ON THE ECONOMICS OF TRIALS: ADVERSARIAL PROCESS, EVIDENCE AND EQUILIBRIUM BIAS

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ABSTRACT

The adversarial provision of evidence is modeled as a game in which two parties engage in strategic sequential search. An axiomatic approach is used to characterize a court's decision based on the evidence provided. Although this process treats the evidence submissions in an unbiased way, the equilibrium outcome may still exhibit bias. Bias arises from differences in the cost of sampling or asymmetry in the sampling distribution. In a multi-stage model, a pro-defendant bias arises in the first stage from a divergence between the parties' stakes. Finally, the adversarial process generates additional costs which screen out some otherwise meritorious cases.

1. Introduction

Many economic analyses implicitly (or explicitly) rely upon incentives derived from the legal system; in such discussions the legal system provides an impartial threat that supports the economic activity of interest. Models with contracts anticipate enforcement or appropriate damages should breach occur; models with care-taking by potential injurers and potential victims anticipate compensation, and this feeds back to the choice of precaution by both parties. Many models of markets assume an economic environment involving truthful advertising or noncooperative behavior, implicitly relying upon the imposition of appropriate penalties for misrepresentation or collusion. Moreover, it is probably a common perspective that while legal processes are costly, agents should expect that (at least on average) legal processes are fundamentally unbiased. After all, if a trial occurs, each participant can hire competent counsel, access the same quality of expert testimony, and so forth. In short, we expect the adversarial process embodied by the legal system to generate (at least, on average) unbiased estimates of liability and damages, and therefore agents in the economy should not anticipate significant relative distortions due to the legal process: a deadweight loss, yes, but one that is not systematically influencing different sides of the market differently.[1]

We show that this need not be true even if the process treats the parties in an unbiased manner and they have access to the same resources. In our model, evidence is generated through strategic sequential search[2], with both litigants sampling the same evidence space. Each litigant develops a case wherein they present the best evidence obtained. Evidence is costly and each party's payoff reflects any potential award for damages as well as the costs that party incurred in developing its case. Thus, in equilibrium, the evidence generated and the resource costs are both stochastic, and each party's decisions and costs are influenced by the presence (and attributes) of the other party.

We abstract from the court's (Bayesian) inference problem of assessing the credibility of evidence by restricting consideration to credible evidence. For instance, experts might be employed by both parties to assess the extent of damages and to testify about their opinions. Different expert witnesses (who are all independent and credible to the court, and use "scientific" methods) may have different opinions or use different (but equally scientific) procedures, though their estimates will be correlated because they all draw from the same distribution of evidence. This allows us to model the court's problem as one of applying rules of evidence and procedure in a systematic way to generate a judgment. This is accomplished by employing a set of axioms (stylized versions of the rules) that characterize the aggregation of credible evidence. These axioms, and our motivation for using a non-Bayesian approach to evidence aggregation, are described in Section 2; this discussion is based on Daughety and Reinganum (1998b; hereafter, DR). While we are not attempting to fully characterize an ideal system (though we do briefly address this issue in Section 3), our purpose is to provide a framework that captures important relevant attributes of the existing legal system, some of which are likely to be consistent with an ideal system. We use this framework to examine the source and nature of biases that arise in an adversarial system.

We analyze trials as a two-stage game (this is partly a simplifying assumption, but there are many sequential aspects to a trial, which we discuss in more detail below). In the first stage, the plaintiff and the defendant separately develop and present evidence pertaining to liability. If the defendant is found not liable the game ends and the payoffs reflect the costs incurred to that point; otherwise, the next stage involves both litigants developing and presenting evidence about damages. Thus, for instance, in a products liability case wherein the trial has been bifurcated into a liability phase, followed by a damages phase, the use of expert witnesses by each side in each phase creates the sort of credible evidence generation and presentation costs modeled in Section 2. The anticipation of this evidence being aggregated into a decision results in strategic behavior by both parties: they sample the space of experts, constructing the best case they can and suppressing inconvenient evidence when possible.

We identify four potential sources of bias which may be relevant to a particular case. First, differences in evidence sampling costs can lead to systematic bias in the liability and/or the damages stage, with the bias operating in favor of the party with the lower sampling costs. Second, asymmetry in the sampling distribution of evidence can lead to bias; which party benefits from this asymmetry may also depend on the level of sampling costs. Third, a multi-stage trial process causes a divergence in the parties' stakes at the liability stage (since, in the damages subgame, the defendant will lose the award plus expected trial costs, while the plaintiff will gain the award minus expected trial costs). This results in an equilibrium pro-defendant bias, as it causes the defendant to search more aggressively than the plaintiff in the liability stage. Generally, this suggests that multi-stage legal processes, involving investments by litigants in the various stages, create incentives for relatively greater investments by defendants in the early stages. Finally, since the first move (filing suit) is the plaintiff's, anticipated equilibrium bias in the liability and damages stages, as well as the noncooperative, socially excessive, investment in evidence generation, also distorts the decision to file. Returning to our products liability case from above, we find that most (if not all) of these biases favor the defendant. First, the defendant (typically a corporation) seems likely to have lower evidence sampling costs than the plaintiff in a products liability suit. Second, when damages estimates are exponentially-distributed and there are high evidence sampling costs, the asymmetry in the sampling distribution tends to favor the defendant (because few draws will be taken and thus the plaintiff is unlikely to obtain a high damages estimate). Third, the defendant is always favored by the divergence in stakes. Finally, these accumulated biases lower the plaintiff's expected return to litigation, while the dissipative investment in evidence gathering raises the costs of litigation, leading to a greater likelihood that such cases will be screened out (i.e., never brought by the plaintiff).

Our analysis raises questions about the distortion in economic decisions due to adversarial legal processes, since systematic bias in the outcomes of such processes is likely to influence markets and bargaining that occurs in the "shadow" of the law. For example, again in the products liability context, the typical plaintiff is a consumer and the typical defendant is a manufacturer. We have shown elsewhere that if both parties anticipate undercompensation of consumers then there are reduced incentives for safety-enhancing R&D (Daughety and Reinganum, 1995) and increased incentives for intentional misrepresentation of product safety (Daughety and Reinganum, 1997, 1998a). As another example, this one in a contracts setting, anticipated undercompensation makes breach more likely, reducing the incentive to make relationship-specific investments.

We discuss some piecemeal remedies in Section 3. Examples of such remedies include taxes and subsidies on evidence gathering, fee-shifting and decoupling of monetary judgments and awards. The main problem with all of these remedies concerns the pervasive asymmetric information between the court and the parties. Employing the above remedies generally relies upon information that courts do not have and are not able to acquire in a purely adversarial system.

These biases, and the market distortions they induce, may be unavoidable and reflect a more fundamental tradeoff involving the costs and benefits of decentralized evidence generation in judicial systems. The adversarial process, as a means by which a judicial system generates and evaluates evidence, is one of the two main procedures employed by democratic legal systems; the other is the inquisitorial process, used in many civil law countries, which involves considerably more centralized management of evidence generation by courts (as opposed to each litigant's counsel). We do not consider alternative processes in this paper, but the concentration of power such a centralized process entails may also induce inefficiencies,[3] possibly in excess of the strategically-induced bias we consider here.

Plan of the Paper

In Section 2 the model of the court's evidence aggregation procedure is described. In addition, models of the liability and damages stages are developed and analyzed. Section 3 illustrates potential sources of equilibrium bias via a series of examples and discusses potential remedies and problems with their implementation. Section 4 provides a brief review of related literature. Section 5 contains a summary and conclusions. Formal statements and proofs of the propositions and related results are contained in the Appendix.

2. Model and Analysis

Imagine the following setting. An incident has occurred in which someone has suffered a harm; that person is the plaintiff (P), who sues the defendant (D). We assume that the likelihood, p, that D actually caused the harm and the level of the harm, d, are common knowledge to both P and D but are not verifiable, so they are unknown to the court.[4] Courts recognize the litigants' incentives to misrepresent the level of p and d, so courts require evidence about the likelihood of liability and about the level of damages. Our model involves the selective presentation of verifiable facts which, in aggregate, make a case. This production and presentation of the case is viewed as occurring in two stages, each of which involves strategic search in the relevant evidence space by both litigants. In the first stage evidence on the likelihood that D is liable is presented by both sides; if D is found liable then the game proceeds to the second stage wherein each side again engages in strategic search, now in the space of damages estimates.

Thus, formally, we study a "bifurcated" trial. Federal Rule of Civil Procedure 42(b) specifies the court's option[5] of conducting separate trials "in furtherance of convenience or to avoid prejudice." For instance, bifurcated trials [6] occur in medical malpractice cases in which the plaintiff was severely affected. Trials have been bifurcated in insurance cases if coverage of an event was disputed; the second stage considered the extent of the insurance company's liability. This procedure is also used in various tort cases and some states require it in actions involving punitive damages awards. A very important sphere of application of bifurcation is to class action suits. In cases involving, for example, a dispute over whether a particular product (or company policy) caused plaintiffs' injuries, the issue of liability may be determined jointly for all plaintiffs, with individual suits for damages following upon a finding of liability (see Federal Rule of Civil Procedure 23).

Finally, an alternative interpretation of our two-stage model is that the first stage represents trial, while the second stage represents appeal. Although we view the trial and appeals stages as being inherently about different things (facts versus law; see DR), the impact of sequentiality is the same: the existence of a second stage makes the first-stage stakes diverge for the parties, inducing the type of liability-stage bias we find in Section 3.

In each stage of our model we focus on the incentives for litigants to develop and present evidence, when there is a given cost for acquiring evidence and a known process which aggregates the evidence submitted. In general, we think of each stage as having three components: 1) evidence generation; 2) determination of the credibility of the evidence submitted; 3) aggregation of both parties' evidence into the court's assessment for that stage. As suggested earlier, we collapse the first two components into a model of strategic search for credible evidence. Since both litigants must anticipate how the court will aggregate the submitted evidence, we turn to that issue first.

Modeling the Court's Evidence Aggregation Process

Any positive analysis of a court faces a basic modeling issue: how to model the outcome of the court as a function of the evidence presented (in Section 4 we briefly review how others have modeled court decision-making). It is tempting to assume that the judge or jury is a sophisticated Bayesian decision-maker. Certainly, there are points in a trial where this seems to be an appropriate model; for example, the court can exercise its discretion in determining the credibility of witnesses, and in interpreting the law (subject to review by a superior court). In addition, there are specific uses of statistical evidence (such as DNA evidence), where the probability of misclassification can be clearly quantified, in which Bayesian inference is suitable.

More generally, in a Bayesian model of the liability stage, a court would posit a subjective prior distribution over the submitted evidence on liability (denoted π^{P*} and π^{D*}) and true liability p. Then it would try to estimate p using π^{P*} and π^{D*}. Note that π^{P*} and π^{D*} are both <u>statistically</u> related to p (since they represent the result of sequential sampling from a distribution conditioned on p) and <u>strategically</u> related to p (since they represent the parties' best observations under strategically-chosen stopping rules). Thus, the court is trying to "unwind" both statistical effects and strategic effects. However, the court lacks much of the usual information which would be useful in this "unwinding" process. For instance, included in the category of "missing information" are:

1) Evidence that is relevant and available, but not presented, either because it is strategically suppressed by the parties or because it is inadmissible under the rules of evidence. For example, less favorable observations are not presented, while character evidence, settlement offers and information concerning the insurance status of the

defendant are inadmissible (under, e.g., Federal Rules of Evidence 404, 408 and 411, respectively).

2) The extent of each party's search behavior (e.g., how much the party spent on evidence-gathering and the stopping rule employed) as well as information needed to compute equilibrium stopping rules (such as the parties' wealth and their costs of search) are also unobservable to the court.

3) Finally, the sampling distributions for evidence are conditional on the true values of p and d, which are unobservable to the court (but known by the parties).

Thus, a Bayesian court's decision process would, of necessity, substitute a subjective prior distribution for this missing data, making the resulting estimate highly prior-dependent. As Posner (1999) points out, to the extent that a court's decision relies on a (possibly strong) subjective prior, this reduces the incentives for the parties to provide evidence. It seems likely that exculpatory evidence will be easier to produce if the defendant really has been careful, so reducing the value of exculpatory evidence also reduces the defendant's incentive to take care. To support the provision of both care and evidence, it is reasonable for the legal system to try to restrict the fact-finder's reliance on subjective priors and to focus it instead on the evidence presented at trial.

Moreover, the trial court process itself is <u>not</u> purely Bayesian, since some rules of evidence and procedure are distinctly inconsistent with Bayesian decision-making. This does not mean that these rules are inefficient, only that they may be designed to promote broader objectives than accurate decision-making in the instant case given the instant evidence.

Posner (1999) discusses efficiency-based rationales for many rules of evidence and procedure and Lewis and Poitevin (1997) and Sanchirico (1997c) provide models wherein a sophisticated Bayesian decision-maker prefers to commit (ex ante of observing the evidence) to a decision rule that would not be optimal ex post.

Some policies clearly conflict with an unconstrained Bayesian treatment. In some cases (e.g., the self-incrimination privilege), no inference is to be drawn from a party's decision not to present certain evidence. On the other hand, if a plaintiff provides only statistical evidence, then the plaintiff loses. As Posner (1992, p. 552) observes, "If, for example, the only evidence the victim of a bus accident had linking the accident to the defendant bus company was that the defendant operated 80 percent of the buses on the route where the accident occurred, the victim could not win without additional evidence of the defendant's liability." This is because the "burden of production" of evidence is (at least initially) allocated to the plaintiff, so as to discourage nuisance suits.

Alternatively, the law sometimes requires a specific inference. For example, in employment discrimination cases, the *McDonnell Douglas* rule "permits a plaintiff ... to establish his prima facie case ... with evidence merely that he was qualified for the job but was passed over in favor of someone of another race. But the rule does more: satisfying the just-described burden of production creates a presumption of discrimination, meaning that if the defendant puts in no evidence the plaintiff is entitled to summary judgment," even though "the probability that he lost the job opportunity *because* he was discriminated against might not seem to be very high if the only evidence is as described" (Posner, 1999).

If a judge determines that the evidence in a case is insufficient to support (that is, cannot be construed as supporting) a verdict of liable, he may dismiss the case, enter a directed verdict in favor of the defendant, or even overrule a jury finding of liability by entering a judgment notwithstanding the verdict (j.n.o.v.). Indeed, self-interest alone is not viewed as a reason to discount evidence which is not otherwise impeached by the adversary. According to James and Hazard (1985, p. 348):

> "Where the proponents, having also the persuasion burden, offer testimonial evidence that strongly supports their side of the case and the opponents fail to shake it on cross-examination and offer no countervailing evidence, the proponents may move for a directed verdict. If at this point no presumption operates in the proponents' favor the question may arise whether the jury may reasonably *disbelieve* their evidence... the prevailing view regards the clear, uncontradicted, self-consistent, and unimpeached testimony of even interested witnesses as sufficient basis for a directed verdict in favor of the party having the persuasion burden as well as the initial production burden."

The aforementioned rules and conventions conflict with a purely Bayesian approach, since one could certainly construct very reasonable subjective priors which would reach a decision opposite to the one implied by the rule or convention. Rather, these rules and conventions seem to focus decision-making on the evidence presented at trial and to discourage the substitution of the court's subjective prior. This focus on the evidence presented at trial, and restrictions on the conclusions that can be drawn from it, may also prevent the judge/jury from exercising ideological preferences that differ from the social objective (which is embodied in the restrictions). James and Hazard (1985, Section 7.4) provide a detailed discussion of devices available to judges (such as the provision of instructions, directed verdicts, j.n.o.v. and special verdicts) for the express purpose of controlling a jury with the intent of focusing them on their mission of fact-finding.

Thus we model the trial court's assessment of credible evidence in non-Bayesian terms, not because we do not believe in Bayesian decision-making, but because we believe that the evidence-aggregation process is highly constrained. Whether one models this as "mostly-Bayesian with a few constraints" or "mostly-constrained with a few opportunities for Bayesian updating" is a judgment call. In this paper we take the latter route, but the former is also potentially interesting. As suggested earlier, we confine the use of Bayesian updating to the assessment of credibility and the interpretation of law, and model the evidence aggregation process axiomatically; that is, we use a set of properties (axioms), representing rules of evidence and procedure, to characterize this process. Moreover, we abstract from the credibility issue by assuming that the evidence presented by the parties and evaluated by the court is credible evidence. Alternatively, one could view the trial process as having a preliminary stage which involves evaluating evidence with respect to credibility (using a Bayesian model to appropriately discount it). Thus, the litigants provide credible evidence whether directly submitted or as the result of "pre-processing" for credibility by the jury/judge.

Elsewhere we have considered the problem of modeling a court's assessment process, whereby it aggregates credible evidence on D's liability into an overall assessment (see DR). In particular, let x and y denote the assessments of the likelihood of D's liability proffered at trial by P and D, respectively, where $x \in [0,1]$ and $y \in [0,1]$. In DR we require that the court's aggregation of credible evidence be: 1) strictly monotonically increasing in each of the submissions; 2) bounded by the minimum and maximum of the cases presented; 3) unbiased in the sense that it is symmetric in the evidence in both an absolute and proportional sense and 4) independent of the order in which individual elements of the submissions are compared.

We have assumed symmetry, that is, the court's assessment would be the same for the credible evidence pair (x,y) and (y,x). Since the court is unable (due to informational problems) to "unwind" both the strategic and statistical relationships between evidence and the true p and d, and in light of the assumption that the evidence is credible, it seems reasonable to examine a process for evidence aggregation which is not biased toward either party. Thus, the responsibility for redressing the impact of a party's evidence on the trial outcome falls on the adversary. In DR we also examine the effect of relaxing the symmetry assumption; we maintain it here because our focus is on how bias might arise within an unbiased (symmetric) system.

In DR we show that the foregoing properties imply that the court's liability assessment function can be represented by a member of the family of continuous functions of the form $\ell(x,y;\, q) = \{(x^q + y^q)/2\}^{1/q}$, $q \in (-\infty, \infty)$, $q \neq 0$; and $\ell(x,y;\, 0) = (xy)^{1/2}$. It can be shown (see DR) that $\ell(x,y;\, q)$ is an increasing function of q (for $x \neq y$), so that as q increases, D is more likely to be found liable for any given evidence pair (x,y). Thus, q can represent the breadth of the court's interpretation of the applicable law, with a broader interpretation working against D. In DR we model how different levels of the court system (trial versus appeals courts) determine an appropriate value of q; in Daughety and Reinganum (1999), we use this model to examine horizontal influence (via inference about q) among a collection of appeals courts. In this paper, we simply assume that a value of q has been determined and is common knowledge, and we examine how the parties gather evidence in anticipation of this aggregation process.

Differentiation of $\ell(x,y; q)$ shows that the cross-partial ℓ_{xy} is positive for $q < 1$, zero if $q = 1$, and negative for $q > 1$. For a given q, the sign of the cross-partial derivative is the same for all possible evidence submissions (x,y). This property will be of significant interest in discussing the slopes of the best response functions of the litigants later in this section.

In the damages stage we could employ a similar notion of a "damages assessment function," but have elected to simply use the average of the damages evidence in that stage of the game. This is for two reasons. First, since the damages stage is a subgame of a fairly complex two-stage game, tractability suggests a simple damages function. Second, simple averaging of the damages estimate is consistent with the court imposing the Nash bargaining solution for the bargaining game that would arise once all evidence has been presented; that is, the court splits the difference between the competing claims. For the sake of brevity, we provide the analysis for the liability stage only, and simply summarize the results of a similar analysis for the damages stage at the end of this section.

The Liability Stage

Let $V^P(d)$ and $V^D(d)$ denote the values of continuing optimally for P and D, respectively, following a finding of liability, when it is common knowledge to the parties that the true harm is d. For P, this value represents the expected award less the expected costs associated with equilibrium evidence generation in the damages stage. For D, this value represents the expected award plus the expected costs associated with equilibrium evidence generation in the damages stage. Thus these values, which represent the "stakes" for the liability stage, will not be equal. Rather, $V^D(d) > V^P(d)$; that is, the defendant has more to lose than the plaintiff has to gain.

In this stage, D's liability is to be determined (or, more precisely, the likelihood that D is liable for P's harm will be assessed, with determination modeled as a coin-flip employing the assessed likelihood). Recall that p is the true probability that D harmed P and that we assume that p is common knowledge to P and D, but is not verifiable to a third party. Hence, in the liability stage, both parties will develop and present evidence regarding p. Evidence is represented by a draw from a distribution function which is conditioned on p; since evidence is assumed to be independent of the parties' preferences (i.e., it cannot be manufactured at will), we assume that both parties draw their observations from the same distribution. However, each party's number of observations and their realizations are assumed to be private information. The best observation[7] among those taken will be presented by each party at trial. We assume that each party must take at least one draw: P must present a case based on some evidence and D must respond with some evidence.

Let π_i^P represent the outcome of a single observation by P; similarly, let π_j^D represent the outcome of a single observation by D. Both are assumed to be drawn from the interval

$[\underline{\pi}, \pi]$ according to the distribution function $G(x|p) = \Pr\{\pi_k \quad x \mid p\}$ with mean p and density function $g(x|p)$, where the interval itself may also depend on p. Both parties may sample as many times as they wish from the distribution $G(\; |p)$. We assume that each draw costs k^P for P and k^D for D. There is also a fixed cost of presenting evidence at trial for each litigant; we denote these costs as K^P and K^D for P and D, respectively. We assume a large number of potential sources of credible evidence, so the sampling is with replacement; thus the draws are independent and identically distributed. Each party will choose as a strategy a <u>stopping rule</u>, which specifies when that party should stop sampling as a function of the observations to date. Since each party's number of draws taken and realized observations are private information, each party's stopping rule can depend only on the outcomes of its own evidence-generation process and a conjectured stopping rule for the other party. Larger observations are preferred by P and smaller observations are preferred by D. Thus an optimal stopping rule for P can be characterized by a <u>minimum</u> stopping value, denoted r^P: stop the first time the evidence draw exceeds r^P. Thus, a higher value of r^P corresponds to <u>more</u> aggressive ("tougher") search behavior on the part of P. Similarly, an optimal stopping rule for D can be characterized by a <u>maximum</u> stopping value, denoted r^D: stop the first time the evidence draw falls below r^D. In this case, a higher value of r^D corresponds to <u>less</u> aggressive ("softer") search behavior on the part of D. Let π^{P*} and π^{D*} denote the best evidence observed by P and D, respectively, using these stopping rules. From the perspective of the parties (who know p), the density function for P's evidence at trial is given by $g(x|p)/[1 - G(r^P|p)]$ on the interval $[r^P, \pi]$. The density function for D's evidence at trial is given by $g(y|p)/G(r^D|p)$ on the interval $[\underline{\pi}, r^D]$.

For arbitrary evidence pairs (x,y), the court uses the function $\ell(x,y)$ to aggregate the evidence so as to assess the likelihood of D's liability (we suppress the parameter q when it is not relevant to the discussion at hand). As will become clear, the sign of ℓ_{xy} determines the sign of the slope of the best response functions for P and D (recall that, given q, this sign is the same for all (x,y) pairs). If this cross-partial derivative is positive, then this suggests that $\ell(x,y)$ displays the property of <u>complementarity of evidence</u>, while if it is negative, $\ell(x,y)$ displays the property of <u>substitutability of evidence</u>.[8] In what follows we will assume that $\ell_{xy} > 0$ for the following theoretical and empirical reasons. Under complementarity, the resulting best response functions will have intuitively reasonable slopes (P's will be positive and D's will be negative) in that they predict that as P becomes more aggressive, D does, too; this prediction seems particularly appropriate as it is D's wealth that is at stake should D be found liable. If we assumed $\ell_{xy} < 0$ (that is, substitutability), our technical analysis would go through, but the slopes of the best-response functions (and some comparative statics results) would be reversed. We do not consider this the most plausible case: we would be predicting that D would become less aggressive in response to P being more aggressive. Moreover, it is complementarity that is consistent with empirical analysis of the slopes of the best response functions in the strategic search for evidence. Shepherd (1999) uses data from 369 federal civil suits and studies the responses of litigants to pre-trial discovery effort; he finds the pattern of response implied by complementarity. For these reasons, we proceed under the assumption that $\ell(x,y)$ displays the property of complementarity; that is, $\ell_{xy} > 0$ at all points in the evidence space E.

Propositions 1 and 2 (see the Appendix for formal statements and derivations) characterize the best-response functions for the parties. For any stopping rule r^D chosen by D, P has a unique best response $BR^P(r^D)$, and for any stopping rule r^P chosen by P, D has a unique best response $BR^D(r^P)$. Our maintained assumption that $\ell_{xy} > 0$ ensures that the function $BR^P(r^D)$ is increasing: as D searches less aggressively (referred to earlier as playing "softer"), P searches more aggressively (plays "tougher"). This same assumption ensures that the function $BR^D(r^P)$ is decreasing: as P searches more aggressively, D searches more aggressively. Proposition 3 (see the Appendix) asserts that there is a unique Nash equilibrium in stopping rules, $(r^{P}*, r^{D}*)$. Figure 1 illustrates the best response functions and the equilibrium for a representative case.

Place Figure 1 about here

The impact of changes in the underlying parameters on the best response functions and on the equilibrium strategies are displayed in Table 1 below.

Place Table 1 about here

The signs in the table indicate the effect of an increase in the column entry on the row entry. In Table 1, a positive entry for BR^P or $r^{P}*$ corresponds to a rightward shift of the curve in Figure 1, while a positive entry for BR^D or $r^{D}*$ corresponds to an upward shift of the curve in Figure 1. If an increase in d leads to increases in both $V^P(d)$ and $V^D(d)$, then the new equilibrium involves D being more aggressive but the effect on P's behavior is indeterminate. Increases in sampling costs have an impact that depends upon whose costs increased. If P alone suffers an increase in both sampling costs (k^P and P's sampling cost in the damages stage, an increase in which lowers $V^P(d)$), then $r^{P}*$ falls and $r^{D}*$ rises: both parties play softer by adjusting their stopping rules, so as to put less effort into evidence gathering. This is because both the direct effect (via k^P) and the indirect effect (via the negative effect of an increase in P's sampling costs in the damages stage on $V^P(d)$) reduce $r^{P}*$ and increase $r^{D}*$. On the other hand, if D alone suffers an increase in both sampling costs (k^D and D's sampling cost in the damages stage, an increase in which raises $V^D(d)$), then the effect is ambiguous for both parties: the direct effect via the liability sampling cost k^D is to make P more aggressive and D less aggressive. The indirect effect (the positive effect of an increase in D's sampling costs for the damages stage on $V^D(d)$) is to make P less aggressive and D more aggressive. The net result will be case-specific.

Since P stops the first time an observation occurs in the interval $[r^{P}*, \pi]$, it follows that the expected number of draws for P is given by $1/[1 - G(r^{P}*|p)]$ and the expected cost of liability evidence for P is given by $k^{P}/[1 - G(r^{P}*|p)] + K^{P}$. Similarly, since D stops the first time an observation occurs in the interval $[\underline{\pi}, r^{D}*]$, it follows that the expected number of draws for D in the liability stage is given by $1/G(r^{D}*|p)$ and the expected cost of liability evidence for D is given by $k^{D}/G(r^{D}*|p) + K^{D}$. Note that, in equilibrium, these expressions are also conditional on d since both $r^{P}*$ and $r^{D}*$ depend on both d and p; we suppress this dependence unless it is of specific interest.

The Damages Stage

Finally, we briefly indicate how the same analysis can be used to derive the continuation values $V^{D}(d)$ and $V^{P}(d)$, which are the equilibrium payoffs for the damages stage (for details, see Daughety and Reinganum, 1998c). Let δ_i^{P} represent the outcome of a single observation by P; similarly, let δ_j^{D} represent the outcome of a single observation by D. Both are assumed to be drawn from the interval $[\underline{\delta}, \delta]$ according to the distribution function $F(x|d) = \Pr\{\delta_k \quad x \mid d\}$ with density function $f(x|d)$ and mean d, where the interval $[\underline{\delta}, \delta]$ may also depend on d. Both parties may sample as many times as they wish from the distribution F(|d), at constant per draw costs of c^{P} and c^{D}, respectively (sampling costs may also depend on true harm d, but we suppress this dependence for notational convenience; we return to this issue in Section 3). There is also a fixed cost of trial associated with presenting the evidence for the damages stage at trial; we denote this cost for P by C^{P} and for D by C^{D}. As before, we assume that P submits only the most favorable evidence at trial, which is denoted $\delta^{P}*$; similarly, D's most favorable evidence is denoted $\delta^{D}*$. Thus, the court observes only the pair ($\delta^{P}*$, $\delta^{D}*$). In the damages stage, we consider the case of q = 1; that is, the award at trial is the simple average of the evidence: $A = (\delta^{P}* + \delta^{D}*)/2$.

An equilibrium stopping rule for P is characterized by a <u>minimum</u> stopping value, denoted $s^{P}*$, while an equilibrium stopping rule for D is characterized by a <u>maximum</u> stopping value, denoted $s^{D}*$. Under these stopping rules, the expected award at trial, given true damages d, is given by $E(A|d) = (1/2)[E(x \mid x \quad s^{P}*; d) + E(y \mid y \quad s^{D}*; d)]$, where the expectation is with respect to the distribution $F(\ |d)$. The expected number of draws for P is given by $1/[1 - F(s^{P}*|d)]$ and the expected cost of damages evidence for P is given by $c^{P}/[1 - F(s^{P}*|d)] + C^{P}$. Similarly, the expected number of draws for D is given by $1/F(s^{D}*|d)$ and the expected cost of damages evidence for D is given by $c^{D}/F(s^{D}*|d) + C^{D}$. Thus, $V^{D}(d) = E(A|d) + c^{D}/F(s^{D}*|d) + C^{D}$ and $V^{P}(d) = E(A|d) - c^{P}/[1 - F(s^{P}*|d)] - C^{P}$.

3. Sources and Examples of Equilibrium Bias

Here we illustrate the sources of equilibrium bias via a series of examples. We employ a uniform distribution for evidence because it allows straight-forward computation and because its symmetry allows us to isolate differences in sampling cost and differences in stakes as sources of bias. We also consider the exponential distribution in the particular case of damages evidence, on the basis that very high damages estimates, substantially in excess of the average estimate, are rare but possible. After presenting the examples we will discuss some potential remedies and problems with their implementation.

Example 1: Uniformly-Distributed Damages Evidence

Conditional on the true harm d, let the distribution of evidence obtained on a single draw be given by the uniform distribution $F(x|d) = (x - \underline{\delta})/\Delta$, where $\Delta \quad \delta - \underline{\delta}$. The endpoints of the interval (δ and $\underline{\delta}$) are assumed to be increasing in d. In order to understand whether adversarial sampling leads to equilibrium bias, assume that simple random sampling would yield an unbiased estimate of the true damages: $E(x|d) = (\delta + \underline{\delta})/2 = d$. In order to ensure interior solutions for s^P* and s^D*, we assume that both sampling costs are less than $\Delta/4$. The equilibrium strategies are $s^P* = \delta - 2(\Delta c^P)^{½}$ and $s^D* = \underline{\delta} + 2(\Delta c^D)^{½}$. The expected award can be calculated to be $E(A|d) = d + \{[(\Delta c^D)^{½}] - [(\Delta c^P)^{½}]\}/2$, where the term in brackets is the difference between the defendant's and the plaintiff's expected sampling costs. Thus, the expected value of the award penalizes the party with the higher sampling cost. If both parties have the same sampling costs ($c^P = c^D = c$), then the award will be unbiased in that the expected award will equal the true harm.[9]

Example 2: Exponentially-Distributed Damages Evidence

Conditional on the true harm d, suppose that the distribution of evidence is given by $F(x|d) = 1 - \exp(-x/d)$ for $x \in [0, \infty)$. Thus, for this case, the support of F is unbounded on the right and $\underline{\delta} = 0$. This sampling distribution represents conditions wherein there is a higher probability that a draw comes from the portion below the mean than from the portion above. For instance, limitations on what the law allows as part of a damages estimate (is mental anguish allowed? how are foregone profits on a new product to be computed?) suggest a higher probability of damages estimates below the mean than above it. Thus, for example, in the case of expert witnesses, this may reflect the accumulation of statutes and precedents which have influenced a sizable proportion of these experts to provide relatively "conservative" estimates of damages. On the other hand, creative accounting, varying choices of future returns and likely discount rates, as well as novel but well-supported arguments about sources of potential losses may result in very high damage estimates. Both possibilities are better-represented by the exponential distribution, which concentrates much of the mass of the distribution below the mean but has a rapidly thinning tail to the right of the mean. While it is true that, in reality, damages estimates are not unbounded, specifying an upper bound creates tractability problems, and adds nothing to the analysis. Note also that the tail of the exponential distribution converges (exponentially!) to the axis, suggesting that the probability of draws even moderately higher than the mean is small.

By construction, the expected value of evidence on any one draw is equal to the true harm: $E(x|d) = d$. Thus, again, simple random sampling will lead to an unbiased estimate of the damages. The equilibrium strategy for P is $s^{P*} = \max\{d\ell n(d/2c^P), 0\}$ (that is, a boundary solution occurs when $d/2c^P$ 1)). D's equilibrium strategy, s^{D*}, is defined implicitly by $(s^{D*}/d) + \exp(-s^{D*}/d) = 1 + (2c^D/d)$. Since the left-hand-side is increasing in s^{D*}, there is a unique interior solution to this equation; moreover, $2c^D < s^{D*} < d + 2c^D$.

The expected award given true harm d is $E(A|d) = d + [s^{P*} + s^{D*} - ds^{D*}/(s^{D*} - 2c^D)]/2$. The term in brackets may be positive, negative or zero; that is, the plaintiff may be over-, exactly-, or under-compensated relative to the actual harm d. Comparative statics analysis indicates that an increase in sampling costs (holding d fixed) makes the respective litigant less aggressive while an increase in harm d (holding sampling costs fixed) makes P more aggressive and D less aggressive.

Recall that the plaintiff's expected cost of gathering damages evidence is $c^P/[1 - F(s^{P}*|d)]$ and that, similarly, the defendant's expected cost of gathering evidence is $c^D/F(s^{D}*|d)$. For the exponential case, it is straightforward to show that the equilibrium strategies, the expected award and these expected evidence costs, as well as the measure of bias $b^A(d) = E(A|d) - d$, are all homogenous of degree 1 in (d, c^P, c^D). Thus, equal proportional increases in the basic model parameters d, c^P, c^D result in equal proportional increases in the equilibrium levels of the stopping rules, the equilibrium expected award and the equilibrium expected evidence costs.

Although we have heretofore suppressed any dependence of the sampling costs on the magnitude of harm, it is not unreasonable to assume that there is some relationship between these two. Assuming that $c^P = c^D = c$, Figure 2 below describes combinations of c and d that yield various outcomes. The dashed line labeled "$b^A = 0$" gives (d,c) combinations for which $E(A|d) = d$. For instance, a case involving more harm may be

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Place Figure 2 about here

(technically) more complex, so one would expect that sampling costs should increase with harm d. Let c(d) denote the sampling costs for P and D as a function of the commonly known damages d. If c(d) is proportional to d, then the equilibrium outcome is associated with a ray in Figure 2; two such rays are illustrated as solid lines from the origin. The uppermost ray corresponds to a high proportional sampling cost. In this case, sampling always yields outcomes in which the resulting equilibrium is biased towards D in the sense that $b^A < 0$. The lowermost ray corresponds to a low proportional sampling cost, yielding outcomes in which the resulting equilibrium is biased towards P in the sense that $b^A > 0$. Note that this means that whatever is true for an outcome of a given level of damages, say d , is true for all levels of damages: in the case of proportional sampling costs, all outcomes are either biased towards D ($b^A < 0$), biased towards P ($b^A > 0$) or unbiased ($b^A = 0$).

The case of c(d) concave is shown as the curved line in Figure 2. This is likely to be a reasonable representation in that increases in the severity of the harm may initially occasion greater reliance on specialized experts, but this specialization effect should eventually disappear: as d increases, the same general level of experts will be used. In the concave-cost case, plaintiffs with low values of d will suffer pro-defendant bias, while those with high levels of d will enjoy pro-plaintiff bias.[10] Thus, the general pattern is one of systematic bias in equilibrium, but who benefits is dependent on the level of actual harm. Plaintiffs with low levels of harm tend to be under-compensated, while those with high levels of harm are potentially over-compensated in equilibrium.

Example 3: Equilibrium Bias in the Liability Stage

Due to the complexity of the analysis of the liability stage, we consider the simplest possible unbiased system, wherein $\ell(x,y) = (x + y)/2$, the distribution of evidence (given p) is uniform on $[\underline{\pi}, \pi]$ with $(\underline{\pi} + \pi)/2 = p$, and $\underline{\pi}$ and π are also functions of p.[11] Thus, the court gives equal weight to both parties' evidence and the common evidence distribution being sampled provides equal likelihood of any piece of evidence being drawn. As shown below, even if the sampling costs in both stages are symmetric (that is, $k^P = k^D$ and $c^P = c^D$), the fixed costs are symmetric ($K^P = K^D$ and $C^P = C^D$) and the damages stage is unbiased (for example, F is the uniform distribution), the liability stage will favor the defendant.

In this example the equilibrium strategies are given by $r^{P*} = \pi - 2(k^P\Pi/V^P(d))^{½}$ and $r^{D*} = \underline{\pi} + 2(k^D\Pi/V^D(d))^{½}$, where $\Pi \quad \pi - \underline{\pi}$.[12] The expected costs of liability evidence for P are $[(\Pi V^P(d)k^P)^{½}]/2$, while for D they are $[(\Pi V^D(d)k^D)^{½}]/2$. Thus, in each case, the expected costs of gathering liability evidence is increasing in both the continuation payoff from the damages stage and in the per sample evidence cost of the liability stage.

The question of bias in the liability stage concerns the liability assessment that such a trial is likely to produce. In particular, the liability stage is unbiased if the expected assessment of liability produced by the trial, $E[\ell(\pi^{P*},\pi^{D*})|p,d]$, equals the true underlying likelihood, p. To measure this, let $b^{\ell}(p,d) \quad E[\ell(\pi^{P*},\pi^{D*})|p,d] - p$. The equilibrium expected liability assessment is given by $E[\ell(\pi^{P*},\pi^{D*})|p,d] = [E(\pi^{P*}|p,d) + E(\pi^{D*}|p,d)]/2 = ([(\pi + r^{P*})/2] + [(\underline{\pi} + r^{D*})/2])/2$. Substituting the equilibrium strategies for P and D yields:

$$E[\ell(\pi^{P}*,\pi^{D}*)|p,d] = p + [(\Pi k^{D}/V^{D}(d))^{½} - (\Pi k^{P}/V^{P}(d))^{½}]/2.$$

Assuming an otherwise symmetric process in which sampling costs are the same for both parties (i.e., $k^P = k^D = k$), it is clear that the liability stage is equilibrium-biased toward defendants, since $V^D(d) > V^P(d)$. In this case,

$$b^{\ell}(p,d) = (\Pi k)^{½}[(V^{D}(d))^{-½} - (V^{P}(d))^{-½}]/2 < 0.$$

Notice that the direction of the liability stage equilibrium bias is independent of both the extent and direction of any damages stage equilibrium bias, including the possibility that the damages stage is unbiased (as was discussed in the uniformly-distributed damages evidence example presented above).[13] Moreover, if there is systematic bias in the damages stage, the liability stage may simply reinforce it. If we consider exponentially-distributed damages evidence with concave sampling costs, then plaintiffs with low actual damages, who expect the damages stage to be pro-defendant equilibrium-biased, also suffer from pro-defendant equilibrium bias in the liability stage. On the other hand, plaintiffs with high actual harm, who expect the damages stage to be pro-plaintiff equilibrium-biased, anticipate a pro-defendant equilibrium bias in the liability stage. Finally, if $V^P(d)$ and $V^D(d)$ are linearly homogeneous in d, then the extent of bias diminishes as d increases.[14]

Example 4: Adversarial Bias

As shown above, systematic bias can readily arise in either stage and the two biases studied need not cancel each other. In each stage bias which favors one party disfavors the other. If we consider the overall game, however, the adversarial procedure as the means for generating evidence may readily work against both parties. To see this, we compare the payoffs from the game (denoted $V^{P}*(p,d)$ and $V^{D}*(p,d)$) with a hypothetical payoff constructed from a non-adversarial alternative (denoted $V^{PN}(p,d)$ and $V^{DN}(p,d)$). For the non-adversarial alternative we consider the expected payoffs if each party drew one observation for each stage and liability and damages were based on these draws using simple averaging for both the liability assessment and the damage award assessment. Thus, $V^{PN}(p,d) = p(d - c^{P} - C^{P}) - k^{P} - K^{P}$ and $V^{DN}(p,d) = p(d + c^{D} + C^{D}) + k^{D} + K^{D}$, while

$$V^{P}*(p,d) = E[\ell(\pi^{P}*,\pi^{D}*)|p,d]\{E(A|d) - c^{P}/[1 - F(s^{P}*|d)] - C^{P}\} - k^{P}/[1 - G(r^{P}*|p)] - K^{P}$$

and

$$V^{D}*(p,d) = E[\ell(\pi^{P}*,\pi^{D}*)|p,d]\{E(A|d) + c^{D}/F(s^{D}*|d) + C^{D}\} + k^{D}/G(r^{D}*|p) + K^{D}.$$

For example, in $V^{P}*(p,d)$, the expression on the right-hand-side in braces is the net expected value to P from the damages stage (expected award minus the expected costs of damages evidence). Multiplying that on the left is the expected outcome from the liability stage while to the right of the braces we subtract the expected costs to P of liability evidence; the terms in $V^{D}*(p,d)$ can be similarly interpreted. In order to discuss <u>adversarial bias</u>, we define $B^{P}(p,d)$ $V^{P}*(p,d) - V^{PN}(p,d)$ and $B^{D}(p,d)$ $V^{D}*(p,d) - V^{DN}(p,d)$.

The presence of variable and fixed costs of evidence-gathering and presentation, even in the non-adversarial case, screens out some otherwise meritorious cases, but this would seem to be an unavoidable friction necessary to ration use of the court system. If $B^{P}(p,d)$ is negative, however, this means that adversarial process results in yet more meritorious cases never reaching trial. As the earlier examples suggest, $B^{P}(p,d)$ is likely to be strongly negative unless the award bias $b^A(d)$ is sufficiently positive. Thus if damages estimates are uniformly distributed (or exponentially distributed with high proportional sampling costs), all plaintiffs would expect to be undercompensated. In the exponential case with concave sampling costs, cases with low-to-moderate harm would be screened out entirely: only cases involving substantial harm are likely to actually benefit from adversarial evidence generation.

The results for the defendant are more mixed. In general, as should be clear from the biases examined earlier in this section, cases involving lower levels of harm are likely to favor the defendant, both in absolute terms and when compared with a non-adversarial process. However, in cases involving high levels of harm, adversarial process may work against the defendant as well (when compared with non-adversarial evidence generation, since adversarial litigants will typically sample more than once). While these conclusions regarding the nature and extent of equilibrium bias are based on computational examples using simple functional forms, it seems unlikely that more complex functional forms will result in a complete "undoing" of the biases described here.

Remedies and Problems of Implementation

While a number of possible piecemeal remedies suggest themselves, all are plagued by problems of implementation due to the limited information available to the court. For example, suspicion of bias due to asymmetry of sampling costs suggests taxing the low-cost (or subsidizing the high-cost) sampler, so as to re-level the playing field. To tax or subsidize each draw necessitates knowing the number of draws. Since this is private information, there are incentives to misrepresent it. Shifting some or all of one litigant's costs to the other creates yet more problems, as it encourages overinvestment in evidence generation by the party able to shift costs. For instance, following a finding of liability, a pure loser-pays rule means that P should spare no expense in the damages stage. Thus, this would both raise costs and contribute to a pro-plaintiff bias in the damages stage; anticipating this will lead both P and D to further overinvest in the liability stage.

As we found in the exponentially-distributed damages evidence example, even when sampling costs are equal, bias arises. Here correction would require that the court know d, the true damages, because the sampling distribution is conditioned on d and the direction of the bias may change as a function of d (as in the nonlinear case illustrated in Figure 2). Of course, "knowing" d begs the question, as the point of the trial is to estimate d. Moreover, since each trial presents biased evidence, one cannot rely upon experience in "similar" cases to generate a valid estimate of the underlying damages evidence distribution: the outcome of a series of trials does not provide, for example, a simple random sample; it provides a complexly-biased sample, with unknown characteristics of how the sample was generated.

A natural solution to the bias induced by the divergence of stakes is to make the stakes equal (a form of decoupling; see Polinsky and Che, 1991). Either society subsidizes at least one of the litigant's costs (with the attendant problems of mis-reporting and over-investment in evidence generation) or the award P receives must be subsidized to equate the stakes. Moreover, the amount of subsidy required depends upon unobservables (e.g., d).

Finally, as discussed in our last example, adversarial litigants sample too much. A tax is the natural remedy, with all the problems raised earlier for taxes and subsidies when the underlying parameters are unknown and the number of draws is unobservable.

A possible solution lies in greater centralization, via either a properly designed mechanism for (decentralized) information gathering and revelation or centralized information gathering. The latter possibility is subject to the problems raised by Posner (1999) and others with respect to inquisitorial systems. While the former is appealing, it cannot be applied to the trial portion of the legal process in a vacuum. Rather, one needs to characterize the optimal mix of incentive constraints and opportunities for discretion throughout the entire legal process, so as to induce efficient choices of care as well as evidence generation and revelation. This does suggest, however, an intermediate remedy that may ameliorate the aforementioned informational effects. Courts in adversarial systems could independently acquire evidence, something that is commonly used in child custody disputes and has been used in a few tort cases (e.g., appointing a scientific panel to evaluate the medical evidence regarding breast implants). A careful analysis of the incentives facing litigants, and the implications for bias in the aggregate decision, generated by use of this option lies beyond the scope of the current paper.

4. Related Literature

There are several different models of trial court decision-making. For instance, one alternative views the trial outcome as an exogenous function of the litigants' levels of effort or expenditure (for a review of much of this literature, see Cooter and Rubinfeld, 1989; specific examples include Danzon, 1983; Braeutigam, Owen and Panzar, 1984; Katz, 1987, 1988; Plott, 1987; Hause, 1989 and Landes, 1993). Our approach differs in that the function which is used by the court to assess the evidence is not specified exogenously, but is derived from a set of axioms (Skaperdas, 1996, has recently provided an axiomatic basis[15] for the relative effort models used in these earlier works). A second difference is that the trial outcome is based on evidence provided by the parties, rather than effort or expenditure, both of which are unobservable in our model. Indeed, we find that trial outcomes cannot be represented by a function of expenditure (and expected trial outcomes are not a function of expected expenditure).[16] Since evidence is obtained through sequential search, trial effort and expenditures are stochastically related to the actual evidence presented in such a way that one cannot substitute effort or expenditure for evidence in the liability determination.

Another expenditure-based approach assumes multiple potential types of defendant (e.g., innocent and guilty; or negligent and non-negligent). A defendant's type is private information; only the level of expenditure can signal (to a sophisticated Bayesian decision-maker) his guilt or innocence. Assuming it is less costly for an innocent defendant to claim innocence, an innocent defendant reveals himself to be innocent by (essentially) outspending a guilty one (specific examples include Rubinfeld and Sappington, 1987; and Sanchirico[17], 1997a,b). In these signaling-based models, the litigants are unable to present evidence which is inherently credible (i.e., "scientific"); rather, it is his willingness to engage in significant expenditures which reveals his type. Sobel (1985), Shin (1994, 1998), Lewis and Poitevan (1997) and Sanchirico (1997c) provide models in which the parties have private information, but may not present it because it is costly to do so. They allow a sophisticated Bayesian arbitrator or court to re-allocate the burden of proof (either ex post, based on the evidence provided, or ex ante, to influence the evidence to be provided).

Milgrom and Roberts (1986) assume that the decision-maker is uninformed and strategically naive, but that both parties know all the pieces of relevant information, which can be conveyed costlessly and credibly to the decisionmaker. They show that the adversarial behavior of the parties results in full revelation; thus the outcome coincides with the full information optimal decision (extensions include Lipman and Seppi, 1995; and Seidmann and Winter, 1997). In our model, the parties have common knowledge of the defendant's true liability and the plaintiff's true damages, but these are unverifiable to the court; and while the outcomes of their evidence draws are verifiable, they are also private information for each party and will therefore only be provided selectively.

Finally, Froeb and Kobayashi (1996) address the issue of trial bias by focusing on liability determination by a jury in a comparative negligence framework (with known damages). They model evidence-generation as a sequence of coin flips conducted by both litigants; each litigant chooses when to stop. The jury is assumed to be strategically naive (i.e., it does not recognize the parties' strategic incentives to present or suppress evidence) and potentially biased. On the other hand, it is statistically sophisticated, updating its prior distribution on the basis of the number of heads and tails reported. Given this updating process and the specific functional form of the sampling distribution, Froeb and Kobayashi show that the jury will nevertheless make unbiased decisions (i.e., its posterior expected liability equals the defendant's true liability). However, this result is sensitive to a number of assumptions, including the form of the sampling distribution, the symmetry of the litigants and the specification of comparative negligence.[18] Farmer and Pecorino (1998) reexamine this model under an alternative specification of jury bias and find that initial bias can be exacerbated (not ameliorated) by selective evidence production. Our model differs from Froeb and Kobayashi's (as well as from the signaling-based literature described above) in that our court is constrained by the rules of evidence and procedure to obey a set of axioms in its aggregation of (credible) evidence, rather than using statistical methods.

5. Conclusions and Extensions

In this paper we have examined aspects of the adversarial trial process which might lead to systematic bias in trial outcomes. Through a collection of algebraic examples we have shown that systematic bias can be imparted in several ways. First, systematic bias can arise due to differences in the cost of sampling evidence. For instance, when the damages stage involves a uniform distribution from which evidence is drawn, the party with the lower sampling costs will sample (on average) more often and the award will be systematically biased in this party's favor. Second, asymmetry in the sampling distribution (given equal sampling costs) can result in systematic bias. When the damages stage involves an exponential distribution from which the evidence is drawn, if sampling costs are identical and proportional to true harm, then the award will exhibit a constant proportional bias which may be either positive or negative, with the direction of the bias a function of the sampling cost parameter. A high value of the cost parameter favors the defendant, since few draws will be taken and the chance of the plaintiff obtaining a draw in the upper tail is low; a low value of the cost parameter favors the plaintiff, since many draws will be taken and the chance of the plaintiff obtaining a draw in the upper tail is higher. If sampling costs are not proportional to actual harm, the award will be downward-biased for some levels of harm and upward-biased for others; however, there is no reason to believe that these biases "cancel out" in expectation. Third, a systematic pro-defendant bias arises in the liability stage due to a divergence between the parties' respective stakes. This divergence is a consequence of sequential decision-making over multiple stages: at each stage, the plaintiff's continuation value is the expected award less future evidence and trial costs, whereas the defendant's continuation value is the expected award plus future evidence and trial costs. Finally, the adversarial process itself generates additional costs relative to a non-adversarial evidence generation process and acts to further screen out otherwise meritorious cases.

Such systematic bias is important because it is likely to have an impact on market processes which rely on legal enforcement. For example, the undercompensation of consumers harmed by products is likely to lead to reduced demand, which may mean fewer products developed or units produced. Products liability defendants who anticipate that consumers will be undercompensated have a further incentive to intentionally misrepresent safety and weakened incentives to improve it. Our example with exponentially distributed damages evidence and concave sampling costs suggests that R&D may be diverted to developing products with a low probability of causing high harms but a relatively high probability of causing low-to-moderate harms. This pattern of bias may also encourage firms to devote resources to legal and political efforts to limit compensatory damages; such limits have been implemented in a number of states. Finally, in a contracts setting, anticipated undercompensation reduces the incentive to make relationship-specific investments, as breach becomes more likely.

The point of this paper is that there is reason to expect that adversarial processes are not unbiased and may create inefficiencies in the economic relationships that depend upon them for enforcement or compensation. The source of such inefficiencies is the now familiar combination of incomplete information and sequential choice by self-interested agents. If agents in economic relationships anticipate a systematic bias in enforcement or compensation, then prediction of the outcome of those relationships (prices charged, units sold, investments made, bargains struck) must also account for this bias.

Appendix

<u>Proposition 1</u>: P's optimal strategy is to stop after m draws with most favorable evidence of π^P_m, given that D uses the stopping rule r^D and the true probability of liability is p, if and only if the expected contribution of the incremental evidence, net of the cost of another draw, is nonpositive:

$$\mathcal{W}^P(\pi^P_m, r^D; p) \quad [V^P(d)/G(r^D|p)] \quad [\ell(x,y) - \ell(\pi^P_m, y)]g(y|p)g(x|p)dydx - k^P \quad 0,$$

where the first integral is over $x \in [\pi^P_m, \pi]$ and the second is over $y \in [\underline{\pi}, r^D]$.

<u>Proof:</u> Since the sampling cost is constant, a myopic stopping rule is optimal. Let $W^P(\pi^P_m, r^D; p)$ denote the payoff to the plaintiff from stopping now with best observation π^P_m, given that the defendant uses the strategy r^D and that the true probability that D harmed P is p; then:

$$W^P(\pi^P_m, r^D; p) = [V^P(d)/G(r^D|p)] \quad \ell(\pi^P_m, y)g(y|p)dy,$$

where the integral is over $y \in [\underline{\pi}, r^D]$. If, rather than stopping with evidence π^P_m, P samples once more and then stops, P's payoff (gross of sampling costs) is given by:

$$EW^P(\pi^P_{m+1}, r^D; p) = W^P(\pi^P_m, r^D; p)G(\pi^P_m|p) + \quad W^P(x, r^D; p)g(x|p)dx,$$

where the integral is over $x \in [\pi^P_m, \pi]$. Thus, it is optimal for P to stop at π^P_m if and only if the benefits of one more draw do not exceed the costs of one more draw. Let the benefit of one more draw net of the cost of one more draw be denoted:

$$\mathcal{W}^P(\pi^P_m, r^D; p) \qquad [W^P(x, r^D; p) - W^P(\pi^P_m, r^D; p)]g(x|p)dx - k^P,$$

where the integral is over $x \in [\pi^P_m, \pi]$. Substituting and simplifying yields $\mathcal{W}^P(\pi^P_m, r^D; p)$

$[V^P(d)/G(r^D|p)] \quad [\ell(x,y) - \ell(\pi^P_m, y)]g(y|p)g(x|p)dydx - k^P$, where the first integral is taken over $x \in [\pi^P_m, \pi]$ and the second is taken over $y \in [\underline{\pi}, r^D]$. QED

Note 1. Notice that $W^P(\pi, r^D; p) < 0$ and that $W^P(\pi^P_m, r^D; p)$ is a decreasing function of π^P_m. The limiting value of $W^P(\pi^P_m, r^D; p)$ as $r^D \quad \underline{\pi}$ is $W^P(\pi^P_m, \underline{\pi}; p) = V^P(d) \quad [\ell(x, \underline{\pi}) - \ell(\pi^P_m, \underline{\pi})]g(x|p)dx$, where the integral is taken over $x \in [\pi^P_m, \pi]$. Under the additional assumption that $W^P(\underline{\pi}, \underline{\pi}; p) > 0$, it follows that for all r^D, P has a unique best response $BR^P(r^D) \in (\underline{\pi}, \pi)$ which is defined implicitly by $W^P(BR^P(r^D), r^D; p) = 0$. The sign of $dBR^P(r^D)/dr^D$ is the same as the sign of

$$W^P/ \ r^D = [V^P(d)g(r^D|p)/(G(r^D|p))^2]$$

$$[\ell(x, r^D) - \ell(\pi^P_m, r^D) - (\ell(x,y) - \ell(\pi^P_m, y))]g(y|p)g(x|p)dydx,$$

where the first integral is taken over $x \in [\pi^P_m, \pi]$ and the second is taken over $y \in [\underline{\pi}, r^D]$.

Our previous assumption that $\ell_{xy} > 0$ ensures that $W^P/ \ r^D > 0$.

Proposition 2: D's optimal strategy is to stop after m draws with most favorable evidence of π^D_m, given P uses the stopping rule r^P and the true probability of liability is p, if and only if:

$$W^D(\pi^D_m, r^P; p) = [V^D(d)/(1 - G(r^P|p))] \quad [\ell(x,\pi^D_m) - \ell(x, y)]g(x|p)g(y|p)dxdy - k^D$$

0,

where the first integral is over $y \in [\underline{\pi},\pi^D_m]$ and the second is over $x \in [r^P, \pi]$.

Proof: Again, since the sampling cost is constant, a myopic stopping rule is optimal. Let $W^D(\pi^D_m, r^P; p)$ denote the payoff to the defendant from stopping now with best observation π^D_m, given that the plaintiff uses the strategy r^P and that the true probability that D harmed P is p. Then:

$$W^D(\pi^D_m, r^P; p) = [V^D(d)/(1 - G(r^P|p)] \quad \ell(x,\pi^D_m)g(x|p)dx,$$

where the integral is taken over $x \in [r^P, \pi]$. If, rather than stopping with evidence π^D_m, D samples once more and then stops, D's payoff (gross of sampling costs) is given by:

$$EW^D(\pi^D_{m+1}, r^P; p) = W^D(\pi^D_m, r^P; p)[1 - G(\pi^D_m|p)] + \quad W^D(y, r^P; p)g(y|p)dy,$$

where the integral is over $y \in [\underline{\pi},\pi^D_m]$. Thus, it is optimal for D to stop at π^D_m if and only if the benefits of one more draw do not exceed the costs of one more draw. Since D wants to minimize loss, the benefit of one more draw net of the cost of one more draw is given by:

$$\mathcal{W}^D(\pi^D_m, r^P; p) \qquad [W^D(\pi^D_m, r^P; p) - W^D(y, r^P; p)]g(y|p)dy - k^D,$$

where the integral is over $y \in [\underline{\pi}, \pi^D_m]$. Substituting and simplifying yields $\mathcal{W}^D(\pi^D_m, r^P; p) = [V^D(d)/(1 - G(r^P|p))] \quad [\ell(x,\pi^D_m) - \ell(x, y)]g(x|p)g(y|p)dxdy - k^D$, where the first integral is over $y \in [\underline{\pi},\pi^D_m]$ and the second is over $x \in [r^P, \pi]$. QED

Note 2: Notice that $\mathcal{W}^D(\underline{\pi}, r^P; p) < 0$ for all r^P and that $\mathcal{W}^D(\pi^D_m, r^P; p)$ is an increasing function of π^D_m. The limiting value of $\mathcal{W}^D(\pi^D_m, r^P; p)$ as $r^P \quad \pi$ is $\mathcal{W}^P(\pi^D_m, \pi; p) = V^D(d) \; [\ell(\pi,\pi^D_m) - \ell(\pi,y)]g(y|p)dy$, where the integral is over $y \in [\underline{\pi}, \pi^D_m]$. Under the additional assumption that $W^D(\pi,\ \pi; p) > 0$, it follows that for all r^P, D has a unique best response $BR^D(r^P) \in (\underline{\pi},\ \pi)$ which is defined implicitly by $W^D(BR^D(r^P), r^P; p) = 0$. The sign of $dBR^D(r^P)/dr^P$ is the opposite of the sign of

$$W^D/\ r^P = [V^D(d)g(r^P|p)/(1 - G(r^P|p))^2]$$

$$[\ \ell(x,\pi^D_m) - \ell(x,y) - (\ell(r^P, \pi^D_m) - \ell(r^P, y))]g(x|p)g(y|p)dxdy,$$

where the first integral is over $y \in [\underline{\pi}, \pi^D_m]$ and the second is over $x \in [r^P, \pi]$. Our previous assumption that $\ell_{xy} > 0$ ensures that $W^D/\ r^P > 0$.

<u>Proposition 3</u>: There exists a unique Nash equilibrium for the liability stage (r^{P*}, r^{D*}).

<u>Proof</u>: The composition of the two continuous monotonic best response functions is a continuous, decreasing function from $[\underline{\pi},\ \pi]$ to itself. Therefore, a fixed point exists and, since the composition function intersects the 45^o-line only once, the fixed point is unique. QED

Footnotes

We thank Luke Froeb, Tracy Lewis, Richard Posner, Kathryn Spier, Nick Zeppos and two anonymous referees for helpful comments and suggestions.

1. Our interest here is in sources of bias in the adversarial process. One might want to affect different sides of the market differently if the issue is deterrence, which is not our focus in this paper.

2. Strategic sequential search was first discussed by Jennifer Reinganum (1982) in the context of R&D by firms in a duopoly.

3. See Posner (Section II.A.1, 1999) for an extensive discussion of the relative efficiencies of adversarial and inquisitorial processes. See also Shin (1998) and Dewatripont and Tirole (1999) for models in which the adversarial process is superior to the inquisitorial process.

4. Our model picks up after any settlement negotiations have failed. Typically, pre-trial negotiation occurs after some preliminary evidence-gathering by each side, but before all the evidence that would be used at trial has been gathered. Thus, the negotiations are conducted under asymmetric information. In a revealing equilibrium for a signaling model of such negotiations (see, e.g., Reinganum and Wilde, 1986) two things happen: the asymmetric information is revealed and some cases fail to settle. Thus, the parties can end up failing to settle despite having learned the true values of p and d. They then continue to gather evidence for the anticipated trial, generating asymmetric information again, now about what can be demonstrated to the court.

5. According to Landes (1993, pp. 99-100), “Rule 42(b) gives courts wide discretion to

separate substantive issues. These include bifurcating liability and damages, separating claims asserted by the plaintiff, separating counterclaims raised by the defendant, deciding whether a contract exists before considering claims based on its existence, and deciding whether a product-liability defendant manufactured the allegedly defective product before considering liability and damages."

6. Usually the two stages follow in close succession, though in some cases there may be a substantial lag. When Polaroid sued Kodak for patent infringement with respect to instant photography, the liability trial occurred in 1985 and the damages trial occurred in 1990 (Landes, 1993, p. 99, fn 1).

7. An alternative (but fundamentally equivalent) approach to that used here is that a case is developed incrementally and is the sum of evidence observations rather than the maximum/minimum. In this approach, the distribution of each additional evidence draw is conditional on the current sum, with an increasingly higher mass point at zero (corresponding to the outcome "no new favorable evidence") to reflect decreasing returns to sampling.

8. In terms of $\ell(x,y; q)$, complementarity implies that $q < 1$ while substitutability implies that $q > 1$. This means that if $\ell(x,y; q)$ reflects complementarity, then it acts like a production function from neoclassical economics (in this case, a symmetric CES production function), while if $\ell(x,y; q)$ reflects substitutability, it acts like a norm, or distance measure.

9. If $c \quad \Delta/16$, then $s^{P*} \quad s^{D*}$; that is, P's evidence will always suggest damages in excess of those suggested by D's evidence. If $c > \Delta/16$, then $s^{P*} < s^{D*}$; in this case, there is a chance

that P's evidence will suggest lower damages than those suggested by D's evidence. This counter-intuitive second possibility can occur if sampling is very costly because of the simultaneous presentation of evidence. One might think that, upon hearing the plaintiff's expert ask for lower damages than the defendant's expert, the defendant would simply stipulate to the plaintiff's estimate. However, this should lead the plaintiff to wonder why the defendant's expert is not testifying and might lead the plaintiff to call the defendant's expert to get his higher estimate into the record as well. This possibility suggests a model involving the sequential submission of evidence and the ability to cross-examine, which is beyond the scope of the present analysis.

10. Note that, if c(d) was a constant positive number, then the same pattern would arise. It is possible, however, that the sampling costs curve eventually becomes convex at high values of d, where congestion effects predominate (e.g., where extensive use of technology-intensive batteries of expert witnesses may be necessary).

11. Note that, in this case, $\ell_{xy} = 0$; thus, the litigants have dominant strategies.

12. In order to ensure that r^{P*} and r^{D*} lie in the interval $[\underline{\pi}, \pi]$, it is necessary to assume that $k^P \quad \Pi V^P(d)/4$ and $k^D \quad \Pi V^D(d)/4$, respectively. Again, it is possible for the stopping sets $[\underline{\pi}, r^{D*}]$ and $[r^{P*}, \pi]$ to overlap if sampling is relatively costly; for the case of symmetric costs ($k^P = k^D = k$), a sufficient condition for $r^{P*} \quad r^{D*}$ is $k \quad \Pi V^P(d)V^D(d)/4[(V^P(d))^{½} + (V^D(d))^{½}]^2$.

13. Landes (1993) uses an "inconsistent priors" model (i.e., parties have individual subjective

assessments of the probability of their winning at trial, which are common knowledge, but do not obey any consistency condition such as being conditional probabilities derived from the same prior) to examine the impact of bifurcating trials on the aggregate cost of litigation. He notes (p. 117) that the sequential nature of a bifurcated trial affects the parties' incentives to invest (lowering the plaintiff's incentives and raising the defendant's), so that the defendant's chance of prevailing (as perceived by either party) is increased relative to a non-bifurcated trial. While he does not address the issue of bias directly, if the non-bifurcated trial were itself unbiased (which issue cannot be addressed using inconsistent priors since there is no "correct" probability), then his finding would be consistent with ours.

14. If we consider the exponential damage estimates case with symmetric sampling and trial costs which are proportional to d, then $V^P(d)$ and $V^D(d)$ are linearly homogeneous in d.

15. We thank Tracy Lewis for pointing out this related paper.

16. This is because we employ sequential search with a continuous evidence space. A model employing non-sequential search, in which parties commit to a specific number of draws (or commit to a specific level of evidence), could generate such a representation.

17. In Sanchirico's principal-agent model, the cost of evidence is actually determined by the court; that is, the defendant is charged a fee which varies with the evidence presented.

18. Since completing this paper, we have become aware of another working paper by Froeb and Kobayashi (1999), in which they model evidence generation as sequential search. Each party presents only their best evidence at trial, and the court aggregates evidence by using a simple average (leading to dominant strategies). Thus, their model is similar to our treatment

of the damages stage. However, they do not address the issue of bias; indeed, they eliminate bias by construction and focus on comparing the adversarial and inquisitorial processes in terms of cost and variance. Moreover, they consider a single stage, rather than the two-stage trial we consider; we also allow more general aggregation procedures, leading to equilibria that do not rely on dominant strategies.

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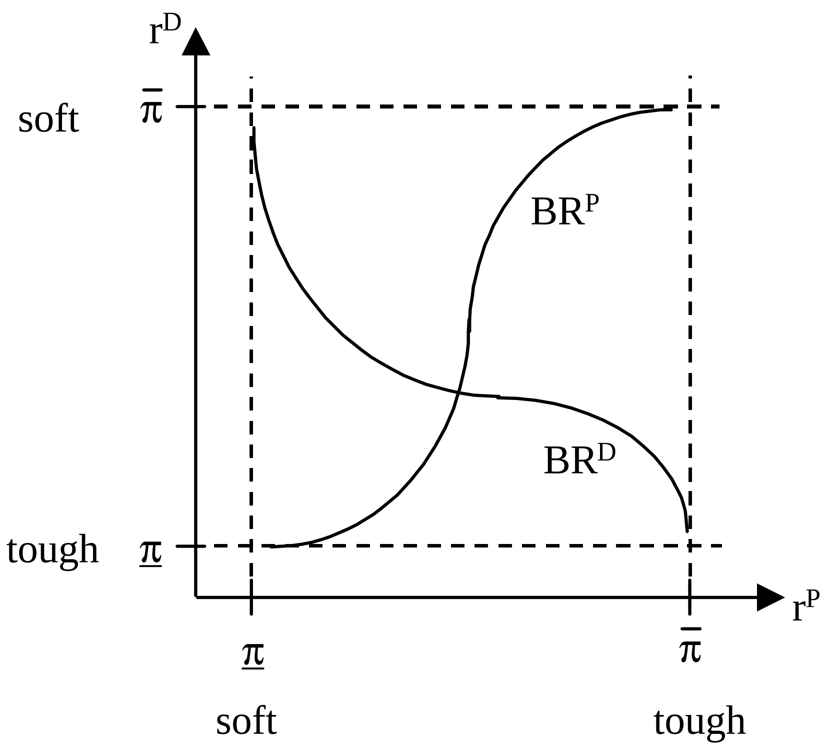
Figure Captions

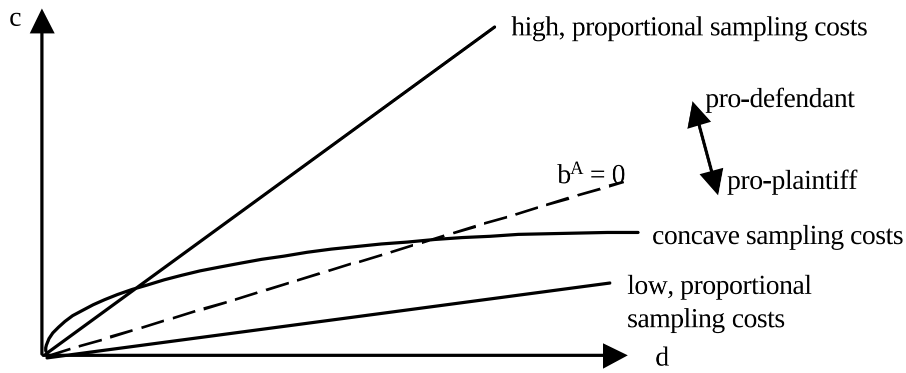
Figure 1: Best Response Functions and Nash Equilibrium

Figure 2: (d,c) Combinations Yielding Various Damages-Trial Outcomes and Three Sampling Cost Functions

Table 1: Comparative Statics

	$V^P(d)$	$V^D(d)$	k^P	k^D
BR^P	+	0	-	0
BR^D	0	-	0	+
r^P*	+	-	-	+
r^D*	-	-	+	+


r^D
soft
$\bar{\pi}$
BR^P
BR^D
tough
$\underline{\pi}$
r^P
$\underline{\pi}$
$\bar{\pi}$
soft
tough


c
high, proportional sampling costs
pro-defendant
$b^A = 0$
pro-plaintiff
concave sampling costs
low, proportional
sampling costs
d