THE JURY EFFECT ON PUNITIVE DAMAGES: AN EMPIRICAL ANALYSIS

by

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Abstract

This paper performs an econometric analysis of punitive damages. A model is developed to describe the probability and amount of punitive awards, which is then applied to two data sets. The data sets, the 1996 and 2001 *Civil Justice Survey of State Courts*, contain information on cases tried to verdict in 45 and 46 counties respectively. The primary results, controlling for a number of trial characteristics, indicate that the probability and amount of punitive awards are higher for juries than for judges. This result is robust with the inclusion of two previously unstudied influences on punitive damages: poverty rates and political leanings. However, the results become inconsistent when controlling for selectivity bias.

Introduction

Is it efficient for a court to award 145 billion dollars in punitive damages? That was the amount given to the plaintiff in the 2000 case *Engle v. R. J. Reynolds Tobacco Co.*[1] To put this amount in better perspective, this award was more than 11,000 times the compensatory damages of $12.7 million for the same case.[2] Recent cases with so-called blockbuster awards, such as the Engle case, have caused a great deal of concern for the manner in which courts assess punitive damages. Although these blockbuster cases are anomalies, they are still important. They set the outer limit for awards so high that litigants always have to consider the possibility of an extreme award. Some states have set caps to limit the amount of punitive damages to some multiple of compensatory damages. Some people have advocated for taking the power to award punitive damages away from juries, allowing only judges to set the amount. The idea that removing the power will curb awards, however, is based on the assumption that juries tend to award higher or more capricious amounts than judges.

This paper develops and implements a model to analyze this assumption. Two articles have been published in recent years on this subject. Hersch and Viscusi (2004) found that juries do award higher levels of punitive damages than judges and that they are more likely to make a punitive award in the first place.[3] On the other hand, Eisenberg et al. (2002) concluded that jury awards do not differ significantly from judge awards.[4] Perhaps the most interesting aspect of these two very different conclusions is that they used the same data set![5] Following many of the same procedures as these two articles, this paper assesses the probability of a punitive award and the amount of the award based on a number of influencing factors. Most importantly, the role that the trial forum, jury trial vs. bench trial, plays in determining the probability and amount will be considered.

This paper uses two data sets to determine the possibility of a jury effect on punitive damages, the 1996 and 2001 versions of the *Civil Justice Survey of State Courts*.[6] The 1996 survey is the data set used by both Hersch and Viscuci (2004) and Eisenberg et al. (2002).[7] Both data sets contain information on over 8,000 cases tried to verdict in state courts.[8] The empirical results indicate that juries tend to award punitive damage more often and in greater amounts than judges. A number of robustness checks are run to confirm these results, which provide support for the conclusion in most cases. However, the results are inconsistent when the model controls for state effects and when selectivity bias in forum selection is considered.

This paper, first, provides a brief description of the economic theory on efficient punitive damage awards. Second, it describes previous research that has been conducted on punitive damages. Third, it develops a model to analyze the probability and amount of punitive damage awards. Fourth, it describes both data sets used for empirical analysis. Fifth, it explains how the model is implemented using the data sets and the econometric techniques employed. And sixth, it provides and explains the results.

I. Theory

The most comprehensive look into the theory on punitive damages comes from A. Mitchell Polinsky and Steven Shavell (1998).[9] The basis of the theory is that damages should be set such that the defendant internalizes the harm caused by his/her action. The defendant internalizing the harm will lead to the appropriate deterrent effect. For example, if a company has a factory that pollutes the air near a small town, it could be sued by the residents for negative health effects. If the pollution causes $100,000 in damages, then it should be assessed that amount of total damages in court. One might think that any higher level of damages would also be effective, perhaps even causing the company to reduce the pollution as much as possible to avoid the damages. However, any measure that the company might take to curb the pollution costs money. An

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excessive damage award would cause the firm to take excessive precautions, spending more than is optimal on pollution prevention. One can take this example to the extreme to illustrate the social costs by saying that the mere threat of excessive damage awards might cause the firm to shut down the factory if the excessive precautionary costs wipe out the profit the factory produces. So, as Polinsky and Shavell (1998) conclude, for deterrence purposes, damages should be set equal to the harm caused.[10]

Setting damages in this manner, however, does not preclude the awarding of punitive damages. In fact, punitive damages are often necessary to produce efficiency. The following definitions are how this paper refers the two types of damages awarded in court. Compensatory damages are the amount awarded to the plaintiff to "compensate" him/her for the harm caused by the defendant's actions in the particular case before the court. Punitive damages are anything awarded to the plaintiff beyond compensatory damages. Polinsky and Shavell (1998) argue that there are two basic purposes for punitive damages, deterrence and punishment.[11] They state that "the punishment objective derives ultimately from the pleasure or satisfaction people obtain from seeing blameworthy parties punished."[12] As a subjective concept, punishment does not lend itself to an efficiency discussion. It should be pointed out, however, that the punishment objective can cause appropriate awards to increase beyond the so-called efficient level, where damages are set equal to the harm caused.

The deterrence objective is basically what has been described, where damages cause the defendant to take efficient precautions. Punitive damages are necessary for this purpose because the defendant may not always be found liable for his/her actions. For example, even though the factory is causing harm by polluting the air, the courts may not find the firm liable for any number of reasons, even down to some legal technicality. Beyond that, the residents may not even attempt to sue the firm. So, punitive damages can be used to equate the damages awarded to the total harm that the defendant has caused, rather than just the harm caused in the particular case before the court. Thus, to obtain efficient deterrence, punitive damages should depend on the probability of being found liable.

Going back to the example, if the factory causes $100,000 in harm every year for three years, but the residents only sue in the third year and only obtain compensation for the harm caused in that year, then the firm will only be assessed a total of $100,000 in damages while it has caused $300,000 in harm. So, if the probability of being found liable is 1/3, then compensatory damages should be multiplied by the reciprocal of this probability, 3, to obtain efficient total damages. Manipulating this relationship, one obtains the result that punitive damages should equal compensatory damages times the ratio of the probability of not being found liable to the probability of being found liable. This ratio is the punitive damages multiplier and it can be written as $(1-p)/p$ where p is the probability of being found liable.[13] It should be noted that this is the probability of being found liable given that the party is liable. To somewhat answer the question posed at the opening of this paper, yes, it may be that punitive damages of $145 billion are efficient if the probability of being found liable is very low.

It is important to realize here that the probability of being found liable is exogenous to the model and it is assumed that the courts always determine liability correctly. Also, the probability will not be the same as the probability as perceived by the plaintiff or defendant. According to Spier (1997), the only time that a trial results from a conflict is when the two parties have different expectations of the outcome from trial.[14] But, this ignores other possible economic reasons for going to trial, such as to make a political statement or to get publicity. These can still be considered economic reasons because they would all fall under the expected utility received from trial. Following Spier's theory, however, if both parties do expect the same result, then they can agree to settle the case out of court with that same result. Both parties would prefer to settle in such a situation because they would avoid the costs associated with going to court. However, if expectations are different, then bargaining may fail and the case will proceed to trial. So, the only way trial will occur is if at least one of the plaintiff or defendant believes the probability of being found liable is different from what the court would determine. And, if the defendant believes the probability is different from what the court determines, then the resulting punitive award may not lead to efficient deterrence.

This can be illustrated with an example. Let's say a firm is deciding whether to install filters on its smoke-stacks to lessen the pollution they emit. If the cost of installing the filters is $75,000, then efficiency would require the firm to install the filters if the harm caused by not installing is more than $75,000. The firm will make the decision based on costs, including an estimation of damage judgments against the firm. Suppose the firm estimates that a judgment against them would amount to $300,000, perhaps based on past judgments. Then, if the firm also estimates the probability of being found liable to be 1/6, it will anticipate a cost of $50,000. Since this is less than the cost to install, it will not install the filters. But, let's say that the correct probability of being found liable, as the court would determine, is 1/3. With a judgment of $300,000, this amounts to an actual cost of $100,000 (the efficient amount according to Polinsky and Shavell (1998)). So the firm should have installed the filters since the efficient cost was more than the cost of installation. Thus, the firm did not take efficient precaution and the formula is dependant upon the defendant correctly estimating the probability.

Now, while Polinsky and Shavell (1998) seem to propose a fairly comprehensive analysis of the general theory, there is other literature that argues against their contentions. For, example, Jonathan M. Karpoff and John R. Lott, Jr. (1999) maintain that "in the absence of externalities, punitive awards are not necessary to assure contractual performance even when firms face less than a 100 percent probability of being sued for contractual breach."[15] Their argument focuses on the effect of private contracting and reputation. Breaching a contract or committing other acts that cause harm will carry costs beyond those that a court may impose. Specifically, if a firm were to produce defective products on a regular basis, this would cause serious harm to its reputation. That reputation is obviously valuable to the firm as it engages in negotiations with suppliers and seeks to attract customers. As a result, firms will take appropriate action to prevent breach of contract without the imposition of punitive damages. The problem with this theory is that the costs of breach are not quantifiable, at least when it comes to reputation, so it is difficult to say that these costs will lead to efficient behavior. Also, while this theory may have some viability with firms, reputation is likely to be less important for individuals.

There is also literature on other factors that should be included in determining the appropriate level of punitive awards. Polinsky and Shavell (1998) argue that any other factors are irrelevant for efficiency because damages should simply equal the harm caused.[16] Two factors that are often even cited in actual court cases as being important are the defendant's financial status and the egregiousness of misbehavior. These are both explained by Eisenberg et al (1997). They say that punitive awards should be related to the defendant's wealth to obtain proper deterrence.[17] Damages equal to the harm caused may be effective for the average individual, but a similar award may have little to no effect on a large corporation with millions of dollars in assets. So, punitive awards ought to be higher for the latter group to ensure deterrence. Eisenberg et al. (1997) also contend that more serious misbehavior should lead to higher punitive awards based on the punishment objective: the more egregious the behavior, the more the defendant deserves to be punished.[18]

But, even assuming the punitive multiplier formula from Polinsky and Shavell (1998)[19] correctly determines the efficient level of punitive damages and ignoring the problems created by the defendant perceiving a different probability of being found liable than the courts, there is still difficulty in applying the formula. Unfortunately, one cannot properly assess the probability of being found liable for numerous reasons, such as the fact that a majority of cases are actually settled out of court. It may be, however, that judges, due to their vast training and experience, are better at assessing the proper level of punitive damages. So it is valuable to examine the question of whether juries award punitive damages similar to judges.

II. Previous Empirical Research

One of the first empirical looks into the determinants of punitive awards was performed by Eisenberg et al. (1997).[20] They use data from the 1992 Civil Justice Survey of State Courts, which contains information on cases tried to verdict in 1991 and 92 in 45 of the 75 most populous counties in the country.[21] It is an older version of the data sets used in this paper. First, Eisenberg et al. (1997) found that punitive damage awards are statistically related to compensatory damage awards: as compensatory damages increase, so do punitive damages.[22] Second, they used the defendant's status as either an individual or a corporation to proxy for the defendant's wealth.[23] The data indicates that mean punitive awards are larger for corporations than for individuals.[24] Regression results confirmed that the level of punitive awards is higher for corporation defendants.[25] Third, they used the type of case to proxy for the egregiousness of misbehavior.[26] For example, one might expect that an intentional tort case would involve worse behavior than an automobile accident, necessitating a higher award. Regression results, however, found that case types had no substantial effect.

Eisenberg et al. (1997) also created a decision model to analyze the determinants of the decision to award punitive damages.[27] Results showed that punitive damages are no more likely with a higher level of compensatory damages.[28] The defendant type also had no effect on the decision to award punitive damages.[29] But, they found that punitive damages are more likely for certain case types, specifically ones involving intentional torts.[30] Eisenberg et al. (1997) did not examine the difference in awards between judge trials and jury trials.

Another study on the determinants of punitive damage awards was conducted by Karpoff and Lott (1999).[31] They used a different data set that only included data on lawsuits with corporations as defendants.[32] Their regression equations contained different variables as well. They looked at the level of compensatory damages, just as Eisenberg et al. (1997) did, but they also included the market value of the company's common stock, the number of defendants, and an index they created representing the firm's exposure to possible punitive awards based on the industry.[33] With compensatory damages, results were partially consistent with Eisenberg et al. (1997). Larger compensatory damage awards led to both a greater likelihood of a punitive award and a higher punitive award.[34] The market value of common stock was used to proxy for the firm's wealth.[35] In their levels model, where the dependent variable was the amount of the punitive award, Karpoff and Lott (1999) found that punitive awards increased with the value of common stock[36], corroborating Eisenberg et al.'s conclusion that awards increase with wealth. They also used a punitive award decision model, where the dependent variable was 0 or 1 corresponding to whether or not a punitive award was made, and found that punitive damage awards were more likely with a higher compensatory award.[37]

Helland and Tabarrok (2003) studied the effects of county demographics on total trial awards, not just punitive damages.[38] They used three different data sets to thoroughly test their results. The primary data set used is Personal Injury Verdicts and Settlements from Jury Verdict Research. It contains 122,444 trials, settlements, and arbitrations taking place between 1988 and 1997.[39] Helland and Tabarrok (2003) use only the observations that are trials where the plaintiff won, of which there are 42,315.[40] The other data sets used are the 1992 *Civil Justice Survey of State Courts* and a data set on federal court cases collected by the Administrative Office of the United States Courts and compiled by the Federal Judicial Center.[41] The demographic data comes from the 1990 census.[42] Helland and Tabarrok (2003) explain that "we hypothesize that the reason that awards vary with county demographics is that awards vary with jury composition and jury composition varies with county demographics. The most important limitation of the data sets, however, is that we must infer the average composition of the jury from county demographics."[43] They found that county poverty rates generally had a positive correlation with total personal injury awards.[44] Breaking down the poverty rates into racial subgroups, they found that black and Hispanic poverty rates had the largest effect with a 1 percent increase leading to an increase in the total award by as much as 10 and 7 percent respectively.[45] It is important to note that the racial subgroup poverty rates used by Helland and Tabarrok (2003) are not the percentage of that group in poverty but instead are the number of individuals in the group below the poverty level as a percentage of the total population in the county.[46]

An earlier study by Helland and Tabarrok (2000) examined the difference in awards between judges and juries.[47] They used data on nearly 60,000 trials over a 9 year period ending in 1996.[48] The primary focus of the study was on possible selection effects that could explain the different award amounts between judges and juries. The data shows that both the mean and median jury awards were significantly higher than judge awards. Mean awards were $696,149 for jury trials and $218,629 for judge trials.[49] Median awards were $74,879 and $17,279 for jury and judge trials respectively.[50] It should be noted that the data is for total awards, not simply punitive damages.[51] Could the difference in awards simply be due to the types of cases that juries see in comparison to the types that judges see? Helland and Tabarrok (2000) built a model that accounted for forum choice (judge trial or jury trial), the settlement decision (to settle out of court or proceed to trial), the difference in win rates between forums, and the different types of cases seen in each forum.[52] Their results showed that "although . . . three-quarters to two-thirds of the differences in mean awards is due to sample differences, there is still a significant unexplained difference in mean awards."[53]

Two articles have been written using regression analysis to determine if juries award punitive damages differently than judges, Hersch and Viscusi (2004)[54] and Eisenberg et al. (2002)[55]. The models developed in this paper are primarily based on these two articles, particularly Hersch and Viscusi (2004). Both articles used the same data set but came to strikingly different results. The data set used was the 1996 Civil Justice Survey of State Courts[56], one of the data sets used in this paper. It is described in section 4.

Both articles used 2 primary models. One analyzed the decision to award punitive damages and the other analyzed the level of punitive damages awarded.[57] Hersch and Viscusi (2004) found a significant jury effect in both models, concluding that juries are more likely to award punitive damages than judges and that juries tend to award higher amounts.[58] Eisenberg et al. (2002), on the other hand, found no significant jury effect on punitive damages.[59] The corresponding models between the two articles were very similar. The variables included, in all four models, were also similar to previous research. Both articles included case types, litigant pairs, the logarithm of compensatory damages, and a dummy variable corresponding to whether or not the trial was a jury trial.[60] The actual categories of case types and litigant pairs differed between the two articles[61], but according to Hersch and Viscusi (2004) this had no effect on the final results.[62] As far as variables are concerned, there are two major differences between the articles. First, Eisenberg et al. (2002) included another variable, an interaction term, which was the product of the logarithm of compensatory damages and the jury trial dummy variable. "The interaction term monitors whether, as compensatory awards increase, juries are more likely than judges to award punitive damages."[63] Hersch and Viscusi (2004) did not include such a variable and actually cite the variable as being a major reason for the vastly different results.[64] Second, Hersch and Viscusi (2004) included 10 dummy variables representing 10 of the 45 counties where the trials occurred.[65] Eisenberg et al. (2002), on the other hand, did not include any such variables, but did adjust equations for county level clustering.[66] Hersch and Viscusi (2004) claim that the different methods used for handling counties did not impact results.[67]

Another difference in models can be found in the regression techniques employed. For the levels model, Hersch and Viscusi (2004) used a tobit regression because of the large number of punitive awards that were 0.[68] Eisenberg et al. (2002), however, did not report the type of regression used for the levels model. It appears as though standard OLS may have been used and the only observations that were included were cases with positive punitive damage awards.[69] This technique assumes that the determination of the amount of punitive damages comes after the decision to award punitive damages, rather than the two occurring simultaneously. For the decision model, Hersch and Viscusi (2004) use a probit regression[70] and Eisenberg et al. (2002) use a logistic regression[71]. Both of these techniques allow for a dependent variable with values restricted to 0 (representing no punitive damage award) and 1 (representing a punitive damage award).

As previously mentioned, the possibility of selectivity bias may affect results. For example, as Hersch and Viscusi (2004) explain, if jury cases are more likely to be settled out of court, then this could understate the difference in awards between judge and jury.[72] As another example, Eisenberg et al. (2002) explain that if juries see cases with a higher probability of award, then the jury effect will be overstated.[73] Both articles attempt to correct for the selectivity bias using a Heckman model.[74] The primary results of the two articles were unaffected.[75] However, with the relatively limited data set, say in comparison to Helland and Tabarrok (2000), it seems troublesome to say that selectivity bias was eliminated with this correction. Given that, according to Helland and Tabarrok (2000), such a large portion of the difference in awards can be explained by self-selection[76], this problem still needs to be addressed more thoroughly.

III. Model

To analyze the contributing factors to punitive damages, two main models will be employed. The first model estimates the various effects on the probability of a punitive damage award. The second model estimates the size of the punitive award based on the same effects.

The probability and amount of a punitive award should depend on the choice of trial forum (jury vs. bench), the amount of compensatory damages, the nature of the litigants, the type of case, the poverty rate of the county where the case is tried, the political leanings of the county, and the state laws applicable in each case. The effect of the trial forum is the main focus of this paper. Based on the results of Hersch and Viscusi (2004)[77], it is expected that juries are more likely to award punitive damages and tend to do so in larger amounts. First of all, juries are far less likely to be familiar with the efficiency effects of punitive damages, so will not likely take them into account. Also, juries may be more likely to punish any wrongdoer since they do not see cases on a day-in, day-out basis. Judges, on the other hand, can compare the offense of a particular defendant to the many others they have seen, only punishing the more egregious acts. For essentially the same reasons, juries will probably award higher amounts of punitive damages. Having no comparisons, juries may want to punish the defendants to a greater degree. Also, juries are probably more likely to simply follow the amount proposed by the plaintiff in a particular case once they have decided to award punitive damages.

Prior research has established a stable, positive correlation between compensatory damages and punitive damages.[78] The positive correlation supports the contentions that higher compensatory damages will more likely result in a punitive damage award and that the award will be in a greater amount. The reason there is a positive correlation may be because the more egregious the act the more people feel the individual should be punished. A higher compensatory award means that the defendant has caused a greater amount of harm against the plaintiff. As such, the act may be more deserving of punishment. Furthermore, the compensatory damages effect may vary depending on the trial forum. For example, juries may be more influenced by the egregiousness of the defendant's action. So, as compensatory damages increase, juries may increase punitive awards at a greater rate than judges. Eisenberg et al. (2002) predicted that the compensatory damages effect would vary by trial forum and included an interaction term in their models to account for that.[79] This paper will allow for this differential effect as well.

Punitive awards may vary based on the nature of the litigants, meaning the type of plaintiff or defendant. For example, one might expect punitive damages to be more likely assessed and assessed in larger amounts against large corporation defendants than against an individual defendant. The logic behind this would be the deterrence effect. A particular dollar amount may seem quite large to a single individual, deterring him/her from doing the act again. However, that same amount could seem trivial to a multi-million dollar corporation. By the same regard, one could also expect awards to more often be given to the sympathetic individual plaintiff rather than the faceless corporation. To account for these possibilities, the litigant pair will be included in the models in the form of plaintiff vs. defendant. For the base models, this paper will use 4 litigant pair categories: individual vs. individual, individual vs. corporation, government, or hospital, non-individual vs. individual, corporation, government, or hospital, and individual & non-individual vs. individual, corporation, government, or hospital.[80] The litigants are categorized in this manner primarily to separate individuals from non-individuals. The individual plaintiff punitive awards can be compared to the non-individual or individual & non-individual plaintiffs. Also, using the same plaintiff type (individual), one can compare the awards levied against individuals and non-individuals. From this base model, the litigant pair types will be expanded to try to delineate the effects of particular plaintiffs and defendants. In particular, the expanded types will include: individual vs. individual, individual vs. corporation, individual vs. government or hospital, non-individual vs. individual, non-individual vs. corporation, non-individual vs. government or hospital, and individual & non-individual vs. individual, corporation, government, or hospital.

Awards may also vary depending on the type of case, such as intentional tort or product liability. The basis for this would again be the egregiousness of misbehavior, meaning the degree to which a third party would perceive the action of the defendant to be inappropriate. For example, punitive damages probably aren't awarded very often in motor vehicle accident cases because nearly everyone has or will be involved in a motor vehicle accident and because such cases are typically exactly what the name entails, accidents. But, when the action is purposeful or knowing, such as with an intentional tort, a jury or judge may feel that the defendant deserves greater punishment. Specifically, the model will include 12 case types: motor vehicle tort, premises liability, product liability, intentional tort, medical or professional malpractice, slander/libel, other tort actions, fraud, cases where a seller or buyer is the plaintiff, employment discrimination or disputes, other contract actions, and real property cases.[81] Motor vehicle tort will be used as the reference category because of the expectation that it will have few punitive awards. So, the other case types, especially ones involving intentional acts, are expected to have positive coefficients.

Another reason to include case types in the models is to isolate the effect of forum selection. Selectivity bias may be a problem in studying punitive damages because the litigants involved in cases that are more likely to result in punitive awards may self-select themselves into jury trials. This could lead one to conclude that juries tend to award punitive damages more often or in higher amounts than judges when actually the result is due to the different cases seen in each forum. To some extent, this problem can be reduced by controlling for the case types. Juries may see certain case types more often than judges, or vice versa. For example, intentional actions, which are expected result in more and higher punitive awards, may be tried more often in front of a jury or judge. So, by controlling for case type the model can begin to isolate the jury effect. This paper will also use a selectivity correction model to further isolate the effect. The selectivity correction model is described in the econometrics section.

The county where the case is tried is also included in the base models to help isolate the jury effect. For any number of reasons, different counties may award punitive damages differently, such as because of the types of judges in the county or the income level of citizens in the county. A jury in a richer county, for example, may be more inclined to award higher punitive awards because small amounts may seem trivial to the jury members. A dummy variable is included in the models for a particular county if it contributes at least two jury trials and two bench trials with punitive awards.[82] Based on this criterion, the county control variables will change between the two different data sets.[83] Since the criterion for including a county in the model is atheoretical, this paper also trades the county control variables for state variables as an additional robustness check. Punitive damages may vary by state for legal reasons. For example, some states have laws that cap the amount of punitive damages that can be awarded by some multiple of the compensatory damages. For the state models, dummy variables are included in the equation for every state where the trial occurs in the data set.[84]

The poverty rate in the county where the case is tried is also included for two reasons. First, Helland and Tabarrok (2003) found that poverty had a significant effect on total damages awarded in personal injury trials.[85] So, it should be included to avoid a possible omitted variables bias. Second, this paper can further test the results of Helland and Tabarrok with the new data set. They found that the higher the poverty rate, the higher the total damages awarded.[86] One can expect a similar result here, that the poverty rate will have a positive effect on punitive awards. The poor may be more likely to award punitive damages because perhaps they feel that others who are committing these egregious acts deserve to be heavily punished monetarily. Poor people probably place more value on money than others and as such may be quicker to take it away from those who don't 'deserve' to have it. The poverty effect may also vary by race. To account for this, the models use poverty subgroups based on race instead of the overall poverty rate in each county. Particularly, this paper will examine white, black, and Hispanic poverty rates. Based on the results from Helland and Tabarrok (2003)[87], one can expect to find a greater effect on punitive damages related to the black poverty rate.

The political leanings of the county where the case is tried may also affect punitive damages. A more liberal rather than conservative population may have a negative effect on punitive awards. Compared to conservatives, liberals are probably less likely to punish defendants beyond compensatory damages, considering, for example, that conservatives and not liberals tend to support the death penalty. So, if a county has a relatively liberal population, then one can expect that most juries in the county will be liberal. Also, in most states, trial court judges are elected by the people in each county. The more liberal a county is, the more likely its citizens are to elect liberal judges. The voting margin in the presidential election serves as a proxy for political leanings. This variable is constructed by subtracting the percentage vote for the republican candidate in each county from the percentage vote for the democratic candidate. Although this variables certainly is not a perfect proxy, one can generally say the greater the differential, the more liberal the county. Political leanings may vary based on the type of defendant as well. For example, a more conservative county is probably less likely to punish corporations with punitive damages.

IV. Data

There are two primary data sets used in this paper: the *1996 Civil Justice Survey of State Courts* and the *2001 Civil Justice Survey of State Courts*.[88] The two surveys are extremely similar. The surveys were funded by the U.S. Department of Justice, Bureau of Justice Statistics and conducted by the National Center for State Courts.[89] The 1996 data contains information on cases tried to verdict in 1996 in 45 of the nation's 75 most populous counties. The data set is a two-stage stratified sample. In the first stage, the 75 counties were divided into 4 strata by the number of cases disposed in the county in 1990. Then, a specified number of counties were selected at random from each stratum. In the second stage, all jury or bench cases tried to verdict in 1996 were coded into the survey. In some counties, if the number of cases was too large, a sample of cases was taken. However, all trials of 3 case types, medical malpractice, professional malpractice, and product liability, were included to over-sample the types.[90] The 2001 data covers cases tried to verdict in 2001 in 46 counties. The sampling process was very similar, except the counties were divided into 5 strata in the first stage, and in the second stage, all trials of case types medical malpractice and product liability (not professional malpractice) were included.[91] The counties used in the two surveys are almost identical, but 2001 adds El Paso, TX and Mecklenburg, NC but drops Norfolk, MA.

The 1996 survey contains a total of 9,025 observations while the 2001 survey contains 8,038, but not all of these are used in the regressions. In the 1996 set, 227 observations were not tried to verdict as a jury or bench trial. 119 observations were missing data on punitive damages, and an additional 97 had nothing for compensatory damages. Of the remaining, 23 were dropped due to missing data on litigant pairs and 63 more with no case type. As Hersch and Viscusi (2004) did, an observation is dropped because it had a compensatory damage award of over $40 billion but $0 in punitive damages. The award was later overturned by the Hawaii Supreme Court.[92] A total of 8,496 observations remain. The plaintiff won in 4,336 of these trials, or 51.0%. As in Hersch and Viscusi (2004), these 4,336 observations are used for the regression analysis. In the 2001 data set, 138 observations were not tried to verdict as a jury or bench trial. 236 observations had no data on punitive damages and 5 more had none on compensatory damages. 53 more were lost with missing data on litigant pairs and 2 more with missing data on whether or not the plaintiff won. This leaves a total of 7,604 observations. Of these, the plaintiff prevailed in 4,153 trials, or 54.6%. These 4,153 observations are used for the analysis.

Table 1 provides a breakdown of the observations in each of the two data sets. It shows the percentage of the total number of observations for the forum type, the litigant pairs, and the case types. Three columns are presented for each data set. The first contains all trials, the second contains trials where the plaintiff prevailed, and the third contains trials with a punitive

Table 1: Breakdown of 1996 and 2001 Data Sets						
	1996			2001		
	All Trials	Plaintiff Win Trials	Punitive Award Trials	All Trials	Plaintiff Win Trials	Punitive Award Trials
Number of Trials	8496	4336	173	7604	4153	199
Forum Type						
Jury Trial	74.29	68.54	68.79	76.32	72.19	76.38
Bench Trial	25.71	31.46	31.21	23.68	27.81	23.62
Litigant Pairs						
Individual vs. Individual	34.91	34.43	34.68	41.71	41.03	40.70
Individual vs. Corporation	36.21	35.61	46.82	30.98	30.48	32.66
Individual vs. Government or Hospital	12.42	8.86	5.78	10.61	7.06	7.54
Non-Individual vs. Individual	4.33	6.07	4.05	5.05	6.48	5.53
Non-Individual vs. Corporation	8.35	10.93	4.62	11.03	14.28	13.07
Non-Individual vs. Government or Hospital	0.54	0.53	0.00	0.60	0.67	0.50
Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital	3.25	3.57	4.05	N/A	N/A	N/A
Case Types						
Motor Vehicle Tort	32.14	35.03	6.94	35.36	38.50	13.57
Premises Liability	15.04	11.55	6.94	11.27	8.86	2.51
Product Liability	2.99	2.44	2.89	1.42	1.25	1.01
Intentional Tort	3.19	3.53	19.65	3.14	3.32	21.11
Medical or Professional Malpractice	10.31	5.24	1.73	11.74	6.24	6.03
Slander/Libel	0.71	0.51	1.73	0.79	0.55	6.53
Other Tort	4.13	4.04	2.31	4.47	4.36	7.04
Fraud	3.92	4.45	15.61	5.23	5.68	17.59
Seller or Buyer Plaintiff	15.62	20.76	15.61	16.71	21.48	8.04
Employment Dispute	3.90	3.71	15.03	3.41	3.37	8.04
Other Contract	6.77	8.05	9.25	4.51	5.01	8.54
Real Property	1.25	0.67	2.31	1.93	1.37	0.00
All values are a percentage of the total number of trials shown at the top of each column						

damage award. The 2001 data set has no observations for the individual & non-individual vs. individual, corporation, government, or hospital litigant pair because this category was removed for the 2001 survey.

Although the total number of cases dropped from 8,496 to 7,604 between 1996 and 2001, the number of punitive award trials actually increased by 15%, from 173 to 199. Jury trials composed about 75% of all cases in both data sets. This percentage drops to about 68% for the trials where the plaintiff won and where punitive damages were awarded in 1996. However, the percentage of jury trials remains higher at 72% and 76% for plaintiff win and punitive award trials respectively in 2001. The proportions of litigant pairs remained relatively stable between the data sets, but there are some significant differences. Individual vs. individual increased noticeably, by about 6% in each of the three subsets, which appears to have been primarily offset by a decrease in the proportion of individual vs. corporation trials. In particular, while nearly 47% of punitive award trials in 1996 were individual vs. corporation, only 33% were this type in 2001. Overall, one can see these changes reflected in the fact that the largest litigant pair in each subset changed from individual vs. corporation in 1996 to individual vs. individual in 2001.

With regard to case types, although some proportions did change a few percentage points, the largest proportions in each subset remained the same type. One notable change is the nearly 7% increase in punitive award trials of the motor vehicle type. Another trend to consider, which is consistent between the surveys, is the sharp increase in the intentional tort proportion moving from plaintiff win trials to punitive award trials. While only about 3% of total trials and plaintiff win trials are intentional torts, closer to 20% of punitive award trials are intentional torts, a 500% increase. Such a jump is to be expected since the literature shows that cases involving intentional actions, meaning more egregious misbehavior, have a greater probability of a punitive award. Also, even though motor vehicle torts are expected to result in less likely punitive awards, it is not surprising to see such a large proportion of punitive award trials of the motor vehicle type. There is about double the number of motor vehicle tort cases in both data sets than any other case type.

In the total sample of cases for 1996, the plaintiff won 51% of the time. Interestingly, the plaintiff won less than half the time in jury trials, 47%, but much more than half the time in bench trials, 62%. In 2001, the data is somewhat similar. The plaintiff won 55% of all trials, but only 52% of jury trials. The percentage point decrease is about the same between the two surveys, but the plaintiff did win more than half the time with a jury trial in 2001. The larger proportion of plaintiff wins in bench trial cases persisted in 2001 at 64%.

There are three other sources for the data used in this paper. First, the poverty data comes from the U.S. Census Bureau. The data used with the 1996 data set is actually poverty levels for 1997 for all ages.[93] There does not seem to be data available for county poverty rates in 1996 or for only ages 18 and up (the required age to sit on a jury). The 1997 poverty rates are estimates based on regression models using previous census data. The data used with the 2001 data set are poverty rates for 1999 for ages 18 and up. This data comes from the 2000 Census Summary File 3.[94] This paper uses poverty rates for 1999 because they are broken down by race: white, black, and Hispanic. Such a breakdown does not seem to be available for 2001. Each racial poverty rate is constructed by dividing the total number of individuals, 18 years of age and older, of the particular race, by the number of individuals, 18 and older, of the race, that are in poverty.

The next source of data is *Dave Leip's Atlas of U.S. Presidential Elections*, available at uselectionatlas.org.[95] It provides voting data by county for the 1996 presidential election. Finally, CNN.com provides voting data by county for the 2001 presidential election.[96] Both of these sources provide the percentage vote for each candidate in each county. The percentages for the Democrat and Republican candidates are used in this paper. CNN.com provided data for Massachusetts by county using a tighter, more detailed county definition. The *Civil Justice Survey of State Courts* uses larger counties that actually encompass a number of these smaller ones. To account for this discrepancy, the actual voting totals in the smaller counties (also available on CNN.com) were added together for each larger county for both democrat and republican. The totals were then divided by the sum of the democrat and republican vote in each larger county.

Table 2 provides summary statistics for the continuous variables to be used in this paper. The first thing to notice is how much larger both the compensatory and punitive awards are in 2001 compared to 1996. Increases such as these over the last several years are largely what have brought concern for the potential inefficiency of damages awarded in court, especially punitive damages. The mean punitive award in the 1996 data set is $1,423,129.54, while in the 2001 data set it is $4,965,798.28. From the plaintiff win trials column, there is a similar increase in compensatory damages: $338,220.02 in 1996 to $546,710.64 in 2001. Also, looking at the punitive award subset, when punitive damages are awarded, they are typically at least twice the level of compensatory damages. In addition, the mean statistics seem to indicate that more conservative counties are more likely to award punitive damages; moving from the plaintiff win sample to the punitive award sample, the mean value of voting margin drops from 20.3 to 14.3 in 1996 and from 17.4 to 10.4 in 2001.

Table 2 also reports summary statistics for the logarithms of both punitive and compensatory damages. The log values are what will be used in the regression analysis. The actual numbers of punitive and compensatory damages are not normally distributed. In a test for normality, using the Kolmogorov-Smirnov statistic, one can reject the null hypothesis of a normal distribution at the 99% level of confidence for both punitive and compensatory damages in both samples. Regression analysis is often sensitive to normality, so this paper uses the logarithms. One cannot reject the null hypothesis when testing for normality with the log values.[97]

The summary statistics for punitive and compensatory damages can also be broken down by jury and bench trials, as shown in table 3. Here is the first indication that juries tend to award larger amounts of punitive damages. In the 1996 data set, the mean punitive award for bench trials is $557,292.06 and the mean award for jury trials is $1,816,030.58, more than three times larger. In 2001 the difference actually gets much larger. The mean awards for bench and jury trials are $155,183.89 and $6,453,290.88 respectively. Now the average jury award is more than 40 times greater. This huge jump is likely a result of a few extremely large awards by juries. In the 2001 data set, the maximum punitive award from a jury is $364,500,000 while the max from a judge is only $3 million.

One cannot draw any conclusions simply from these mean values. There are other factors that may be contributing to the difference between judge and jury awards. First, as mentioned previously, juries may see different types of cases than judges, particularly ones that are more likely to result in high punitive awards. Second, there may be a self-selection bias, where litigants hoping for large awards opt for a jury trial based on a belief that juries award higher amounts. Using the proposed model, this paper attempts to control for such problems to find if there really is a jury effect.

V. Econometric Issues

To estimate the probability of a punitive damage award, this paper constructs a decision model using a number of dummy variables. First, the dependent variable is a dummy variable equal to 1 if there was a punitive damage award and 0 otherwise. Then, for the base model, all independent variables will be dummy variables except compensatory damages. Forum choice will be represented with a dummy variable, jury trial, equal to 1 for a jury trial and 0 for a bench trial. The litigant pairs will be included with a dummy variable for each category described in the model section. Non-individual vs. individual, corporation, government, or hospital will be left out of the regression equation as the reference group since there are no

Table 2: Summary Statistics for 1996 and 2001 Data Sets					
1996					
	All Trials	**Plaintiff Win Trials**	**Punitive Award Trials**	**Minimum**	**Maximum**
Punitive Damages	29,184.7 (1,568,070.87)	56,780.77 (2,194,696.94)	1,423,129.54 (10,928,939.16)	1.00	138,000,000.00
Compensatory Damages	179,971.87 (1,258,851.16)	338,220.02 (1,647,057.34)	697,012.03 (2,694,440.06)	0.00	38,500,000.00
log(Punitive Damages)	0.228 (1.581)	0.420 (2.127)	10.516 (2.686)	0.00	18.74
log(Compensatory Damages)	5.617 (5.460)	10.552 (2.053)	11.047 (2.373)	0.00	17.47
Poverty Rate	13.175 (5.113)	13.209 (5.071)	13.255 (5.281)	3.60	25.60
Voting Margin	20.656 (21.284)	20.309 (21.299)	14.301 (19.743)	-13.80	66.20
2001					
	All Trials	**Plaintiff Win Trials**	**Punitive Award Trials**	**Minimum**	**Maximum**
Punitive Damages	133,620.97 (5466379.55)	237,946.99 (7384669.12)	4,965,798.28 (33465675.61)	20.00	364,500,000.00
Compensatory Damages	303,358.05 (3102640.55)	546,710.64 (4173150.17)	2,220,149.83 (11114347.12)	0.00	124,500,000.00
log(Punitive Damages)	0.296 (1.839)	0.525 (2.419)	10.954 (2.802)	3.00	19.71
log(Compensatory Damages)	5.945 (5.476)	10.564 (2.163)	11.218 (3.143)	0.00	18.64
Poverty Rate	11.162 (4.229)	11.185 (4.254)	10.998 (3.937)	3.44	20.05
Poverty Rate - White	7.935 (3.100)	7.976 (3.201)	8.140 (3.368)	2.72	19.28
Poverty Rate - Black	18.423 (5.860)	18.498 (5.817)	16.875 (5.605)	7.19	29.75
Poverty Rate - Hispanic	19.246 (6.324)	19.229 (6.340)	18.446 (5.041)	8.40	37.27
Voting Margin	17.883 (24.346)	17.433 (24.125)	10.357 (22.117)	-16.00	68.00
Mean values are reported with standard deviations in parentheses. The minimum and maximum values for punitive damages and log(punitive damages) are the min and max for the punitive award trial subset. The min and max values for all other variables are for the full data set.					

expectations regarding punitive awards for this plaintiff-defendant combination. Case types will also be represented with dummy variables for each case type listed in the previous section. Motor vehicle torts will be used as the reference category since it is expected to have the fewest and smallest punitive awards. The county control variables will also be included with a dummy variable for each county; Fulton, GA will be the reference group. The only continuous variable in the equation will be compensatory damages. As mentioned in the data section, the model will actually use the logarithm of compensatory damages. The decision model equation will be estimated using only cases where the plaintiff wins because the decision to award punitive damages would come only after the verdict for the plaintiff. The base model equation to be estimated is as follows:

$$\text{Punitive Award}_i = \beta_0 + \beta_1 {*} \text{Jury Trial}_i + \beta_2 {*} \log(\text{Compensatory Damages})_i + \beta_3 {*} LP_i + \beta_4 {*} CT_i + \beta_5 {*} CTY_i + e_i$$

where LP is the array of litigant pairs, CT is the array of case types, and CTY is the array of county variables. β_3, β_4, and β_5 are arrays of coefficients.

Table 3: Summary Statistics for 1996 and 2001 Data Sets

	All Trials		Plaintiff Win Trials		Punitive Award Trials		Minimum		Maximum	
1996										
	Jury Trials	**Bench Trials**	**Jury Trials**	**Bench Trials**	**Jury Trials**	**Bench Trials**	**Jury Trials**	**Bench Trials**	**Jury Trials**	**Bench Trials**
Punitive Damages	34,498.08 (1791233.34)	13,828.42 (540717.55)	72,714.55 (2610078.94)	22,062.88 (684167.07)	1,816,030.58 (12974299.72)	557,292.06 (3425465.72)	1.00	1.00	138,000,000.00	25,182,770.00
Compensatory Damages	208,152.15 (1385318.28)	98,527.77 (780868.82)	423,527.92 (1868729.10)	152,343.85 (982626.44)	598,496.62 (1625065.60)	914,110.80 (4196589.55)	0.00	0.00	38,500,000.00	24,582,770.00
log(Punitive Damages)	0.217 (1.559)	0.260 (1.645)	0.428 (2.170)	0.402 (2.031)	10.683 (2.835)	10.147 (2.307)	0.00	0.00	18.74	17.04
log(Compensatory Damages)	5.254 (5.577)	6.664 (4.962)	10.800 (2.071)	10.013 (1.903)	11.258 (2.299)	10.580 (2.486)	0.00	0.00	17.47	17.02
2001										
	All Trials		**Plaintiff Win Trials**		**Punitive Award Trials**		**Minimum**		**Maximum**	
	Jury Trials	**Bench Trials**	**Jury Trials**	**Bench Trials**	**Jury Trials**	**Bench Trials**	**Jury Trials**	**Bench Trials**	**Jury Trials**	**Bench Trials**
Punitive Damages	173,617.13 (6256836.04)	4,749.39 (80590.89)	327,184.86 (8690090.25)	6,314.84 (93658.42)	6,453,290.88 (38197582.70)	155,183.89 (443233.52)	20.00	627.00	364,500,000.00	3,000,000.00
Compensatory Damages	354,497.08 (3476323.31)	138,583.04 (1292958.00)	683,452.44 (4813303.03)	191,773.90 (1521685.59)	2,843,733.24 (12660108.08)	203,454.55 (372947.95)	0.00	0.00	124,500,000.00	44,444,357.00
log(Punitive Damages)	0.300 (1.873)	0.283 (1.724)	0.565 (2.535)	0.421 (2.084)	11.139 (2.996)	10.354 (1.962)	3.00	6.44	19.71	14.91
log(Compensatory Damages)	5.644 (5.597)	6.915 (4.947)	10.738 (2.246)	10.111 (1.858)	11.278 (3.480)	11.023 (1.651)	0.00	0.00	18.64	17.61

Mean values are reported with standard deviations in parentheses.
The minimum and maximum values for punitive damages and log(punitive damages) are the min and max for the punitive award trial subset.
The min and max values for all other variables are for the full data set.

Probit regression will be used to estimate the decision model.[98] Standard ordinary least squares regression cannot be used here because the dependent variable is not continuous. Probit regression allows for a binary dependent variable. The regression functions in the decision model must estimate the joint probability of a punitive award based on the given parameters. Probability estimation is restricted between 0 and 1. If standard OLS were used in such a case, the results could produce an equation where, with certain parameters, the solution is not between 0 and 1. OLS is an inappropriate technique with a zero-one dependent variable. Probit regression uses a different functional form to restrict the results. It allows for a non-linear S-shaped probability curve. For example, say there is a positive relationship between a particular parameter and the probability. So, as the parameter increases, so does the probability. This can be reflected with OLS, but since OLS uses linear functions, the slope of the curve is constant. A constant slope means that, if the parameter were high enough, the probability would be greater than 1. A non-linear curve can prevent this problem because the slope is not constant and can be restricted to go to 0 as the curve approaches the minimum and maximum values, 0 and 1. The S-shaped probit function says that as the parameter increases, the slope increases slowly at first, then much faster. But, eventually, as the parameter continues to increase, the slope will start to decrease, slowly at first then more rapidly as the function approaches one. At 1, the slope goes to 0, so the probability is restricted at 1. In functional form, the probit model can be represented as follows:

$$y^*=\beta_0 + \beta X + e$$
$$y=1, \text{ if } y^*>0$$
$$y=0, \text{ if } y^*\leq 0$$

where y* is the latent probability of a punitive award without censoring the results between 0 and 1, with X as the array of independent variables, and y is the observed value of the independent variable, whether or not there is a punitive award.

Some of the results reported in this paper for the decision model will actually be a result of the dprobit regression technique. The only difference between probit and dprobit is the units in which the results are reported. With standard probit models, coefficients must be interpreted using the Z-distribution. In other words, a particular positive coefficient, call it x_1, would be interpreted as follows: a 1 unit increase in the variable leads to an increase in the probit index by x_1 standard deviations. The dprobit technique transforms the values into probability units. So, the dprobit coefficient x_2 would be interpreted as: a 1 unit increase in the variable leads to an increase of x_2 in the probability calculated at the mean. Results in this form are more easily understood.

To estimate the size of a punitive damage award, this paper constructs a levels model. The dependent variable is the amount of the punitive award in each case. Actually, the model will use the logarithms of the punitive awards to ensure normality. For a large number of observations, the punitive award will be 0 because the regressions will use all cases where the plaintiff wins. Using only cases where there is a punitive award relies on the assumption, as mentioned in the previous empirical research section, that the amount of punitive damages is decided only after the decision to award punitive damages. This may seem logical, but the decision not to award punitive damages can simply be considered a decision to award an amount of 0. Using all plaintiff win cases avoids making any assumptions about the decision process. To avoid the mathematical problem of taking the logarithm of 0, all 0 punitive awards are recoded to 1 before taking the logarithm. The independent variables for the levels model are the same as for the decision model. The base model equation to be estimated is the same as shown above for the decision model except the left-hand side of the equation, the dependent variable, changes to log(punitive damages).

Tobit regression will be used to estimate the levels model.[99] OLS cannot be used in this case because the dependent variable is censored at 0. There cannot be a negative punitive award and there are a significant number of cases where the punitive award is 0. OLS does not account for this limit at 0, but rather treats the observations as being continuous throughout the distribution. Tobit regression estimates an equation for the positive observations while at the same time taking into account the probability of a positive observation. This is done through a censored distribution, essentially a normal distribution curve truncated at 0. The functional form of the tobit model is as follows:

$$y^*=\beta_0 + \beta X + e$$
$$y=y^*, \text{ if } y^*>0$$
$$y=0, \text{ if } y^*\leq 0$$

where y* is the unobserved estimation of the amount of punitive damages without a censored distribution, with X as the array of independent variables, and y is the observed values of punitive awards.

Dtobit will also be used to compute marginal effects at the means of the independent variables. Dtobit is an alternate tobit procedure that first estimates the standard tobit model and then converts the coefficients into marginal effects. The results will not change, only the interpretation. Specifically, marginal effects will be calculated for the expected value of the dependent variable. So, the marginal effect will provide the change in the dependent variable at the mean, given a 1 unit change in the independent variable at the mean. For dummy variables, the marginal effect is for a discrete change in the dummy variable from 0 to 1.

From the base models for both the decision and levels models, this paper will perform several iterations primarily designed to test the robustness of the results from the base models. First, an interaction term will be included in the models that will allow for the compensatory damages effect to vary by trial forum. The interaction term is the jury trial dummy variable multiplied by the log(compensatory damages) variable. Another iteration on the base model will be expanding the litigant pair categories as described in the model section. One can also test the robustness of the base model results by using state instead of county control variables. The state variables are constructed in the same manner as the county variables, with a dummy variable for each state. Arizona is used as the reference group.

An expanded model is constructed as a further robustness check on the base model and to analyze the possible effects of poverty and political leanings on punitive damages. The expanded model is used for both the decision and levels models. The regression equation is the same as in the base model, except two new variable categories are included. First, poverty is included using the overall poverty rate in the county. Then, for the 2001 data, 3 poverty subgroups by race are used: white, black, and Hispanic. Each subgroup is included with a separate variable for the county poverty rate for each particular racial group. There does not seem to be data available on poverty rates broken down by race for 1996 or the immediately preceding or following years. So, subgroups could not be used for the 1996 data set. The second new variable category is the political leanings of the county, specifically the voting margin.[100]

Adding the jury trial-compensatory damages interaction term to the base model may actually induce multi-collinearity. In order to asses the extent of multi-collinearity, this paper will use a variance inflation factor. Collinearity is a data problem that leads to a statistical problem. In this case, the interaction term may be collinear with the jury trial variable. Since jury trial is a dummy variable, multiplying it by compensatory damages will mean the interaction term is 0 whenever jury is 0 and it is positive whenever jury is 1. The statistical problem occurs when estimating the regression equations because, since the two variables match up so well, it is difficult to attribute which of the two is correlated with changes in the dependent variable.

The variance inflation factor is the inverse of 1 minus R^2_k. R^2_k comes from regressing the independent variable being examined for multi-collinearity on all of the other independent variables in the original regression. So, the higher R^2_k gets, the higher the VIF. A high R^2_k means that the variation in the independent variable in question is highly correlated with the variation of the other independent variables. So, a high VIF would indicate multi-collinearity. The problem is that there is no definite cutoff point, meaning there is no specific value for which one can say any VIF higher than it indicates multi-collinearity and is causing problems in the results. A conservative value to consider as a cutoff though is 10, but the best method will be to compare the VIF's of all the variables in an equation. However, to confirm potential multi-collinearity problems, the condition index method proposed by Belsley, Kuh, and Welsch (1980)[101] will also be used. As explained by Greene (2003), the condition index is "the square root ratio of the largest characteristic root of $X'X$ to the smallest," where X is the data matrix and X' is the transpose of the data matrix.[102] Belsley, Kuh, and Welsch suggest a value of 30 or higher to be highly indicative of a multi-collinearity problem.[103]

Forum selection may bias the results of the regression models. If the regression results indicate that juries do award higher punitive damages than judges, is this necessarily a conclusive result? It might not be if juries see those cases that are more likely to result in punitive awards. Essentially, a particular case that resulted in a jury-awarded punitive award may have also resulted in punitive award from a judge, perhaps even a higher one. This paper will use a treatment effects model to correct for selectivity bias. Following Hersch and Viscusi (2004)[104], the treatment effects model is estimated using a two-stage approach. In the first stage, the jury trial dummy variable is regressed on a number of other independent variables. Hersch and Viscusi use the independent variables of the total number of plaintiffs, the total number of defendants, the number of pro se plaintiffs and defendants, and the predicted time to verdict.[105] It is expected that the more plaintiffs or defendants involved, the more likely one party will request a jury trial. Pro se plaintiffs or defendants, who are those individuals that represent themselves in court, are probably more likely to prefer a bench trial. Finally, the decision will be based on the expected cost of each forum, for which the predicted time to verdict will serve as a proxy. Predicted time to verdict comes from another regression. Using standard OLS, the time from filing to verdict is regressed against the case types, the county, and the year in which the claim was filed. Using the estimates resulting from this regression, the predicted values for the dependent variable are obtained.

Based on the first-stage regression, the treatment effects model estimates a selectivity correction term, which is then included in the second-stage regression. The second stage is simply the standard equation with the correction term included as an independent variable. With the treatment effects model, one can also test to see if the equations indicated a selectivity bias. This test is done by a likelihood-ratio test, which compares the error terms from the first and second stage regressions. If the test shows that the error terms are uncorrelated, then selectivity bias is not a problem in the data set.

Finally, this paper will use quantile regression to examine the jury effect on punitive damages across different levels of awards. In other words, the results will answer the question: does a jury trial have a greater impact on punitive damages for the largest punitive awards? Quantile regression differs from OLS by minimizing the sum of the absolute residuals instead of minimizing the sum of the squared residuals. Also, while OLS finds a regression line that goes through the mean of the dependent variable, quantile regression finds a line that goes through the q^{th} value of the dependent variable when the values are put in succession, where q is the specified quantile. So, for the 0.50 quantile, the regression line would pass through the median of the dependent variable, depending on the values of the independent variables.

For simplicity's sake, the following is a simple example. Suppose there are 10 observations of punitive awards, 5 are jury trials and 5 are bench trials. Now to perform a quantile regression of punitive awards on the jury trial dummy variable, say for the 0.33 quantile, the regression line will find coefficients so that the line passes through the 0.33 value of the punitive award amounts for each of the two groups, jury and bench trials. So, for the bench trial group, where jury=0, it will take the 5 observations, put them in ascending order, and assign the lowest observation to be the 0 quantile. So, the second observation would be the 0.2 quantile and the third would be the 0.4 quantile. Since the 0.33 quantile is in between these, it will be rounded down to the nearest quantile to find the coefficient. Since this is only a one independent variable case, and the group has an independent variable value of 0, the coefficient will be the constant. Here, the constant is the second lowest punitive award given by a judge. The quantile regression technique that will be employed in this paper uses bootstrapping to calculate standard errors. Bootstrapping means standard errors are calculated by randomly re-sampling the data a specified number of times. Unfortunately, this random re-sampling means the standard errors will not be stable over each run. Increasing the number of iterations of re-sampling that are done, however, will create some stability.

VI. Results

To first validate the base model, this paper replicates the equations of Hersch and Viscusi (2004)[106] and Eisenberg et al. (2002)[107]. Compared to Hersch and Viscusi (2004), the results should be nearly identical given the use of the same data and variables. With regard to Eisenberg et al. (2002), results should be similar, but not as close as with Hersch and Viscusi (2004) because the variables and model procedures are slightly different. For example, Eisenberg et al. (2002) adjust for clustering in the data sample[108], but this paper does not. So, the more general results will be of greater importance, such as which variables are significant and insignificant, particularly jury trial, log(compensatory damages), and the jury-log(compensatory damages) interaction term.

Table 4 compares the estimates of Hersch and Viscusi (2004)[109] to the primary base models of this paper. The results for the base models using the 1996 data set are very similar to Hersch and Viscusi (2004). The probit estimates are nearly identical with the largest difference being 0.5%, in the product liability coefficient. The tobit estimates are not as close, but the numbers are certainly similar. Most importantly, using the 1996 data, the tobit estimates yield the same basic results as Hersch and Viscusi (2004). The jury trial coefficient is significant and positive, although the confidence level drops to 95% for the levels model. Specifically, in the decision model, jury trial has a coefficient of 0.256 and a standard error of 0.100 for both the 1996 base model and Hersch and Viscusi (2004). Jury trial is significant at the 99% level. To interpret this result, a dprobit model is more appropriate. The dprobit coefficient is 0.011, representing 27.6% of the probability of receiving a punitive award for the plaintiff win sample, 4.0%.[110] In the levels model, the jury trial coefficient actually increases for the base model compared to Hersch and Viscusi (2004), from 4.777 to 4.810 (with standard deviations of 1.875 and 1.917 respectively). The higher coefficient means that juries tend to award even higher amounts than judges using the base model instead of Hersch and Viscusi (2004). So, for the 1996 sample of cases, a jury trial is more likely to result in a punitive award and juries tend to award higher punitive damages than judges. The dtobit coefficient on jury trial for the 1996 base model is 0.089.[111] So, a jury trial results in an 8.9% higher logarithm of punitive damages. Converting the coefficient from a percentage of log values to actual dollars, it becomes 0.093, meaning juries tend to award punitive damages 9.3% higher than judges.[112] Evaluated at the mean of punitive awards, $56,780.77, jury trial awards are on average $5,285.19 higher than judges. The jury trial effect is also present in the 2001 data: the coefficient is significant and positive. So, the new data set confirms the models of Hersch and Viscusi (2004). The jury trial coefficient increases in the new sample, compared to the 1996 data, for both the probit and tobit regressions and it is significant at the 99% level. The dprobit coefficient for 2001 is 0.017, which is 19.4% of the probability of a punitive award, 4.4%. The dtobit coefficient is 0.145, or 0.156 when converted to a percentage of actual dollars. So, in the 2001 sample, jury trial awards are on average $37,129.15 higher than judges. So, the marginal effect of jury trial decreases in the 2001 sample for the decision model, but it increases for the levels model.

The results for other variables in the 1996 base model also match the results of Hersch and Viscusi (2004). Notably, the coefficient on log(compensatory damages) remains significant and positive in both the decision and levels models, implying that the higher the compensatory award, the more likely and higher the punitive award. This positive correlation was predicted previously. Also, individual plaintiffs are more successful than the reference category, non-individual plaintiffs. The two litigant pairs with individual plaintiffs tend to receive punitive awards more often and in higher amounts. This may indicate that the courts tend to favor the “little guy” plaintiff over a corporation or government. However, there is no evidence of the expectation that corporations or governments tend to have higher amounts awarded against them because of their deep pockets. Rather, in the levels model, the individual defendant, in the individual vs. individual litigant pair, has a coefficient of 13.268. The individual vs. corporation, government, or hospital litigant pair, on the other hand, has a coefficient of 10.548, which is 20% lower. The dtobit coefficients for the two pairs are 0.461 and 0.279 after converting to a percentage of dollars, representing awards that are on average $26,165.89 and $15,836.13 higher than the omitted category of non-individual vs. individual, corporation, government, or hospital.

For the 2001 data set, neither of the two litigant pairs in the regression is significant. The coefficients are also much lower compared to the 1996 values. So then do the courts no longer consider the litigants in awarding punitive damages? Although this is a possibility, there may be other factors causing the change. For example, since the 2001 survey did not include the option of an individual and non-individual vs. individual, corporation, government, or hospital litigant pair, there may be a kind of omitted variable bias at play. The cases that should have been classified in this litigant pair category may have instead been classified in a different category, which could confuse the analysis. So, one should hesitate to draw any major conclusions with regard to the change in litigant pair type significance. One can expect that non-individual vs. individual, corporation, government, or hospital will be negatively correlated with the other two litigant pair categories since each case

Table 4: Hersch and Viscusi (2004) and Base Model Probit and Tobit Estimates

Independent Variables	Probit: Hersch and Viscusi (2004)	Probit: Base Model 1996	Probit: Base Model 2001	Tobit: Hersch and Viscusi (2004)	Tobit: Base Model 1996	Tobit: Base Model 2001
Jury Trial	0.256** (0.100)	0.256** (0.100)	0.308** (0.102)	4.777** (1.875)	4.810* (1.917)	5.918** (1.889)
Log(Compensatory Damages)	0.047* (0.020)	0.047* (0.020)	0.051** (0.017)	1.081** (0.377)	1.155** (0.386)	1.125** (0.315)
Litigant Pairs						
Individual vs. Individual	0.666** (0.145)	0.666** (0.145)	0.241 (0.124)	12.650** (2.825)	13.268** (2.921)	4.274 (2.281)
Individual vs. Corporation, Government, or Hospital	0.515** (0.141)	0.515** (0.141)	0.074 (0.118)	9.891** (2.702)	10.548** (2.796)	1.335 (2.159)
Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital	0.325 (0.233)	0.325 (0.233)	N/A[a]	6.357 (4.351)	6.854 (4.452)	N/A[a]
Case Types						
Premises Liability	0.456** (0.175)	0.456** (0.175)	-0.001 (0.204)	8.435** (3.315)	8.483* (3.374)	-0.316 (3.745)
Product Liability	0.806** (0.247)	0.810** (0.248)	0.323 (0.345)	15.372** (4.690)	15.580** (4.779)	5.798 (6.321)
Intentional Tort	1.740** (0.160	1.740** (0.160)	1.692** (0.142)	31.981** (3.582)	32.084** (3.650)	30.597** (3.085)
Medical or Professional Malpractice	0.096 (0.262)	0.096 (0.262)	0.417* (0.168)	1.630 (4.861)	1.531 (4.949)	7.498* (3.123)
Slander/Libel	1.414** (0.359)	1.415** (0.359)	2.379** (0.274)	26.330** (6.948)	26.706** (7.075)	41.408** (5.124)
Other Tort	0.415 (0.251)	0.415 (0.251)	0.766** (0.166)	7.969 (4.682)	8.004 (4.769)	14.647** (3.149)
Fraud	1.505** (0.169)	1.505** (0.169)	1.223** (0.148)	28.073** (3.605)	28.066** (3.677)	23.014** (3.012)
Seller or Buyer Plaintiff	0.882** (0.157)	0.882** (0.157)	0.274 (0.152)	16.812** (3.105)	17.175** (3.167)	5.286 (2.811)
Employment Dispute	1.528** (0.174)	1.529** (0.174)	1.017** (0.180)	28.841** (3.704)	28.876** (3.773)	19.118** (3.465)
Other Contract	1.073** (0.176)	1.073** (0.176)	0.995** (0.172)	20.507** (3.529)	20.929** (3.601)	18.644** (3.339)
Real Property	1.409** (0.329)	1.409** (0.329)	PFP[b]	26.735** (6.313)	27.244** (6.427)	PFP[b]
Constant	-3.900** (0.284)	-3.901** (0.283)	-3.251** (0.243)	-75.958** (7.270)	-78.260** (7.525)	-62.663** (5.843)
Number of observations	4,336	4,336	4,153	4,336	4,336	4,153
R^2		0.204	0.208		0.113	0.114

* Coefficient is significant at the 95% level of confidence

** Coefficient is significant at the 99% level of confidence

[a] The Individual & Non-Individual, Corporation, Government, or Hospital litigant pair type was not available in the 2001 survey

[b] Real property predicts failure perfectly when included in the equation because there are no real property cases with punitive awards in the 2001 data set, so it was not included in the equation

Standard errors are given in parentheses

The dependent variable in the probit models is a dummy variable for whether or not punitive damages were awarded

The dependent variable in the tobit model is log(punitive damages) can only be classified as one type. So, given that the coefficient is positive using the 1996 data, the negative correlation with the other litigant pair types means that the estimates for individual vs. individual and individual vs. corporation, government, or hospital are biased downward. The downward bias may explain why significance is lost.

The case type results are the same between the 1996 base model and Hersch and Viscusi (2004). Every case type has a positive coefficient, as expected, since the reference category, motor vehicle tort, is the least likely to result in a punitive award and when an award does occur, it will likely be a smaller amount. Motor vehicle torts are almost always accidental and not intentional. Also, most of the coefficients for the case types are significant. The only types that are insignificant are malpractice cases and the general category of other tort. The case types with the largest coefficients, in both the decision and levels models, are intentional tort, employment dispute, and fraud. Again, this was expected because intentional torts, employment disputes, and fraud are case types that tend to involve intentional actions, which would probably be seen as more egregious misbehavior. Specifically, intentional tort has the highest coefficients in both models: 1.740 in the decision model and 32.084 in the levels model. The dprobit coefficient is 0.334, which is 837% of the probability of a punitive award. So, compared to motor vehicle torts, the magnitude of the intentional tort effect on the probability of a punitive award is 837%. The dtobit coefficient is 3.97, or 51.98 after converting to dollar percentage. Evaluated at the mean of punitive awards, intentional torts result in punitive awards that are $2,951,721.69 higher than motor vehicle torts.

The case type results are similar for the 2001 data set. The largest coefficients in the 1996 regressions remain high, positive, and significant in the 2001 regressions. One difference, though, is that the slander/libel case type replaces intentional tort as the type with the highest coefficients in the two models. But, again, this is not surprising because this case type also tends to involve intentional actions. Another difference with the newer data is that the premises liability case type actually becomes negative and insignificant. The product liability coefficients also lose significance, even though they do remain positive. So, it would appear that, in the 2001 sample, juries and judges no longer had a tendency to distinguish between motor vehicle torts and premises liability or product liability cases.

To compare the base models proposed in this paper to Eisenberg et al. (2002), the interaction term of jury trial times log(compensatory damages) is introduced. Table 5 displays the results of Eisenberg et al. (2002)[113] and the 1996 and 2001 base models including the interaction term. Only the results for jury trial, log(compensatory damages), and the interaction term are displayed, but the regressions included all of the variables shown in table 4. While the results are not nearly as close as those with Hersch and Viscusi (2004) because the models and the regression techniques are different, one can examine the significance of the most important variables, jury trial, log(compensatory damages), and jury trial times log(compensatory damages). The 1996 base model produces the same results as Eisenberg et al. (2002), with jury trial and the interaction term insignificant in both the decision and levels models. Repeating this process with the 2001 data, however, yields different results: jury trial actually becomes significant, at the 99% level in the decision model and at the 95% level in the levels model. The presence of a jury effect in the new data even when the interaction term is included raises doubt about the conclusions of Eisenberg et al. (2002). Hersch and Viscusi (2004) argue that the results of Eisenberg et al. (2002) ignore a multi-collinearity problem induced by the interaction term.[114] The fact that there is a jury effect even when there may be multi-collinearity makes the jury effect a more robust conclusion.

One can assess the degree of multi-collinearity in the data to test the argument of Hersch and Viscusi (2004). The VIF assesses the extent of multi-collinearity by estimating the correlation between a particular variable and every other independent variable in the equation. In the 1996 Base Model, the VIF is 36.48 for the interaction term and 31.31 for jury trial. In comparison, the next highest VIF is 3.87 for log(compensatory damages). One can also compare these values to the VIF's for the 1996 base model without the interaction term. The highest VIF there is 3.01 for individual vs. corporation, government, or hospital. So, the VIF's for the interaction term and jury trial are significantly higher than normal implying there is a multi-collinearity problem. Repeating this process for 2001, there is a VIF of 37.54 for the interaction term and 30.94 for jury trial. One criticism of the VIF, however, is that there is no definite cutoff value where one can say there is a multi-collinearity problem. To solve this, Belsley, Kuh, and Welsch propose a condition index and argue that a value above 30 indicates a potential problem.[115] Using the 1996 decision model, a condition index of 45.05 is obtained, clearly above the proposed threshold of 30. The proportions of variation for each variable then indicate that four variables are multi-collinear: jury trial, compensatory damages, the interaction term, and the constant. The 2001 data yields the same pattern with a condition index of 49.26.

Based on the collinearity diagnostics, there is clearly a high degree of collinearity making it difficult for the model to separate the effects caused by each variable, especially jury trial and the interaction term. Furthermore, since the jury effect always seems to be significant when there is no interaction term and sometimes, at least with the 2001 data, even when there is an interaction term, this paper rejects the results of Eisenberg et al. (2002).

However, one cannot conclude that there is a jury effect without further tests of robustness. Other influences may affect punitive damages which have been neglected by Hersch and Viscusi (2004) and Eisenberg et al. (2002). The expanded model attempts to account for two other possible influences. Table 6 presents the results of the expanded model for both the decision and levels models. The 1996 regressions included only the general poverty rate while the 2001 regressions were done in two iterations; first, the general poverty rate was included and second, three poverty subgroups by race were included.

Table 5: Eisenberg et al. (2002) and Base Model with Interaction Term Regressions						
	Decision Model			Levels Model		
Independent Variables	Eisenberg et al. (2002) Odds Ratio[a]	1996	2001	Eisenberg et al. (2002)	1996	2001
Jury Trial	1.660	0.684 (0.459)	1.343** (0.510)	-0.360 (1.047)	15.634 (8.937)	23.645* (9.459)
log(Compensatory Damages)	1.371**	0.075* (0.035)	0.132** (0.043)	0.854** (0.144)	1.857** (0.691)	2.529** (0.800)
Jury Trial*log(Compensatory Damages)	0.821	-0.040 (0.042)	-0.097* (0.046)	0.029 (0.225)	-1.017 (0.815)	-1.658 (0.855)
Number of observations	4,336	4,336	4,153	171	4,336	4,153
R^2	0.187	0.205	0.211	0.621	0.114	0.115

* Coefficient is significant at the 95% level of confidence

** Coefficient is significant at the 99% level of confidence

[a] Eisenberg et al. (2002) report the odds ratio, the amount by which the odds of a case having punitive award should be multiplied, compared to a reference category

Standard errors are given in parentheses

Eisenberg et al.'s (2002) decision model is a logistic regression and their levels model appears to be OLS but the regression technique is not reported

The 1996 and 2001 base decision models are probit regression and the 1996 and 2001 base levels models are tobit regression

The dependent variable in the decision models is a dummy variable for whether or not punitive damages were awarded

The dependent variable in the levels models is log(punitive damages)

Jury trial is significant in both the probit and tobit estimates for all three regressions. The values of the jury trial coefficients are very similar to the results with the base model. With the 1996 data, jury trial has a coefficient of 0.238 in the decision model and 4.424 in the levels model. Jury trial is significant at the 95% confidence level. With the 2001 data, for the decision and levels models respectively, the coefficients are 0.292 and 5.592 when only the general poverty rate is included and 0.309 and 5.858 when the poverty subgroups are included. All four of these jury trial coefficients are significant at the 99% level.

The results also show the new variables to be significant in most cases. The general poverty rate is significant at the 90% level with the 1996 sample, but not significant in the 2001 sample. In all four cases, the coefficient is positive. A positive value confirms the results of Helland and Tabarrok (2003): a higher poverty rate leads to a greater probability of punitive damages and higher amounts.[116] Using the subgroups within the 2001 sample, two subgroups are found to be significant in both models, white and black, but the Hispanic poverty rate is not significant. The white poverty rate is positive and significant at the 90% level and the coefficients are higher than for the general poverty rate in either 1996 or 2001. The black poverty rate, on the other hand, is negative and significant at the 99% level. So, as the black poverty rate increases in a particular county, the probability and level of punitive awards decreases. This contradicts the results of Helland and Tabarrok (2003) to some extent. Not only did they always find a positive relationship, the black and Hispanic poverty rates were the most significant and had the highest magnitudes.[117] However, their research examined total tort awards for personal injury cases[118], whereas this paper is looking at punitive awards for torts, contract cases, and real property cases. Also, the definition for the racial subgroup poverty rate used in this paper differs from that of Helland and Tabarrok (2003). Their white poverty rate, for example, is the number of white people in poverty as a percentage of the total county population.[119] The white poverty used in this paper is the number of white people in poverty as a percentage of the total white population in the county. It appears that more research is necessary to determine the exact nature of the poverty effect on court awarded damages.

The voting margin variable is significant, at least at the 90% level, and negative in every situation. As expected, the more democratic the county, the less likely and lower the punitive awards. Given the significance of these new variables, poverty and voting margin, it appears that they are an important aspect in the determination of punitive damages and should be included in any such research.

With the expanded model, there were a few changes in the other independent variables. The litigant pairs, with the 1996 data, all became insignificant. In the base model, both types with individual plaintiffs were positive and significant. The sign

Table 6: Expanded Model Tobit and Probit Estimates

	Probit			Tobit		
Independent Variables	**1996**	**2001 A**	**2001 B**	**1996**	**2001 A**	**2001 B**
Jury Trial	0.238** (0.100)	0.292*** (0.103)	0.309*** (0.102)	4.424** (1.913)	5.592*** (1.887)	5.858*** (1.873)
log(Compensatory Damages)	0.052** (0.020)	0.052*** (0.017)	0.053*** (0.018)	1.236*** (0.394)	1.145*** (0.317)	1.157*** (0.317)
General Poverty Rate	0.021* (0.012)	0.016 (0.012)		0.410* (0.223)	0.304 (0.220)	
White Poverty Rate			0.029* (0.017)			0.537* (0.300)
Black Poverty Rate			-0.028*** (0.011)			-0.517*** (0.196)
Hispanic Poverty Rate			0.016 (0.011)			0.293 (0.203)
Voting Margin	-0.007** (0.003)	-0.005** (0.002)	-0.004* (0.003)	-0.123** (0.053)	-0.096** (0.044)	-0.080* (0.048)
Litigant Pairs						
Individual vs. Individual	0.349 (0.220)	0.246** (0.124)	0.245** (0.125)	6.517 (4.156)	4.33* (2.274)	4.302* (2.276)
Individual vs. Corporation, Government, or Hospital	0.191 (0.215)	0.076 (0.118)	0.089 (0.119)	3.694 (4.044)	1.386 (2.154)	1.608 (2.153)
Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital	-0.330 (0.233)	N/A[a]	N/A[a]	-6.953 (4.438)	N/A[a]	N/A[a]
Case Types						
Premises Liability	0.480*** (0.177)	0.029 (0.204)	0.036 (0.206)	8.857*** (3.397)	0.215 (3.743)	0.352 (3.745)
Product Liability	0.833*** (0.254)	0.362 (0.343)	0.386 (0.341)	15.846*** (4.861)	6.483 (6.269)	6.892 (6.186)
Intentional Tort	1.763*** (0.161)	1.699*** (0.143)	1.723*** (0.143)	32.292*** (3.658)	30.567*** (3.079)	30.743*** (3.077)
Medical or Professional Malpractice	0.112 (0.263)	0.423** (0.170)	0.412** (0.171)	1.821 (4.952)	7.521** (3.144)	7.247** (3.141)
Slander/Libel	1.377*** (0.358)	2.389*** (0.274)	2.388*** (0.275)	25.882*** (7.025)	41.419*** (5.109)	41.148*** (5.075)
Other Tort	0.422* (0.252)	0.757*** (0.166)	0.765*** (0.167)	8.062* (4.758)	14.402*** (3.137)	14.445*** (3.135)
Fraud	1.505*** (0.170)	1.202*** (0.149)	1.206*** (0.149)	27.889*** (3.671)	22.510*** (2.997)	22.435*** (2.983)
Seller or Buyer Plaintiff	0.890*** (0.157)	0.255* (0.153)	0.270* (0.154)	17.253*** (3.163)	4.892* (2.810)	5.139* (2.804)
Employment Dispute	1.563*** (0.176)	1.008*** (0.180)	0.983*** (0.182)	29.405*** (3.793)	18.874*** (3.452)	18.244*** (3.451)
Other Contract	1.069*** (0.176)	0.983*** (0.172)	0.974*** (0.173)	20.716*** (3.588)	18.334*** (3.234)	18.025*** (3.315)
Real Property	1.422*** (0.330)	PFP[b]	PFP[b]	27.370*** (6.413)	PFP[b]	PFP[b]
Constant	-3.758*** (0.359)	-3.328*** (0.264)	-3.213*** (0.292)	-74.683*** (8.425)	-63.872*** (6.165)	-61.339*** (6.440)
Number of observations	4,336	4,153	4,153	4,336	4,153	4,153
R^2	0.208	0.211	0.217	0.116	0.116	0.119

* Coefficient is significant at the 90% level of confidence
** Coefficient is significant at the 95% level of confidence
*** Coefficient is significant at the 99% level of confidence
[a] The Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital litigant pair type was not available in the 2001 survey
[b] Real Property predicts failure perfectly when included in the equation because there are no real property cases with punitive awards in the 2001 data set, so it was not included in the equation
Standard errors are given in parentheses
The dependent variable in the probit models is a dummy variable for whether or not punitive damages were awarded
The dependent variable in the tobit models is log(punitive damages)

for the individual and non-individual vs. individual, corporation, government, or hospital litigant pair also flips from positive to negative, although it is still insignificant. In the 2001 base model, no litigant pair was significant, but with the expanded model, individual vs. individual is now positive and significant. Case types remain very similar in the expanded model compared to the base model. The significance of every case type remains the same, all coefficients are still positive, and the values are similar as well.

In order to further check the robustness of the jury effect as well as the other results this paper performs other iterations of the models. First, since the results have thus far been inconsistent with regard to litigant pairs, the categories are expanded. The literature suggests that punitive awards may be higher when levied against corporation defendants with big pockets, but with the broad litigant pair categories used thus far, it is difficult to determine if such an effect exists. So, the litigant pairs are expanded into the categories previously listed in the model section, but, unfortunately, the expanded pairs do not aid in the analysis. Individual vs. individual is the only category that is ever significant in any of the iterations and it is not even consistent, although it is always positive. Using the expanded pairs also induces a multi-collinearity problem between certain litigant pair types in some cases. However, despite these problems, the major results don't change; the positive jury effect is still present in all cases with expanded pairs.

Another robustness check is to use state control variables rather than county. All of these cases take place in state courts, so the law is constant across states rather than just counties. Table 7 shows the results for the major variables for each of the base and expanded models for both 1996 and 2001. Although only the major variables are reported, the same independent variables were included in the regressions as described previously except state control variables were used instead of county controls. The results for litigant pairs and case types were the same as previously. Also, log(compensatory damages) is still significant and positive in all cases. Jury trial, on the other hand is only weakly significant for the 1996 decision model and not significant at all for the 1996 levels model. But, jury trial is highly significant, at 99%, for all 2001 models. There are also some changes for the poverty rates. Poverty is not significant for the 1996 expanded model, but is for 2001. However, the white poverty rate is the only consistently significant subgroup. So, there are some inconsistent results with state control variables. It is difficult to draw conclusions here, especially regarding the jury effect. Jury trial does become significant in all cases at 85% level of confidence, but this is not a standard significance level. So there does seem to still be a jury effect, but using state control variables seems to weaken that conclusion.

Another econometric issue that must addressed is selectivity bias. Even within a particular case type or litigant pair, juries may only see cases that are more likely to result in high punitive awards. To attempt to correct for selectivity, this paper uses a treatment effects model. A number of variables can affect the selection of a jury or bench trial, which are included in the first stage regression. First, however, this paper estimates the predicted time to verdict for the entire data set using a preliminary regression. The selection of trial forum will likely be based on expected costs of the trial, which one can proxy for using predicted time to verdict. The actual time to verdict cannot be used because this is an ex-post figure that wouldn't be known to the parties when choosing a trial forum. The actual time from filing to verdict is regressed against the detailed case types (18 types were used in the regression, one was left out as a reference group), all of the counties (44 included, one left out as reference), and the year the case was filed. The predicted time to verdict should depend on the type of case being tried because some types, such as motor vehicle torts, will probably be shorter trials, while others, such as product liability, will last longer. Also, different counties may take longer to try a case because of a busier court docket or slightly different procedures. Finally, from year to year, individuals may have different perceptions about trial time especially with the recent growth in litigation; so, the year of filing is included.

In the first stage regression of the treatment effects model, jury trial is regressed against variables expected to affect forum selection. In one model, the variables used by Hersch and Viscusi (2004) are included: predicted time to verdict, the number of plaintiffs and defendants, and the number of pro se plaintiffs and defendants.[120] But, one might also expect other variables to influence forum selection such as the type of plaintiff or defendant, the type of case, and the county where the case is to be tried. Individual defendants may prefer juries so they can play the sympathy card, while corporation defendants may wish to avoid juries who might have something against big business. Those in product liability cases may prefer judges due to potentially complicated evidence while other case types may prefer juries. Also, certain counties may have judges that tend to favor the plaintiff or defendant, pushing the litigants toward or away from juries. So this paper estimates the first stage of the model using just the variables from Hersch and Viscusi (2004), then using those variables as well as the litigant pairs, the case types, and the county control variables used in previous regressions. The second stage of the treatment effects model includes the same variables that were used in the base models. Along with the base variables, the model includes a selectivity correction term which comes from the first stage regression.[121]

Another consideration when estimating the treatment effects model is which observations to include. Hersch and Viscusi (2004) include the plaintiff win trials[122], as has been done with every regression thus far in this paper. This is because the decision on punitive damages would only come after a decision was made in favor of the plaintiff. However, in the treatment effects model, forum selection is made by every party in every case, not just those where the plaintiff wins. The expected award, used in the forum selection decision, as determined ex-ante by each party is conditional on winning the case. So, not including all observations may be inappropriate. To account for this possibility, this paper estimates the treatment effects model using only cases where the plaintiff wins and using all observations.

Table 7: Base and Expanded Models with State Control Variables					
Probit					
	1996		**2001**		
	Base Model	**Expanded Model**	**Base Model**	**Expanded Model A**	**Expanded Model B**
Jury Trial	0.164* (0.099)	0.169* (0.099)	0.348*** (0.104)	0.340*** (0.104)	0.368*** (0.105)
log(Compensatory Damages)	0.048** (0.021)	0.050** (0.021)	0.057*** (0.018)	0.058*** (0.018)	0.060*** (0.018)
General Poverty Rate		0.018 (0.013)		0.030* (0.015)	
White Poverty Rate					0.063*** (0.021)
Black Poverty Rate					-0.022* (0.013)
Hispanic Poverty Rate					-0.000 (0.015)
Voting Margin		-0.006* (0.003)		-0.006** (0.003)	-0.005* (0.003)
Number of observations	4,336	4,336	4,153	4,153	4,153
R^2	0.220	0.223	0.216	0.220	0.226
Tobit					
	1996		**2001**		
	Base Model	**Expanded Model**	**Base Model**	**Expanded Model A**	**Expanded Model B**
Jury Trial	2.935 (1.853)	3.007 (1.857)	6.605*** (1.909)	6.415*** (1.905)	6.833*** (1.907)
log(Compensatory Damages)	1.152*** (0.398)	1.182*** (0.399)	1.225*** (0.320)	1.240*** (0.320)	1.266*** (0.320)
General Poverty Rate		0.361 (0.234)		0.511* (0.275)	
White Poverty Rate					1.087*** (0.383)
Black Poverty Rate					-0.414 (0.234)
Hispanic Poverty Rate					0.016 (0.276)
Voting Margin		-0.113* (0.059)		-0.105** (0.045)	-0.083* (0.047)
Number of observations	4,336	4,336	4,153	4,153	4,153
R^2	0.122	0.124	0.119	0.121	0.124

* Coefficient is significant at the 90% level of confidence
** Coefficient is significant at the 95% level of confidence
*** Coefficient is significant at the 99% level of confidence
Standard errors are given in parentheses
Each model also contains other variables as described in the text and listed in previous tables
The dependent variable in the probit models is a dummy variable for whether or not punitive damages were awarded
The dependent variable in the tobit models is log(punitive damages)

Table 8 displays the major results of the treatment effects model. Four iterations were performed for each data set using different combinations of the observations included and the first-stage independent variables. Only the jury trial coefficients and standard errors are shown, but the results for the other independent variables were very similar to the original base model regressions. Also shown on the table is the p-value for the independence test or likelihood ratio test of the model. Here, the null hypothesis is that the error terms for the first and second stage regressions are uncorrelated, meaning there is no

Table 8: Selectivity Correction Regressions								
	1996				2001			
Number of Observations	4326	8475	4326	8475	4147	7592	4147	7592
1st Stage: All or Viscusi Variables	Viscusi	Viscusi	All	All	Viscusi	Viscusi	All	All
Decision Model								
Jury Trial	0.033* (0.018)	0.023** (0.009)	0.031** (0.014)	0.022*** (0.007)	-0.274*** (0.010)	-0.194*** (0.006)	0.023 (0.019)	0.020** (0.010)
Jury Trial p-value	0.071	0.015	0.033	0.002	0.000	0.000	0.215	0.041
Independence Test p-value	0.507	0.440	0.458	0.284	0.000	0.000	0.966	0.970
Levels Model								
Jury Trial	0.365* (0.201)	0.297*** (0.098)	0.336** (0.154)	0.272*** (0.079)	-3.219*** (0.107)	-2.278*** (0.065)	0.303 (0.211)	0.284*** (0.109)
Jury Trial p-value	0.070	0.002	0.030	0.001	0.000	0.000	0.152	0.009
Independence Test p-value	0.522	0.279	0.467	0.245	0.000	0.000	0.948	0.813

* Coefficient is significant at the 90% level of confidence
** Coefficient is significant at the 95% level of confidence
*** Coefficient is significant at the 99% level of confidence
Standard errors are given in parentheses
The dependent variable in the probit models is a dummy variable for whether or not punitive damages were awarded
The dependent variable in the tobit models is log(punitive damages)

selectivity bias problem.

With the 1996 data, the results of Hersch and Viscusi (2004) are confirmed in all iterations. Jury trial is still positive and significant and there is no selectivity bias problem. Using the 2001 data, however, jury trial is only positive and significant using all observations and all of the first-stage independent variables. Using all first-stage variables and only plaintiff win trials, jury trial remains positive, but becomes insignificant. When only the Hersch and Viscusi (2004) first-stage variables are used, the jury trial coefficient becomes negative and highly significant. The independence test also indicates that there is a selectivity problem. This means that, after adjusting for forum selection, juries are less likely to award punitive damages and they do so in lower amounts than judges. So, the jury effect may not be robust when adjusting for selectivity bias. A better selection model with more data may be needed to determine the true effect of forum selection. These two data sets are limiting because they only include cases tried to verdict, no cases that were settled out of court, and they don't contain other variables that could effect forum selection, such as damages request or expectations of the parties involved. The 2001 survey did ask for the damages request, but only 1,915 cases actually had the information and only 1,184 were plaintiff win cases. Including the damages request in the regression estimating time to verdict and only using the 1,184 observations in the treatment effects model, jury trial is negative and significant in both the decision and levels model and the independence test indicates there is a selectivity bias problem.

Another way to analyze the jury effect on punitive damages is through quantile regressions. The jury effect may be more prominent with the highest punitive awards. Table 9 contains the results of the quantile regressions for 1996 and 2001. Only jury trial and log(compensatory damages) were included as independent variables in the regressions because quantile regressions cannot handle a large number of variables with a large data set. Hersch and Viscusi (2004) performed quantile regressions and found the jury trial coefficient to only be significant for the 0.90 quantile.[123] As shown in table 9, jury trial is not significant at the 90% level for any quantile in either 1996 or 2001. This is likely due to omitted variable bias since the other independent variables are not included. The regression yields different results than Hersch and Viscusi (2004) using the 1996 data because of the use of bootstrap standard errors. Every time the regression is estimated using the bootstrapping technique the standard errors will change. Increasing the number of iterations will stabilize the standard errors, but they will still vary. The quantile regressions shown in table 9 were done with 20,000 iterations. After several runs, the jury trial coefficient was never significant at the 90% level. The highest level of significance was 89%, for the 0.90 quantile using the 1996 data set. For 2001, however, the p-value for jury trial in the 0.90 quantile is 0.258, far from significance. The limitation on independent variables in quantile regressions makes them somewhat unreliable for studying the jury effect.

Conclusions

Based on the results of this paper, a decisive conclusion cannot be drawn regarding the jury effect. The base models and expanded models did indicate a positive jury effect; juries are more likely to award punitive damages than judges and they do

Table 9: Quantile Regressions on Punitive Damages					
1996					
	0.1	**0.25**	**0.5**	**0.75**	**0.9**
Jury Trial	-0.706 (0.526)	-0.249 (0.243)	-0.019 (0.255)	0.481 (0.358)	0.924 (0.575)
log(Compensatory Damages)	0.912*** (0.111)	0.830*** (0.076)	0.866*** (0.102)	0.642*** (0.187)	0.446*** (0.209)
Constant	-0.791 (1.478)	0.587 (0.838)	0.945 (1.139)	4.211* (2.148)	6.958*** (2.333)
Number of observations	173	173	173	173	173
R^2	0.277	0.328	0.295	0.245	0.210
2001					
	0.1	**0.25**	**0.5**	**0.75**	**0.9**
Jury Trial	0.138 (0.445)	0.420 (0.389)	0.672 (0.425)	0.321 (0.361)	0.729 (0.643)
log(Compensatory Damages)	0.796*** (0.128)	0.700*** (0.084)	0.688*** (0.105)	0.672*** (0.110)	0.538*** (0.189)
Constant	-0.404 (1.532)	1.438 (0.969)	2.649** (1.207)	4.284*** (1.245)	6.574*** (2.209)
Number of observations	199	199	199	199	199
R^2	0.209	0.255	0.257	0.243	0.200

* Coefficient is significant at the 90% level of confidence
** Coefficient is significant at the 95% level of confidence
*** Coefficient is significant at the 99% level of confidence
Standard errors are given in parentheses
Bootstrap standard errors are reported in parentheses
The dependent variable is log(punitive damages)

so in higher amounts. This result controlled for compensatory damages, litigant pairs, case types, and county effects. It was also robust with respect to the inclusion of an interaction term that induces multi-collinearity, including new variables that have a significant influence on punitive damages, and expanding the litigant pair categories. The positive influence of jury trials on the probability of a punitive award also held when using state control variables instead of county controls. However, the jury effect on the amount of punitive awards only held in the 2001 sample with the state controls; jury trial was not significant using the 1996 data set. Also, results with the jury effect were inconsistent between surveys when correcting for forum selection bias. The positive jury effect was maintained for the 1996 data in the selection model, but not 2001. In some cases, when following the selection model of Hersch and Viscusi (2004), the jury effect actually becomes negative and significant. However, their model may neglect possible influences. Using the expanded selection model from this paper and all survey observations, the positive jury effect is still present.

Consistent with prior research, this paper found a positive correlation between compensatory damages and the probability and amount of punitive damages. This result is robust under every situation. Result varied with regard to litigant pairs. The individual vs. individual litigant pair type was found most often to have a positive effect on punitive awards compared to non-individual vs. individual, corporation, government, or hospital, even with a suspected downward omitted variable bias with the 2001 expanded models. No evidence was found to support the deterrence-argument prediction that punitive damages are higher when levied against corporations. Most case types were found to have a positive effect on punitive awards compared to the reference category of motor vehicle torts. In particular, case types involving intentional actions had the largest impact on increasing both the probability and amount of punitive awards; this was predicted based on the egregiousness of misbehavior.

The overall county poverty rate was generally found to have a weak positive correlation with punitive damages. The positive correlation was stronger with the white poverty subgroup. But, black poverty rates had a negative correlation and Hispanic rates were insignificant, an unexpected result considering the conclusions of Helland and Tabarrok (2003). The previously unstudied influence of political leanings was found to be significant in all model iterations. The voting margin had a negative effect on punitive damages, leading to the conclusion that more liberal county populations lead to less likely and smaller punitive awards.

Overall, more research is needed to determine the true nature of the jury effect on punitive damages, especially with new and better data. Specifically, the possibility of selectivity bias must be studied using a more appropriate data set that includes cases not tried to verdict, such as those settled out of court. The several model iterations performed in this paper suggest that there is at least a weak positive jury effect. However, even if this result was conclusive, the effects on efficiency are far from being understood. If juries do award punitive damages more often and in larger amounts than punitive damages, this does not mean the power to award should be stripped from juries. The fact that there appear to be several other influences on punitive damages, such as the litigants, case types, and political leanings, indicates that neither judges nor juries award punitive damages in an economically efficient manner.

Appendix A: DProbit Estimates of 1996 and 2001 Models					
	1996		2001		
Independent Variables	**Base Model**	**Expanded Model A**	**Base Model**	**Expanded Model A**	**Expanded Model B**
Jury Trial	0.011** (0.004)	0.010** (0.004)	0.017** (0.005)	0.016*** (0.005)	0.016*** (0.005)
log(Compensatory Damages)	0.002* (0.001)	0.002** (0.001)	0.003** (0.001)	0.003*** (0.001)	0.003*** (0.001)
General Poverty Rate		0.001* (0.001)		0.001 (0.001)	
White Poverty Rate					0.002* (0.001)
Black Poverty Rate					-0.002*** (0.001)
Hispanic Poverty Rate					0.001 (0.001)
Voting Margin		-0.0003** (0.0001)		-0.0003** (0.0001)	-0.0003* (0.0001)
Litigant Pairs					
Individual vs. Individual	0.041** (0.011)	0.018 (0.013)	0.016 (0.008)	0.016** (0.008)	0.015** (0.008)
Individual vs. Corporation, Government, or Hospital	0.027** (0.008)	0.009 (0.011)	0.005 (0.008)	0.005 (0.007)	0.005 (0.007)
Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital	0.021 (0.020)	-0.012 (0.007)	N/A[a]	N/A[a]	N/A[a]
Case Types					
Premises Liability	0.031** (0.016)	0.033*** (0.016)	-0.0001 (0.013)	0.002 (0.013)	0.002 (0.013)
Product Liability	0.083** (0.042)	0.086*** (0.044)	0.027 (0.037)	0.031 (0.039)	0.033 (0.039)
Intentional Tort	0.334** (0.052)	0.339*** (0.052)	0.360** (0.050)	0.360*** (0.050)	0.365*** (0.050)
Medical or Professional Malpractice	0.005 (0.015)	0.006 (0.015)	0.037* (0.019)	0.037** (0.020)	0.035** (0.019)
Slander/Libel	0.237** (0.113)	0.0223*** (0.109)	0.064** (0.098)	0.643*** (0.097)	0.639*** (0.098)
Other Tort	0.029 (0.024)	0.029* (0.024)	0.090** (0.030)	0.088*** (0.030)	0.089*** (0.030)
Fraud	0.250** (0.049)	0.247*** (0.049)	0.195** (0.039)	0.188*** (0.039)	0.186*** (0.039)
Seller or Buyer Plaintiff	0.074** (0.019)	0.074*** (0.019)	0.020 (0.013)	0.018* (0.012)	0.019* (0.012)
Employment Dispute	0.026** (0.052)	0.269*** (0.053)	0.146** (0.043)	0.143*** (0.043)	0.135*** (0.042)
Other Contract	0.125** (0.034)	0.122*** (0.034)	0.138** (0.039)	0.134*** (0.038)	0.129*** (0.038)
Real Property	0.235** (0.103)	0.236*** (0.103)	PFP[b]	PFP[b]	PFP[b]
Number of observations	4,336	4,336	4,153	4,153	4,153
R^2	0.204	0.208	0.208	0.211	0.217

* Coefficient is significant at the 90% level of confidence

** Coefficient is significant at the 95% level of confidence

*** Coefficient is significant at the 99% level of confidence

[a] The Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital litigant pair type was not available in the 2001 survey

[b] Real Property predicts failure perfectly when included in the equation because there are no real property cases with punitive awards in the 2001 data set, so it was not included in the equation

Standard errors are given in parentheses

The dependent variable is a dummy variable for whether or not punitive damages were awarded

Appendix B: DTobit Estimates of 1996 and 2001 Models					
	1996		2001		
Independent Variables	**Base Model**	**Expanded Model A**	**Base Model**	**Expanded Model A**	**Expanded Model B**
Jury Trial	0.089** (0.039)	0.081** (0.038)	0.145*** (0.053)	0.136*** (0.052)	0.138*** (0.051)
log(Compensatory Damages)	0.024*** (0.008)	0.025*** (0.008)	0.032*** (0.009)	0.032*** (0.009)	0.031*** (0.009)
General Poverty Rate		0.008* (0.004)		0.008 (0.006)	
White Poverty Rate					0.015* (0.008)
Black Poverty Rate					-0.014*** (0.005)
Hispanic Poverty Rate					0.008 (0.005)
Voting Margin		-0.002** (0.001)		-0.003** (0.001)	-0.002* (0.001)
Litigant Pairs					
Individual vs. Individual	0.379*** (0.060)	0.151 (0.083)	0.127* (0.064)	0.127** (0.063)	0.123* (0.062)
Individual vs. Corporation, Government, or Hospital	0.246*** (0.057)	0.077 (0.081)	0.038 (0.061)	0.039 (0.060)	0.045 (0.058)
Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital	0.210 (0.091)	-0.108 (0.089)	N/A[a]	N/A[a]	N/A[a]
Case Types					
Premises Liability	0.265** (0.069)	0.277*** (0.068)	-0.009 (0.106)	0.006 (0.104)	0.010 (0.101)
Product Liability	0.814*** (0.098)	0.830*** (0.097)	0.231 (0.178)	0.266 (0.174)	0.284 (0.167)
Intentional Tort	3.969*** (0.075)	4.009*** (0.073)	4.526*** (0.087)	4.503*** (0.086)	4.535*** (0.083)
Medical or Professional Malpractice	0.034 (0.101)	0.040 (0.099)	0.317** (0.088)	0.315** (0.087)	0.293** (0.085)
Slander/Libel	2.712*** (0.145)	2.495*** (0.141)	10.094** (0.144)	10.094*** (0.142)	9.912*** (0.137)
Other Tort	0.261* (0.098)	0.259* (0.095)	0.943*** (0.089)	0.907*** (0.087)	0.897*** (0.085)
Fraud	2.794*** (0.075)	2.730*** (0.074)	2.253*** (0.085)	2.137*** (0.083)	2.098*** (0.081)
Seller or Buyer Plaintiff	0.714*** (0.065)	0.709*** (0.063)	0.181* (0.079)	0.163* (0.078)	0.168* (0.076)
Employment Dispute	3.046*** (0.077)	3.160*** (0.076)	1.597*** (0.098)	1.547*** (0.096)	1.425*** (0.093)
Other Contract	0.1.333*** (0.074)	1.289*** (0.072)	1.476*** (0.094)	1.418*** (0.092)	1.352*** (0.090)
Real Property	2.836*** (0.132)	2.845*** (0.129)	PFP[b]	PFP[b]	PFP[b]
Constant	-1.605*** (0.154)	-1.498*** (0.169)	-1.766*** (0.165)	-1.776*** (0.171)	-1.661*** (0.174)
Number of observations	4,336	4,336	4,153	4,153	4,153

* Coefficient is significant at the 90% level of confidence

** Coefficient is significant at the 95% level of confidence

*** Coefficient is significant at the 99% level of confidence

[a] The Individual & Non-Individual vs. Individual, Corporation, Government, or Hospital litigant pair type was not available in the 2001 survey

[b] Real Property predicts failure perfectly when included in the equation because there are no real property cases with punitive awards in the 2001 data set, so it was not included in the equation

Standard errors are given in parentheses

The dependent variable is log(punitive damages)

Footnotes

[1] Joni Hersch & W. Kip Viscusi, *Punitive Damages: How Judges and Juries Perform*, 33 J. Legal Stud. 1, 8 (2004).
[2] Id.
[3] Id. at 34.
[4] Theodore Eisenberg et al., *Juries, Judges, and Punitive Damages: An Empirical Study*, 87 Cornell L. Rev. 743, 779 (2002).
[5] Id. at 747.; Hersch & Viscusi, *supra*, at 10.
[6] Civil Justice Survey of State Courts, 2001, http://webapp.icpsr.umich.edu/cocoon/ICPSR-STUDY/03957.xml (last visited Feb., 2005).; Civil Justice Survey of State Courts, 1996, http://webapp.icpsr.umich.edu/cocoon/ICPSR-STUDY/02883.xml (last visited Feb., 2005).
[7] Eisenberg et al., *Juries*, *supra*, at 747.; Hersch & Viscusi, *supra*, at 10.
[8] Civil Justice Survey of State Courts, 2001, *supra*.; Civil Justice Survey of State Courts, 1996, *supra*.
[9] A. Mitchell Polinsky & Steven Shavell, *Punitive Damages: An Economic Analysis*, 111 Harv. L. Rev. 869, (1998).
[10] Id. at 873.
[11] Id. at 873.
[12] Id. at 948.
[13] Id. at 890.
[14] Kathryn E. Spier, *A Note on the Divergence Between the Private and the Social Motive to Settle Under a Negligence Rule*, 26 J. Legal Stud. 613, 614 (1997).
[15] Jonathan M. Karpoff & John R. Lott Jr., *On the Determinants and Importance of Punitive Damage Awards*, 42 J. L. & Econ. 527, 527 (1999).
[16] Polinsky & Shavell, *supra*, at 878, 887-88.
[17] Theodore Eisenberg et al., *The Predictability of Punitive Damages*, 26 J.Legal Stud. 623, 628 (1997).
[18] Id. at 629.
[19] Polinsky & Shavell, *supra*, at 890.
[20] Eisenberg et al., *Predictability*, *supra*.
[21] Id. at 632-33.
[22] Id. at 637-39.
[23] Id. at 639.
[24] Id. at 639-40.
[25] Id. at 649.
[26] Id. at 629-30.
[27] Id. at 644.
[28] Id. at 646.
[29] Id. at 646.
[30] Id. at 644-46.
[31] Karpoff & Lott, *supra*.
[32] Id. at 534-35.
[33] Id. at 540-42.
[34] Id. at 543-45.
[35] Id. at 540-41.
[36] Id. at 544.
[37] Id. at 545.
[38] Eric Helland & Alexander Tabarrok, *Race, Poverty, and American Tort Awards: Evidence from Three Data Sets*, 32 J. Legal Stud. 27, 27 (2003).
[39] Id. at 29.
[40] Id. at 29-30.
[41] Id. at 30-31.
[42] Id. at 32.
[43] Id. at 32.
[44] Id. at 34-35.
[45] Id. at 51-52.
[46] Id. at 38.
[47] Eric Helland & Alexander Tabarrok, *Runaway Judges? Selection Effects and the Jury*, 16 J. L. Econ. & Org. 306, 306 (2000).
[48] Id. at 309-10.
[49] Id. at 310.
[50] Id. at 310.
[51] Id. at 309-10.

[52] Id. at 316.
[53] Id. at 327.
[54] Hersch & Viscusi, *supra*.
[55] Eisenberg et al., *Juries*, *supra*.
[56] Id. at 747.; Hersch & Viscusi, *supra*, at 10.
[57] Eisenberg et al., *Juries*, *supra*, at 757-58, 771-72.; Hersch & Viscusi, *supra*, at 21-24.
[58] Hersch & Viscusi, *supra*, at 34.
[59] Eisenberg et al., *Juries*, *supra*, at 779.
[60] Id. at 757-758, 771-72.; Hersch & Viscusi, *supra*, at 17-21. The case type is the general category of civil law that the case falls under. Examples of case type are motor vehicle accident, product liability, and intentional tort. The litigant pair is the classification of the plaintiff and defendant from the case. Possible classifications include individual and non-individual for the plaintiff and individual, corporation, government, and hospital for the defendant.
[61] Eisenberg et al., *Juries*, *supra*, at 760, 781-82.; Hersch & Viscusi, *supra*, at 17-21.
[62] Hersch & Viscusi, *supra*, at 31-32.
[63] Eisenberg et al., *Juries*, *supra*, at 759.
[64] Hersch & Viscusi, *supra*, at 33-34.
[65] Id. at 21.
[66] Eisenberg et al., *Juries*, *supra*, at 760, 781-82.
[67] Hersch & Viscusi, *supra*, at 32.
[68] Id. at 21-24.
[69] Eisenberg et al., *Juries*, *supra*, at 771-72.
[70] Hersch & Viscusi, *supra*, at 24.
[71] Eisenberg et al., *Juries*, *supra*, at 759.
[72] Hersch & Viscusi, *supra*, at 4.
[73] Eisenberg et al., *Juries*, *supra*, at 766.
[74] Id. at 774.; Hersch & Viscusi, *supra*, at 25-26. The standard Heckman model uses a two-stage approach. First, a probit regression is estimated. In this case, this would basically be the decision model. Second, standard OLS is used and a selectivity correction variable is included that is estimated from the probit regression. This new variable accounts for a selectivity bias in the sample.
[75] Eisenberg et al., *Juries*, *supra*, at 774.; Hersch & Viscusi, *supra*, at 26-27.
[76] Helland & Tabarrok, *Runaway*, *supra*, at 330.
[77] Hersch & Viscusi, *supra*, at 34.
[78] See Hersch & Viscusi, *supra*, at 22-23; Eisenberg et al., *Juries*, *supra*, at 760, 781-82; Eisenberg et al., *Predictability*, *supra*, at 637-39, 646; Karpoff & Lott, *supra*, at 543-45.
[79] Eisenberg et al., *Juries*, *supra*, at 759.
[80] These are the same litigant pair categories used by Hersch & Viscusi (2004).
[81] These are the same case type categories used by Hersch & Viscusi (2004).
[82] This is the same criterion for county control variables used by Hersch & Viscusi (2004).
[83] All 1996 regressions with county controls include the following county variables: Cuyahoga, OH, Bergen, NJ, Harris, TX, Los Angeles, CA, Middlesex, NJ, Orange, CA, Pima, AZ, Ventura, CA, and Du Page, IL. All 2001 regressions with county controls include the following county variables: Franklin, OH, Dallas, TX, Fairfax, VA, Harris, TX, Los Angeles, CA, Orange, CA, San Bernardino, CA, San Francisco, CA, St. Louis, MO, and Pima, AZ.
[84] All 1996 regressions with state controls include the following state variables: California, Connecticut, Florida, Georgia, Hawaii, Illinois, Indiana, Kentucky, Massachusetts, Michigan, Minnesota, Missouri, New Jersey, New York, Ohio, Pennsylvania, Texas, Virginia, Washington, and Wisconsin. All 2001 regressions with state controls include the same state variables as for 1996, except Michigan and Minnesota are dropped and North Carolina is added.
[85] Helland & Tabarrok, *Race*, *supra*, at 33-35.
[86] Id. at 33-35.
[87] Id. at 51-52.
[88] Civil Justice Survey of State Courts, 2001, *supra*.; Civil Justice Survey of State Courts, 1996, *supra*.
[89] Civil Justice Survey of State Courts, 2001, *supra*.; Civil Justice Survey of State Courts, 1996, *supra*.
[90] Civil Justice Survey of State Courts, 1996, *supra*.
[91] Civil Justice Survey of State Courts, 2001, *supra*.
[92] Hersch & Viscusi, *supra*, at 11.
[93] U.S. Census, Education, Income, and Poverty, http://www.census.gov/prod/2002pubs/00ccdb/cc00_tabB5.pdf (last visited Feb., 2005).
[94] American FactFinder, Detailed Tables, http://factfinder.census.gov (select "Data Sets" button; select "Census 2000 Summary File 3"; select "Detailed Tables" hyperlink; select "County" in "Select a geographic type" drop-down list; select

each state in "Select a state" drop-down list; select "All Counties" in "Select one or more geographic areas" drop-down list; select "Add" button; select "Next" button; select "P87. Poverty Status in 1999 by Age," ""P159A. Poverty Status in 1999 by Age (White Alone)," "P159B. Poverty Status in 1999 by Age (Black Alone)," and "P159H. Poverty Status in 1999 by Age (Hispanic)" in "Select one or more tables and click 'Add'" list; select "Add" button; select "Show Result" button) (last visited Feb., 2005).

[95] Dave Leip's Atlas of U.S. Presidential Elections, http://uselectionatlas.org/USPRESIDENT/index.html (select "1996" in "General by Year" drop-down list; select each state in "Results for an Individual State" drop-down list; follow "Retrieve" button; follow "County Data (Graphs)" hyperlink) (last visited Feb., 2005).

[96] CNN.com, 2000 Election Results, http://www.cnn.com/ELECTION/2000/results (follow "PRESIDENT" hyperlink; then follow "by county" hyperlink for each state) (last visited Feb., 2005).

[97] Logarithms of both punitive damages and compensatory damages were used by both Hersch & Viscusi (2004) and Eisenberg et al. (2002).

[98] Probit regression is the technique that was used by Hersch and Viscusi (2004) for their decision model.

[99] Tobit regression is the technique that was used by Hersch and Viscusi (2004) for their levels model.

[100] The voting margin was also included in some cases in an interaction term with certain litigant pairs to test if political leanings vary by defendant type. These interaction terms were never significant.

[101] David A. Belsley et al., *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity* 105 (1980).

[102] William H. Green, *Econometric Analysis* 57-58 (5th ed. 2003).

[103] Belsley et al., *supra*, at 105.

[104] Hersch & Viscusi, *supra*, at 25-27.

[105] Id.

[106] Id. at 20-24.

[107] Eisenberg et al., *Juries*, *supra*, at 758-60, 771-72, 781-82.

[108] Id. at 760, 781-82.

[109] Hersch & Viscusi, *supra*, at 22-23.

[110] The dprobit results are available in appendix A.

[111] The dtobit results are available in appendix B.

[112] The dtobit coefficient is converted to a percentage of dollars in the following manner: $e^{(\beta_t)}-1$, where β_t is the original dtobit coefficient.

[113] Eisenberg et al., *Juries*, *supra*, at 760, 781-82.

[114] Hersch & Viscusi, *supra*, at 33-34.

[115] Belsley et al., *supra*, at 105.

[116] Helland & Tabarrok, *Race*, *supra*, at 33-35.

[117] Id. at 36-42.

[118] Id. at 29.

[119] Id. at 38.

[120] Hersch & Viscusi, *supra*, at 25-26.

[121] Both the decision and levels models were estimated using OLS linear probability regression since the treatment effects model does not allow for probit or tobit regression.

[122] Hersch & Viscusi, *supra*, at 26.

[123] Id. at 28.