torts:				
Airplane	310	121	8.3	20.0
Airplane product liability	315	13	61.5	12.5
Assault, libel	320	107	30.8	18.2
Federal employer	330	320	9.4	46.7
Marine	340	543	13.8	42.7
Marine product liability	345	5	.0	
Motor vehicle	350	337	11.3	34.2
Motor vehicle product liability	355	24	4.2	.0
Other personal injury	360	639	23.8	15.1
Medical malpractice	362	143	18.2	19.2
Product liability	365	243	42.8	1.0
Asbestos	368	10	20.0	.0
Other fraud	370	210	21.0	29.5
Truth in lending	371	5	40.0	50.0
Other property damage	380	249	13.3	36.4
Property damage product liability	385	27	18.5	.0
State reapportionment	400	1	100.0	.0
Antitrust	410	98	19.4	31.6
	420	6	16.7	100.0
Bankruptcy:				
Appeal	422	240	2.1	20.0
Withdrawal	423	13	7.7	.0
Banking	430	36	30.6	54.5
Civil rights:				
Other civil rights	440	685	46.9	10.0
Voting	441	21	47.6	30.0
Employment	442	666	30.6	13.7
Housing	443	17	29.4	.0

TABLE 2 (*Continued*)

Nature of Suit	Code	Cases Filed (*N* = 25,490)	Trial Probability (%)	Plaintiff Win Rate (%)
Welfare	444	10	50.0	.0
Commerce/ICC	450	107	11.2	83.3
Deportation	460	165	10.3	11.8
RICO	470	95	28.4	29.6
Prisoner petitions:				
Vacate sentence	510	129	7.8	.0
Habeas corpus	530	1,017	69.8	3.7
Mandamus	540	155	13.5	.0
Civil rights	550	1,295	58.1	2.1
Forfeiture/penalty:				
Agriculture	610	13	46.2	.0
Other food and drug	620	121	70.2	89.4
Liquor laws	630	1	.0	
Airline regulations	650	1	.0	
OSHA	660	4	25.0	.0
Other	690	86	62.8	94.4
Labor:				
Fair labor	710	43	53.5	60.9
Labor/management relations	720	626	27.2	61.2
Labor/Management Reporting and Disclosure Act	730	64	26.6	17.6
Railway Labor Act	740	28	32.1	11.1
Other	790	106	19.8	42.9
ERISA	791	1,324	35.1	86.0
Selective service	810	1	.0	
Property rights:				
Copyrights	820	757	32.2	68.4
Patent	830	170	30.6	55.8
Trademark	840	881	37.1	75.8
SEC	850	664	27.1	41.7
Social security:				
HIA	861	9	44.4	50.0
Black lung	863	213	47.9	21.6
SSID	864	255	39.6	18.8
RSI	865	36	44.4	25.0
Federal tax suits:				
Taxes U.S. plaintiff or defendant	870	141	31.2	45.5
IRS—third party	871	32	21.9	14.3
Customer challenge	875	2	.0	
Other statutory actions	890	1,460	18.8	39.4
Agricultural acts	891	28	10.7	33.3
Economic Stabilization Act	892	1	100.0	100.0
Environment	893	33	42.4	42.9
Freedom of Information Act	895	51	31.4	.0
Appeal of fee determination under equal access to justice	900	1	.0	
Constitutionality of state statutes	950	35	31.4	27.3
	990	1	.0	

raise the probability that its cases are assigned to senior judges. As a consequence, caseloads would differ, on average, across judges.

Perhaps less remote than the last concern is the third deviation from simple random assignment, that a plaintiff can claim his case is related to previously filed cases. In this situation, the plaintiff argues that the judge who was assigned the related case should hear his case. If the judge accepts this argument, then the case is not assigned randomly. According to Gary Lee of the clerk's office of SDNY, in 1991, for example, approximately 8 percent of filed cases were accepted as related in SDNY.

These deviations from pure random assignment of cases to judges suggest ways of examining the data so that average differences across judges reflect differences across judges rather than across caseloads. First, to avoid the problem that senior judges may not have been assigned cases randomly from all three wheels, I simply excluded them from the analysis. By including only judges who are assigned cases from all wheels, I ensure that judges are assigned similar caseloads.[13]

Related cases create a separate and more difficult problem. The data do not indicate whether a case is related to other cases. Related cases are typically filed within a few weeks, so it may be possible to observe related case filings in the data as unexplainably large clusters of cases of a particular type assigned to a judge in a short space of time. In the analysis below, I point out a few anomalies in assignment patterns that apparently result from related case rules. I perform analyses below excluding judges with anomalous caseloads.

The data set ultimately employed includes 25,940 cases filed and assigned to 23 judges. Table 2 shows the distribution of cases filed by case type. This is quite similar to Eisenberg's (1990) table A1 except that I show both the trial rate and the plaintiff win rate. Table 3 shows the distribution of cases by judges (for the 23 judges included) for the three major case types examined.

IV. Tests of the Selection Hypothesis

A. *The Relationship between* P *and* T *across Case Types*

Trial rates and plaintiff win rates vary widely across case types, even if one ignores case types with few cases (see table 2). For example, compare tort cases (codes 310–85) with prisoner petitions (codes 530–50). Less than a third of tort cases filed go to trial, and of those

[13] Alternatively, if one believes that cases are assigned to wheels according to observable characteristics of the suit, then one could control for them.

TABLE 3

Cases, Trial Rates, and Plaintiff Win Rates by Judge: SDNY Cases Filed, 1984–87

	All Cases			Contract Cases		
Judge	Cases Filed (N = 25,490)	Trial Rate (%)	Plaintiff Win Rate (%)	Cases Filed (N = 10,391)	Trial Rate (%)	Plaintiff Win Rate (%)
1	1,280	34.5	34.4	478	25.3	72.7
2	1,135	20,3	66.1	471	16.6	91.0
3	1,283	29.6	43.9	517	26.1	65.2
4	1,181	22.4	57.6	504	18.7	84.0
5	1,158	25.6	42.2	489	20.4	64.0
6	1,237	27.0	45.5	528	22.9	71.1
7	1,121	25.2	67.4	467	17.6	92.7
8	1,414	32.5	42.6	547	18.5	73.3
9	1,188	30.9	49.9	492	26.6	74.8
10	1,026	23.0	66.5	442	24.2	88.8
11	850	20.5	52.3	376	18.1	70.6
12	1,121	30.0	50.6	467	25.5	69.7
13	1,004	30.1	61.9	487	34.3	82.0
14	1,097	30.3	52.1	454	24.2	80.9
15	950	20.9	51.8	396	16.7	75.8
16	1,088	30.1	58.5	455	25.5	79.3
17	1,046	31.8	36.9	416	24.3	74.3
18	1,075	23.8	68.0	473	23.3	86.4
19	1,074	21.8	56.4	451	18.2	81.7
20	657	23.7	55.8	263	20.9	74.5
21	1,024	29.4	48.2	439	21.9	68.8
22	1,031	28.5	55.1	444	25.2	75.9
23	1,450	54.9	10.4	335	21.5	68.1

	Property Rights Cases			Tort Cases		
Judge	Cases Filed (N = 1,808)	Trial Rate (%)	Plaintiff Win Rate (%)	Cases Filed (N = 2,996)	Trial Rate (%)	Plaintiff Win Rate (%)
1	85	27.1	65.2	256	59.0	2.6
2	69	31.9	86.4	136	8.1	63.6
3	94	31.9	36.7	154	18.2	17.9
4	92	28.3	88.5	153	9.8	46.7
5	72	34.7	28.0	153	19.6	26.7
6	96	34.4	54.5	152	20.4	25.8
7	105	41.0	95.3	142	18.3	34.6
8	153	46.4	90.1	137	11.7	43.8
9	81	32.1	76.9	135	16.3	27.3
10	65	32.3	81.0	126	7.1	33.3
11	45	24.4	63.6	125	11.2	28.6
12	75	36.0	85.2	123	14.6	50.0
13	56	41.1	65.2	120	9.2	36.4
14	92	37.0	47.1	120	13.3	25.0
15	73	20.5	80.0	117	11.1	53.8
16	84	40.5	73.5	116	14.7	11.8
17	61	29.5	83.3	111	21.6	8.3
18	75	28.0	85.7	110	7.3	37.5
19	86	8.1	100.0	108	13.0	21.4
20	41	41.5	70.6	101	13.9	50.0
21	83	56.6	74.5	101	21.8	31.8
22	69	34.8	66.7	95	14.7	28.6
23	56	44.6	32.0	105	37.1	7.7

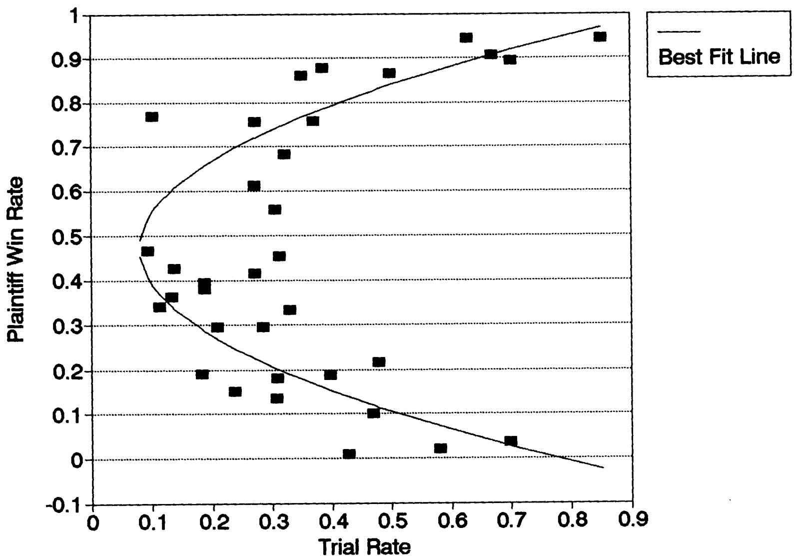

FIG. 2.—Trial and plaintiff win rate, by nature of suit, for cases with over 25 trials

that do, the plaintiff wins about a third of the time. Over half of prisoner petitions result in trials, and the plaintiff prevails less than 4 percent of the time.

Although one cannot say a priori whether the decision standard, stake asymmetries, or the uncertainty parameter provides the dominant variation across case types, it is nevertheless interesting to plot (P, T) combinations across case types. Figure 2 presents this plot for case types with more than 25 trials. The plot shows a striking parabolic relationship. Case types with low trial rates have plaintiff win rates at trial near 50 percent. As trial rates increase, plaintiff win rates diverge from 50 percent in both directions. Above $P = 0.50$, the points bear a positive relationship; below $P = 0.50$, the points bear a negative relationship.

Figure 2 is consistent with the simple prediction of the selection model with symmetric stakes: The higher the trial rate, the higher the deviation of the plaintiff win rate from 50 percent. The following relationship estimated by nonlinear least squares confirms what is visible to the naked eye:

$$\underset{(35.26)}{(P_i - 0.477)^2} = \underset{(13.19)}{0.264T_i}, \tag{4}$$

with t-statistics in parentheses. The higher the trial rate, the greater the squared deviation of the plaintiff win rate at trial from 47.7 percent. This equation is estimated across 34 case types. One cannot reject the hypothesis that $P = 0.5$ when $T = 0$ or that, as the trial rate approaches zero, the plaintiff win rate approaches 50 percent. The fitted relationship between P and T is the plotted line in figure 2. A possible rationalization of the relationship in figure 2 is that decision standards vary above and below zero across case types—hence plaintiff win rates are above and below 50 percent—but that σ provides the dominant source of variation, inducing a positive relationship between P and T above $P = 50$ percent and a negative relationship below. As the discussion of the model above suggests, this particular interpretation must be tempered by recognition that we do not know the source of variation of P and T across case types. Nevertheless, the existence of a strong relationship between P and T is evidence for the selection effect, and the relationship we observe is also consistent with the 50 percent rule.

B. The Relationship between P *and* T *across Judges*

For the tests of the selection effect using judge data, I analyze the data two ways. First, I examine the relationship between trial rates and plaintiff win rates over all cases. Second, I examine the relationship between trial rates and plaintiff win rates across judges within each of three broad case types: contracts, intellectual property, and torts. The goal here is to find evidence for the selection hypothesis. Although I assume that α is constant across judges whereas D and σ vary, this restriction does not generate specific predictions about the shape of the relationship between P and T. Hence, we are still simply looking for a relationship between P and T across judges, as is minimally required if the selection hypothesis is correct.

An empirical necessity for the success of interjudge comparisons in this study is that trial rates differ across judges. If propensities to go to trial are not significantly different when parties come before different judges, then there is no scope for examining the effect of the selection of cases for trial on plaintiff win rates. On the other hand, if trial rates differ across judges with, on average, similar caseloads, these differences are due to characteristics of the judges and can induce differences in plaintiff win rates, if the selection effect operates.

Table 3 shows trial rates, by judge, for all cases and each of the three case types. There is a large amount of variation in trial rates across judges for all cases and within case types. Before we analyze these data, note that judge 1 is assigned a disproportionate number of tort cases and judge 23 a disproportionate number of prisoner cases. We can presume that these patterns result from related case assignments, and below judge 1 is excluded from the analysis of tort

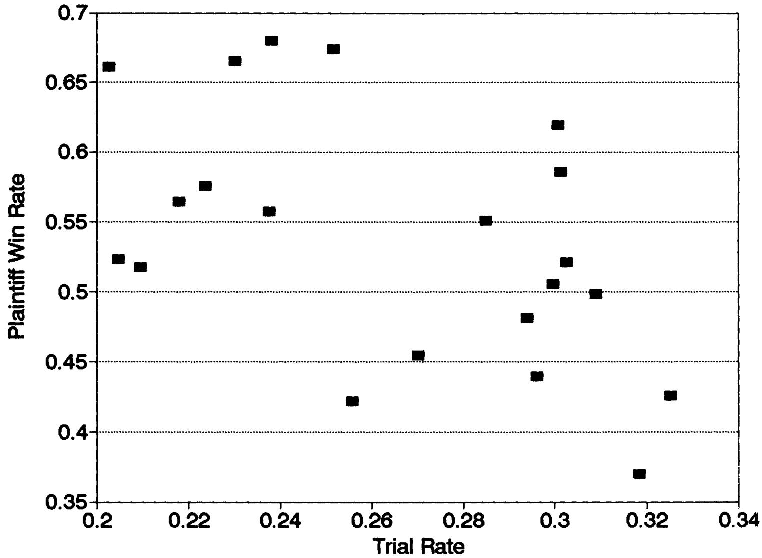

FIG. 3.—Trial rates and plaintiff win rates, all cases, by judge (judges 1 and 23 excluded).

cases. Judges 1 and 23 are both excluded from the analysis of the composite category of all cases.

Even when judges 23 and 1 are excluded, trial rates for all cases vary between 20 and 30 percent, and the hypothesis of equal trial rates is rejected at the 1 percent level. Similarly, the hypothesis of no interjudge differences in trial rates is rejected at the 1 percent level for each of the separate case types. This significant variation in trial rates across judges provides wide scope for testing the selection hypothesis across judges.

Figure 3 shows the plaintiff win rate (on the vertical axis) and the trial rate (on the horizontal axis) for all cases, by judge, and shows a clear negative relationship between trial rates and plaintiff win rates. Judges with low trial rates (below 25 percent) have plaintiff win rates between 50 and 70 percent, whereas judges with high trial rates (above 25 percent) have plaintiff win rates that cluster mainly between 35 and 55 percent. The weighted least squares regression (with the number of filed cases per judge used as weights) is

$$\underset{(7.39)}{P_i = 0.86} - \underset{(-2.82)}{1.21T_i}, \tag{5}$$

where $N = 21$ and $R^2 = 29$ percent.[14] The hypothesis that plaintiff

[14] Judges 1 and 23 are excluded from this regression. Here, and with the individual case type regressions, a logistic regression gives substantively similar results.

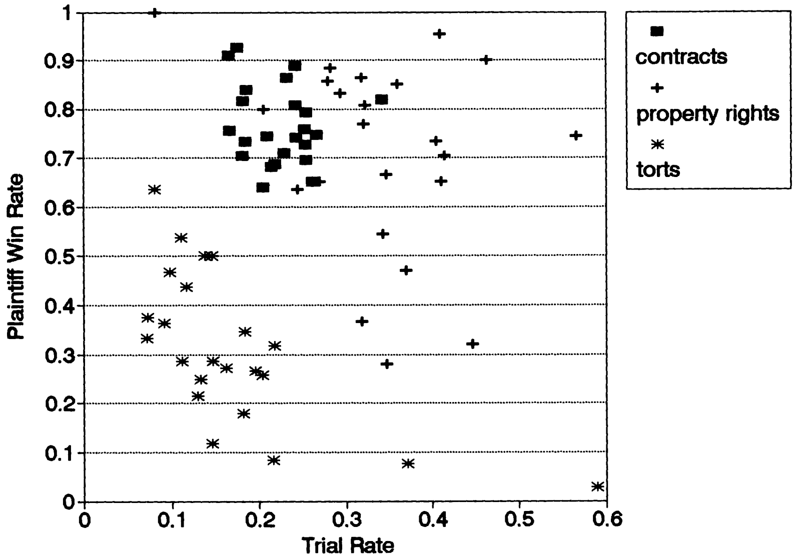

FIG. 4.—Trial rates and plaintiff win rates, by judge

win rates are independent of trial rates across judges is rejected. The higher the trial rate, the lower the plaintiff win rate. This is strong evidence of the operation of the selection effect.

Figure 4 shows the relationship between plaintiff win rates and trial rates across judges for contract, intellectual property, and tort cases. The judges' trial rates and plaintiff win rates cluster together by case type, and the clusters for each case type occupy different locations in T-P space. The T-P combinations for contracts cluster tightly near $T = 0.20$ and $P = 0.75$. Because there is little interjudge variation in T, there is little variation in P. There is a slight negative relationship between P and T, but it is not significant, as the weighted least squares regression indicates:

$$P_i = \underset{(8.86)}{0.84} - \underset{(-0.76)}{0.32}T_i, \tag{6}$$

where $N = 23$ and $R^2 = 2.7$ percent. The lack of a relationship between P and T gives no evidence for the selection effect for contract cases.

Trial rates in intellectual property cases vary substantially across judges, from 10 to 50 percent, whereas the associated plaintiff win rates vary from 30 percent to over 90 percent. The weighted least squares regression shows that the relationship between P and T is negative, though not significant:

$$P_i = \underset{(5.35)}{0.83} - \underset{(-0.74)}{0.32}T_i, \tag{7}$$

where $N = 23$ and $R^2 = 3$ percent.

Let us now turn to tort cases. The use of tort cases supports comparison with existing empirical work (see Priest and Klein 1984; Priest 1985, 1987; Wittman 1985). The tort data cluster at low trial rates and low plaintiff win rates and clearly show a negative relationship between T and P. The cluster of points is near a 50 percent plaintiff win rate for trial rates nearer to zero. The weighted least squares regression confirms what is visible to the naked eye:

$$P_i = \underset{(8.27)}{0.54} - \underset{(-3.54)}{1.42}T_i, \tag{8}$$

where $N = 22$ and $R^2 = 38.5$ percent. The scatter plot and the regression equation indicate a negative relationship between P and T below $P = 50$ percent.

For torts, the judge with the highest trial rate and lowest plaintiff win rate is judge 23. In the model, high trial rates result from high plaintiff error in predicting case quality (or low $[C - S]/J$). It is interesting to note that judge 23 is described by some lawyers as unpredictable. The *Almanac of the Federal Judiciary* quotes a lawyer saying that judge 23 "has a tendency to rule right off the bench without knowing what the law is" (see Prentice Hall Law and Business 1992, 1:47). The tort regression excluding judge 23 is quite similar, so the results are not driven by judge 23 alone.

Evidence in this section supports the selection hypothesis. Plaintiff win rates vary systematically with trial rates, both across case types and across judges. While the absence of statistically significant relationships between P and T for contract and intellectual property cases does not support the selection hypothesis, it also does not necessarily contradict the selection hypothesis. Evidence that the selection effect operates motivates estimation of the structural model.

V. Estimating the Structural Model

The selection model generates a precise relationship between model parameters (D, σ, and α) and rates of trial and plaintiff victory (T and P), allowing us to refer to the probability expressions in Section II as $P(D, \sigma, \alpha)$ and $T(D, \sigma, \alpha)$. If we index judges by j and case types by c, then the observed trial rates and plaintiff win rates have model analogues: $T_j^c = T(D_j^c, \sigma_j^c, \alpha_j^c)$ and $P_j^c = P(D_j^c, \sigma_j^c, \alpha_j^c)$. For each case type and judge, we have two pieces of data and three unknown parameters and therefore an infeasible estimation problem. However, random assignment of cases to judges allows us to reasonably assume that the degree of stake asymmetry does not vary across judges. By assuming that α varies only across case type whereas D and σ vary across both case type and judge, we have a feasible estimation problem. The estimation problem is to find 53 parameters (three stake asymmetry parameters, decision standards, and uncertainty parameters, plus 22 judge effects on the decision standard and uncertainty parameter: $3 + 3 + 3 + 22 + 22 = 53$) to best fit the model's expressions for P and T with the data.

A. *Estimation*

There are two obstacles to estimating this model. First, there is no closed form for the probability expressions used in the model. A possible solution would be to estimate the model by the method of simulated frequencies (Lerman and Manski 1981). The second obstacle, however, is that we have 53 parameters to estimate and therefore an infeasibly large parameter space over which to simulate.

A natural solution, pursued here, is to find functions approximating the model's relationship between P and D, σ, and α and between T and D, σ, and α. Given such functions, the estimation procedure can optimize some objective (a quasi likelihood function) by searching the functions rather than checking the quasi likelihood value at the P's and T's implied by a new simulation draw.

The strategy employed for creating functions relating P and T to α, D, and σ is to simulate the model for a range of values of α, D, and σ and then to fit the resulting simulated P and T to fully interacted polynomials in α, D, and σ. I simulate P and T for (α, D, σ) over the following ranges: α runs from 0.625 to 2.00 by increments of 0.125, D runs from -2.50 to 2.50 by 0.25, and σ runs from 0.50 to 3.00 by 0.25. Thus the simulated data have 2,772 observations. To ensure that the estimated probabilities fall between zero and one, I estimate logistic regressions. I simulate P and T on the basis of a large number (10,000) of draws for each parameter combination to make the error stemming from the data small.

By the criterion of R^2, the third-order logistic regressions fitting simulated T and P to terms in D, α, and σ fit well.[15] The R^2's for the regressions on third-order terms are 99.6 percent (P) and 98.5 percent (T). The fitted probabilities from the third-order approximations can be referred to as

$$\hat{T} = \frac{e^B}{1 + e^B}, \tag{9}$$

[15] I experimented with estimation based on both second- and third-order approximations and obtained similar results. I report only third-order results. Note that the fully interacted third-order polynomial has 64 terms.

where

$$B = \sum_{i=0}^{3} \sum_{j=0}^{3} \sum_{k=0}^{3} (\alpha)^i (D)^j (\sigma)^k \hat{\tau}_{ijk}, \tag{10}$$

and

$$\hat{P} = \frac{e^A}{1 + e^A}, \tag{11}$$

where

$$A = \sum_{i=0}^{3} \sum_{j=0}^{3} \sum_{k=0}^{3} (\alpha)^i (D)^j (\sigma)^k \hat{\pi}_{ijk}, \tag{12}$$

in which $\{\pi_{ijk}\}$ and $\{\tau_{ijk}\}$ are parameters from the logistic regressions.

We can parameterize the model, in which all three parameters vary across case type, and the decision standard and the uncertainty parameter vary across judges, as follows:

$$\alpha = \sum_{c=1}^{3} \delta^c \alpha^c, \tag{13}$$

$$\sigma = (s^1 \delta^1 + s^2 \delta^2 + \delta^3) \sum_{j=1}^{23} \delta_j \sigma_j, \tag{14}$$

and

$$D = \sum_{c=1}^{3} \delta^c D^c + \sum_{j=2}^{23} \delta_j D_j, \tag{15}$$

where δ^c is a case type dummy, δ_j is a judge dummy, and superscripts and subscripts refer to case types and judges, respectively. The 53 parameters to be estimated are $\{\alpha^1, \ldots, \alpha^3, D^1, \ldots, D^3, D_2, \ldots, D_{23}, \sigma_1, \ldots, \sigma_{23}, s^1, s^2\}$. The last two parameters, s^1 and s^2, are scale parameters showing the average size of the uncertainty parameter for contracts (s^1) and intellectual property (s^2), relative to torts.

The probability of observing a given trial probability *and* plaintiff win rate for a given case type and judge is the product of binomials:

$$\frac{N!}{N_T!(1 - N_T)!} \hat{T}^{N_T} (1 - \hat{T})^{(N - N_T)} \times \frac{N_T!}{N_P!(1 - N_P)!} \hat{P}^{N_P} (1 - \hat{P})^{(N_T - N_P)}, \tag{16}$$

where N is the total number of cases of a given type assigned to this

TABLE 4

STRUCTURAL PARAMETER ESTIMATES BY CASE TYPE

	Decision Standard (D)*	Stake Asymmetry (α)	Uncertainty Parameter (σ)†
Contracts	−.629	1.225	.293
	(.060)	(.011)	(.083)
Intellectual property	−.158	1.336	.716
	(.212)	(.046)	(.202)
Torts	.510	.946	1.697
	(.109)	(.036)	(.239)

NOTE.—All parameters (decision standard, stake asymmetry, and uncertainty) vary by case type; the decision standard and uncertainty parameters vary by judge as well. Adjusted standard errors are in parentheses.

* Calculated as $D^1 + \Sigma_{n=2}^{23} D_j/22$.

† Calculated as $s^i(\Sigma_{j=2}^{23} \sigma_j/22)$ for contracts ($i = 1$) and intellectual property ($i = 2$). For torts, $s = 1$.

judge, N_T is the number going to trial, and N_P is the number in which the plaintiff wins. The quasi likelihood function is the product of this expression across three case types and 23 judges.[16]

Derivative techniques failed in estimating the model, and it was estimated using the downhill simplex method (see Press et al. 1989). Obtaining correct standard errors for this model is complicated by two things. First, because I maximize a quasi likelihood function, I follow White's (1982) procedure for calculating standard errors. Second, I must adjust the standard errors to account for the use of estimated, rather than true, π and τ parameters in the logistic functions incorporated in $T(D, \alpha, \sigma)$ and $P(D, \alpha, \sigma)$. This adjustment is described in Appendix A.

Table 4 presents estimates of implied decision standards, stake asymmetry parameters, and uncertainty parameters for each of the three case types. (All parameters are reported in Appendix B, table B1.) Table 5 reports actual plaintiff win rates at trial, along with the fraction of plaintiff winners (if all filed cases went to trial) implied by the models, for each of the three case types.

B. *Estimates*

The decision standard parameters indicate the fraction of filed cases that would result in plaintiff wins at trial. The estimated decision standard for contract cases is −0.629, far (and significantly) below zero, indicating that 73.5 percent of filed contract cases would result in plaintiff victories if tried (see table 5). This is slightly but statistically significantly below the actual fraction of plaintiff wins among tried

[16] Note that judge 1 is excluded for tort cases, resulting in 68, rather than 69, observations.

TABLE 5

Implied and Actual Plaintiff Win Rates (%)

	Implied Plaintiff Win Rate*	Actual Plaintiff Win Rate
Contracts	73.52 (1.96)	76.6
Intellectual property	56.28 (8.37)	71.3
Torts	30.49 (3.80)	21.8

Note.—Adjusted standard errors are in parentheses.
* Calculated as $1 - F(D)$, where $F(\ )$ is the cumulative normal and D is an estimated decision standard.

contract cases, 76.6 percent, indicating that tried contract cases are somewhat unrepresentative of filed contract cases.[17] The property rights decision standard estimated in the model is -0.158, insignificantly below zero, indicating that 56.3 percent of filed intellectual property cases would result in plaintiff victories if tried. This is considerably—and statistically significantly—lower than the actual fraction of plaintiff wins among tried contract cases, 71.3 percent, indicating that tried intellectual property cases are systematically different from the underlying population of filed cases. The estimated tort decision standard is 0.510, far (and significantly) above zero, indicating that 30.5 percent of filed tort cases would result in plaintiff wins at trial, significantly above the actual figure of 21.8. Thus, according to the model, tried tort cases are also unrepresentative of filed tort cases.

A few remarks are in order about the estimated decision standards. First, the selection effect operates: Tried cases are significantly different from—and unrepresentative of—filed cases in all three categories, especially intellectual property and torts. Second, the tort decision standard estimated in the model accords with the commonly held belief that many filed tort cases are frivolous and that few filed tort cases are winners.[18] Third, while the selection effect operates, it does not operate as a simple convergence toward a 50 percent plaintiff win rate. In the symmetric stakes version of the selection model, selection causes the actual plaintiff win rate at trial to be nearer to 50 percent than the fraction of would-be plaintiff winners in the population of filed cases. Yet the actual plaintiff win rate among litigated cases is actually farther from 50 percent than each of the fractions of plaintiff winners among tried cases implied by the model. The reason for this nonstandard selection is stake asymmetry.

[17] This statistical test assumes that the actual fraction is estimated without error.

[18] See Huber (1988) for a discussion of tort cases and the tort system.

One would expect the degree of stake asymmetry to vary across case types.[19] When a tort defendant loses, she is often exposed to potential liability from additional plaintiffs. Similarly, a losing intellectual property plaintiff opens the door to additional encroachment. Hence one would expect higher plaintiff stakes for intellectual property and relatively higher defendant stakes for torts. The results largely accord with this intuition: The highest stake asymmetry parameter (α) estimated in the model pertains to intellectual property; it is 1.336 and is significantly above one, indicating that plaintiffs stand to gain 33.6 percent more than defendants stand to lose in intellectual property cases. The tort estimate is the lowest. One would expect the tort parameter to reflect higher stakes for the defendant, and the estimated parameter (0.946 and marginally significantly below one) supports this. The contracts parameter is in between the others, at 1.225, reflecting significantly higher plaintiff than defendant stakes.

Advocates of tort reform criticize the tort system for unpredictability (see Huber 1988; Huber and Litan 1991). Unpredictability is viewed as an undesirable feature because (as in the present model) it encourages trials. The uncertainty parameter estimated in the model supports the view of tort system critics: It is highest for torts and lowest for contracts, suggesting that, among the case types examined here, tort cases are the most difficult for parties to predict.[20] The high degree of uncertainty that the model attaches to tort cases is not obvious from the raw data. In figure 4, tort cases clearly have the lowest trial rates among the three case types examined. Thus the structure of the model is needed to draw this inference from the data. Figure 5 shows the actual data, along with fitted values of P and T from the model.

We can calculate Wald statistics to test whether decision standards and uncertainty parameters vary across judges. The restriction that all judges have the same decision standard is sharply rejected ($\chi^2_{(22)} = 277.27$, far above the 99 percent critical value of 40.29). The restriction that each judge has the same uncertainty parameter is rejected even more sharply ($\chi^2_{(22)} = 4{,}043.62$). Hence, the dense parameterization of the model is necessary.

What have we learned from this estimation exercise? Viewed through the structure of the Priest and Klein (1984) model (and its identifying assumptions), the observed relationship between T and P

[19] See Clermont and Eisenberg (1992, pp. 1130–31) for a discussion of stake asymmetry.

[20] Recall, however, that differences across case types in estimated σ may partly reflect differences in relative trial costs, $(C - S)/J$, assumed constant across case types in the model. Higher σ corresponds to lower relative trial costs.

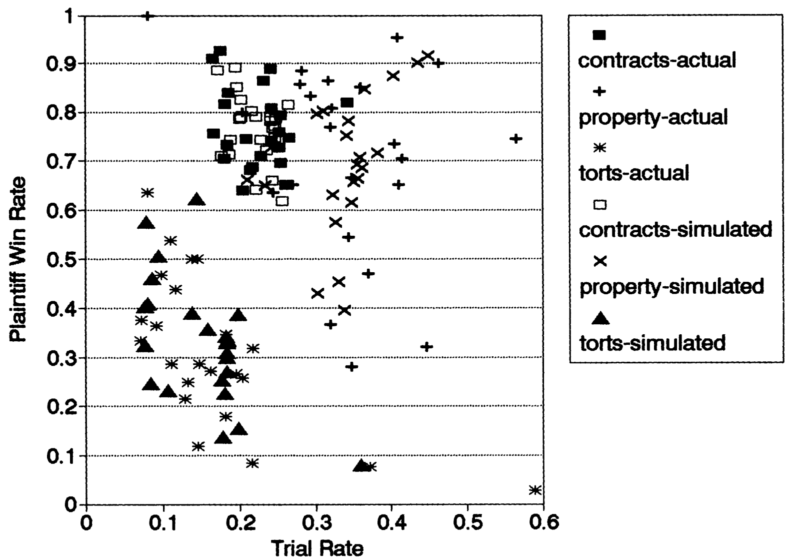

FIG. 5.—Actual and simulated data

implies the following. First, the estimated decision standards imply that relatively few filed tort cases (30 percent), about half of filed intellectual property cases, and nearly three-quarters of filed contracts cases (74 percent) would yield plaintiff victory at trial. Second, plaintiffs have much higher stakes than defendants in intellectual property cases, somewhat higher stakes in contracts cases, and slightly lower stakes in tort cases. Third, tort cases engender much higher uncertainty than contract or intellectual property cases.

Had we attempted to infer the decision standard from the fraction of plaintiff winners among tried cases, we would have done reasonably well with contract cases but poorly with tort and intellectual property cases. The approach of this paper thus allows more accurate determination of the decision standard than would be available directly from plaintiff win rates at trial. Further, this approach allows us to infer case characteristics that are not observable. The other parameters, stake asymmetry and uncertainty, do not have observable analogues and cannot be estimated without a structural model.

In addition to inferences about case types, our estimates also allow inferences about judges. We have estimated, and can infer, the decision standards and uncertainty parameters associated with each judge. Figure 6 shows the implied fraction of filed tort cases that would yield plaintiff victory at trial, by judge.[21] They vary substan-

[21] The other case categories' decision standards differ from the tort decision standard by a scalar; I report torts for illustrative purposes. Recall that judge 1 is excluded from the analysis of torts.

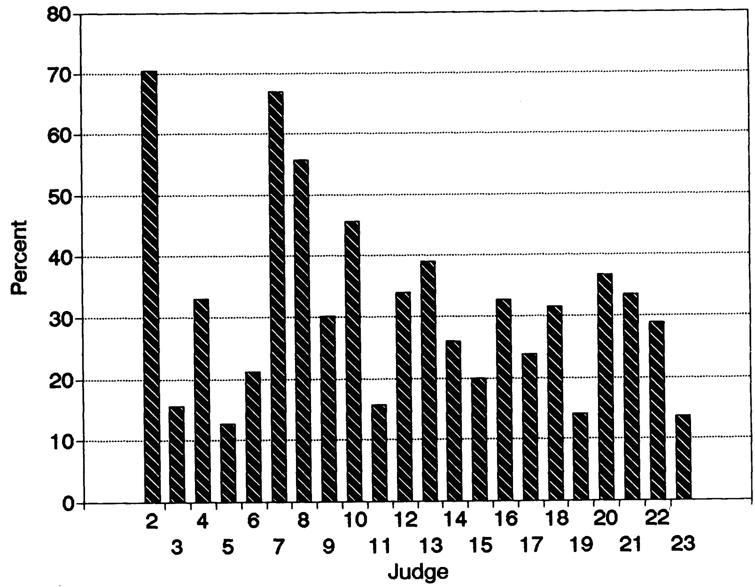

FIG. 6.—Percentage of filed tort cases that would yield plaintiff victory, by judge

tially across judges, from 10 to 15 percent for five judges to over 40 percent for four other judges. Tort plaintiffs prevail four times as often with the same underlying cases before one judge than another, and these differences are both economically and statistically significant.[22] Observed plaintiff win rates (see table 3) suggest this interjudge disparity but cannot be interpreted to reflect decision standards because tried cases are a selected sample of filed cases. Figure 7 shows the implied tort uncertainty parameter, by judge. Interjudge variation in this parameter, reflecting judges' predictability, is large and statistically significant. While σ is below 0.5 for four judges, it is over five times as high for five other judges. These results, indicating substantial interjudge disparity in civil adjudication tendencies, are consistent with measurements of interjudge disparity in federal criminal sentencing (see Waldfogel 1991).

VI. Conclusion

In this paper I have derived testable hypotheses about the relationship between trial rates and plaintiff win rates from the Priest and Klein model. I find strong statistical relationships between trial rates

[22] The hypothesis H_0: $F(D^1 + D_j) = F(D^1 + D_2), j = 3, \ldots, 23$, is rejected, $\chi^2_{(21)} = 913.54$, far above the 99 percent critical value of 38.93.

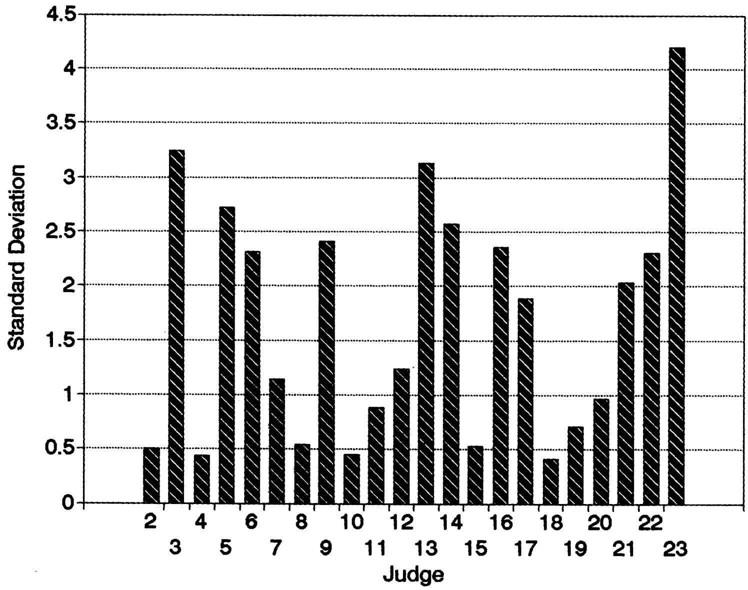

FIG. 7.—Tort uncertainty parameters, by judge

and plaintiff win rates, both across case types and across judges. Having found evidence in favor of the selection effect, I directly estimate the selection model, inferring the decision standard, the degree of stake asymmetry, and the level of party uncertainty for three case types. Structural estimation results indicate that litigated cases are unrepresentative of filed cases, that plaintiffs have higher stakes in contract and property rights cases and lower stakes in tort cases, and that tort cases engender the greatest uncertainty. While the higher tort uncertainty parameter is also consistent with lower trial costs for this case type, it is nevertheless consistent with the view of tort system critics who argue that the legal standard is less clear for torts than for other case types.

Appendix A

Obtaining Adjusted Standard Errors

Define the parameter vector (α, σ, D) as Θ, and define the parameters of the logistic regressions (π, τ) as Π. The complication addressed in this Appendix is that, when the quasi likelihood function is maximized with respect to Θ, we use an estimate of the unknown Π, say $\underline{\Pi}$. Thus the standard errors must be adjusted to account for the inclusion of parameter estimates that are obtained from estimation in an earlier stage.

To show how the standard errors are adjusted, we first derive standard errors for the usual case and then adapt the framework to the present case with estimated parameters from an earlier stage.

The log quasi likelihood is

$$\log \mathcal{L}(\Theta, \Pi) = \Sigma\{N_T \log T(\Theta, \Pi) + (N - N_T)\log[1 - T(\Theta, \Pi)] + N_P \log P(\Theta, \Pi) + (N_T - N_P)\log[1 - P(\Theta, \Pi)]\}.$$

If we write the first-order condition for Θ as $(\partial \log \mathcal{L})/\partial\Theta = 0$ as $0 = \Sigma\, \Psi(\Theta, \Pi)$ (where Ψ is the first derivative of the likelihood function with respect to Θ, for an observation), then the mean value theorem implies that

$$0 = \Sigma\Psi(\Theta_0, \Pi_0) + \left(\frac{\partial}{\partial\Theta'}\right)[\Psi(\Theta^*, \Pi_0)](\underline{\Theta} - \Theta_0),$$

where an underbar denotes the estimator, subscript 0 denotes the true value, and an asterisk indicates a value between the estimator and the true value. Note that $E[\Psi(\Theta_0, \Pi_0)] = 0$, so that the generalized method of moments may be invoked. Consequently, the distribution of $\sqrt{n}(\underline{\Theta} - \Theta_0)$ converges to $N(0, \Lambda_\Theta)$, where

$$\Lambda_\Theta = \left\{E\left[\frac{\partial\Psi(\Theta_0, \Pi_0)}{\partial\Theta'}\right]\right\}^{-1} E[\Psi(\Theta_0, \Pi_0)\Psi(\Theta_0, \Pi_0)']\left\{E\left[\frac{\partial\Psi(\Theta_0, \Pi_0)}{\partial\Theta'}\right]\right\}^{-1\prime}.$$

With Π estimated in a prior stage, the first-order condition becomes $0 = \Sigma\, \Psi(\Theta, \underline{\Pi})$. The mean value theorem allows this to be rewritten as

$$0 = \left(\frac{1}{n}\right)\Sigma\Psi(\Theta_0, \Pi_0) + \left(\frac{\partial}{\partial\Theta'}\right)[\Psi(\Theta^*, \Pi^*)]\sqrt{n}(\underline{\Theta} - \Theta_0) + \left(\frac{1}{n}\right)\Sigma\left(\frac{\partial}{\partial\Pi'}\right)[\Psi(\Theta^*, \Pi^*)]\sqrt{n}(\underline{\Pi} - \Pi_0).$$

Consequently, the distribution of $\sqrt{n}(\underline{\Theta} - \Theta_0)$ converges to $N(0, \Lambda)$, where

$$\Lambda = \left[E\left(\frac{\partial\Psi}{\partial\Theta'}\right)\right]^{-1}\left\{E[\Psi(\Theta_0, \Pi_0)\Psi(\Theta_0, \Pi_0)'] + \left(\frac{\partial\Psi}{\partial\Pi'}\right)\Lambda_\Pi\left(\frac{\partial\Psi}{\partial\Pi}\right)\right\}\left[E\left(\frac{\partial\Psi}{\partial\Theta'}\right)\right]^{-1\prime}.$$

This exceeds the usual White (1982) standard errors by a positive semidefinite matrix.

Appendix B

TABLE B1

STRUCTURAL MODEL PARAMETER ESTIMATES

	Coefficient	Standard Error	Parameter
	Decision Standards		
Contracts	−.675	.227	D^1
Intellectual property	−.205	.331	D^2
Torts	.463	.258	D^3
	Tort Uncertainty Parameter, by Judge		
Judge 1	2.091	.758	σ_1
Judge 2	.505	.225	σ_2
Judge 3	3.247	.308	σ_3
Judge 4	.428	.154	σ_4
Judge 5	2.717	.840	σ_5
Judge 6	2.311	.609	σ_6
Judge 7	1.141	.188	σ_7
Judge 8	.544	.228	σ_8
Judge 9	2.406	1.088	σ_9
Judge 10	.446	.231	σ_{10}
Judge 11	.884	.088	σ_{11}
Judge 12	1.243	.721	σ_{12}
Judge 13	3.137	.393	σ_{13}
Judge 14	2.565	.507	σ_{14}
Judge 15	.523	.120	σ_{15}
Judge 16	2.360	.569	σ_{16}
Judge 17	1.883	.469	σ_{17}
Judge 18	.407	.117	σ_{18}
Judge 19	.701	.320	σ_{19}
Judge 20	.967	.204	σ_{20}
Judge 21	2.031	.519	σ_{21}
Judge 22	2.302	.630	σ_{22}
Judge 23	4.197	.079	σ_{23}
	Uncertainty Scale Parameter (Relative to Tort)		
Contracts	.173	.065	s^1
Intellectual property	.422	.124	s^2
	Stake Asymmetry Parameter		
Contracts	1.225	.011	α^1
Intellectual property	1.336	.046	α^2
Torts	.946	.036	α^3
	Decision Standards (by Judge)		
Judge 2	−.998	.487	D_2
Judge 3	.549	.237	D_3
Judge 4	−.026	.292	D_4
Judge 5	.683	.284	D_5
Judge 6	.335	.244	D_6
Judge 7	−.903	.436	D_7
Judge 8	−.607	.353	D_8

TABLE B1 (*Continued*)

	Coefficient	Standard Error	Parameter
		Decision Standards (by Judge)	
Judge 9	.054	.233	D_9
Judge 10	−.352	.313	D_{10}
Judge 11	.547	.252	D_{11}
Judge 12	−.047	.325	D_{12}
Judge 13	−.183	.231	D_{13}
Judge 14	.180	.300	D_{14}
Judge 15	.380	.314	D_{15}
Judge 16	−.016	.277	D_{16}
Judge 17	.250	.277	D_{17}
Judge 18	.016	.324	D_{18}
Judge 19	.614	.313	D_{19}
Judge 20	−.123	.306	D_{20}
Judge 21	−.038	.434	D_{21}
Judge 22	.090	.230	D_{22}
Judge 23	.633	.286	D_{23}

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