When the Shadow is the Substance: Judge Gender and the Outcomes of Workplace Sex Discrimination Cases

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Abstract

The number of workplace sex discrimination charges filed with the Equal Employment Opportunity Commission (EEOC) approaches 25,000 annually. Do the subsequent judicial proceedings suffer from a discriminatory gender bias? Exploiting random assignment of federal district court judges to civil cases, I find that female plaintiffs filing workplace sex discrimination claims are substantially more likely to settle and win compensation whenever a female judge is assigned to the case. Additionally, female judges are 15 percentage points less likely than male judges to grant motions filed by defendants, which suggests that final negotiations are shaped by the emergence of the bias.

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1 Introduction

The Equal Employment Opportunity Commission (EEOC) is responsible for enforcing laws against workplace discrimination on the basis of race, sex, disability, national origin, and age. In particular, the EEOC decides, from the set of nearly 90,000 discrimination charges filed annually, which cases to bring forth in the court of law. Though they ostensibly have the authority to punish employers that exercise taste-based discrimination, they are only effective insofar as the court appropriately punishes offending parties when merited. Where the judicial system enforcing the law is biased on the basis of race, sex, or disability, for example, the ability of the EEOC to protect workers from unlawful behavior may be compromised. Moreover, failing to punish employers guilty of engaging in discriminatory practices may well propagate future unlawful behavior to the extent that successful claims have a deterrence effect. Victims of discrimination would also face weaker incentives to report employer misconduct, which would further prop up the equilibrium rate of workplace discrimination.

Prior studies examining the existence of judicial gender biases have found either null or imprecise results. However, the existing literature has focused almost exclusively on judge gender-specific *trial* victory rates in order to detect such a bias. This approach ignores a key insight, which is that a case will proceed to litigation only when the plaintiff and defendant sufficiently disagree over what would be the trial outcome (as was first noted by Priest and Klein 1984). In fact, even the most optimistic estimates suggest that cases reach trial just 20% of the time (Kiser et al. 2008), while the sample used in this study and an abundance of others in the literature report litigation rates under 5% (Galanter 2004; Landsman 2004; Ostrom et al. 2004; Eisenberg and Lanvers 2009; Schneider 2010; Langbein 2012; Boyd and Hoffman 2013). Alternatively, when the parties agree, they settle so as to avoid litigation costs.

To study judicial bias reflected in settlement rates, I leverage a sample of approximately 1,000 workplace sex discrimination cases brought forth by the EEOC between 1997 and

2006. Exploiting the random assignment of federal district court judges to civil cases, I find that female plaintiffs filing workplace sex discrimination claims are 6-7 percentage points more likely to settle (off a baseline of 85.5%) and 5-7 percentage points more likely to win compensation (off a baseline of 88.8%) whenever a female judge is assigned to the case. Importantly, these differences persist in spite of the fact that the trial victory rate for the same types of cases is statistically indistinguishable across male and female judges.

These findings highlight the importance of considering judge gender-specific settlement rates to detect bias in the judicial system, rather than using only the trial outcomes officially decided by the judge. This important omission explains why the prior literature has collectively underestimated the amount of judicial gender bias prevailing in workplace sex discrimination cases.[1]

Additionally, this paper presents new evidence on the mechanism by which parties learn of the bias; that is, plaintiffs and defendants observe how often judges grant and deny pre-trial motions. In particular, I find that whenever female plaintiffs are assigned to a female judge in workplace sex discrimination cases, pre-trial motions filed by the defendant are 15 percentage points less likely to be granted (off a baseline of 41.2%). The litigants are subsequently able to infer the result of a prospective trial and bargain accordingly. To this point, I verify that motion success rates do in fact partially explain differences in settlement and win rates across judges. Our incorporation of motion filing data allows us to trace out how the within-case actions of judges directly translate to observed outcomes, which represents a substantial contribution to the judicial discrimination literature.

The magnitude of the effect found in the paper is economically significant. From 1997 to 2013 the percentage of female judges working in federal district courts has grown from 18 percent to 30 percent. My estimates imply that about 1 percent more cases are settled in favor of the female plaintiff in 2013, relative to 1997, solely due to the increase in female

[1] I show that even under random assignment of judges to cases, a simple comparison of plaintiff victory rates across male and female judges can systematically fail to detect a judicial bias where one is in fact present.

judicial appointments over this time period. If the percentage of female judges were to rise from today's level of 30 percent to 50 percent then the estimates imply that an additional 1.5 percent of cases would be settled in favor of the alleged victim. There is little evidence, however, to suggest that female plaintiffs' compensation amounts respond to the gender of the judge assigned.[2]

Importantly, I also show that these results cannot be explained by a change in the selectivity or composition of the types of cases induced by the transition from a Democratic to Republican Presidential Administration at the turn of the 21st century. Using a variety of metrics, I verify that the volume, composition, and selectivity of sex discrimination cases brought forth by the EEOC are unaffected by the party shift. Neither is it the case that the treatment effect of assignment to a female judge changed following the election. This latter finding rules out the possibility that the results are driven by ideologically motivated differences in how Democratic-nominated versus Republican-nominated female judges view workplace sex discrimination.

While the study design does not allow one to conclude whether female judges possess an absolute bias in favor of female sex discrimination plaintiffs (or if the converse is true), I construct a series of additional tests to determine whether the direction of the bias can indeed be recovered. In particular, I analyze both case appeal rates and decision reversal rates by judge gender to assess whether either group is more likely to be mistaken in its initial rulings. I find statistically insignificant evidence that male judges' pro-defendant decisions are more likely to be challenged and reversed relative to female judges' pro-defendant decisions. However, I also test whether a judge's leniency in non-sex discrimination cases is consistent with his or her leniency in sex discrimination cases under the assumption that judge leniency is a fixed judge characteristic that does not respond to case type. Under this latter series of assumptions and tests, I find evidence for the opposite conclusion; that

[2]The regression-based estimates are exceedingly noisy due to the large variance in award amounts and absence of data on the case characteristics and precedents used to determine those awards. Section B of the Appendix explores the intensive margin effects of judge gender in more detail.

male judges are relatively correct in their decisions while female judges possess a pro-plaintiff bias. These contrasting results do not permit a definitive conclusion regarding which group is biased. All that can be discerned with certainty is that female judges are more favorable to female sex discrimination plaintiffs, relative to male judges.

This paper fits into a broader economic literature on discrimination. The findings in this paper show that discrimination is present in the legal setting, despite the fact that sophisticated litigation teams and judges have a considerable amount of time to evaluate evidence and make deliberations. This scenario is in stark contrast to the environments in which gender or racial biases have been uncovered in much of the prior literature. In those cases, agents are required to make relatively fast or even split-second decisions so that unconscious or 'implicit biases' are more likely to emerge (Bertrand et al. 2005; Payne et al. 2002). Evidence of such discrimination has materialized, for example, among hiring managers making interview decisions (Bertrand and Mullainathan 2004; Neumark et al. 1996), symphony orchestra auditions (Goldin and Rouse 2000), car dealers negotiating prices (Ayres and Siegelman 1995), police officers' searches and arrests (Antonovics and Knight 2009; Donohue III and Levitt 2001; Knowles et al. 2001), and by referees in the National Basketball Association (Price and Wolfers 2010).

This study also complements a growing literature showing that resources are allocated very differently when those belonging to diverse groups hold positions of power. For example, Chattopadhyay and Duflo (2004) show that when females hold Village Council head positions in India, these leaders are more likely to invest in public goods and other infrastructure that are relevant to the needs of women. In a similar vein, Pande (2003) provides evidence that mandated political representation by minorities in India increases benefit transfers to its minority constituents. In the context of labor markets, Åslund et al. (2014) use linked employer-employee data from Sweden to provide evidence that managers exhibit preferential treatment toward workers who share the same national origin; these workers are hired

with greater frequency, receive higher wages, and are less likely to separate from the firm.[3] In-group favoritism, however, is just as much a part of the fabric of U.S. institutions. For example, using data from a prominent U.S. retail firm, Giuliano et al. (2009) find that the share of black employees falls when a non-black manager assumes control of hiring duties.[4] In a related paper, Giuliano et al. (2011) chronicle further evidence that the concordance of manager-employee race reduces quit and dismissal rates while bolstering promotion opportunities. Thus, the finding that female judges are more pro-plaintiff in cases of female-targeted workplace sex discrimination is congruent with previously documented evidence of own-group biases in a variety of familiar institutional settings.

Another unique aspect of the bias studied in this paper is that it is possible for the bias to be driven entirely by the perceptions of the legal teams, even if the judges hold no actual bias in these cases. However, given the transparency of judges' prior ruling tendencies along with their observed responses to pre-trial motions, a more compelling explanation for the finding is that male and female judges do indeed apply different standards in workplace sex discrimination cases. Evidence suggests that female judges are better able to perceive less egregious forms of sex discrimination. Prior studies point to the fact that female judges, who are themselves the minority in a male-dominated profession, may have had similar experiences to alleged victims of sex discrimination, which would give them an advantage in recognizing evidence of this unlawful behavior relative to their male counterparts (Chew 2011).[5] While one would expect that male and female judges would reach the same conclusions in clear-cut cases, it could be that the more marginal cases account for the overall difference in settlement and plaintiff compensation rates.

Relatedly, I explore the extent to which shared experiences among female judges and

[3]Note that the study does show that the findings are better explained by profit-maximization concerns than by taste-based discrimination. Nonetheless, the observed outcomes are observationally equivalent.

[4]Similarly, Stoll et al. (2004) observe that black job applicants are more likely to be hired when the hiring agents are black, rather than white.

[5]This observation is not restricted to women serving as judges. Recent evidence, for example, indicates that the initial decision to include female jurors in criminal courts significantly increased the conviction rate for sex offenses and violent crimes against women (Anwar et al. 2016).

plaintiffs contribute to the pairing's higher success rate. For example, others have found that judges who happen to have daughters are relatively more likely to take a pro-feminist stance in cases involving gender issues (Glynn and Sen 2015). I indeed find that the gender gap in plaintiff success rates grows by a factor between two and three when restricting attention to a subset of cases that are exclusively (or near exclusively) female issues, such as pregnancy discrimination, equal pay discrimination, and harassment cases.

In spite of these apparent advantages, increases in female representation on the bench are also accompanied by increases in reports of workplace sex discrimination in the districts overseen by those courts. For example, a one standard deviation increase in the fraction of females serving on a state's bench (a 4.2 percentage point increase) is associated with both a 3-4 percentage point increase and 7-8 percentage point increase in total sex discrimination charges filed and equal pay act charges filed, respectively. While these associations merely constitute descriptive evidence, what is clear is that gender diversity on the bench comoves with either an increase in female workers' propensity to report sex discrimination, an increase in workplace sex bias, or a combination of both phenomena.

The rest of the paper proceeds as follows. Section 2 summarizes how discrimination charges are handled by the EEOC and the ensuing process by which judges are assigned to federal district court cases. It subsequently proposes a conceptual framework that motivates the study's empirical predictions before concluding with a recapitulation of the prior literature on judicial bias. Section 3 describes the data and how the study sample was constructed. Section 4 details the judge randomization tests and estimation strategy. Section 5 describes the specific empirical results of the test for judicial bias in workplace sex discrimination cases. It also explores both the nature of the bias and competing explanations for what might be driving it. Section 6 concludes.

2 Institutional Background

2.1 The EEOC and its Role in Discrimination Litigation

Once a discrimination charge is filed, the EEOC typically coordinates a mediation session between the employer and employee(s). If the parties cannot reach a voluntary agreement, the EEOC conducts an independent investigation to determine whether discrimination has actually occurred. The EEOC subsequently attempts to resolve well-founded charges through its administrative enforcement process. As a last resort to litigation, the EEOC is required to facilitate a conciliation during which the parties may negotiate an appropriate remedy for the alleged discrimination. Nearly 93% of all charges are resolved through one of these informal methods.

Remaining unresolved cases are then turned over to the Office of General Counsel (OGC), which may file a civil suit for the EEOC on behalf of the alleged victim. The OGC prioritizes cases on the basis of "the seriousness of the violation, the type of legal issues in the case, and the wider impact the lawsuit could have on EEOC efforts to combat workplace discrimination."[6] Upon filing a civil case with the federal judicial court system, a judge is assigned to handle all ensuing proceedings. Crucially, all pretrial activities, including settlement and alternative dispute resolution efforts, begin only *after* a judge has been assigned to the case.[7]

Identifying the causal effect of judge gender assignment on case outcomes requires that 1) judges are assigned prior to the commencement of dispute resolution; and 2) judges are randomly assigned to civil cases. Consequently, we investigate the veracity of the latter claim in the next part of the discussion.

[6]source: http://www.eeoc.gov/eeoc/litigation/procedures.cfm
[7]source: http://www.fjc.gov/federal/courts.nsf

2.2 Random Assignment of Judges to Cases in Federal District Courts

Prior to the early 1970s, federal district courts utilized a master calendar system whereby the chief judge of the district allocated judicial duties to judges over the course of the year. In this system, the chief judge could then subjectively assign cases to judges according to judge experience, expertise, and interest. Apart from being inefficient, the system made it easy for plaintiffs to 'judge-shop' since claimants could predict which judge would be assigned according to when the case was filed. Federal district courts have since replaced the master calendar system with an individual calendar system under which assignment is made on a rotational and otherwise random basis. Under the prevailing system, inexperienced and veteran judges are equally likely to be assigned complex cases (Bird 1975).

According to the Federal Judicial Center, "Each court with more than one judge must determine a procedure for assigning cases to judges. Most district and bankruptcy courts use random assignment, which helps to ensure a fair distribution of cases and also prevents 'judge shopping,' or parties attempts to have their cases heard by the judge who they believe will act most favorably. Other courts assign cases by rotation, subject matter, or geographic division of the court."[8] The United States Courts website further remarks that the majority of courts use some form of a random drawing, simply rotating the names of available judges.[9] This randomization process is critical to my identification strategy for detecting the presence of judicial bias.

2.3 Conceptual Framework for Detecting Relative Judicial Biases

This section explores three connected theoretical questions that motivate much of the subsequent empirical analysis. These questions are as follows: 1) What determines whether the plaintiff and defendant are able to strike an agreement through settlement rather than

[8]source: http://www.fjc.gov/federal/courts.nsf
[9]source: http://www.uscourts.gov/Common/FAQS.aspx

relinquish control of their fates to a judge through litigation? 2) How can one infer a relative judicial gender bias among male and female judges based on differences in the outcomes of the litigation selection process? 3) What should be the resulting plaintiff trial victory rates among male and female judges when the associated distributions of the cases that reach litigation differ?

To answer the above questions, I outline and extend the intuition of a formal framework developed in Priest and Klein's seminal paper on litigation selection (Priest and Klein 1984). The full model and associated predictions are provided in Appendix Section A. Assume, as in Priest and Klein (1984), that a legal dispute occurs whenever a plaintiff claims that she has incurred damages due to the actions of the defendant. The dispute is resolved either by an out-of-court settlement reached by the dueling parties or, failing to reach such an agreement, by a verdict in the court of law. I call the former resolutions settlements and the latter litigated cases. When a case is litigated, it must reach one of two possible outcomes: a plaintiff verdict or defendant verdict. If the third-party arbiter rules in favor of the plaintiff, the defendant is required to pay the plaintiff some amount of damages determined before the proceedings.[10] If the judge instead rules in favor of the defendant, the defendant pays nothing to the plaintiff and suffers only the costs of litigation.

Of particular importance is the assumption that each judge has a decision standard, or threshold for evidence of wrongdoing beyond which she will rule in favor of the plaintiff. The decision standard is assumed to be common knowledge among both parties. What is not precisely known, however, is the true level of defendant fault in a case. Rather, the plaintiff and defendant each estimate defendant fault with some error, reflecting uncertainty over case evidence. Each party then evaluates the likelihood that the plaintiff wins the case by forming predictions as to whether the true level of defendant fault exceeds their assigned

[10] I assume, as in Priest and Klein (1984), that this amount is fixed and known prior to deliberation. This assumption is reasonable in many litigious settings. In cases of employment discrimination, there are specific rules that determine the amount that may be awarded based on the number of firm employees, the the type of alleged discrimination or harassment, and the number of affected employees. Thus, parties are arguing over whether the defendant is at fault rather than the magnitude of the damages.

judge's decision standard.

If both parties knew exactly what would be the outcome of a looming trial, they would always settle in order to spare themselves the costs of litigation. In practice, however, the amounts that the defendant and plaintiff would be willing to offer and accept in settlement negotiations depend upon the amounts the parties expect to pay and receive in a prospective trial, net of litigation costs. If a case is especially 'powerful'; that is, the true fault level far exceeds or is exceeded by the decision standard, there will be little uncertainty over the outcome and so the parties will agree on settlement terms. Conversely, uncertainty over how a judge may rule breeds disagreement over expected outcomes which, in turn, leads to disagreement over the amount the plaintiff is entitled to request during settlement negotiations.

Recall that both parties estimate the true fault level with error. It follows that outcome uncertainty will be the highest for marginal cases since it will be especially difficult to accurately gauge whether the true fault level is above or below the judge's decision standard whenever the true fault level is indeed close to the judge's decision standard. Accordingly, it is much more likely that the plaintiff and defendant estimate divergent plaintiff victory probabilities in marginal cases than in powerful ones. The cases whose fault levels are sufficiently close to the judge's decision standard, therefore, are the ones for which settlement negotiations are most likely to break down and give way to litigation.

In the current context, a higher settlement rate among female judges would imply that the cases they face are stronger relative to their decision standards. However, random assignment of cases to judges ensures that the distribution of fault levels in cases overseen by male and female judges are the same. Consequently, one can deduce that the average defendant fault level must lie farther away from the female judge's decision standard than from the male judge's decision standard. This implies that male and female judges have different decision standards–i.e., a relative judicial bias exists. Having identified a bias from the difference in settlement rates, one can determine the direction of the bias by simply comparing the

unconditional plaintiff victory rates across judge gender. A higher victory rate when facing a female judge, for example, would indicate that female judges have lower decision standards, relative to male judges.

Embedded in the preceding analysis is the precise logic motivating the Priest and Klein '50% hypothesis'; that the plaintiff success rate in litigated cases will tend toward 50%. First note that under the assumption of symmetric stakes (i.e., an awarded judgment hurts the defendant just as much as it helps the plaintiff in absolute terms), the plaintiff and defendant will be equally likely to tolerate trial losses. In other words, cases with fault levels that exceed a judge's decision standard by a particular margin or less will yield litigation just as cases whose fault levels fall short of the judge's decision standard by that same margin or less will also result in litigation. This is true regardless of where the decision standard lies. So long as the distributions of case fault levels faced by male and female judges are continuous around their respective decision standards, their trial victory rates will approximate 50%.

Symmetric stakes, though, may not be a realistic assumption if, for example, losing a sex discrimination case damages the offending firm by an amount that exceeds the official judgment once reputational costs are considered. Even still, higher defendant stakes simply decrease his tolerance for trial defeats. Among cases for which he would be willing to enter litigation, the maximum margin by which the fault level may exceed the decision standard decreases. As a result, these cases whose fault levels now surpass the decision standard by too much vis-à-vis the defendant–despite being candidates for litigation under the symmetric stakes assumption–are settled instead. Thus, litigated cases become proportionally more likely to result in a defendant verdict and so the expected plaintiff trial victory rate drops below 50%. Even in the absence of symmetry, however, the stakes should not be differentially asymmetric across cases assigned to male and female judges due to random assignment. Therefore, the plaintiff *trial victory rate* should tend toward a common value regardless of the gender of the judge.

2.4 Prior Literature on Judicial Biases

There is a substantial and growing body of literature that exposes the existence of 'in-group' judicial biases. Even though judges are expected to adhere to a strong norm of non-discrimination, recent evidence has demonstrated that they are prone to offering preferential treatment to the social group to which they belong. These biases have been demonstrated along the dimensions of race (Abrams et al. 2012; Chew and Kelley 2009; Crowe 1999; Cameron and Cummings 2003; Depew et al. 2016; Rachlinski et al. 2009) and ethnicity (Shayo and Zussman 2011; Gazal-Ayal and Sulitzeanu-Kenan 2010).

Analogous studies have examined the existence of a gender bias among judges with mixed results. A review of the legal literature supports the hypothesis that differences in the ways in which female and male judges rule appear most prominently in sex discrimination cases (Chew 2011). However, much of the literature focuses on appellate rather than district court decisions. Appellate cases, unlike district court cases, arise only when the losing party asks the court of appeals to review the case and are only an option for cases that initially go to trial.[11] This feature limits the generalizability of what can be learned from judge voting behavior since this setting is not representative of the unconditional distribution of cases filed with federal courts.

More importantly, this study is the first to provide quasi-experimental evidence of a judicial gender bias as prior studies rely primarily on matching techniques rather than random assignment for identification. For example, after matching judges by age, ideology, and time period, Boyd et al. (2010) find that the inclusion of one female judge on a three-judge appellate panel increased the probability of plaintiff success by 20 percent in sex discrimination cases but not for other types of cases. A bevy of other studies find substantively similar results (Davis et al. 1993; Farhang and Wawro 2004; Songer et al. 1994; Peresie 2005; Crowe 1999). Massie et al. (2002) also find gender biases in the outcomes of the broader set of cases involving civil liberties.

[11] source: http://www.fjc.gov/federal/courts.nsf

Still, studies of gender biases in sex discrimination cases in federal district courts have been far less conclusive. This ambiguity is due to three main factors: the restriction to published court opinions, a paucity of female judges in the data, and the analysis' exclusion of settled cases and of intermediate judicial decisions.

As Kim et al. (2009) remark, a common issue with many of these studies is that the data are extracted from published opinions only, which constitutes only one quarter of all briefed and submitted cases. Published and unpublished opinions also vary systematically; published opinions tend to be more politically motivated and ones for which judges are less likely to exercise personal discretion since they are subject to public scrutiny. Cases with unpublished opinions are also disproportionately difficult cases. For example, Songer et al. (1994) found that more than half of appeals cases with reversals or non-unanimous decisions were reviewing unpublished district court opinions.

An additional complication in the literature is that because female judges have been historically underrepresented, existing studies contain small sample sizes that preclude the researchers from uncovering precise effects as in Segal (2000), Manning (2004), and Kulik et al. (2003). Even though Ashenfelter et al. (1995), who also find no evidence of a judicial gender bias, study both the published and unpublished opinions of randomly assigned judges, their 1980-1981 sample contains only 5 female judges out of 47 total judges across three federal district courts. Ashenfelter et al. (1995) is also unique in that it tracks the rates with which plaintiffs win or settle.

The seminal dispute selection model of Priest and Klein (1984) explores the extent to which litigated cases, which make up only 5 percent of all civil cases, are not representative. Thus, when all cases that are resolved prior to litigation are excluded, one misses the opportunity to learn about judicial biases and perceived judicial biases from the cases whose outcomes are far more common. Moreover, the extant literature ignores the degree to which judicial decision-making during the proceedings might influence the eventual outcomes. In contrast, I study judicial responses to filed motions so as to better understand the role that

demonstrated bias plays in shaping the negotiations of the forward-looking disputants.

3 Data and Sample Construction

The data begin with approximately 2,300 federal district court cases of workplace discrimination brought forth by the Equal Employment Opportunity Commission (EEOC) between 1997 and 2006.[12] These data were collected by Professors Pauline Kim, Margo Schlanger, and Andrew Martin as part of the EEOC Litigation Project, whose goal was to study the litigation activities of the EEOC.[13,14] I supplement these data by adding to the sample the missing sex discrimination cases not collected by the aforementioned researchers by way of a Freedom of Information Act (FOIA) request. With the exception of a small number of cases for which I was unable to obtain court dockets, the final sample is virtually exhaustive.

Importantly, the EEOC only pursues litigation on roughly 0.4 percent of all discrimination claims filed (or 330 cases per year among 90,000 or so charges filed).[15] Therefore, even though the sample of litigated cases here constitute an unbiased sample of all litigated cases, they are not random in the sense that the EEOC had selectively deemed these cases as having had enough merit to make the pursuit of litigation worthwhile. Because these cases are particularly strong, the settlement rates in the study data are uniformly higher than in the unconditional population of employment discrimination cases.[16] That said, the data avoid many of the selection problems plaguing other legal studies by including all court decisions (published and unpublished) and a variety of outcomes (pretrial adjudication, settlements, and post-trial judgments). These features make the data a suitable candidate for uncovering the causal effects of the assignment of different judge characteristics on case outcomes.

[12] By filing a Freedom of Information Act (FOIA) Request, I was able to obtain additional data on workplace sex discrimination cases not included in the original sample. Thus, the study sample of sex discrimination cases approximates the total number of sex discrimination cases filed.

[13] The master database is housed at http://eeoclitigation.wustl.edu/.

[14] Their subsequent work can be found in Kim et al. (2009) and Schlanger and Kim (2014).

[15] source: http://www.eeoc.gov/eeoc/statistics/enforcement/index.cfm

[16] For example, in a study of *all* employment discrimination cases filed across two federal district courts in 2001-2002, Eisenberg and Lanvers (2009) report settlement rates of approximately 80 and 65 percent. This is in contrast with a settlement rate of nearly 90 percent in this study's sample.

The aforementioned researchers began with a list of basic case information, such as the name of the defendant, case basis and issues, case outcome, and date filed, obtained from the EEOC. They then used each case's corresponding docket number in conjunction with an online resource for researching court cases, called "Public Access to Court Electronic Records" (PACER), in order to extract more detailed case information such as all events and motions ordered along with the demographic characteristics of the judges presiding over the litigation.[17]

Since the focus was on detecting the presence of judicial bias, I isolated one type of case that would be most subject to such forces: sex discrimination cases.[18] In the data, there are roughly 1,000 cases of workplace sex discrimination against females. Of these 1,000 cases, 80 percent were overseen by male judges, who also make up 80 percent of the total population of judges (440 of 549 judges are male) as would be expected given random assignment of judges to cases.[19]

While over 95% of these cases are assigned to federal district court judges, a small minority are handled by federal magistrate judges. The primary differences between the two judge types are characterized by their method of appointment and the depth of their duties. Federal district court judges are exclusively nominated by the President, whereas magistrate judges are appointed by a majority rule vote among the federal district judges of a given district. Moreover, magistrate judges are often paired with a presiding district court judge to serve him or her in an auxiliary role. Historically, a spike in caseloads beyond what the district court judges could reasonably manage would sometimes result in direct assignment

[17]When necessary, judges' biographical information was supplemented with the records from online judge databases, such as http://www.fjc.gov/public/home.nsf/hisj, which maintains a directory of all federal judges appointed from 1789 through the present day.

[18]While racial discrimination cases are a worthwhile subject of study, the sample included only 230 racial discrimination cases filed by African-American plaintiffs, 31 of which were assigned to African-American judges. Consequently, there is not a sufficient amount of power to test whether the assignment of African-American judges to racial discrimination cases involving African-American plaintiffs has led to different outcomes than when white judges were assigned.

[19]In the following section, I devote a considerable discussion and empirical examination of the extent to which cases are randomly assigned by judge gender.

of new cases to magistrate judges McCabe (2014).[20] In this paper, I consider the demographic characteristics of only the presiding judge as it is she who wields ultimate discretion in determining case outcomes. Additionally, all results are insensitive to whether magistrate judges are included in the analysis.

Table 1 introduces the main outcome measures used in the study, providing both definitions and means across the study's sample. Appendix Table C1 shows the distribution of final case resolutions according to whether a case was settled, litigated, or reached pre-trial adjudication. Consistent with the literature, the overwhelming majority of cases settle before reaching trial. Additionally, the study data are unique in that they include all of the pre-trial motions filed by the litigants, by whom each motion was filed, and whether the judge granted or denied each motion.[21] Appendix Table C10 shows the distribution of the types of defendant motions filed partitioned by the judge's gender for the 397 cases in which at least one motion was filed by the employer's litigation team. Appendix Table C11 presents analogous summary information for plaintiff motions filed among the 386 cases in which at least one motion was filed by the EEOC.

While historical studies of judicial sex discrimination have been hampered by power issues, the current study benefits from the recent trend of greater appointments of female federal judges. The relatively small number of cases collected, while still more than many past studies of sex discrimination litigation, however, works against my being able to detect a precise estimate of the extent to which a judicial bias may exist.

[20] Following the end of the current study's sample period, however, it has become an increasingly common practice to include magistrate judges directly on the wheel for direct assignment of civil cases. As of 2014, nearly 25% of district courts have adopted this approach.

[21] The motion-filing data corresponds only to the 828 sex discrimination cases collected in the original Kim, Schlanger, and Martin dataset. While I was able to obtain judge assignment and case outcome data on 192 additional cases retrieved through a FOIA request, I was unable to obtain motion-filing behavior for these extra cases.

Table 1: Definitions and Means of Dependent Variables

Variable Name	Mean (Obs.)	Definition
Settlement Rate	0.868 (1,020)	fraction of cases in which parties reach an agreement as to the monetary damages prior to jury trial or official judgment
Plaintiff Win Rate	0.901 (1,020)	fraction of cases in which the plaintiff wins monetary compensation
Plaintiff Motion Filing Success Rate	0.726 $(386)^{\sigma}$	fraction of total plaintiff motions filed that are granted by the judge in a case
Defendant Motion Filing Success Rate	0.387 $(397)^{\theta}$	fraction of total defendant motions filed that are granted by the judge in a case
Relief Per Beneficiary	\$56,538.75 $(993)^{\rho}$	monetary compensation awarded to plaintiff divided by # of beneficiaries

$^{\sigma}$There were 386 cases in which the EEOC filed at least one pre-trial motion.
$^{\theta}$There were 397 cases in which the defendant filed at least one pre-trial motion.
$^{\rho}$Award amounts were undisclosed for 27 of the 1,020 cases.

4 Identification and Estimation

I perform a series of randomization tests to see whether the data are consistent with randomization by judge gender. First, I perform a series of χ^2 tests to determine whether overall caseloads and sex discrimination caseloads are independent of the judge's gender. Additionally, I test for balance on case covariates across female and male judges.

4.1 Judge Randomization Tests

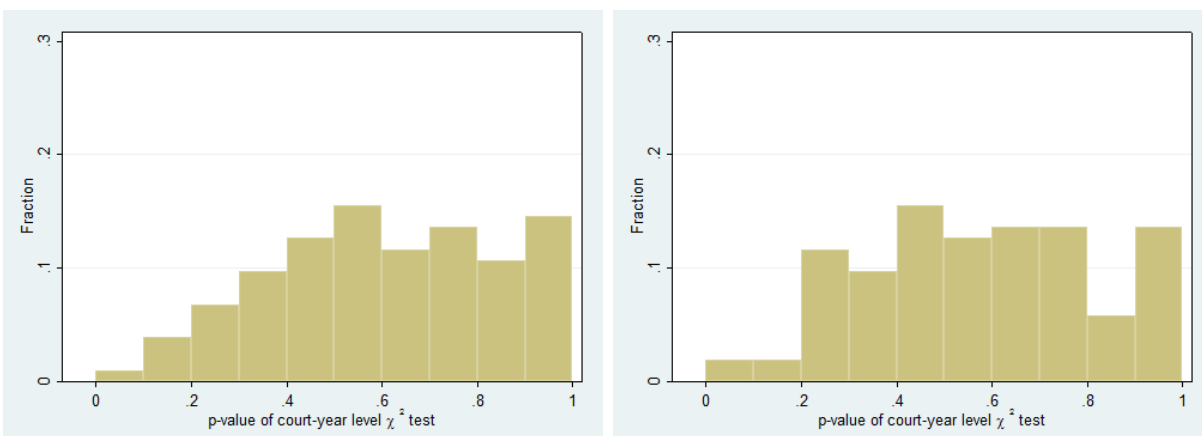
An ideal randomization test would check to see that the proportion of total cases assigned are the same across male and female judges within a district court in a given year. The proportion of sex discrimination cases assigned should also be independent of the judge's gender.

Because the sample contains fewer than one case per judge-year, any test at the court-year level would be underpowered and devoid of informational content. As an alternative, I partition the sample into an 'early' period (1996-2001) and a 'late' period (2002-2006). The number of active judges serving at each district court is the same in both periods. I further exclude district courts whose active judges are either all male or all female. 59 district courts

remain in both the early and late periods.

I perform two series of χ^2 tests. The first of these determines whether the total caseload is independent of the judge gender at the court-period level. Under random assignment, 90% of these test statistics would be less than the .90 critical value of the χ^2 distribution. Figure 1A shows the distribution of p-values associated with the 118 χ^2 tests. It is evident from the diagram that one can not reject independence.

The second series of tests checks whether the proportion of sex discrimination cases assigned is also independent of the judge's gender. Figure 1B shows the distribution of p-values associated with these 118 additional χ^2 tests. Again, fewer than 10% of the sample contains p-values under .1 (and all tests have a p-value exceeding .05), which is consistent with the notion that sex discrimination cases are randomly assigned with respect to judge gender.



(A) χ^2 Tests for H_0: Judge Gender $\perp\!\!\!\perp$ Caseload (B) χ^2 Tests for H_0: Judge Gender $\perp\!\!\!\perp$ Sex Cases

Figure 1: Tests of Independence between Judge Gender and Cases Assigned at the Court-Time Period Level

The left panel shows the distribution of p-values associated with the 118 χ^2 tests of independence between judge gender and total caseload at the court-period level. The right panel shows the distribution of p-values associated with the 118 χ^2 tests of independence between judge gender and total sex discrimination cases assigned at the court-period level.

Table 2 reports the means and mean differences for plaintiff and case characteristics. The absence of a difference in average case characteristics, basis for the case, issues raised in the

case, and location of where the employer was located provides additional evidence of random assignment.

Table 2: Balance Table, Case Covariates by Judge Gender

	Female Judge		Male Judge		Difference	
	Mean	SD	Mean	SD	Mean	p-value
Plaintiff Characteristics:						
# Complainants	4.33	16.18	4.59	37.12	-0.26	0.93
# Benefited Persons	31.99	236.29	41.69	505.53	-9.70	0.80
Basis:						
Equal Pay	0.068	0.252	0.057	0.232	0.011	0.56
Pregnancy/Maternity	0.146	0.354	0.120	0.325	0.026	0.32
Retaliation	0.432	0.497	0.453	0.498	-0.021	0.60
Race-Black	0.052	0.223	0.063	0.243	-0.011	0.58
Nationality-Hispanic	0.031	0.174	0.016	0.124	0.015	0.15
Age	0.026	0.160	0.028	0.164	-0.002	0.89
Issue:						
Harassment	0.635	0.483	0.652	0.477	-0.017	0.66
Sexual Harassment	0.604	0.490	0.591	0.492	0.014	0.73
Hiring	0.094	0.292	0.105	0.307	-0.011	0.64
Discipline	0.031	0.174	0.050	0.217	-0.018	0.28
Discharge/Layoff	0.573	0.496	0.567	0.496	0.006	0.88
Terms/Conditions	0.203	0.403	0.176	0.381	0.027	0.39
Wages	0.109	0.313	0.112	0.316	-0.003	0.91
Location:						
Northeast	0.099	0.299	0.126	0.332	-0.027	0.31
Midwest	0.198	0.399	0.180	0.384	0.018	0.56
South	0.411	0.493	0.434	0.496	-0.022	0.58
West$^{\psi}$	0.281	0.451	0.254	0.435	0.028	0.43
Right-to-work state	0.516	0.501	0.473	0.500	0.043	0.29
Observations	192		828		1020	

Notes: ***, ** and * denote differences that are statistically significant at 1 percent, 5 percent and 10 percent levels, respectively.
$^{\psi}$ More appropriately, the female:male ratio of judges is equal conditional on the composition of judge gender within the region. For example, the total fraction of female and male judges residing in Western states are .238 and .208, respectively.

Finally, Table 3 displays the results of a standard randomization test in which I regress the treatment variable (judge gender) on all of the case-specific covariates. Since the randomization is done at the court level, I am also careful to control for interacted court and

time period effects. After splitting the sample into all cases and sex discrimination cases only, I find that only 1 of 20 (and 1 of 19) covariates has predictive power in determining the treatment variable of interest at 5% significance levels. These results also support the case for random assignment.

4.2 Estimation Strategy

Because judges are randomly assigned, one could simply compare mean settlement rates by judge gender. Controlling for additional case covariates should do nothing to change the estimate of the effect of female judge assignment on settlement rates, though doing so may potentially improve the precision of the estimate. However, because judge characteristics are not randomly assigned conditional on judge gender, adding other judge-specific controls should help determine whether it is in fact the "gender" part of the judge characteristic bundle that is driving the difference in outcomes. The most comprehensive regression specification will be of the form:

$$\begin{aligned}\mathbb{1}(Case\ settled)_{ijt} = \beta_0 &+ \beta_1(judge\ gender)_{ij} + \beta_2(judge\ age)_{jt} \\ &+ \beta_3(judge\ experience)_{jt} + \beta_4(judge\ race)_j \\ &+ \beta_5(Democratic\ appointee)_j + \beta_6(\#\ complainants)_i \\ &+ administration_j + year_t + district\ court_i + \epsilon_{ijt}\end{aligned} \tag{1}$$

where i, j, t indexes the case number, judge assigned, and year in which the discrimination claim was filed.[22] Standard errors are clustered at the judge level since the 'treatment' is the assigned judge's gender.[23] Additional controls include age, experience, and political

[22] One increasingly popular method for assessing relative bias between two groups of individuals is the rank-order test as in Anwar and Fang (2006). This would require a comparison of case outcomes among the four combinations of {male judge, female judge} × {male plaintiff, female plaintiff}. However, the data include just 59 cases of sex discrimination against males, only 11 of which are assigned to female judges. Thus, any rank-order test would be severely underpowered.

[23] As a robustness check, standard errors are clustered at the district court level as the randomization occurs at the district court level. The regression results associated with this alternate level of clustering are included in the Appendix.

Table 3: Tests for Random Assignment of Civil Court Cases to Judges

Dependent Variable = $\mathbb{1}$(Female Judge)	All Cases		Sex Cases	
	Coeff.	Std. Err	Coeff.	Std. Err
Number of Complainants	-0.0002	(0.0002)	-0.0003	(0.0002)
Basis:				
Sex Discrimination	0.001	(0.026)		
Title VII Basis	0.003	(0.028)	0.007	(0.044)
EPA Basis	0.013	(0.057)	-0.044	(0.070)
Pregnancy Discrim.	0.003	(0.041)	-0.004	(0.046)
Retaliation	-0.016	(0.021)	-0.065**	(0.029)
Race Discrim.	-0.048	(0.052)	-0.049	(0.100)
Race-Black	-0.050	(0.049)	-0.087	(0.091)
Nationality-Hispanic	0.064	(0.039)	0.182	(0.117)
Age	-0.020	(0.037)	0.007	(0.086)
Issue:				
Harassment	-0.047	(0.030)	-0.024	(0.048)
Sexual Harassment	0.033	(0.033)	0.031	(0.042)
Hiring	-0.015	(0.030)	-0.046	(0.047)
Discipline	-0.033	(0.042)	-0.094	(0.063)
Discharge	-0.019	(0.021)	0.024	(0.029)
Any Compensation	-0.003	(0.074)	-0.052	(0.107)
Wages	-0.019	(0.077)	0.008	(0.107)
Terms/Conditions	0.065**	(0.025)	0.018	(0.038)
Promotion	0.015	(0.039)	0.026	(0.059)
Demotion Issue	0.002	(0.050)	0.008	(0.067)
Observations	1855		1020	
joint F-statistic	0.79		0.77	
p-value	[0.73]		[0.75]	

The reported coefficients correspond to OLS regressions of an indicator for whether the judge is female on all case covariates. The sample includes EEOC litigated sex discrimination cases spanning the period from 1997-2006. All estimations include controls for trial court fixed effects, year fixed effects, and trial court x time period fixed effects. The F-statistic reported is a joint test of the null hypothesis for all case covariates listed. Robust standard errors, clustered at judge level, are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

party. Table 4 shows that the female judges in the database are 6 years younger, 29 percentage points more likely to have been appointed by Democratic presidents, and have nearly 3 fewer years of experience than male judges. As a result, adding these controls should alleviate the concern that judge gender is simply proxying for other predictors of elevated settlement rates. I also control for the particular president responsible for the appointment of a judge with administration fixed effects. To the extent that presidents hand-pick judges based on ideological compatibility, it is important to capture how this might manifest in ruling behavior (Friedly and Honoree 2007). It is also important to control for the number of complainants in the case since the greater are the number of plaintiffs, the less likely it is that the defendant will be found without fault. The settlement rate should accordingly increase with the number of complainants since uncertainty over the potential trial outcome diminishes as well. To capture the possibility that the tolerance threshold for what constitutes workplace sex discrimination has decreased over time (i.e., decision standards have become lower), year fixed effects are added. Additionally, the inclusion of district court fixed effects allows for these attitudes to vary by location.

Still, the estimated effect of female judge assignment on settlement rates should remain stable as I control for case covariates. Large fluctuations in the estimates would potentially cast doubt on the plausibility of random assignment. As a subsequent robustness check, probit and random effects models are used to determine whether the estimate of the coefficient of interest, β_1, is invariant to the model choice.

To sign the direction of the potential judicial bias, I further test whether a female plaintiff is more likely to win compensation, in either the pre-trial or litigation stage, when a female judge is assigned to the case. This test uses the same regression framework as in Equation 2, only replacing dependent variable $\mathbb{1}(Case\,settled)$ with $\mathbb{1}(Plaintiff\,compensated)$. In particular, if female plaintiffs filing sex discrimination suits are more likely to win compensation when a female judge is assigned to a case, it must mean that female judges are more favorable to female plaintiffs than are male judges (or alternatively, that male judges disfavor

Table 4: Case Outcomes and Judge Characteristics, by Judge Gender

	Female Judge		Male Judge		Difference
	Mean	SD	Mean	SD	
Case Outcomes:					
Settled	0.922	0.269	0.855	0.352	0.067**
Plaintiff Compensated	0.958	0.200	0.888	0.316	0.071***
Litigated	0.047	0.212	0.054	0.227	-0.007
Trial Won $^{\phi}$	0.667	0.500	0.600	0.495	0.067
Award per Beneficiary	49,036	53,989	58,223	121,508	-9,187
Appeal Filed	0.026	0.160	0.054	0.227	-0.028
% Def. Motions Granted †	0.259	0.320	0.412	0.418	-0.153***
Def. Motions Granted †	1.375	2.651	1.057	1.428	0.318
Def. Motions Filed †	4.078	7.058	2.676	3.024	1.402***
% EEOC Motions Granted +	0.680	0.398	0.734	0.377	-0.054
EEOC Motions Granted +	1.661	2.072	1.373	1.200	0.288
EEOC Motions Filed +	2.564	3.237	1.975	1.626	0.589**
Judge Characteristics:					
Cases per Judge	3.495	2.651	3.607	2.560	-0.111
Age	54.536	6.624	60.994	9.003	-6.458***
Years of experience	8.615	5.796	11.412	7.876	-2.797***
Democratic Appointee	0.609	0.489	0.361	0.481	0.248***
White	0.786	0.411	0.793	0.405	-0.007
Black	0.099	0.299	0.082	0.275	0.017
Hispanic	0.057	0.233	0.045	0.207	0.013
Other race	0.016	0.124	0.007	0.085	0.008
Observations	192		828		1020
Number of Judges	109		440		549

Notes: ***, ** and * denote differences that are statistically significant at 1 percent, 5 percent and 10 percent levels, respectively.

† Of the 397 cases in which the defendant filed at least one pre-trial motion, 64 were assigned to female judges and 333 to male judges. Motions granted includes those that were granted in part.

+ Of the 386 cases in which the EEOC filed at least one pre-trial motion, 62 were assigned to female judges and 324 to male judges. Motions granted includes those that were granted in part.

$^{\phi}$ The trial win, or plaintiff victory, rates are conditional upon the case reaching the litigation stage. 9 cases and 45 cases reached the litigation stage when the case was assigned to a female and male judge, respectively.

female plaintiffs relative to female judges).

One of the more unique features of these data is that they include all of the motions filed by the defendant and plaintiff along with the judge's response to each of those motions. The plaintiff and defendant can predict the likelihood of a trial victory based on how judges respond to to these within-case motions. As the bargaining position of the plaintiff improves (worsens), the rates of settlement and plaintiff compensation should increase (decrease).

Under the null hypothesis of no judicial gender discrimination, one should expect to see that pre-trial motions filed by defendants are equally likely to be granted by male and female judges. I test this hypothesis in much the same way that we estimated how case outcomes vary across judge gender. Specifically, we again estimate Equation 2 separately for plaintiffs and defendants after replacing $\mathbb{1}(Case\ settled)$ with $Fraction\ motions\ granted$.

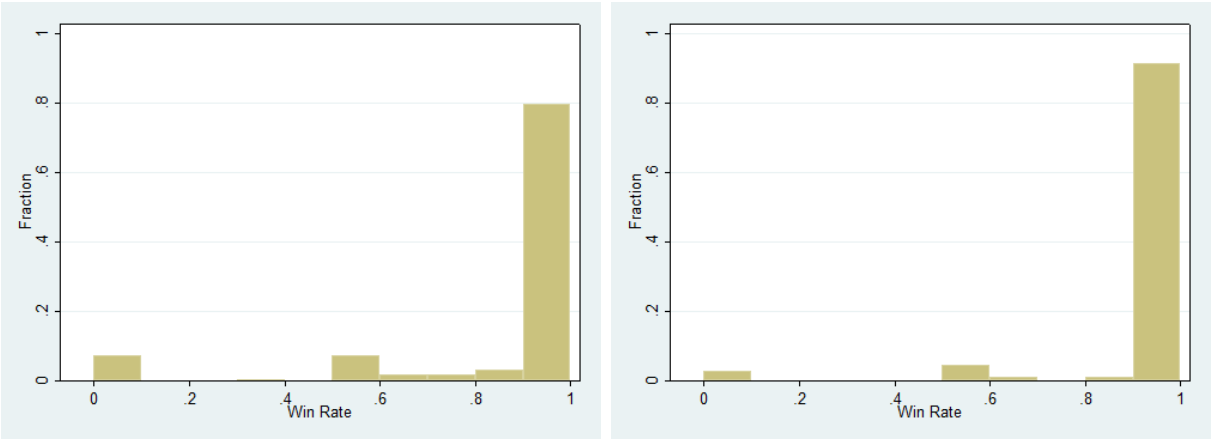
5 Results

5.1 Main Estimates and Placebo Tests

Table 4 shows that workplace sex discrimination cases are 6.7 percentage points (base of 85.5%) more likely to settle (significant at the 5 percent level) and 7.1 percentage points (base of 88.8%) more likely to result in a judgment being awarded to the plaintiff (significant at the 1 percent level) whenever a female judge is assigned to the case. Among male judges, the standard deviation of the win rate is 0.27 while the standard deviation of the settlement rate is 0.30. Thus, the gender effect is approximately one-fourth of the size of a standard deviation change in both win rates and settlement rates across the distribution of male judges.[24] Additionally, female judges are 15 percentage points less likely to grant motions (base motion success rate is 41.2%) filed by the defendant (significant at the 1 percent level) in workplace discrimination cases. Since a base level of 'non-discrimination' cannot

[24]Figures 2A and 2B show the distribution of sex discrimination case win rates across all male and female judges in the sample, respectively. Appendix figures 11A and 11B show the analogous distributions for sex discrimination case settlement rates.

be discerned from this particular study design, this analysis may reflect either female judges favoring plaintiffs or male judges disfavoring plaintiffs.[25]



(A) Male Judges (B) Female Judges

Figure 2: Distribution of Win Rates in Female Sex Discrimination Cases, by Judge Gender

The left panel shows the distribution of average win rates across male judges in the sample while the right panel shows the analogous distribution for female judges.

Trial victories are also 7 percentage points (base of 60.0%) more common among cases overseen by female judges though this difference is insignificant as fewer than 5 percent of cases ever reach this stage of litigation. Appeals are approximately 3 percentage points more likely (off a baseline of 2.6%) among male judges though this difference is also insignificant. This latter finding follows logically from the joint observation that plaintiffs account for 72% of all case appellants and that plaintiff non-compensation is more likely among male judges.[26]

Table 5 presents the main results for the effect of male judge assignment on settlement rates in workplace sex discrimination cases. The estimated effect is highly stable and significant, ranging from -6 to -7 percentage points (on a base of 92.2%) at the 1 or 5 percent level. Column (3) shows that the estimates do become slightly less precise when district court and year fixed effects are added, though they still retain significance at the 10 percent level. That said, adding district court and year fixed effects reduces the degrees of freedom by

[25]Section 5.4 explores the extent to which the results are driven by absolute biases of male and female judges.

[26]Of the 170 appeals filed, 122 were submitted by plaintiffs.

70, which is a non-trivial reduction when the number of observations is slightly above 1,000. Nonetheless, the year during which the claim was filed should explain some of the variation in settlement rates if the decision standards for what constitutes workplace sex discrimination have been evolving over time. While I do find that settlement rates are increasing over time, year fixed effects are not jointly significant. Combined with the main findings, this suggests that it is the growth in the appointment of female judges, rather than evolving attitudes over time, that is responsible for the increasing frequency with which female plaintiffs are successful in workplace discrimination cases.[27]

Next, Table 6 reports the results of a placebo test for whether male judge assignment is more or less likely to lead to settlement in non-sex based discrimination cases. Columns (2) and (3) also separately test whether judge gender affects the outcomes of either race discrimination or age discrimination cases, respectively, which comprise two of the most commonly adjudicated categories of non-sex based discrimination. A rejection of the placebo test hypothesis would indicate that male judges happen to have different decision standards on all matters rather than just those involving alleged sex discrimination against women. However, I find that male judge assignment is no more or less likely to result in a settlement in all types of non-sex discrimination cases, which further validates the findings that male judges possess a relative pro-defendant bias in sex discrimination cases filed by female workers.

Consistent with the earlier prediction, the greater are the number of complainants, the more likely it is that a case will settle. If, for example, the parties calculate the probability that the defendant fault level exceeds the decision standard for at least one of the complainants, the likelihood of a defendant fault verdict should increase monotonically with the number of complainants. Moreover, a one year increase in the age of the judge increases the likelihood of a settlement by 0.4 percentage points. This too is unsurprsing if litigating parties are better able to predict the ruling tendencies of judges who have amassed a larger body of prior work.

[27] In Section 5.2, I indeed rule out the possibility that an ideological shift concurrent with the 2001 presidential administration transition is responsible for the observed results.

Table 5: Effect of Male Judge Assignment on Sex Discrimination Case Outcomes

	Dependent Variable = 𝟙(Case settled)			Dependent Variable = 𝟙(Plaintiff wins)		
	(1)	(2)	(3)	(4)	(5)	(6)
Male judge	-0.067***	-0.057*	-0.061**	-0.071***	-0.056**	-0.074***
	(0.025)	(0.032)	(0.026)	(0.020)	(0.024)	(0.018)
𝟙(Pre-2001) × Female judge			0.038			-0.013
			(0.058)			(0.065)
Age of judge		0.004**			0.003	
		(0.002)			(0.002)	
Experience of judge		0.005			0.003	
		(0.004)			(0.004)	
White judge		-0.014			0.007	
		(0.037)			(0.027)	
Black judge		0.043			0.082*	
		(0.053)			(0.042)	
Democratic Appointee		0.131			0.026	
		(0.092)			(0.076)	
Number of Complainants		0.0003**			0.0002**	
		(0.0002)			(0.0001)	
Observations	1020	1020	1020	1020	1020	1020
R^2	0.006	0.161	0.030	0.009	0.174	0.040
Model	OLS	OLS	OLS	OLS	OLS	OLS
Administration FE	NO	YES	NO	NO	YES	NO
District Court FE	NO	YES	NO	NO	YES	NO
Year FE	NO	YES	NO	NO	YES	NO

Dependent variables are indicated in the column headings. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5, I also present the main results for the effect of male judge assignment on the rate with which a plaintiff receives compensation in workplace sex discrimination cases. Here, the results are substantively similar to those shown in the settlement regressions and are slightly more precise. I find that male judge assignment reduces the likelihood that a female plaintiff receives compensation by 6-7 percentage points (off a base of 95.8%) at significance levels of 1 percent. Precision is reduced to 5 percent significance levels when district court and year fixed effects are added. These results provide further evidence suggesting that male judges possess a relative bias against (female judges possess a relative bias in favor of)

Table 6: Placebo Tests: Effect of Male Judge Assignment on Outcomes in Non-Sex Discrimination Cases

	Dependent Variable = $\mathbb{1}$(Case settled)			Dependent Variable = $\mathbb{1}$(Plaintiff wins)		
	(1)	(2)	(3)	(4)	(5)	(6)
Male judge	-0.017	-0.021	-0.067	0.030	0.001	-0.013
	(0.030)	(0.050)	(0.101)	(0.035)	(0.058)	(0.156)
Age of judge	0.001	0.003	0.004	-0.001	-0.000	-0.002
	(0.002)	(0.003)	(0.009)	(0.002)	(0.004)	(0.012)
Experience of judge	0.004	0.003	0.012	0.005	0.014	-0.006
	(0.006)	(0.011)	(0.024)	(0.006)	(0.012)	(0.037)
White judge	-0.023	-0.058	-0.003	0.043	-0.002	0.127
	(0.037)	(0.061)	(0.161)	(0.041)	(0.080)	(0.175)
Black judge	0.014	-0.072	-0.152	0.091	0.041	0.293
	(0.053)	(0.089)	(0.260)	(0.059)	(0.100)	(0.333)
Democratic Appointee	-0.331	-0.581**	0.410**	-0.216	0.055	0.157
	(0.202)	(0.270)	(0.184)	(0.214)	(0.361)	(0.349)
Number of Complainants	0.003*	0.001*	0.013**	0.003**	0.002**	0.012
	(0.002)	(0.001)	(0.006)	(0.001)	(0.001)	(0.009)
Observations	993	344	116	993	344	116
R^2	0.151	0.311	0.600	0.156	0.311	0.493
Discrim. Type	Non-Sex	Race	Age	Non-Sex	Race	Age
Model	OLS	OLS	OLS	OLS	OLS	OLS
Administration FE	YES	YES	YES	YES	YES	YES
District Court FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Dependent variables are indicated in the column headings. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

women filing sex discrimination claims. Table 6 provides an analogous set of placebo tests for all types of non-sex discrimination cases, racial discrimination cases, and age discrimination cases. As with the settlement rate placebo tests, the gender of the judge has no bearing on the likelihood of plaintiff compensation. Combined with the main results of Table 5, the placebo tests demonstrate that male judges are no more or less likely to compensate plaintiffs except when the plaintiff is a female filing a sex discrimination claim against her employer.

Finally, Table 7 depicts how male judge assignment affects the percentage of a defendant's

motions that are honored during a case. Case assignment to a male judge increases the defendant's motion success rate by 15 percentage points (baseline of 25.9%) at significance levels of 1 percent. As with the earlier estimations, the result is robust to the inclusion of additional judge, case, time, and location characteristics. Columns (4)-(6) of Table 7 also show how male judge assignment affects the percentage of a plaintiff's motions that are honored during a case. No pattern of judicial gender differences emerges from this latter analysis.[28]

Taken together, these results are consistent with the notion that a judge's willingness to grant motions acts as an additional signal from which parties can infer their respective bargaining positions. In fact, I estimate that a 10 percentage point increase in the defendant's motion success rate reduces the likelihood that a plaintiff wins compensation by approximately 1 percentage point.[29]

In general, any such information that reduces uncertainty over the expected outcome increases the likelihood of settlement, since both parties would prefer to avoid litigation costs. Overall, workplace sex discrimination cases are 5 percentage points more likely to settle (at significance levels of 1 percent) than all other types of cases. This paper argues that that margin of difference is the result of the judicial gender bias demonstrated during the motion filing stage.

[28]Nonetheless, it is also important to note that the number of defendant and plaintiff-initiated motions filed with female judges exceeds those filed with male judges, as can be seen in Table 4. In particular, the defendant files 4.08 and 2.68 motions per case when assigned to female and male judges, respectively (p-value of the difference is less than 0.01). Additionally, the plaintiff files 2.56 and 1.97 motions per case when assigned to female and male judges, respectively (p-value of difference is less than 0.05). However, in two additional rows of Table 4, I show that the number of motions granted does not differ by judge gender. This suggests that the 15 percentage point deficit in the fraction of defendant motions granted by female judges is being driven by differences in the denominator rather than the numerator. I further unpack these differences by decomposing the number of motions filed by both type of motion and corresponding success rates in Appendix Tables C10 and C11. From these tables it is apparent that substantive discovery motions–which are used to obtain evidence from the other party by way of the production of documents, admissions, and depositions–account for both the differences in total motions filed and success rates across female and male judges.

[29]See Table C24 of the Appendix.

Table 7: Effect of Male Judge Assignment on Motion Filing Succes Rates in Sex Discrimination Cases

	Dependent Variable: D Motions Granted			Dependent Variable: P Motions Granted		
	(1)	(2)$^{\lambda}$	(3)	(4)	(5)$^{\lambda}$	(6)
Male judge	0.153***	0.144**	0.124**	0.054	0.054	0.052
	(0.047)	(0.071)	(0.057)	(0.055)	(0.055)	(0.073)
Age of judge		-0.005	-0.001		-0.001	-0.005
		(0.004)	(0.004)		(0.003)	(0.004)
Experience of judge		-0.005	-0.036**		-0.000	-0.009
		(0.005)	(0.014)		(0.004)	(0.014)
White judge		-0.106	-0.087		0.005	0.020
		(0.069)	(0.071)		(0.054)	(0.073)
Black judge		-0.055	-0.115		0.030	0.011
		(0.122)	(0.108)		(0.078)	(0.111)
Democratic Appointee		-0.006	-0.147		-0.046	-0.099
		(0.006)	(0.111)		(0.044)	(0.106)
Number of Complainants		-0.001	0.000		0.006	-0.006*
		(0.001)	(0.000)		(0.005)	(0.003)
Observations	397	397	397	386	386	386
R^2	0.019	0.026	0.326	0.003	0.014	0.273
Model	OLS	Probit	OLS	OLS	Probit	OLS
Administration FE	NO	NO	YES	NO	NO	YES
District Court FE	NO	NO	YES	NO	NO	YES
Year FE	NO	NO	YES	NO	NO	YES

Dependent variable is the fraction of the defendant's (plaintiff's) motions that are granted by the judge. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.
$^{\lambda}$ Marginal Effects reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Sensitivity of Results to the Change in Presidential Administrations

The shift from a Democratic to Republican administration in 2001 may have altered the perceived probability of winning certain types of employment discrimination cases. Given the high costs of filing employment discrimination lawsuits, the EEOC may have responded

to this shift by altering the volume and types of cases it had pursued. Even the composition of employment discrimination charges filed–that is, the pool of claims from which the EEOC selects–may not have proven impervious to the change in political winds.

To address the concern that the prior estimates partially reflect a change in both the number and selectivity of cases litigated when moving from the Clinton to W. Bush administrations, I compile nationally aggregated annual EEOC statistics on the number of charges and lawsuits filed by type of discrimination over these time periods.[30] Appendix Table C5 shows that the annual number of total EEOC charges filed was approximately 79,500 across either period. Additionally, the annual number of lawsuits filed was 385 and 406 (p-value of difference = 0.47), respectively. I also provide two measures of 'case selectivity.' The first measure simply divides the number of lawsuits filed by the total charges filed and is hence called the suit-to-charge ratio. These ratios are approximately .005 in both the Clinton and W. Bush eras. The second measure of selectivity is the fraction of lawsuits "with merit." According to the EEOC, merits suits include those which "allege violations of the substantive provisions of the statutes enforced by the Commission and [those which] enforce administrative settlements." The fraction of suits with merit hovers around 91% for both presidential eras.

I further evaluate how charges, lawsuits, and selectivity compare across the Clinton and W. Bush eras for finer gradations of workplace discrimination, such as Title VII (which includes discrimination based on sex, race, color, national origin, and religion) and sex discrimination violations. For each type of discrimination, the number of charges, lawsuits, and selectivity appear not to be different across administrations.

Appendix Figure 12 shows trends in EEOC workplace discrimination complaints filed over time. In particular, it plots the annual level of charges filed according to whether the discrimination was a violation of Title VII, the Americans with Disability Act (ADA), the Equal Pay Act (EPA), the Age Discrimination in Employment Act (ADEA), or the sex

[30] Aggregated National data for all charges filed and EEOC enforcement suits were extracted from: https://www.eeoc.gov/eeoc/statistics/enforcement/index.cfm.

discrimination provision of Title VII. Interestingly, disability discrimination charges exceed age discrimination charges in the Clinton era, are overtaken by age discrimination charges in the W. Bush era, and then again exceed age discrimination charges in the Obama era. Figure 3 shows the number of lawsuits filed for each type of charge from 1993 through 2015 as well. The same presidential party-specific trend arises with disability and age discrimination lawsuits. Between 2007 and 2015, there is a striking 66% decline in the number of Title VII lawsuits filed. However, I also show that the number of EEOC staff members declined by roughly 25% over the preceding period, suggesting that the large decline in Title VII suits likely reflects EEOC budget cuts rather than a change in the priorities of the EEOC. The level of staffing resources is a pivotal input for determining the annual number of cases that the EEOC can feasibly manage. The lag between EEOC staffing cuts and annual cases litigated, in turn, arises from the time it takes for contemporaneously filed cases to work their way through the judiciary system.

Appendix Figure 13 shows the suit-to-charge ratios for each type of discrimination charge. These patterns also mirror those described in Figures 3 and 12. Appendix Figure 14 shows the fraction of all suits "with merit," which is stable over the entire sample period and beyond.

Though it appears that the charge filing behavior and selectivity of which cases were pursued were largely unaffected by the administration change, it still does not put to rest the possibility that judicial decision-making changed with the results of the 2000 Presidential Election. Particularly because federal district judges are nominated directly by the president, the impact of the judge's gender on sex discrimination case outcomes may have shifted in 2001 to the extent that ideological compatibility shaped the rationale underlying new judicial selections. Therefore, I further assess whether there is a change in the treatment effect of having a female judge before versus after the administration change in columns (3) and (6) of Table 5.[31] In particular, I regress the plaintiff settlement rate (win rate) on judge gender,

[31] More detailed sensitivity tests appear in Tables C6 and C7 of the Appendix.

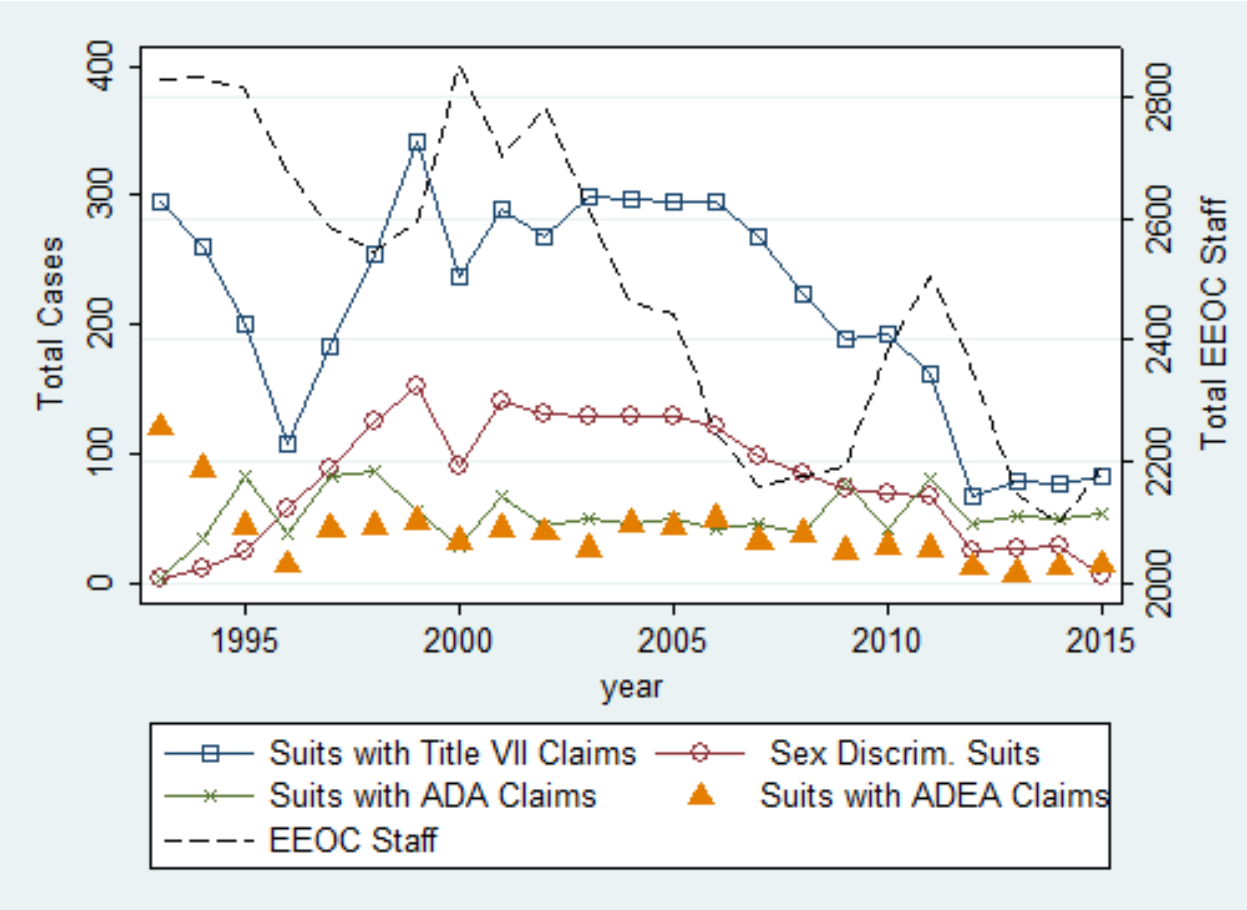


Figure 3: EEOC Lawsuits Filed by Type

This illustrates the number of lawsuits filed by the EEOC by type of infraction from 1993-2015. Title VII covers discrimination on the basis of race, sex, color, national origin, and religion. Sex Discrimination suits include those filed by men, which account for approximately 16% of all sex discrimination cases. ADA (Americans with Disabilities Act of 1990) protects disabled employees, ADEA (Age Discrimination in Employment Act of 1967) protects individuals over the age of 40, and the EPA (Equal Pay Act of 1963) prohibits sex-based wage discrimination. The dashed line displays the number of EEOC staff members employed over time.

an indicator for whether the case was filed before 2001, and the interaction of the female judge indicator with the time period dummy. The interaction term is small and insignificant in both specifications, which suggests that female judges were not differentially more harsh or lenient after the administration change relative to male judges. The interaction term's coefficient is especially small in the specification that estimates win rates. Specifically, the F-test cannot reject the hypothesis that the effects of female judge assignment on settlement and win rates are the same across both periods, respectively (p-value ranges from 0.20 to

0.51 in settlement rate regressions and from 0.84 to 1.00 in the win rate regressions).

5.3 The Role of Shared Experiences in Determining Case Outcomes and Broader Patterns of Sex Discrimination

Almost as important as quantifying the own-group gender bias among judges is developing an understanding of the underlying mechanism that generates these disparities in observed outcomes. Others have found evidence that shared experiences or empathy may play a role in determining how judges decide their cases. For example, Glynn and Sen (2015) find that, conditional on the number of children that a U.S. Court of Appeals judge has, those with daughters are more likely to take a pro-feminist stance in cases involving gender issues.

In the current context, a shared experiences story would gain traction if, for example, pro-plaintiff effects in pregnancy discrimination cases are larger among female judges with children. Similarly, such a mechanism would be empirically supported by the finding that female judges are especially favorable to Equal Pay Act plaintiffs in districts where higher gender pay gaps prevail.[32]

While these are intuitively appealing mechanisms, I am unable to explore the role of shared experiences in determining the outcomes of pregnancy, harassment, or female pay cases as–when assigned to female judges–they result in plaintiff victories a striking 100%, 100%, and 96% of the time, respectively. Nonetheless, I isolate these three types of charges, which are near uniformly female-specific issues, and show how male judge assignment affects win probabilities in Table 8. Specifically, win rates among male judges are 10-15 percentage points lower for all sub-types analyzed (as compared to just 5-7 percentage points lower among all sex discrimination cases), which provides suggestive evidence that shared experiences may have indeed assumed a role in generating the observed outcomes.

A related question with important implications for the types of cases that are eventually assigned to these district court judges is whether gender diversity on the bench might

[32] I credit an anonymous referee for making these insightful comments.

Table 8: Effect of Male Judge Assignment on Win Rates by Type of Charge

Dependent Variable = $\mathbb{1}$(Plaintiff compensated)	Female pay		Pregnancy/Maternity		Harassment	
	(1)	(2)	(3)	(4)	(5)	(6)
Male judge	-0.102*	-0.074	-0.152***	-0.063	-0.129***	-0.115**
	(0.053)	(0.090)	(0.035)	(0.055)	(0.028)	(0.049)
Age of judge		0.003		-0.004		0.001
		(0.005)		(0.005)		(0.004)
Experience of judge		0.001		0.023**		0.011
		(0.009)		(0.012)		(0.008)
White judge		-0.054		-0.034		-0.018
		(0.071)		(0.071)		(0.057)
Black judge		-0.014		0.001		-0.020
		(0.091)		(0.087)		(0.095)
Democratic Appointee		0.011		0.287		0.155
		(0.104)		(0.261)		(0.147)
Number of Complainants		0.002*		-0.037**		0.008
		(0.001)		(0.01)		(0.006)
Mean(Win rate$_{female\ judge}$)	0.96	0.96	1.00	1.00	1.00	1.00
Observations	131	131	127	127	176	176
R^2	0.015	0.444	0.038	0.261	0.024	0.222
Model	OLS	OLS	OLS	OLS	OLS	OLS
Administration FE	NO	YES	NO	YES	NO	YES
Region FE	NO	YES	NO	YES	NO	YES
Year FE	NO	YES	NO	YES	NO	YES

Dependent variable is an indicator for whether the plaintiff wins compensation (in either the settlement or litigation stage). Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

subdue workplace sex biases. One way to discern if female empowerment at the court level has positive implications for the way women are treated in the workforce more broadly is to measure whether increased female representation on the bench affects the number of sex discrimination charges filed in the associated geographical area. One crucial caveat to consider is that the number of sex discrimination charges more precisely reflects the amount of *reported* workplace sex discrimination rather than the absolute level of sex bias. Hence, if we were to observe an increase in sex discrimination charges in a district, this could reflect

an increase in the absolute level of sex bias, an increase in employees' willingness to report sex discrimination when it occurs, or a combination of both effects.

The EEOC reports sex discrimination charges at the state level from 2009 through 2015. To construct the proposed test, I use this additional source of aggregate data in concert with data on district court judge appointments and terminations from the Federal Judiciary Center Database over the same period. Because the state is the finest level at which sex discrimination charges are reported, I aggregate my measure of judge gender composition from the district court to the state level.

Before exploring the relationship between the two variables of interest–changes in the fraction of female judges serving on a district court bench in a state and changes in the number of sex discrimination charges filed in that state–I show that one important determinant of the number of reported discrimination claims of any kind is the unemployment rate. In particular, Appendix Figure 15 documents a strong positive relationship between movements in state unemployment rates and associated changes in the number of total EEOC discrimination charges filed, which is consistent with earlier work (Siegelman and Donohue III 1995). Discrimination claims are countercyclical for three related reasons: 1) When the economy is struggling, the number of layoffs increases. The employer will necessarily exercise discretion when choosing whom to fire. To the extent that those dismissed belong to a historically marginalized group, the scope for filing discrimination claims will have increased. 2) Slackness in the labor market decreases the cost of exercising taste-based discrimination since, by definition, the ratio of job applicants to positions available will be high. 3) Lastly, the opportunity cost of filing a discrimination claim is lower during recessions since opportunities for gaining employment elsewhere are limited. Given the countercyclical nature of discrimination claims, it will be important to control for economic conditions whenever estimating changes in charges filed over time.

Appendix Figure 16 provides evidence of a positive relationship between changes in the fraction of females serving on one of the corresponding state's district courts and changes in

the rate at which sex discrimination claims are filed. This provides evidence counter to the initially proposed hypothesis; that gender diversity on the bench should decrease the prevalence of sex discrimination of the workplace. However, it is worth re-emphasizing that sex discrimination charges filed measures reported sex discrimination rather than the absolute level of discrimination. It is then equally plausible that greater representation of women on the bench empowers female workers by emboldening them to report workplace injustices at a higher rate. In other words, increased gender diversity on the bench may not affect the amount of sex bias in the workplace but may instead increase the willingness to report any such incidence of sex bias. Additionally, state-level sex discrimination charges used to construct the correlation plot include charges filed by men, which account for approximately 16% of all sex discrimination claims. Such noise should attenuate the estimated correlation toward zero. To further address this concern, I separately plot log changes in Equal Pay Act charges filed against changes in female representation on the bench in Appendix Figure 17. Equal Pay Act charges are nearly exclusively filed by women, which should allow for a cleaner estimate between the variables of interest. The relationship strengthens, suggesting that gender diversity on the bench and the reported sex discrimination charges filed by women are indeed positively correlated.

Finally, I formally estimate the relationship between the fraction of female judges serving on a district court in a state and the number of sex discrimination charges filed in the following manner:

$$\begin{aligned}\Delta Log\,(Charges)_{st} = \beta_0 &+ \beta_1(\Delta Fraction\ Female\ Judges_{st}) + \beta_2(\Delta\overline{Judge\ Age}_{st}) \\ &+ \beta_3(\Delta Fraction\ White\ Judges_{st}) + \beta_4(\Delta\overline{Judge\ Experience}_{st}) \\ &+ \beta_5(\Delta Log\,(Unemp.\ Rate_{st}) + year_t + \epsilon_{st}\end{aligned} \tag{2}$$

I estimate the equation in a fixed effects model, where the coefficients can be interpreted as elasticities. I present the results of the estimation in Table 9. The estimated coefficient on $\Delta Fraction\ Female\ Judges$ in columns (1) and (2) imply an elasticity of sex discrimination

charges with respect to female representation on the bench of approximately .8 to .9. In more explicit terms, a one standard deviation increase in the fraction of female judges serving on the bench (which equals 4.2 percentage points) increases the number of sex discrimination charges filed by between 3.2 and 3.8 percentage points. Note that these estimates are suggestive at 10% significance levels. In columns (3) and (4), I perform an analogous estimate for Equal Pay Act (EPA) charges. As in the correlation graphs, the relationship strengthens in both magnitude and precision; the elasticity of EPA charges with respect to the fraction of female judges in a state is between 1.6 and 2.0. Thus, a one standard deviation increase in the fraction of female judges increases the number of sex discrimination charges by between 6.8 and 8.4 percentage points at 10% and 5% significance levels, respectively. Lastly, I show the relationship between total EEOC charges and gender diversity on the bench. No such relationship exists between these two variables though we do observe additional evidence of the strong countercyclical trend in discrimination claims in column (5).

Though this latter analysis is instructive, it is also purely descriptive; presidential appointments of female judges are almost certainly endogenous with more progressive attitudes toward women in the workplace. Consequently, none of these pieces of evidence provide grounds for claiming a causal relationship. In contrast to the motivating hypothesis, however, the relationship between gender diversity on the bench and sex discrimination claims filed is positive in all cases.

5.4 Absolute versus Relative Biases of Judges

To this point in the paper, I have established evidence in support of the hypothesis that male judges are *relatively biased* against female sex discrimination plaintiffs. However, the preceding analysis does not allow us to determine whether an *absolute bias* exists. That is, the empirical findings are consistent with a scenario in which male judges are biased against (in favor of) female sex discrimination plaintiffs (defendants) or one in which female judges are biased in favor of (against) female sex discrimination plaintiffs (defendants). Discerning

Table 9: State-level Gender Diversity on the Bench and Sex Discrimination Charges Filed

Dependent Variable = ΔLog (Charges)	Sex Charges		EPA Charges†		Total Charges	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔFrac. Female Judges	0.911*	0.769*	2.029**	1.565*	-0.286	-0.361
	(0.487)	(0.404)	(0.815)	(0.817)	(0.436)	(0.447)
$\Delta\overline{\text{Judge Age}}$	0.0003	0.0002	0.0003	0.0003	0.0004**	0.0003**
	(0.0002)	(0.0001)	(0.0004)	(0.0003)	(0.0001)	(0.0001)
ΔFrac. White Judges	0.285	0.450	0.426	0.542	0.229	0.307
	(0.548)	(0.536)	(1.912)	(2.059)	(0.405)	(0.404)
$\Delta\overline{\text{Judge Exper.}}$	0.003	0.006	-0.080***	-0.105***	-0.001	0.002
	(0.014)	(0.014)	(0.027)	(0.029)	(0.010)	(0.009)
Δ Log (Unemp. Rate)	0.162	-0.533	0.233	-0.566	0.427***	-0.0143
	(0.143)	(0.443)	(0.373)	(0.557)	(0.103)	(0.148)
Observations	306	306	306	306	306	306
R^2	0.027	0.116	0.062	0.107	0.101	0.170
Model	FE	FE	FE	FE	FE	FE
Year FE	NO	YES	NO	YES	NO	YES

Dependent variable measures year-to-year changes in the natural log of the number of EEOC charges of the specified type filed in a given state. Robust standard errors, clustered at state level, are in parentheses. Sample includes all EEOC charges filed and judge characteristics aggregated to the state level from 2009-2015.
† EPA charges reflect alleged violations of the Equal Pay Act.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the direction of the bias is of first-order policy importance as it would provide a welfare-based justification either for or against increasing female representation on the bench. To address this question of absolute bias, I further analyze appeal decisions and outcomes. Additionally, I estimate whether a given judge's leniency in non-sex based cases is consistent with his or her leniency in sex-based cases under the assumption that leniency is a fixed characteristic of judges.

5.4.1 Evidence from Appeal Filing Behavior

Filing an appeal is costly in terms of time, money, and other resources. Hence, one can interpret a losing party's decision to file an appeal as a costly signal that the initial ruling

may have been inequitable. A positive difference in defendant-initiated appeals rates across female and male judges, respectively, for example, would suggest that female judges are biased against sex discrimination defendants and that male judges are correct (or at least, less biased) in their pro-plaintiff rulings. Conversely, a negative difference in plaintiff-initiated appeals rates across female and male judges would indicate that male judges are biased against sex discrimination plaintiffs and that female judges are correct in their pro-defendant rulings.

Extending this logic a step further, an appeal that leads to a decision reversal is an especially strong indicator that the initial ruling was incorrect. Previous studies in the economics of law literature have even used a judge's reversal rate as a measure of judge "quality" or performance (Choi et al. 2010; Epstein et al. 2013; Sen 2014). Assuming the male and female judges are equally competent on average, gender differences across win and loss reversal rates would indicate that either female judges are biased against defendants or male judges are biased against plaintiffs.[33]

In Appendix Table C12, I compare mean plaintiff appeals rates, defendant appeals rates, along with both loss and win reversal rates across male and female judges. I define the plaintiff appeals rate as the number of cases for which a plaintiff appealed the case outcome divided by the total number of cases in which the plaintiff lost. The loss reversal rate divides successful case reversals by the total number of plaintiff losses.[34] While sex discrimination plaintiff appeals rates and loss reversal rates are 9 and 10 percentage points higher among male judges (which would indicate that male judges are biased against plaintiffs), this difference is insignificant due to the small number of losses in the sample. No statistically or economically significant differences emerge across defendant appeals or win reversal rates either. Additionally, I compute judge gender-specific differences for these same four summary statistics in all non-sex discrimination cases and race discrimination cases as

[33]Note, however, that I am unable to obtain data on the circumstances of each appeals case. This feature makes the appeals rate more attractive as a measure of correctness rather than the appeals success rate, where there are likely omitted factors determining the outcome of whether a reversal has occurred.

[34]Analogous definitions follow for the defendant appeals rate and win reversal rates.

benchmark comparisons. These subsequent tests similarly fail to reveal the presence of an absolute gender-based bias though one should exercise caution before reading too much into the results of this series of severely underpowered tests.

5.4.2 Evidence from Variation in Within-Judge Leniency

In an additional attempt to pin down the precise nature of the absolute bias, I invoke an assumption that I will call "correlated leniency." Correlated leniency requires that if a judge is more lenient–that is, rules in favor of the plaintiff with a higher frequency–in type A cases then that same judge will also be more lenient in type B cases. This rules out the possibility of non-monotonic sentencing patterns, whereby judges may be both more favorable to sex discrimination plaintiffs and less empathetic toward allleged victims of disability discrimination, for example (Mueller-Smith 2016).

The correlated leniency assumption is a slight twist on the logic used to generate a commonly used instrument in the economics of crime literature. In particular, a series of papers has used judge stringency–that is, the average incarceration (or conviction) rate in other cases handled by a judge–to instrument for how a judge will rule in the current case. This technique has been used to recover causal estimates of the effects of incarceration on recidivism and employment (Bhuller et al. 2016), the effects of electronic monitoring of felons on recidivism (Di Tella and Schargrodsky 2013), and the effects of instrumented judge decisions on a multitude of other non-crime outcomes (Autor et al. 2015; Belloni et al. 2012; Dahl et al. 2014; Dobbie and Song 2015; Doyle 2007, 2008; French and Song 2014; Maestas et al. 2013).

In general, the first stage of these instruments shows that a judge with a high (low) conviction rate in a series of other cases is more (less) likely to sentence the suspect in the current case. In the current context, I assume that judges with higher win rates in sex discrimination cases will also have higher win rates in non-sex discrimination cases. Under this assumption, a judge will be considered biased whenever the win rates among the two

types of cases are negatively correlated relative to some baseline.

I test for an absolute bias under the correlated leniency assumption by using two different approaches. First, I partition all of the judges in the sample on the basis of whether they are assigned both sex discrimination and non-sex discrimination cases or whether they are only assigned one type of case. I call the former 'dual-type' judges and the latter 'single-type' judges. The single-type judges are the benchmark control group against which I compare the dual-types in order to assess bias. I then compare the average win rates in sex cases across dual-type male judges and single-type male judges, as in Appendix Table C13. The positive difference (though not statistically significant) of 2.6 percentage points indicates that the dual-type male judges in the sample are more lenient in sex discrimination cases than are their single-type counterparts. Correlated leniency requires that these dual-type male judges should too be more lenient than average when litigating non-sex discrimination cases. Indeed, I find that the dual-type male judges are 3.8 percentage points more likely to rule in favor of the plaintiff than are single-type male judges overseeing non-sex discrimination cases. I then perform the same exercise on female judges, finding that win rates among female judges overseeing sex discrimination cases are 2.8 percentage points higher among dual-types than they are among single-types. However, while dual-type male judges are also more lenient than single-types in litigating non-sex cases, dual-type female judges are 4.1 percentage points less lenient than are single-type female judges in litigating non-sex cases. These findings suggest that it is the female judges who possess an absolute bias against sex discrimination defendants (or in favor of sex discrimination plaintiffs). That said, the aforementioned differences are not statistically significant and are hence suggestive only.

The second test for absolute bias uses only the sample of dual-type judges in a regression-based approach. The basic idea is similar to the previous one; I assess whether male judges who are more lenient in sex discrimination cases are also more lenient in non-sex cases, relative to female judges. To operationalize this approach, I regress the average win rates in all non-sex cases seen by a judge on his or her corresponding win rate in sex cases, an

indicator for whether the judge is male, and the interaction of these two terms. The coefficient of interest is the one attached to the interaction term, which tells us whether male judges who are more lenient in sex cases are also more lenient in non-sex cases as compared to female judges. The corresponding results in Appendix Table C14 align with those of the previous test: for each 10 percentage point increase in a male judge's sex case win rate, his non-sex case win rate is 2 to 3 percentage points ($p < 0.10$) higher relative to a female judge. Moreover, these results approach significance at the 5% and 1% levels when standard errors are clustered at the trial court level.[35] The primary estimates appear to be robust to the inclusion of other judge-specific controls, time fixed effects, and trial court fixed effects as well. That said, these estimates are only mildly significant and so I would caution against considering the results to be anything more than suggestive. Furthermore, the tentative conclusion that female judges are biased against (in favor of) sex discrimination defendants (plaintiffs) is predicated on the somewhat stronger assumption that a judge's leniency is transferable across different case types, rather than merely across different cases of the same type (as has been externally validated in the literature).

While the comparisons of plaintiff-initiated repeals and loss reversal rates suggest that male judges may be biased, the comparison of dual-type and single-type judges and subsequent dual-type judge regression analysis suggests the opposite may be true (though the former evidence is especially imprecise while the latter relies on the perhaps overly strong assumption of "correlated leniency"[36]). Given the conflicting evidence and the relatively weak precision with which these estimates are made, these data do not provide an authoritative answer as to the direction of the bias among male and female judges.

[35] See Table C21 of the Appendix.

[36] Mueller-Smith (2016), in fact, provides an instructive empirical analysis of how this assumption breaks down in the context of criminal sentencing.

6 Conclusion

In this paper, I show that one can more reliably learn about judicial biases by studying the outcomes of cases *not officially decided by the judge* and how those outcomes are shaped by the preceding judge-litigant interactions. In particular, I find that pre-trial motions filed by defendants accused of workplace sex discrimination are 15 percentage points (off a base of 41.2%) less likely to be granted by randomly assigned female judges, relative to male judges. As a result of this demonstrated bias, plaintiffs and defendants are more inclined to agree over what the expected case outcome would be and thus settle 6-7 percentage points (baseline of 85.5%) more often. The plaintiff's chances of winning compensation also increase by 5-7 percentage points (baseline of 88.8%). Because the EEOC takes up only a small fraction of especially strong discrimination cases, the settlement and win rates in the sample are higher than those seen for the entire distribution of employment discrimination cases. This type of selection should accordingly compress any observed difference in judge gender-specific win rates, and so I interpret the estimates as a lower bound on the extent of judicial gender bias.

These results make two major contributions to the literature. First, I document among the first evidence that, relative to female judges, male judges disfavor female workers who allege that they are victims of workplace sex discrimination—60% of which come in the form of sexual harassment. Such a finding stands in contrast to recent work that shows no effect of judge gender on outcomes (Lim et al. 2016). However, Lim et al. (2016) focus on criminal rather than civil cases and do not distinguish between different types of crime. Mueller-Smith (2016), in contrast, shows that judges may have heterogeneous preferences across different types of criminal cases; for example, some may be relatively more harsh with suspected violent criminals yet relatively more lenient toward drug offenders. All of this is to say that the judge's gender may be important for only a subset of cases and that this study identifies cases of workplace sex discrimination as a member of that subset. This work is especially resonant with that of Boyd et al. (2010), who use semiparametric matching methods and

find that male judges are 10 percentage points more likely to rule against sex discrimination plaintiffs. Likewise, they fail to uncover gender-specific differences in the outcomes of cases belonging to 12 other areas of law. Importantly, I find evidence for gender discrimination in spite of the fact that these data share with the literature the trait that plaintiff litigation success rates are indistinguishable across judge gender. I argue that the practice of focusing exclusively on trial outcomes has led researchers to systematically understate the extent of judicial biases. Second, I provide evidence on how litigants learn of judicial biases and how such knowledge shapes the observed case outcomes. In other words, I demonstrate that litigants are more inclined to bargain in the shadow of the judge when the outline of that shadow is clearer.

This study also provides a framework for examining the existence of judicial biases along other dimensions, such as race and age. Candidate extensions of this work include a further analysis of the determinants of workplace discrimination and whether plaintiff victories have a deterrence effect that encourages employers to reform their culture of workplace discrimination.

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A Priest and Klein (1984) Model and Extension

A.1 Basic Definitions

Suppose that all judges apply a specific standard for evaluating whether the defendant is at fault; I call this benchmark the decision standard, Y*. Let Y* be a scalar that is fixed for a given judge. Then let X be the set of case characteristics used by the judge to determine the level of defendant fault, Y. As in PK, let Y = $H(X)$, where $H(X)$ is a mapping from the case characteristics to a determined level of defendant fault. Whenever Y>Y*, the perceived level of defendant fault is above the minimum threshold required for the judge to rule in favor of the plaintiff. Conversely, if Y<Y*, the judge would rule in favor of the defendant. As in PK, I also assume that the plaintiffs and defendants know the decision standard Y* once assigned a judge. Figure 4 shows an arbitrary distribution of disputes so as to depict the relationship between Y, Y*, and the outcome of the case conditional on reaching litigation.

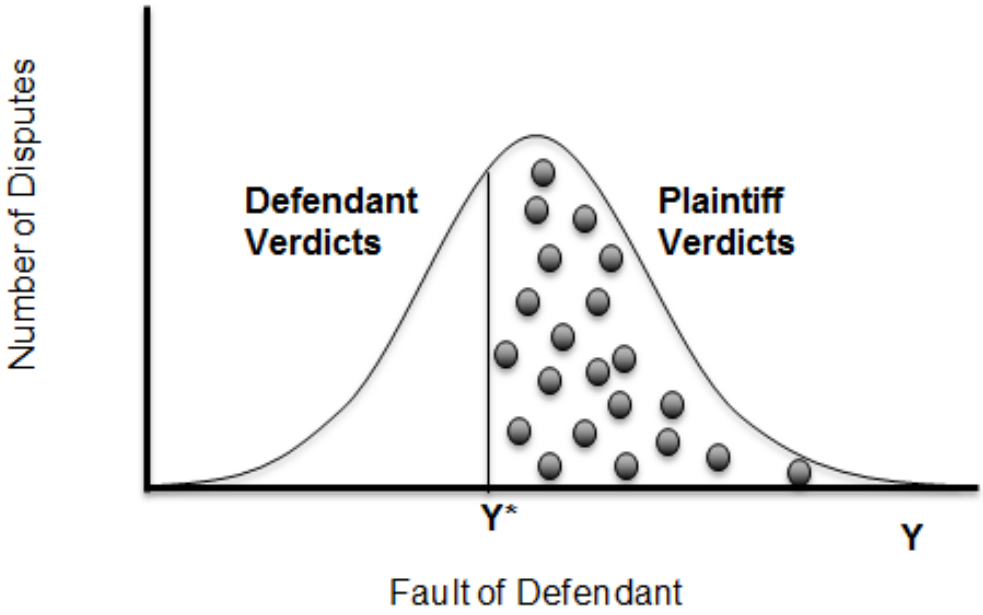


Figure 4: Decision Standard and Plaintiff Outcomes

A.2 Parties' Expectations of the Defendant Fault Level

Further suppose that Y', the true level of defendant fault in a case, is randomly drawn from the distribution of disputes. Also assume that each party, the defendant and plaintiff, knows Y* for the given judge. However, the defendant and plaintiff are less interested in Y' than they are in where Y' is in relation to Y*. That is, they would like to know the probability that the judge finds a verdict in favor of the plaintiff. To do this, they must form expectations over Y' based on the case evidence and circumstances. As in PK, the plaintiff and defendant estimate Y' with some error to reflect the uncertainty over the case evidence.

Following the notation of PK, I denote $\hat{Y'}_p$ to be the plaintiff's estimate of Y' and $\hat{Y'}_d$ to be the defendant's estimate of Y'. Then for a given dispute:

$$\hat{Y'}_p = Y' + \epsilon_p \tag{3a}$$

$$\hat{Y'}_d = Y' + \epsilon_d \tag{3b}$$

where ϵ_p and ϵ_d are independent random variables with mean 0 and variance σ_ϵ^2. Thus, each party's estimate of Y' is independent and unbiased.

Figure 5 shows an example of the mean value of a plaintiff's estimate of the defendant fault level for a particular dispute, given by $\hat{Y'}_p$. The shaded region to the right of Y* indicates the plaintiff's estimated likelihood that the judge would rule in favor of the plaintiff. I denote the area of this region as $\hat{P'}_p$. The complementary area of the distribution corresponds to the plaintiff's estimated likelihood that the defendant would win the trial. An analogous distribution exists for the defendant and equations (3a) and (3b) require that $E(\hat{Y'}_p) = E(\hat{Y'}_d) = Y'$.

The decision standard is normalized so that Y*= 0. Then each party's estimate of the likelihood of a plaintiff verdict given their respective estimates of Y is as follows:

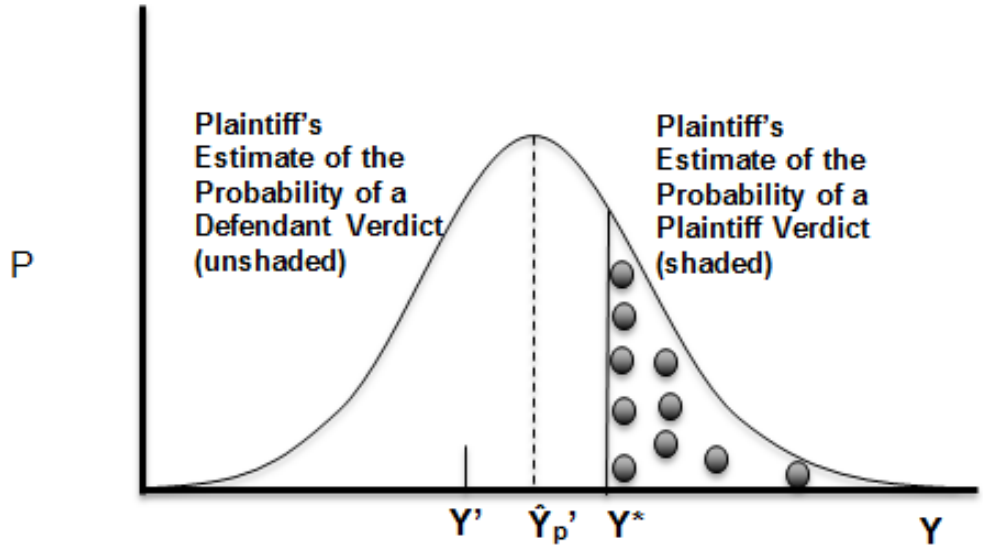


Figure 5: Probability Distribution around Plaintiff's Fault Estimate

$$\hat{P'}_p = P(Y \geq 0 | \hat{Y'}_p) \tag{4a}$$

$$\hat{P'}_d = P(Y \geq 0 | \hat{Y'}_d) \tag{4b}$$

As in PK, substitute equations (3a) and (3b) in for equations (4a) and (4b), respectively. The result is that each party's estimate of the likelihood of a plaintiff verdict is equivalent to the likelihood that either party's error term is less than their estimate of a plaintiff victory, as follows:

$$\hat{P'}_p = P(\epsilon_p \leq \hat{Y'}_p) \tag{5a}$$

$$\hat{P'}_d = P(\epsilon_d \leq \hat{Y'}_d) \tag{5b}$$

Since both ϵ_p and ϵ_d have mean 0 and standard error σ_ϵ, each party's estimate can be written as:

$$\hat{P}_p = F(\hat{Y'}_p) \tag{6a}$$

$$\hat{P}_d = F(\hat{Y'}_d) \tag{6b}$$

where $F(\hat{Y'}_p)$ and $F(\hat{Y'}_d)$ are cumulative distribution functions for ϵ_p and ϵ_d, respectively. Figure 6 then represents P'_p as the region to the left of $\hat{Y'}_p$ in the distribution of the plaintiff's error term. An analogous relationship also holds for the defendant.

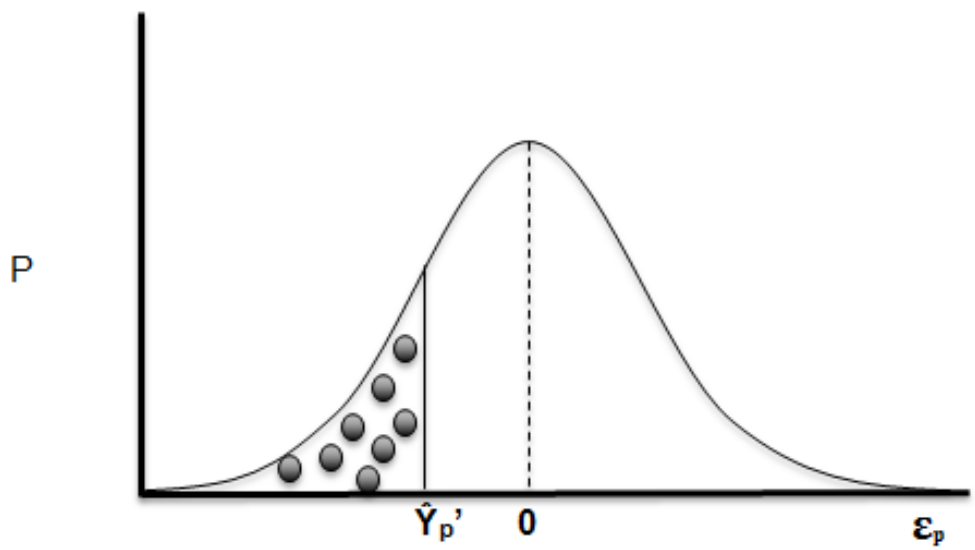


Figure 6: Distribution of Plaintiff's Error Term

A.3 The Litigation Selection Process

Next, I model the parties' decision to settle or proceed to litigation. Following the notation of PK, let A represent the plaintiff's mimimum settlement demand and B the defendant's maximum settlement offer. Then define (C_p, S_p) and (C_d, S_d) as the litigation and settlement costs to the plaintiff and defendant, respectively. Lastly, define J as the expected judgement

should a liability verdict be upheld.[37] Then A and B can be represented as follows:[38]

$$A = (P_p \times J) - C_p + S_p \tag{7a}$$

$$B = (P_d \times J) + C_d - S_d \tag{7b}$$

When the plaintiff's minimum demand (A) exceeds the defendant's maximum offer (B), the case will proceed to litigation. Priest and Klein (1984) combine equations (7a) and (7b) to show that $A > B$ whenever:

$$P_p - P_d > \frac{C - S}{J} \tag{8}$$

where $C = C_p + C_d$ and $S = S_p + S_d$. PK further assume that litigation costs exceed settlement costs, i.e. $\frac{C-S}{J} > 0$. Also, $\frac{C-S}{J} < 1$ as otherwise, litigation would never occur because $P_p - Pd \ngeq 1$.

A.4 The Role of Uncertainty over Outcomes in Litigation Selection

Equations (6a) and (6b) imply that $P_p - P_d = F(\hat{Y'}_p) - F(\hat{Y'}_d)$, where the F's are the CDFs of the plaintiff and defendant error terms. This equation shows that the difference in the expected outcome depends upon the difference in their estimates of the true level of defendant fault, Y'.

Denote the difference in expected outcome of the trial, $P_p - P_d$, as the "disagreement area." Figure 7 shows the disagreement area graphically for two pairs of potential estimates

[37] The use of J for both plaintiffs and defendants presumes that the stakes are symmetric across both parties. See Priest and Klein (1984) for a framework for analyzing settlement and litigation decisions when stakes are not symmetric.

[38] Since A is the settlement demand that makes the plaintiff indifferent between settlement and litigation, it must be the case that $A - S_p = (P_p \times J) - C_p$. B is similarly the settlement offer for which the defendant is is indifferent between settlement and litigation. Thus, $-B - S_d = -(P_d \times J) - C_d$. These equations can be rearranged to form equations (7a) and (7b).

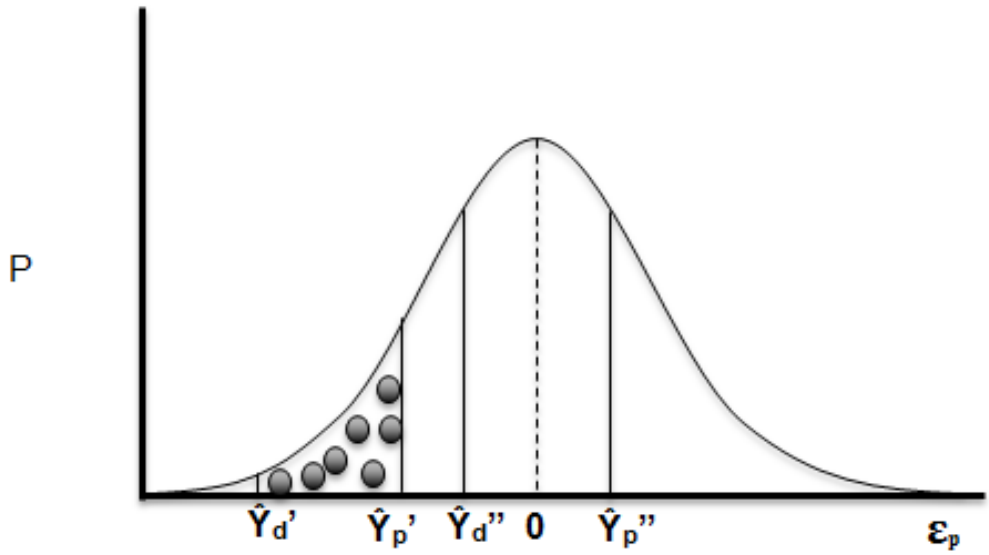


Figure 7: Differences between Plaintiff and Defendant Estimate of the Likelihood of a Plaintiff Victory

of defendant fault, $(\hat{Y'}_d, \hat{Y'}_p)$ and $(\hat{Y''}_d, \hat{Y''}_p)$.[39] Importantly, the graph demonstrates that the closer are these estimates to the decision standard, Y*, the greater will be the area of disagreement over expected outcomes and accordingly, the likelihood that the case goes to trial (Y* is again normalized to 0). Even though the parties' estimates of the defendant fault, $\hat{Y'}$ and $\hat{Y''}$, differ by the same amount (i.e., $|\hat{Y'}_p - \hat{Y'}_d| = |\hat{Y''}_p - \hat{Y''}_d|$), the disagreement area bounded by $\hat{Y''}_p$ and $\hat{Y''}_d$ (unshaded area) is far greater than the corresponding disagreement area bounded by $\hat{Y'}_p$ and $\hat{Y'}_d$ (shaded area).

Intuitively, a case will go to trial whenever the plaintiff and defendant sufficiently disagree on the expected outcome of the case, i.e. there is a large enough degree of uncertainty over the expected outcome among the two parties. Uncertainty over the outcome, in turn, increases the closer are the estimates of the fault levels to the judge's switching point for ruling in favor of the plaintiff. Estimates of the fault level will be close to the decision standard whenever the true fault level, Y', is near the decision standard. Therefore, litigated disputes will constitute the set of cases for which the true fault level is sufficiently close to the decision standard.

[39] I assume, as in PK, that the error term is distributed normally.

A.5 Applying the Model to Detect Judicial Bias by Judge Gender

Now suppose one would like to test for the existence of judicial bias according to a particular background characteristic of a judge. The specific application is to see whether female judges have lower (or higher) decision standards than do male judges in cases of sex discrimination against women. The validity of this test requires the identifying assumption that judges are assigned to cases randomly by gender. More precisely, random assignment implies $E[\hat{Y'}_p|\text{female judge}] = E[\hat{Y'}_p|\text{male judge}]$ and $E[\hat{Y'}_d|\text{female judge}] = E[\hat{Y'}_d|\text{male judge}]$.[40] This guarantees that, on average, the distance between the plaintiff and defendant's estimates of Y are the same across judges.

If the settlement rate is higher when a female judge presides, it must be the case that the estimates of defendant fault lie further away from a female judge's decision standard than from a male judge's decision standard. Equivalently, one can conclude that female and male judges have different decision standards in sex discrimination cases, which is to say that a judicial bias exists. In summary, a simple test for detecting the existence of judicial bias is to compare the settlement rates of randomly assigned cases according to a particular judge characteristic.

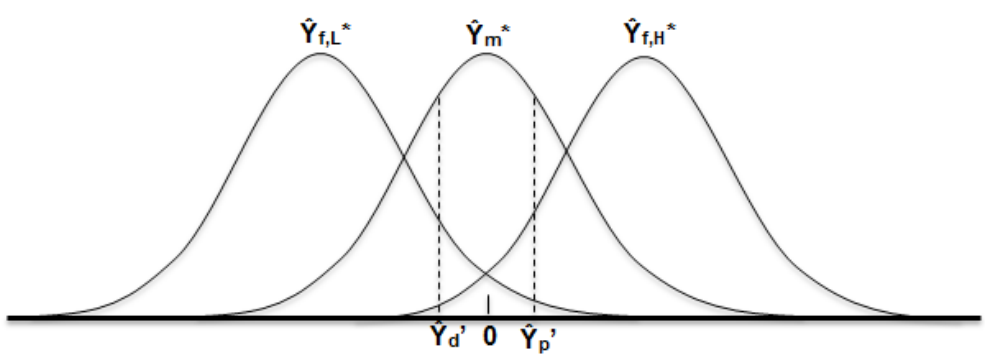


Figure 8: Possible Distributions of Error Terms Given Settlement Rate $_{Y_m^*}$ < Settlement Rate $_{Y_f^*}$

[40] Additionally, all of the other relevant parameters of the cases by judge gender will be the same on average. For example, J, the size of the judgement, will be equal in expectation across cases assigned to male and female judges.

Figure 8 demonstrates the set of possible distributions of error terms across sex discrimination cases by judge gender given that settlement rate ${Y_f^*}$ exceeds settlement rate ${Y_m^*}$. First, random assignment guarantees that the distance between $\hat{Y'}_p$ and $\hat{Y'}_d$ are the same on average across judge gender. The relatively smaller disagreement area for cases overseen by female judges, which is implied by the higher settlement rate, must mean that the decision standard Y_f^* is further away from $\hat{Y'}_p$ and $\hat{Y'}_d$ than is Y_m^*. One can sign the direction of the bias by simply comparing the unconditional plaintiff victory rates in cases overseen by male and female judges. If the victory rate among female judges exceeds that associated with male judges, then $Y_f^* < Y_m^*$.

A last important point is that a divergence in settlement rates across judge gender implies that the litigating parties *perceive* an own-gender judicial bias. However, if the bias itself were truly apocryphal, both parties could then receive a higher expected payoff by settling more often with male judges or less frequently with female judges. Thus, a difference in settlement frequencies would not exist in equilibrium unless there was an underlying gender bias across judges.

B Intensive Margin Effects

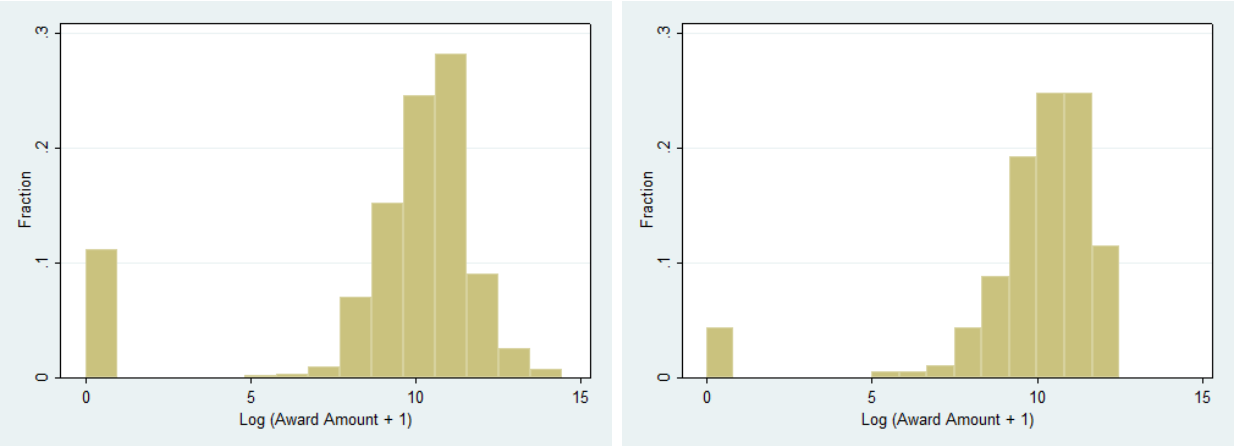
In light of the finding that male judge assignment results in fewer victories for female sex discrimination plaintiffs, a natural follow-up question to ask is whether and by how much male judge assignment affects the amount that such claimants are compensated. Before estimating the effect of judge gender on the amount awarded, however, it is instructive to compare some of the more salient properties of the distributions of awarded amounts. Doing so will also inform the judgment of which estimation procedure is most appropriate.

Table 4 shows that the amount awarded per beneficiary is $49,036 among female judges and $58,223 among male judges. However, this difference is not statistically different. Moreover, a simple comparison of the means masks important differences in the associated distributions, which are quite skewed. For example, the median amount awarded per complainant is $31,125 among female judges, as compared to just $27,692 among male judges. The reversed ordinal rankings of the means and medians reflects the fact that the male judge's distribution is particularly given to extreme values, with 7 percentage points more mass on $0 along with a top 5th percentile that ranges from $213,000 to $1.84 million (as compared to an analogous range between $182,500 and $262,500 for female judges). This skewness is well-captured by the ratio of the variances of the two distributions, which narrowly exceeds 5. That said, it appears that male judges were assigned to a handful of outlier cases in which the defendant's behavior was egregious, bordering on if not far surpassing the threshold for pursuing additional criminal charges.[41] To prevent the possibility of outliers driving the results, I exclude cases in the top 1% of the distribution of awarded amounts (10 cases overall)

[41] In one case, a 15 year-old female employee was the victim of persistent physical sexual harassment, subsequently suffering emotional trauma and signs of post-traumatic stress disorder. Another involved a female employee who, after withstanding weeks of racial and sexual harassment from a co-worker, eventually became embroiled in the following incident: "On or about March 26, 2004, Mr. A, without any provocation from Ms. B, struck Ms. B in the face and knocked her down, then continued to pummel her when she was on the ground. Co-workers managed to extricate Ms. B from Mr. A's grasp and separate them. Ms. B suffered serious injuries due to this assault." The last case involved a supervisor who forcibly raped the plaintiff multiple times and subsequently caused her to fear for her and her family's safety. All three of these cases understandably resulted in plaintiff compensation amounts that ranked in the top 10 of all award amounts in the full sample of cases.

in the main analysis. I also re-examine the results on the full sample as a robustness check.

In Appendix Figures 9A, 9B, and 10, I compare both the probability density functions and cumulative distribution functions of awards by judge gender after disciplining the influence of outliers on the distributions by performing a logarithmic transformation of award amounts plus $1. Both figures unequivocally demonstrate that assignment to a male judge adds mass to both the left and right tails of the award amount distributions. Furthermore, OLS estimates of the effect of judge gender on award amounts will fail to capture their nonlinear relationship (Mullahy 1998; Manning and Mullahy 2001; Dunn 2016). In its place, Deb et al. (2006) propose alternate approaches for estimating marginal effects in cases where the outcomes are both skewed and equal to zero for a non-trivial fraction of observations.



(A) Male Judges (B) Female Judges

Figure 9: Distribution of Log (Award Amount + 1) in Female Sex Discrimination Cases, by Judge Gender

The left and right panels show the distribution of log (award amount + 1) in cases overseen by male and female judges, respectively.

First, I apply a box-cox model to test for the appropriate functional form. The results of this test suggest using a log transformation of the data. Since least squares models may also be biased in the presence of heteroscedasticity, I apply a Park test to see whether the error structure is related to the independent variables. Indeed, the test demonstrates that a linear relationship exists between the square of the least squares residuals and at least a

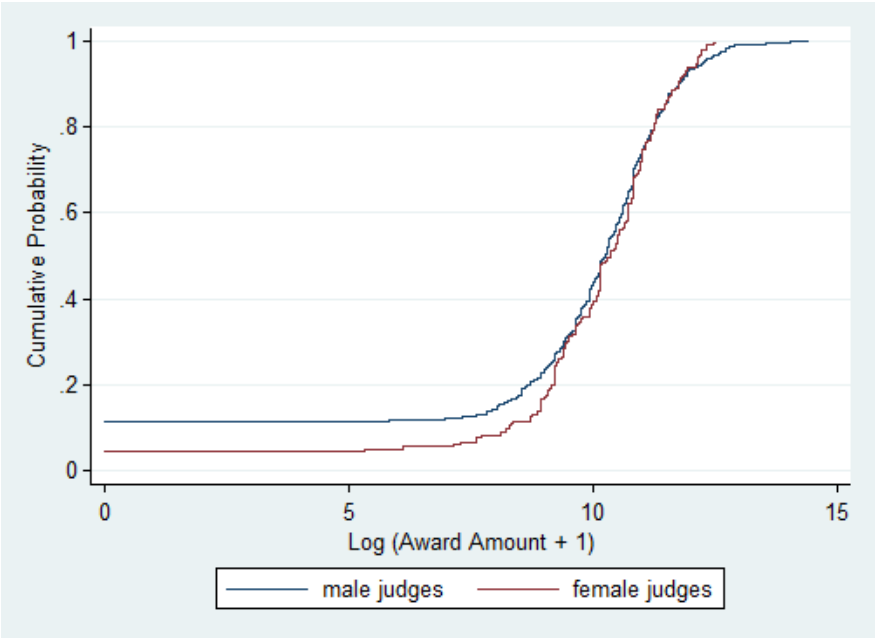


Figure 10: CDF of Log (Award Amount + 1) in Female Sex Discrimination Cases, by Judge Gender

The above diagram shows the cumulative distribution functions for log (award amount + 1), by judge gender

few of the independent variables. This revelation suggests that I should apply a generalized linear model (GLM) to estimate the marginal effect of judge gender on the award amount in place of a more traditional OLS model as the nature of the heteroscedasticity is complex. Next, Manning and Mullahy (2001) recommend using a GLM Family Test (also known as a Modified Park Test) to estimate the relationship between conditional mean of the dependent variable and the variance of the error. The model shows that the standard deviation of the errors is approximately proportional to the conditional mean, which implies a Gamma distribution. One cannot reject the hypothesis that the error variance is proportional to the cubed root of the mean as well, which would be consistent with an inverse Gaussian distribution.

These tests imply that the optimal functional form for estimating the effect of judge gender on plaintiff award amounts is a gamma distribution with a log linking function in a GLM framework. As a robustness check, I also estimate a two-part model, which separately

models both whether the plaintiff will win and, conditional on winning, how much the plaintiff will be awarded. The extensive margin is estimated with a probit model while the intensive margin is again estimated in a GLM framework using a Gamma distribution with a log linking function.[42] Standard errors are estimated using a bootstrapping technique with 1,000 replications. Though best practice dictates the use of GLM and two-part models in favor of OLS models in the presence of skewed outcomes and a zero mass problem, I estimate the OLS model with a log-transformed dependent variable as a final robustness check. In this latter specification, I estimate log (compensation amount + c), where c is a parameter that is estimated by way of a grid search that minimizes the root-mean square error of observed minus predicted award amounts.[43]

Finally, in Appendix Table C17, I provide estimates of the effect of male judge assignment on the amount that plaintiffs are compensated. Using the preferred specification of a GLM model with a gamma distribution and log linking function, I estimate that assignment to a male judge reduces average plaintiff compensation by a small and statistically insignificant 5 percentage points. Estimation using a log-transformed dependent variable in an OLS framework shows a sharper decrease of 15 percentage points but is also insignificant at conventional levels. In Table C18, I re-estimate the effect of male judge assignment on award amounts in a two-part model and find results similar to the GLM specification; compensation is reduced by a statistically insignificant 6.4 percentage points (or $3,628). Including the outliers in the estimation sample does flip the sign of the coefficient in some cases but nonetheless, all of the effect sizes are statistical zeroes.[44]

It is important to reiterate the fact that there are rules governing how much a plaintiff may be compensated on the basis of state laws, the size of the firm, and other factors that are not captured in these data. For example, the maximum payout is limited by the size of the offending firm and the total employee counts are unavailable in the data. For these reasons,

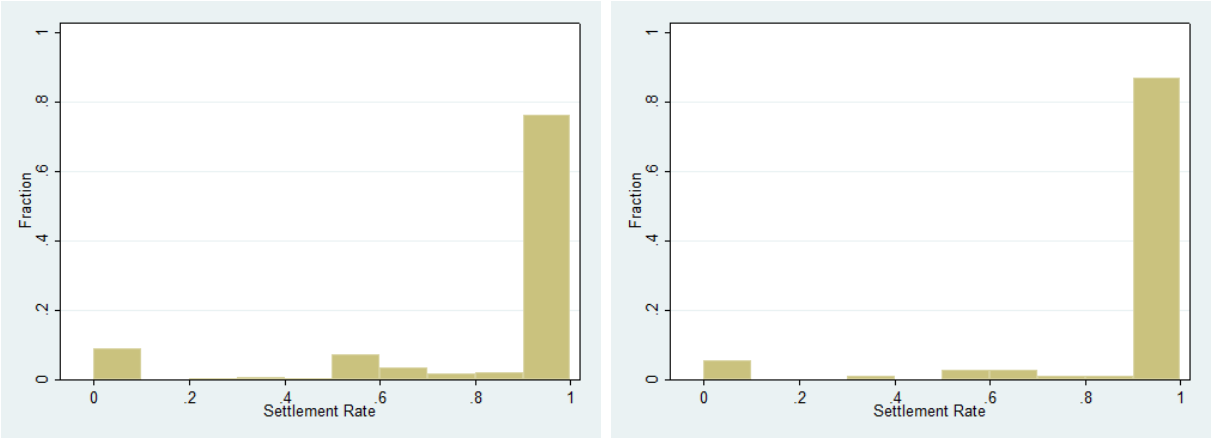
[42] I also re-estimate the two-part model using the Inverse Gaussian distribution to estimate intensive margin outcomes as an additional robustness check. See Table C20 of the Appendix for results.

[43] After completing a crude grid search, I conclude that c should be set to 36,100.

[44] See Table C19 of the Appendix for results with outliers included.

the above specifications likely suffer from omitted variable biases that materially weaken the precision of the estimates. Accordingly, the absence of an estimated relationship between judge gender and plaintiff compensation amounts should be interpreted as suggestive but certainly not an unassailable conclusion.

C Additional Figures and Tables



(A) Male Judges (B) Female Judges

Figure 11: Distribution of Settlement Rates in Female Sex Discrimination Cases, by Judge Gender

The left panel shows the distribution of average settlement rates across male judges in the sample while the right panel shows the analogous distribution for female judges.

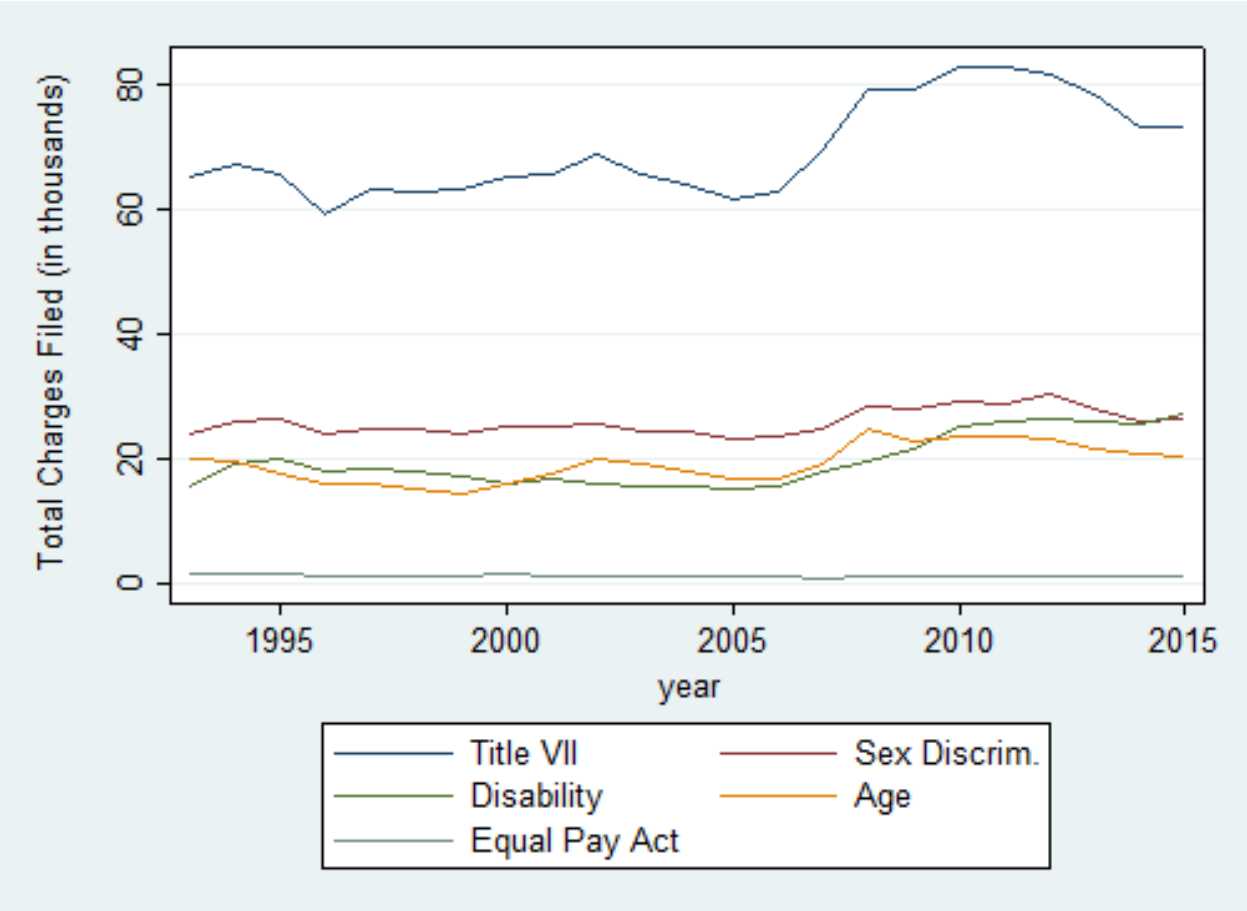


Figure 12: EEOC Charges Filed by Type

This illustrates the number of charges filed by type of infraction from 1993-2015. Title VII covers discrimination on the basis of race, sex, color, national origin, and religion.

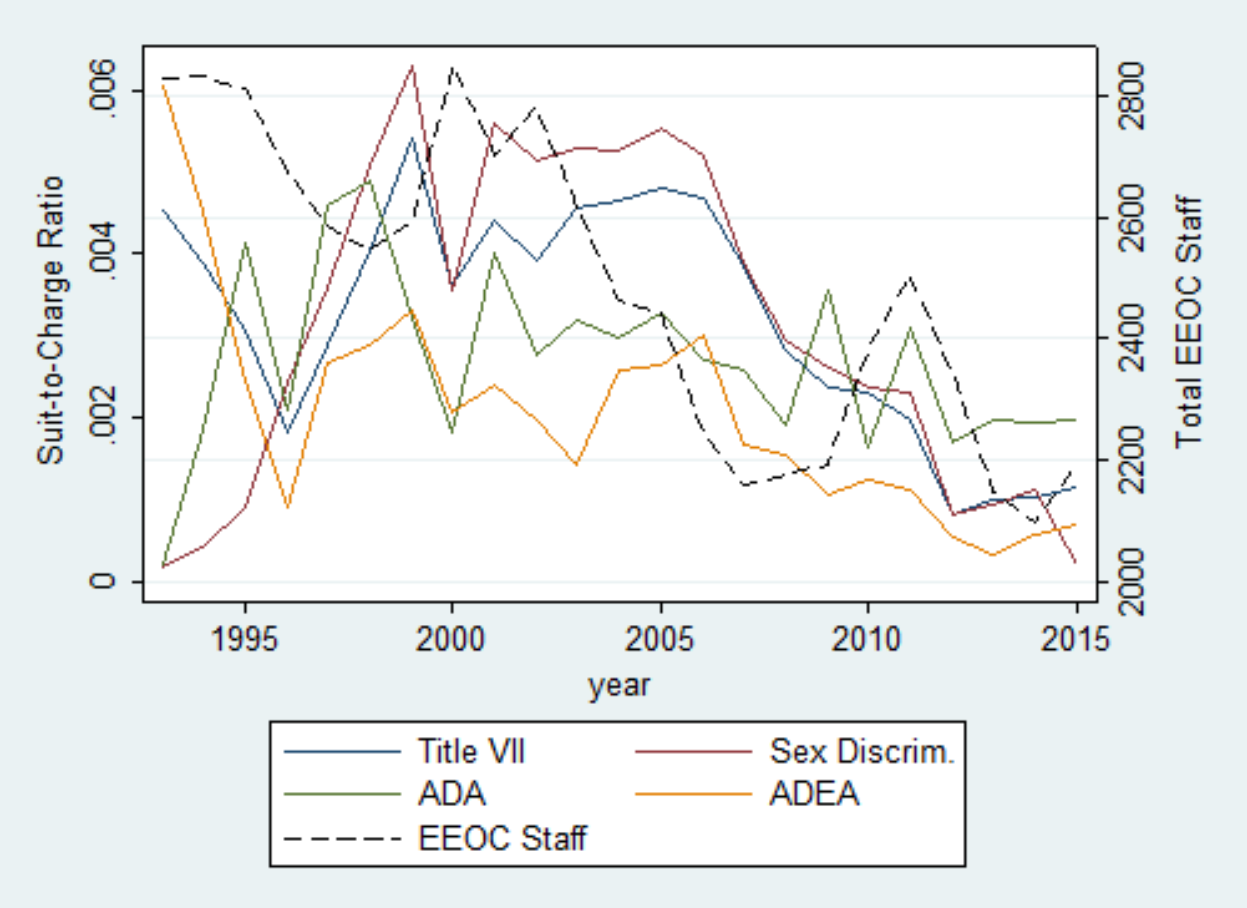


Figure 13: Lawsuit-to-Charge Ratio

This illustrates the number of lawsuits filed by the EEOC divided by the number of charges filed for each type of infraction from 1993-2015. Title VII covers discrimination on the basis of race, sex, color, national origin, and religion. ADA (Americans with Disabilities Act of 1990) protects disabled employees, and ADEA (Age Discrimination in Employment Act of 1967) protects individuals over the age of 40. The dashed line displays the number of EEOC staff members employed over time.

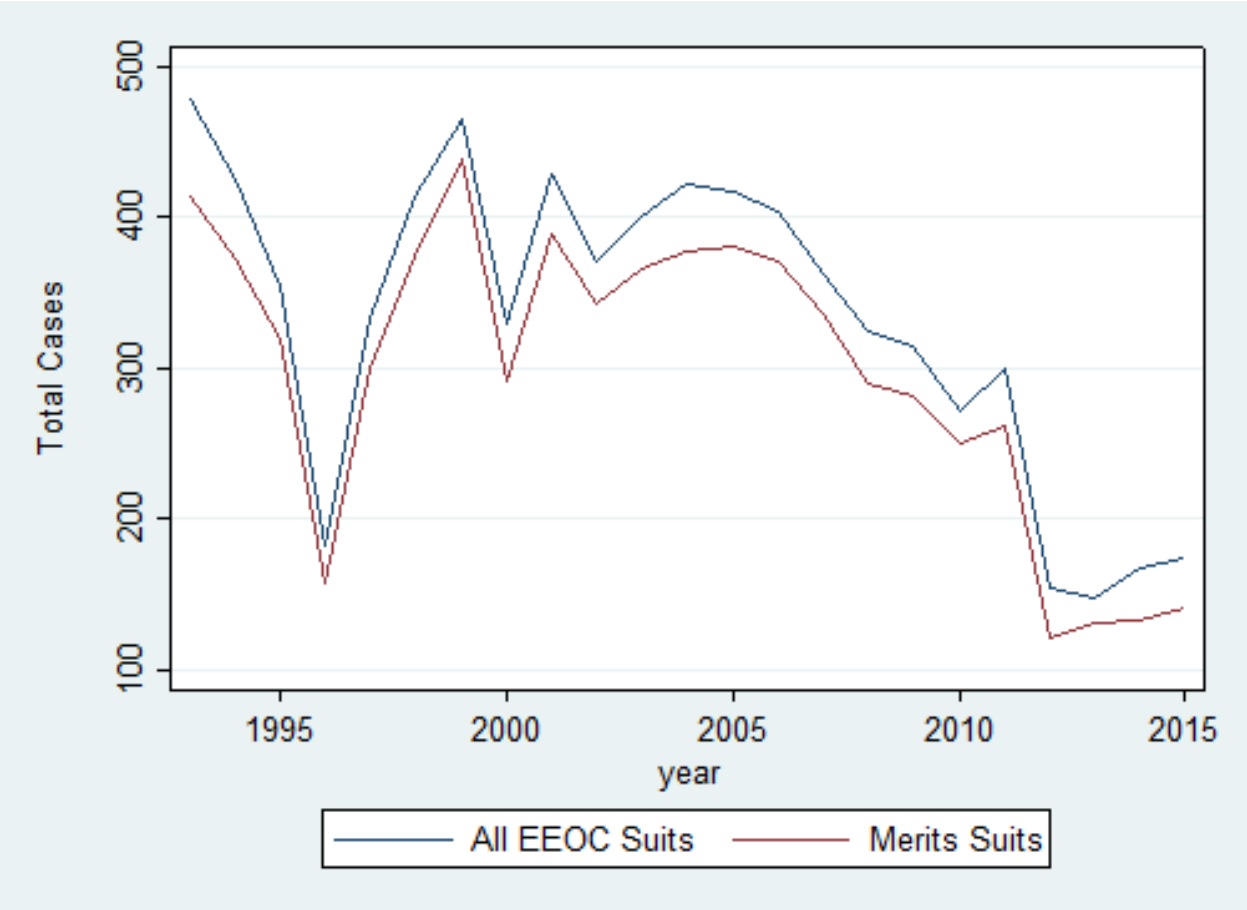


Figure 14: "Merits Suits" by Year

This illustrates the total number of lawsuits filed by the EEOC and the number of "merits suits" from 1993-2015. According to the EEOC, merits suits "include direct suits and interventions alleging violations of the substantive provisions of the statutes enforced by the Commission and suits to enforce administrative settlements."

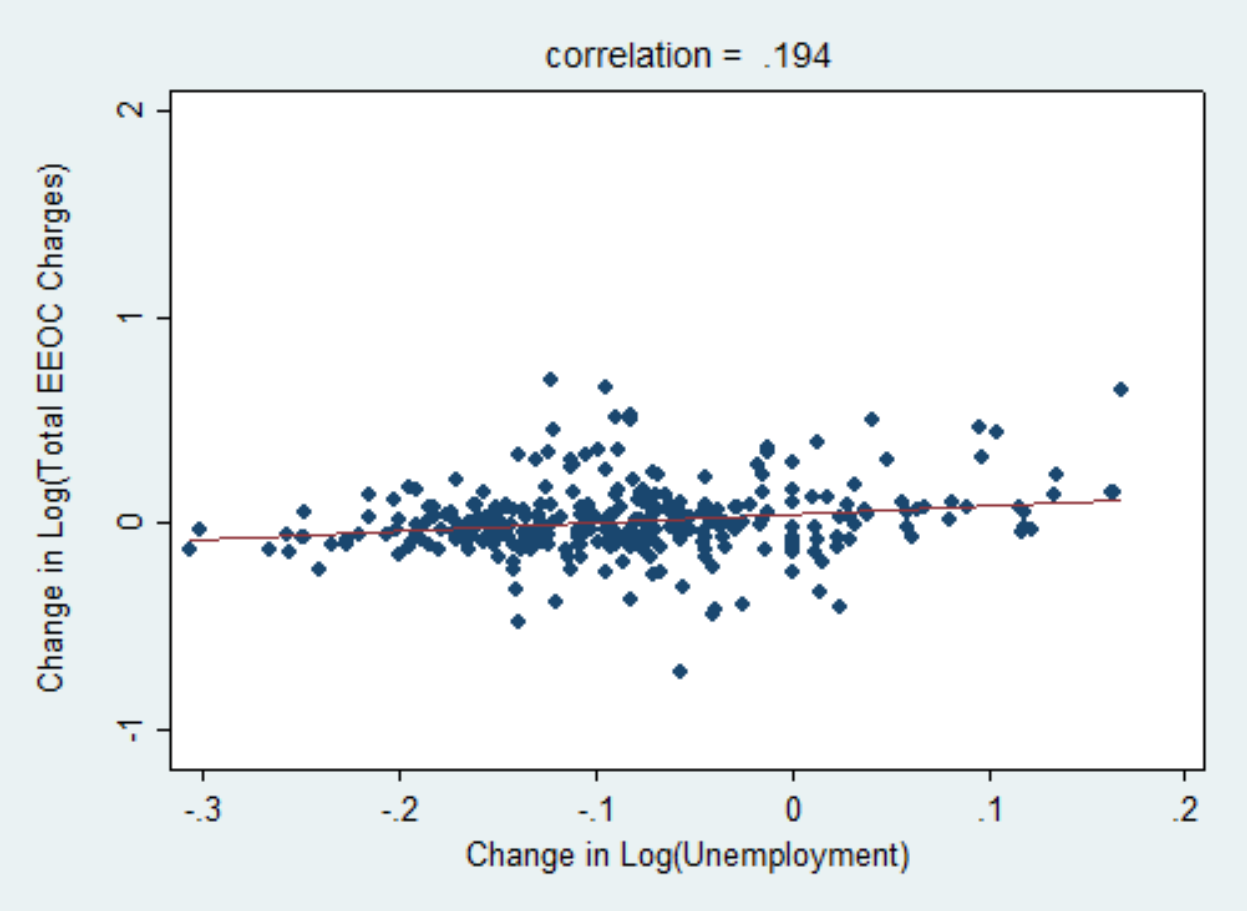


Figure 15: Changes in Total Discrimination Charges Filed and State-level Unemployment Rates

The above diagram shows the correlation between Δ Log(Total EEOC Charges) and Δ Log(State Unemployment Rates) for all states from 2009-2015.

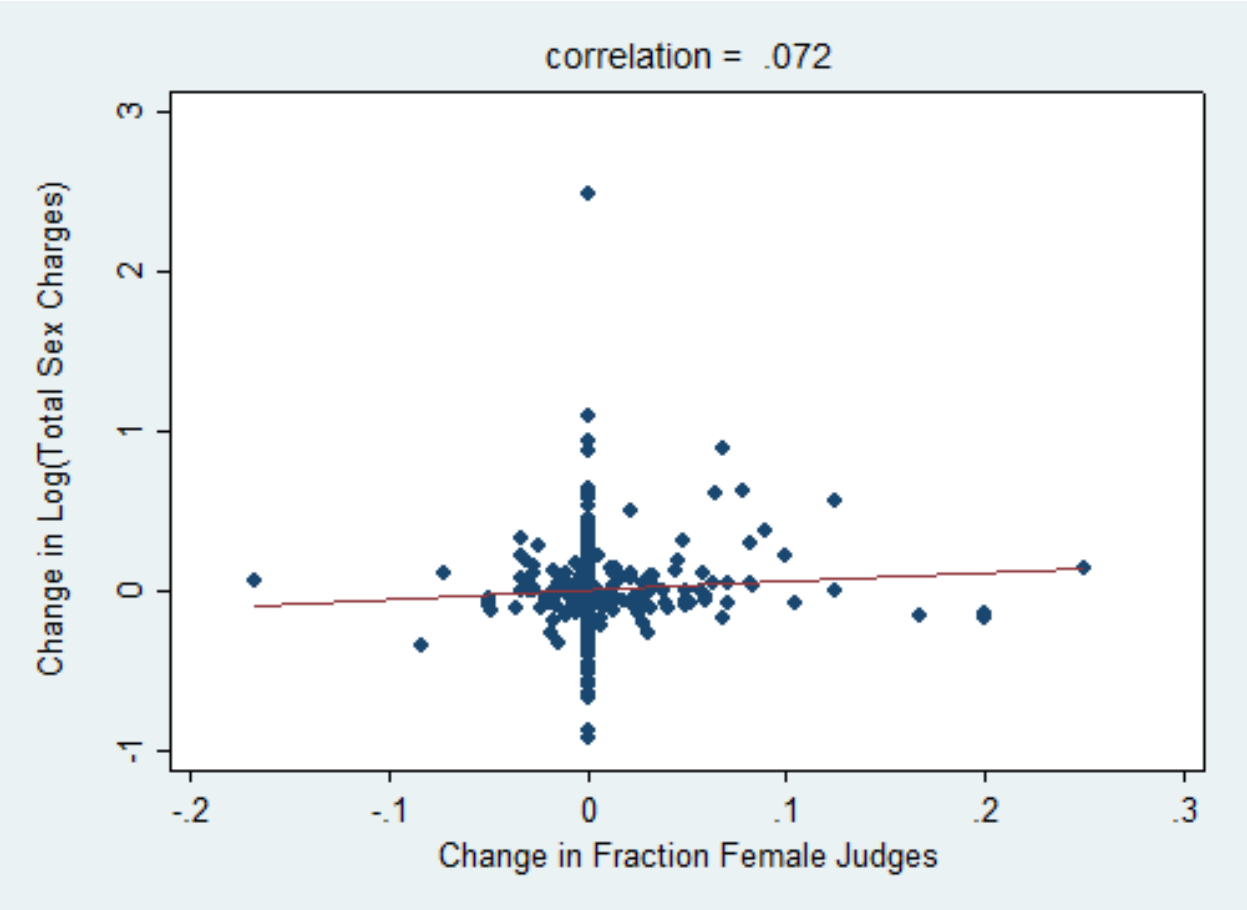


Figure 16: Changes in Sex Discrimination Charges Filed and Fraction of Female Judges at the State-level

The above diagram shows the correlation between Δ Log(State-level Sex Charges) and Δ Fraction of Female Judges serving on a district court in a state from 2009-2015.

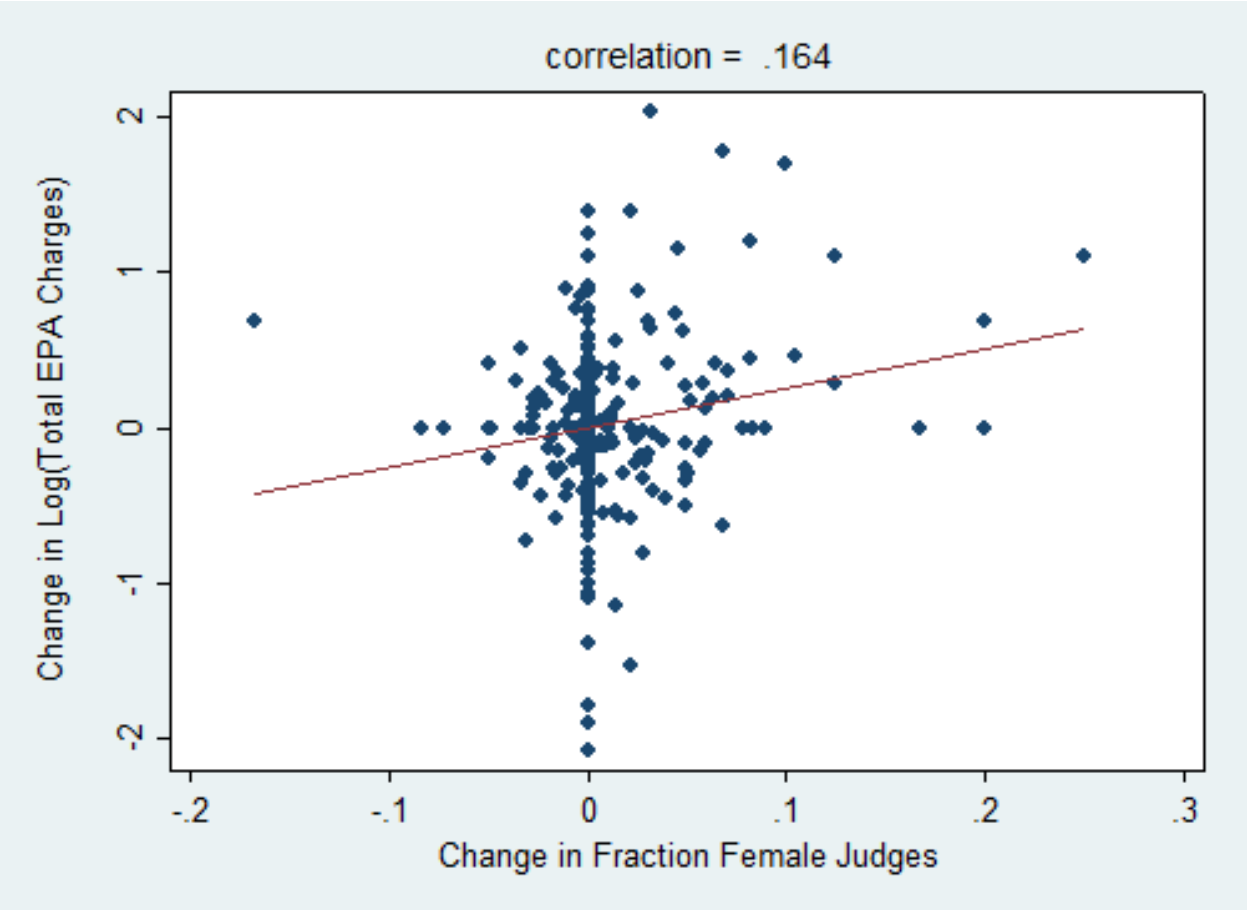


Figure 17: Changes in Equal Pay Act Charges Filed and Fraction of Female Judges at the State-level

The above diagram shows the correlation between Δ Log(State-level EPA Charges) and Δ Fraction of Female Judges serving on a district court in a state from 2009-2015.

Table C1: Classification by Final Resolution Type, Sex Discrimination Cases only

Final Resolution	Total	Settled	Plaintiff Victory	Plaintiff Defeat
Consent Judgment$^{\theta}$	807	807	791	16
Voluntary Dismissal- Settlement	78	78	67	11
Voluntary Dismissal- Non-Settlement	19	0	3	16
Involuntary Dismissal	2	0	0	2
Court Judgment^{+}	60	0	25	35
Jury or Bench Verdict	54	0	33	21
Observations	1,020	885	919	101

This table maps the final resolution type for each case into at least one dependent variable of interest.

$^{\theta}$ Consent Judgments are issued when two parties agree to a settlement that terminates the lawsuit. The agreement is enforceable once it is signed by the presiding judge. In rare cases, these are coded as plaintiff defeats when only injunctive relief (i.e., a court order for the defendant to take or discontinue a specified action) is agreed upon.

$^{+}$ Court Judgments are binding rulings made by the judge that arise prior the conclusion of a trial. These include summary judgments, default judgments, and judgments as a matter of law. Summary judgments occur when the judge grants the moving party's motion, which contends that there is no dispute as to the facts of the case. Informally, these occur when either party has a case so strong that the outcome of a possible trial is obvious. Default judgments are entered for one party when the other party fails to take a required action, such as responding to the charges or appearing in court. Judgments as a matter of law are summary judgments that are made during a trial.

Table C2: Effect of Male Judge Assignment on Settlement Rates in Sex Discrimination Cases

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = $\mathbb{1}$(Settlement reached)					
Male judge	-0.067***	-0.067**	-0.074**	-0.057*	-0.057*
	(0.025)	(0.027)	(0.32)	(0.032)	(0.030)
Age of judge		0.003	0.003*	0.004**	0.004*
		(0.002)	(0.002)	(0.002)	(0.002)
Experience of judge		0.005	-0.004**	0.005	0.005
		(0.003)	(0.002)	(0.004)	(0.004)
White judge		-0.046	-0.047	-0.014	-0.016
		(0.032)	(0.030)	(0.037)	(0.036)
Black judge		-0.023	-0.013	0.043	0.041
		(0.045)	(0.053)	(0.053)	(0.052)
Democratic Appointee		0.118	0.025	0.131	0.131
		(0.0960)	(0.021)	(0.092)	(0.092)
Number of Complainants		0.0003**	0.0050	0.0003**	0.0003**
		(0.0001)	(0.0036)	(0.0002)	(0.0002)
Observations	1020	1020	1020	1020	1020
R^2	0.006	0.035	0.027	0.161	0.161
Model	OLS	OLS	Probit	OLS	RE
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is an indicator for whether the parties reach a settlement. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.

Table C3: Effect of Male Judge Assignment on Plaintiff Win Rates in Sex Discrimination Cases

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = $\mathbb{1}$(Plaintiff compensated)					
Male judge	-0.071***	-0.066***	-0.081***	-0.056**	-0.056**
	(0.020)	(0.022)	(0.031)	(0.024)	(0.024)
Age of judge		0.001	0.001	0.003	0.003
		(0.002)	(0.001)	(0.002)	(0.002)
Experience of judge		0.003	-0.001	0.003	0.003
		(0.003)	(0.002)	(0.004)	(0.004)
White judge		-0.036	-0.035	0.007	0.007
		(0.026)	(0.024)	(0.027)	(0.027)
Black judge		0.005	0.012	0.082*	0.082**
		(0.037)	(0.042)	(0.042)	(0.042)
Democratic Appointee		0.002	0.019	0.026	0.026
		(0.083)	(0.018)	(0.076)	(0.076)
Number of Complainants		0.0002**	0.0032	0.0002**	0.0002**
		(0.0001)	(0.0030)	(0.0001)	(0.0001)
Observations	1020	1020	1020	1020	1020
R^2	0.009	0.026	0.027	0.174	0.182
Model	OLS	OLS	Probit	OLS	RE
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is an indicator for whether the plaintiff wins compensation (in either the settlement or litigation stage). Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.

Table C4: Robustness: Effect of Male Judge Assignment on Sex Discrimination Case Outcomes

	Dependent Variable = $\mathbb{1}$(Case settled)			Dependent Variable = $\mathbb{1}$(Plaintiff wins)		
	(1)	(2)	(3)	(4)	(5)	(6)
Male judge	-0.062**	-0.071**	-0.071**	-0.052**	-0.052**	-0.052**
	(0.026)	(0.032)	(0.032)	(0.025)	(0.026)	(0.026)
Age of judge		0.005**	0.005**		0.003	0.003
		(0.002)	(0.002)		(0.002)	(0.002)
Experience of judge		0.001	0.001		0.001	0.001
		(0.004)	(0.004)		(0.004)	(0.004)
White judge		-0.021	-0.021		-0.002	-0.002
		(0.041)	(0.041)		(0.029)	(0.029)
Black judge		0.067	0.067		0.081*	0.081*
		(0.057)	(0.057)		(0.045)	(0.045)
Democratic Appointee		0.137	0.137		0.078	0.078
		(0.101)	(0.101)		(0.079)	(0.079)
Number of Complainants		0.0004**	0.0004**		0.0002	0.0002
		(0.0002)	(0.0002)		(0.0001)	(0.0001)
Observations	1020	1020	1020	1020	1020	1020
R^2	0.218	0.242	0.242	0.233	0.253	0.253
Model	OLS	OLS	RE	OLS	OLS	RE
District Court FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Court x Time Pd. FE	YES	YES	YES	YES	YES	YES
Administration FE	NO	YES	YES	NO	YES	YES

Dependent variables are indicated in the column headings. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C5: Annual EEOC Charges and Cases Litigated, by Presidential Administration

	Clinton Era$^{\phi}$		G.W. Bush Era$^{\pi}$		Difference	
	Mean	SD	Mean	SD	Mean	p-value
All EEOC Claims:						
Total Charges Filed	79,403	1,384	79,534	3,462	-131	0.94
Total Lawsuits	385.0	66.3	406.3	20.7	-21.3	0.47
Total Suit-to-Charge Ratio	0.0048	0.0009	0.0051	0.0004	-0.0003	0.55
Fraction of Suits "With Merit"$^{\theta}$	0.909	0.023	0.913	0.010	-0.004	0.69
Title VII Claims:						
Total Title VII Charges Filed	63,505	1,110	64,463	2,520	-958	0.50
Total Title VII Lawsuits	253.3	66.0	290.2	11.3	-36.9	0.20
Title VII Suit-to-Charge Ratio	0.0040	0.0011	0.0045	0.0003	-0.0005	0.28
Sex Discrimination Claims$^{\psi}$:						
Total Sex Charges Filed	24,571	538	24,271	980	299	0.60
Total Sex Lawsuits	113.5	29.8	129.7	6.5	-16.2	0.22
Total Sex Suit-to-Charge Ratio	0.0046	0.0013	0.0053	0.0002	-0.0007	0.22
Observations (Years)	4		6		10	

Notes: ***, ** and * denote differences that are statistically significant at 1 percent, 5 percent and 10 percent levels, respectively.

$^{\phi}$ Clinton Era corresponds to the years during which the Clinton Administration and study sample overlap, i.e. from 1997 through 2000.

$^{\pi}$ G.W. Bush Era corresponds to the years during which the G.W. Bush Administration and study sample overlap, i.e. from 2001 through 2006.

$^{\theta}$ According to the EEOC, merits suits "include direct suits and interventions alleging violations of the substantive provisions of the statutes enforced by the Commission and suits to enforce administrative settlements."

$^{\psi}$ Sex discrimination lawsuits–but not charges–are limited to those reported by females.

Table C6: Sensitivity Tests: Treatment Effect on Settlement Rates, Pre v. Post 2001

	(1)	(2)	(3)	(4)
Dependent Variable = $\mathbb{1}$(Settlement reached)				
Male judge	-0.061**	-0.061**	-0.040	-0.039
	(0.026)	(0.027)	(0.029)	(0.029)
$\mathbb{1}$(Pre-2001) × Female judge	0.038	0.047	0.073	0.072
	(0.058)	(0.058)	(0.057)	(0.057)
Age of judge		0.003	0.004*	0.004*
		(0.002)	(0.002)	(0.002)
Experience of judge		0.005	0.005	0.005
		(0.004)	(0.004)	(0.004)
White judge		-0.043	-0.013	-0.015
		(0.033)	(0.037)	(0.036)
Black judge		-0.014	0.046	0.044
		(0.046)	(0.053)	(0.053)
Democratic Appointee		0.136	0.132	0.132
		(0.089)	(0.092)	(0.092)
Number of Complainants		0.0003*	0.0003**	0.0003**
		(0.0002)	(0.0002)	(0.0002)
Observations	1020	1020	1020	1020
R^2	0.030	0.056	0.162	0.162
Model	OLS	OLS	OLS	RE
Administration FE	NO	YES	YES	YES
District Court FE	NO	NO	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C7: Sensitivity Tests: Treatment Effect on Win Rates, Pre v. Post 2001

	(1)	(2)	(3)	(4)
Dependent Variable = $\mathbb{1}$(Plaintiff Compensated)				
Male judge	-0.074***	-0.069***	-0.056**	-0.056**
	(0.018)	(0.021)	(0.024)	(0.024)
$\mathbb{1}$(Pre-2001) $\times$ Female judge	-0.013	-0.007	0.000	0.000
	(0.065)	(0.066)	(0.066)	(0.066)
Age of judge		0.001	0.003	0.003
		(0.002)	(0.002)	(0.002)
Experience of judge		0.003	0.003	0.003
		(0.003)	(0.004)	(0.004)
White judge		-0.034	0.007	0.007
		(0.027)	(0.027)	(0.027)
Black judge		0.010	0.082**	0.082**
		(0.037)	(0.042)	(0.042)
Democratic Appointee		0.023	0.026	0.026
		(0.080)	(0.076)	(0.076)
Number of Complainants		0.0002*	0.0002**	0.0002**
		(0.0001)	(0.0001)	(0.0001)
Observations	1020	1020	1020	1020
R^2	0.040	0.057	0.174	0.174
Model	OLS	OLS	OLS	RE
Administration FE	NO	YES	YES	YES
District Court FE	NO	NO	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C8: Effect of Male Judge Assignment on Defendant's Motion Filing Success Rate in Sex Discrimination Cases

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = Frac. Motions Granted					
Male judge	0.153***	0.173***	0.144**	0.124**	0.124**
	(0.047)	(0.052)	(0.071)	(0.057)	(0.057)
Age of judge		-0.000	-0.005	-0.001	-0.001
		(0.003)	(0.004)	(0.004)	(0.004)
Experience of judge		-0.019**	-0.005	-0.036**	-0.036**
		(0.008)	(0.005)	(0.014)	(0.014)
White judge		-0.089	-0.106	-0.087	-0.087
		(0.057)	(0.069)	(0.071)	(0.071)
Black judge		-0.006	-0.055	-0.115	-0.115
		(0.099)	(0.122)	(0.108)	(0.108)
Democratic Appointee		-0.056	-0.006	-0.147	-0.147
		(0.0769)	(0.006)	(0.111)	(0.111)
Number of Complainants		-0.001	-0.001	0.000	0.000
		(0.001)	(0.001)	(0.000)	(0.000)
Observations	397	397	397	397	397
R^2	0.019	0.068	0.026	0.326	0.326
Model	OLS	OLS	Probit	OLS	RE
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is the fraction of defendant's motions that are granted by the judge. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.

Table C9: Effect of Male Judge Assignment on Plaintiff's Motion Filing Success Rate in Sex Discrimination Cases

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = Frac. Motions Granted					
Male judge	0.054	0.048	0.054	0.052	0.058
	(0.055)	(0.060)	(0.055)	(0.073)	(0.074)
Age of judge		-0.002	-0.001	-0.005	-0.005
		(0.003)	(0.003)	(0.004)	(0.004)
Experience of judge		-0.007	-0.000	-0.009	-0.010
		(0.008)	(0.004)	(0.014)	(0.014)
White judge		0.048	0.005	0.020	0.009
		(0.052)	(0.054)	(0.073)	(0.076)
Black judge		0.118	0.030	0.011	0.024
		(0.089)	(0.078)	(0.111)	(0.112)
Democratic Appointee		-0.060	-0.046	-0.099	-0.069
		(0.071)	(0.044)	(0.106)	(0.110)
Number of Complainants		-0.001	0.006	-0.006*	-0.005
		(0.002)	(0.005)	(0.003)	(0.003)
Observations	386	386	386	386	386
R^2	0.003	0.055	0.014	0.273	0.273
Model	OLS	OLS	Probit	OLS	RE
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is the fraction of the plaintiff's motions that are granted by the judge. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.

Table C10: Defendant Motions Filed and Successful in Sex Discrimination Cases, by Type

	Female Judge		Male Judge		Difference	
	total	granted	total	granted	total	granted
Motion to Dismiss 12(b)(6)	3.45	62.5	5.05	22.9	-1.60	29.6**
Motion to Dismiss- Jurisdiction or Venue	0.77	0.0	3.25	21.4	-2.48**	-21.4
Motion to Dismiss-Voluntary	2.68	100	2.92	100	-0.24	0.0
Motion to Dismiss-Involuntary	10.73	5.6	10.33	32.7	0.40	-27.2**
Motion for Judgment on the Pleadings	0.77	0.0	0.79	20.0	-0.02	-20.0
Motion for Joinder	0.0	N/A	0.22	0.0	-0.22	N/A
Motion for Severance	0.38	0.0	1.01	0.0	-0.63	0.0
Substantive Discovery Motion	50.57	50.9	35.35	78.0	15.22***	-27.1***
Motion for Summary Judgment	25.29	44.7	33.56	48.2	-8.3**	-3.5
Motion to Alter/Amend Judgment	0.0	N/A	1.91	47.1	-1.14	N/A
Motion for Judgment as Matter of Law	2.68	0.0	3.70	16.0	-1.02	-16.0
Motion for Injunction	0.38	100	0.11	100	0.27	0.0
Motion for Remittitur/Additur	0.0	N/A	0.22	50.0	-0.22	N/A
Motion for New Trial	0.77	0.0	0.90	0.0	-0.13	0.0
Motion to Consolidate	0.38	100	0.56	100	-0.18	0.0
Number of Motions Filed	261		891		1152	
Number of Cases	64		333		397	

These data correspond to the 397 cases in which the defendant filed at least one motion.
Note: all values are recorded in % terms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C11: Plaintiff Motions Filed and Successful in Sex Discrimination Cases, by Type

	Female Judge		Male Judge		Difference	
	total	granted	total	granted	total	granted
Motion to Dismiss 12(b)(6)	0.62	100	0.0	N/A	0.62**	N/A
Motion for Default Judgment	3.14	66.7	4.06	100	-0.92	-33.3**
Motion to Dismiss-Voluntary	10.7	100	15.3	99.0	-4.62	1.02
Motion for Preliminary Injunction	0.62	0.0	0.16	0.0	0.47	0.0
Motion for Judgment on the Pleadings	1.26	0.0	0.0	N/A	1.26***	N/A
Motion for Joinder	0.0	N/A	0.94	83.3	-0.94	N/A
Substantive Discovery Motion	71.1	77.3	61.4	82.9	9.66**	-5.61
Motion for Summary Judgment	8.80	75.0	10.2	55.6	-1.35	19.4
Motion to Alter/Amend Judgment	1.26	100	2.66	70.6	-1.40	29.4
Motion for Judgment as Matter of Law	0.0	N/A	0.62	0.0	-0.62	N/A
Motion for Injunction	2.51	50.0	2.03	70.0	0.48	-20.0
Motion for New Trial	0.0	N/A	1.09	14.3	-1.09	N/A
Motion to Consolidate	0.0	N/A	1.56	90.0	-1.56	N/A
Number of Motions Filed	159		640		799	
Number of Cases	62		324		386	

These data correspond to the 386 cases in which the plaintiff filed at least one motion.
Note: all values are recorded in % terms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C12: Plaintiff Appeals and Loss Reversal Rates by Judge Gender

	Female Judge		Male Judge		Difference	
	Mean	SD	Mean	SD	Mean	p-value
Sex Discrimination Cases:						
Plaintiff Appeals	0.25	0.46	0.34	0.48	-0.09	0.59
Loss Reversals	0.00	0.00	0.10	0.30	-0.10	0.36
N (Losses)	8		93			
Defendant Appeals	0.016	0.127	0.018	0.132	-0.001	0.90
Win Reversals	0.00	0.00	0.001	0.037	-0.001	0.62
N (Wins)	184		735			
Non-sex Cases:						
Plaintiff Appeals	0.33	0.47	0.38	0.49	-0.05	0.52
Loss Reversals	0.06	0.24	0.02	0.15	0.04	0.17
N (Losses)	49		210			
Defendant Appeals	0.019	0.138	0.028	0.164	-0.008	0.50
Win Reversals	0.005	0.070	0.013	0.112	-0.008	0.33
N (Wins)	206		942			
Race Discrimination Cases:						
Plaintiff Appeals	0.44	0.53	0.28	0.45	0.16	0.35
Loss Reversals	0.00	0.00	0.02	0.15	-0.02	0.66
N (Losses)	9		46			
Defendant Appeals	0.00	0.00	0.021	0.143	-0.021	0.25
Win Reversals	0.005	0.070	0.013	0.112	-0.008	0.33
N (Wins)	62		240			

For each category of cases listed, the rates with which plaintiffs file an appeal in cases they lose and the corresponding appeal reversal rates are reported by judge gender. Reversals include appeals that are reversed, remanded, vacated, or reversed in part. Defendant appeals and win reversal rates are tabulated in an analogous way.

***, **, and * denote differences that are statistically significant at 1 percent, 5 percent and 10 percent levels, respectively.

Table C13: Win Rates by Case Type, by Judge Gender

	Dual-Types	Single-Types	Difference
Male Judges:			
Sex Cases	0.895	0.868	0.026
	(0.015)	(0.025)	(0.028)
	[N=301]	[N=140]	
Non-sex Cases	0.812	0.775	0.038
	(0.016)	(0.023)	(0.027)
	[N=301]	[N=255]	
Female Judges:			
Sex Cases	0.951	0.923	0.028
	(0.023)	(0.043)	(0.044)
	[N=71]	[N=39]	
Non-sex Cases	0.746	0.787	-0.041
	(0.041)	(0.054)	(0.067)
	[N=71]	[N=52]	

Each cell shows the average case win rates for one of the 8 combinations of {Male judge, Female Judge} × {Sex cases, Non-sex cases} × {Dual-type judges, Single-type judges}. Dual-type judges are those who are assigned to both sex and non-sex cases in the sample while single-type judges are assigned only to either sex or non-sex cases in the sample.
***, **, and * denote differences that are statistically significant at 1 percent, 5 percent and 10 percent levels, respectively.

Table C14: Tests of Absolute Bias among Dual-Type Judges under Correlated Leniency Assumption

	(1)	(2)	(3)	(4)
Dependent Variable = Non-sex Case Win Rate				
Sex Case Win Rate	-0.150	-0.135	-0.243*	-0.231
	(0.120)	(0.132)	(0.125)	(0.143)
Male judge	-0.148	-0.119	-0.185	-0.195
	(0.124)	(0.140)	(0.141)	(0.158)
Sex Case Win Rate × Male judge	0.230*	0.211	0.280*	0.288*
	(0.138)	(0.152)	(0.153)	(0.168)
Age of judge		-0.005*	-0.005	-0.006*
		(0.003)	(0.003)	(0.003)
Experience of judge		0.006	0.011	0.003
		(0.006)	(0.007)	(0.009)
White judge		-0.002	-0.018	-0.021
		(0.047)	(0.054)	(0.057)
Black judge		0.038	0.014	0.007
		(0.061)	(0.079)	(0.082)
Democratic Appointee		0.373	0.530	0.473
		(0.347)	(0.360)	(0.328)
Observations	372	372	372	372
R^2	0.014	0.049	0.259	0.292
Model	OLS	OLS	OLS	OLS
Administration FE	NO	YES	YES	YES
District Court FE	NO	NO	YES	YES
Year FE	NO	NO	NO	YES

Dependent variable is the average win rate in all non-sex discrimination cases for a particular judge. Robust standard errors, clustered at judge level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C15: Effect of Male Judge Assignment on Settlement Rates (Standard Errors Clustered at District Court Level)

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = $\mathbb{1}$(Settlement reached)					
Male judge	-0.067***	-0.067**	-0.074**	-0.057	-0.056
	(0.024)	(0.028)	(0.032)	(0.035)	(0.035)
Age of judge		0.003	0.003*	0.004*	0.004*
		(0.002)	(0.002)	(0.002)	(0.002)
Experience of judge		0.005	-0.004**	0.005	0.005
		(0.003)	(0.002)	(0.005)	(0.005)
White judge		-0.046	-0.047	-0.014	-0.016
		(0.029)	(0.029)	(0.037)	(0.037)
Black judge		-0.023	-0.013	0.043	0.041
		(0.044)	(0.052)	(0.054)	(0.054)
Democratic Appointee		0.118	0.025	0.131	0.131
		(0.107)	(0.019)	(0.109)	(0.109)
Number of Complainants		0.0003**	0.0050	0.0003*	0.0003*
		(0.0001)	(0.0076)	(0.0002)	(0.0002)
Observations	1020	1020	1020	1020	1020
R^2	0.006	0.035	0.027	0.161	0.161
Model	OLS	OLS	Probit	OLS	RE
Sex Discrimination Cases	YES	YES	YES	YES	YES
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is an indicator for whether the parties reach a settlement. Robust standard errors, clustered at the district court level, are in parentheses. Sample includes a drawing of EEOC litigated sex discrimination cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.

Table C16: Effect of Male Judge Assignment on Plaintiff Win Rates (Standard Errors Clustered at District Court Level)

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = $\mathbb{1}$(Plaintiff compensated)					
Male judge	-0.071***	-0.066***	-0.081***	-0.056**	-0.056**
	(0.022)	(0.020)	(0.030)	(0.028)	(0.028)
Age of judge		0.001	0.001	0.003	0.003
		(0.002)	(0.001)	(0.002)	(0.002)
Experience of judge		0.003	-0.001	0.003	0.003
		(0.003)	(0.002)	(0.005)	(0.005)
White judge		-0.036	-0.035	0.007	0.007
		(0.023)	(0.023)	(0.027)	(0.027)
Black judge		0.005	0.012	0.082**	0.082**
		(0.031)	(0.034)	(0.041)	(0.041)
Democratic Appointee		0.002	0.019	0.026	0.026
		(0.083)	(0.018)	(0.082)	(0.082)
Number of Complainants		0.0002**	0.0032	0.0002***	0.0002***
		(0.0001)	(0.0033)	(0.0001)	(0.0001)
Observations	1020	1020	1020	1020	1020
R^2	0.009	0.026	0.029	0.174	0.174
Model	OLS	OLS	Probit	OLS	RE
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is an indicator for whether the plaintiff wins compensation (in either the settlement or litigation stage). Robust standard errors, clustered at the district court level, are in parentheses. Sample includes a random drawing of EEOC litigated sex discrimination cases spanning the period from 1997-2006.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
$^{\lambda}$ Marginal Effects reported.

Table C17: Effect of Male Judge Assignment on Plaintiff Compensation Amounts per Beneficiary

	$E(Y\|X)$ (1)	$E(Y\|X)$ (2)	$log(Y+c)$ (3)	$log(Y+c')$ (4)
Male judge	-0.052	0.077	-0.152	-0.143
	(0.106)	(0.116)	(0.100)	(0.102)
Age of judge	0.007	0.012	0.009	0.010*
	(0.007)	(0.008)	(0.006)	(0.006)
Experience of judge	0.015	0.010	0.021*	0.022*
	(0.014)	(0.016)	(0.011)	(0.011)
White judge	-0.158	-0.218	0.006	0.004
	(0.125)	(0.185)	(0.104)	(0.106)
Black judge	-0.279	-0.472**	0.038	0.012
	(0.186)	(0.235)	(0.141)	(0.144)
Democratic Appointee	0.211	0.174	0.325	0.330
	(0.339)	(0.346)	(0.264)	(0.268)
Number of Complainants	-0.004***	-0.004***	0.006***	0.006***
	(0.0005)	(0.0005)	(0.001)	(0.001)
Observations	983	993	983	993
R^2			0.275	0.274
Model	GLM	GLM	OLS	OLS
Family	Gamma	Gamma		
Outliers	NO	YES	NO	YES
Administration FE	YES	YES	YES	YES
District Court FE	NO	NO	YES	YES
Year FE	NO	NO	YES	YES

Dependent variable is the award amount per beneficiary in female sex discrimination cases. Robust standard errors, clustered at judge level, are in parentheses. The first two specifications use a gamma distribution with a log linking function. The constants c and c' were chosen by way of a grid search to minimize the root-mean squared error of predicted versus observed award amounts.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C18: Effect of Male Judge Assignment on Plaintiff Compensation Amounts using a Two-Part Model

	GLM Model: Gamma with Log link		
	$Pr.(Y > 0)$	$E(Y\|Y > 0)$	$E(Y\|X)$
	(1)	(2)	(3)
Male judge	-0.087**	-0.058	-3,628
	(0.034)	(0.104)	(4,947)
Observations	983	983	983
R^2	0.029		0.041
Model	Probit	GLM	TPM
Outliers	NO	NO	NO

Dependent variables are indicated in the column headings. Robust standard errors, clustered at judge level, are in parentheses. The two-part model uses a gamma distribution with a log linking function. Two-part model standard errors are estimated through a bootstrapping approach that repeats the two-stage procedure using 1,000 random draws with replacement.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C19: Robustness: Effect of Male Judge Assignment on Plaintiff Compensation Amounts using a Two-Part Mode (With Outliers)

	GLM Model: Gamma with Log link		
	$Pr.(Y > 0)$	$E(Y\|Y > 0)$	$E(Y\|X)$
	(1)	(2)	(3)
Male judge	-0.085**	0.087	3,909
	(0.034)	(0.116)	(6,731)
Age of judge	0.001	0.014*	805*
	(0.001)	(0.008)	(443)
Experience of judge	-0.001	-0.006	-308
	(0.002)	(0.010)	(533)
White judge	-0.044	-0.177	-10,505
	(0.031)	(0.181)	(10,407)
Black judge	0.009	-0.391*	-22,144
	(0.051)	(0.225)	(13,553)
Democratic Appointee	0.023	-0.044	-2,716
	(0.021)	(0.117)	(6,693)
Number of Complainants	0.004	-0.004***	14
	(0.004)	(0.0005)	(431)
Observations	993	993	993
R^2	0.028		0.026
Model	Probit	GLM	TPM

Dependent variables are indicated in the column headings. Robust standard errors, clustered at judge level, are in parentheses. The two-part model uses a gamma distribution with a log linking function. Two-part model standard errors are estimated through a bootstrapping approach that repeats the two-stage procedure using 1,000 random draws with replacement.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C20: Robustness: Effect of Male Judge Assignment on Plaintiff Compensation Amounts using a Two-Part Model

	GLM Model: I. Gaussian with Log link		
	$Pr.(Y > 0)$	$E(Y\|Y > 0)$	$E(Y\|X)$
	(1)	(2)	(3)
Male judge	-0.087**	-0.046	-2,907
	(0.034)	(0.104)	(5,428)
Age of judge	0.001	0.010	504
	(0.001)	(0.007)	(448)
Experience of judge	-0.001	-0.010	-463
	(0.002)	(0.008)	(413)
White judge	-0.044	-0.178	-8,821
	(0.032)	(0.126)	(6,152)
Black judge	0.010	-0.261	-12,683
	(0.051)	(0.182)	(9,409)
Democratic Appointee	0.022	-0.024	-1,811
	(0.021)	(0.085)	(4,526)
Number of Complainants	0.004	-0.003***	45
	(0.004)	(0.0002)	(349)
Observations	983	983	983
R^2	0.029		0.027
Model	Probit	GLM	TPM

Dependent variables are indicated in the column headings. Robust standard errors, clustered at judge level, are in parentheses. The two-part model uses an inverse gaussian distribution with a log linking function. Two-part model standard errors are estimated through a bootstrapping approach that repeats the two-stage procedure using 1,000 random draws with replacement.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C21: Tests of Absolute Bias among Dual-Type Judges under Correlated Leniency Assumption (Standard Errors Clustered at District Court Level)

	(1)	(2)	(3)	(4)
Dependent Variable = Non-sex Case Win Rate				
Sex Case Win Rate	-0.150	-0.135	-0.243**	-0.231
	(0.116)	(0.122)	(0.101)	(0.141)
Male judge	-0.148	-0.119	-0.185*	-0.195
	(0.097)	(0.113)	(0.098)	(0.123)
Sex Case Win Rate × Male judge	0.230**	0.211*	0.280***	0.288**
	(0.107)	(0.115)	(0.103)	(0.129)
Age of judge		-0.005*	-0.005	-0.006
		(0.003)	(0.004)	(0.004)
Experience of judge		0.006	0.011	0.003
		(0.006)	(0.008)	(0.009)
White judge		-0.002	-0.018	-0.021
		(0.062)	(0.046)	(0.050)
Black judge		0.038	0.014	0.007
		(0.084)	(0.085)	(0.086)
Democratic Appointee		0.373	0.530	0.473
		(0.370)	(0.410)	(0.366)
Observations	372	372	372	372
R^2	0.014	0.049	0.259	0.292
Model	OLS	OLS	OLS	OLS
Administration FE	NO	YES	YES	YES
District Court FE	NO	NO	YES	YES
Year FE	NO	NO	NO	YES

Dependent variable is the average win rate in all non-sex discrimination cases for a particular judge. Robust standard errors, clustered at the district court level, are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C22: Effect of Male Judge Assignment on Defendant's Motion Filing Success Rate in Sex Discrimination Cases (Standard Errors Clustered at District Court Level)

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = Frac. Motions Granted					
Male judge	0.153***	0.173***	0.144*	0.124	0.124
	(0.052)	(0.058)	(0.083)	(0.076)	(0.076)
Age of judge		-0.000	-0.005	-0.001	-0.001
		(0.004)	(0.004)	(0.005)	(0.005)
Experience of judge		-0.019**	-0.005	-0.036**	-0.036**
		(0.009)	(0.006)	(0.015)	(0.015)
White judge		-0.089	-0.106	-0.087	-0.087
		(0.063)	(0.079)	(0.090)	(0.090)
Black judge		-0.006	-0.055	-0.115	-0.115
		(0.102)	(0.124)	(0.119)	(0.119)
Democratic Appointee		-0.056	-0.006	-0.147	-0.147
		(0.077)	(0.055)	(0.115)	(0.115)
Number of Complainants		-0.001	-0.001	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Observations	397	397	397	397	397
R^2	0.019	0.068	0.026	0.326	0.326
Model	OLS	OLS	Probit	OLS	RE
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is the fraction of defendant's motions that are granted by the judge. Robust standard errors, clustered at district court level, are in parentheses. Sample includes a drawing of EEOC litigated cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.

Table C23: Effect of Male Judge Assignment on Plaintiff's Motion Filing Success Rate in Sex Discrimination Cases (Standard Errors Clustered at District Court Level)

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = Frac. Motions Granted					
Male judge	0.054	0.048	0.054	0.052	0.058
	(0.058)	(0.062)	(0.056)	(0.095)	(0.097)
Age of judge		-0.002	-0.001	-0.005	-0.005
		(0.003)	(0.003)	(0.006)	(0.005)
Experience of judge		-0.007	-0.000	-0.009	-0.010
		(0.007)	(0.004)	(0.016)	(0.017)
White judge		0.048	0.005	0.020	0.009
		(0.056)	(0.058)	(0.092)	(0.089)
Black judge		0.118	0.030	0.011	0.024
		(0.084)	(0.070)	(0.123)	(0.118)
Democratic Appointee		-0.060	-0.046	-0.099	-0.069
		(0.063)	(0.045)	(0.117)	(0.125)
Number of Complainants		-0.001	0.006	-0.006*	-0.005
		(0.002)	(0.004)	(0.003)	(0.003)
Observations	386	386	386	386	386
R^2	0.003	0.055	0.014	0.273	0.273
Model	OLS	OLS	Probit	OLS	RE
Administration FE	NO	YES	NO	YES	YES
District Court FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES

Dependent variable is the fraction of the plaintiff's motions that are granted by the judge. Robust standard errors, clustered at judge level, are in parentheses. Sample includes a random drawing of EEOC litigated cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.

Table C24: Effect of Defendant's Motion Filing Success Rate on Plaintiff Win Rates in Sex Discrimination Cases

	(1)	(2)	(3)$^{\lambda}$	(4)	(5)
Dependent Variable = $\mathbb{1}$(Plaintiff compensated)					
Frac. motions granted	-0.124**	-0.117***	-0.121**	-0.108**	-0.096*
	(0.048)	(0.044)	(0.048)	(0.048)	(0.057)
Age of judge				-0.000	0.002
				(0.003)	(0.003)
Experience of judge				0.011	0.004
				(0.007)	(0.010)
White judge				-0.080	0.013
				(0.049)	(0.057)
Black judge				-0.019	0.072
				(0.076)	(0.088)
Democratic Appointee				0.090*	0.032
				(0.053)	(0.082)
Number of Complainants				0.001*	0.000
				(0.001)	(0.000)
Observations	397	397	397	397	397
R^2	0.019	0.021	0.026	0.053	0.358
Model	OLS	Probit	OLS	OLS	OLS
Sex Discrimination Cases	YES	YES	YES	YES	YES
No. of Motions Filed	NO	NO	YES	YES	YES
Administration FE	NO	NO	NO	YES	YES
District Court FE	NO	NO	NO	NO	YES
Year FE	NO	NO	NO	NO	YES

Dependent variable is an indicator for whether the plaintiff wins compensation (in either the settlement or litigation stage). Robust standard errors, clustered at judge level, are in parentheses. Sample includes a drawing of EEOC litigated discrimination cases spanning the period from 1997-2006.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$^{\lambda}$ Marginal Effects reported.