Severity of Employee Discrimination and Firm Profitability – Evidence from EEOC Payout Gaps

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Abstract

We develop a proxy to estimate the *severity* of discrimination within an industry by using the men-women gap in U.S. Equal Employment Opportunity Commission (EEOC) litigation payouts, after controlling for all observable case characteristics. We validate that the gap proxies for discrimination severity, and we find that it associates with a reduction of firm-level ROA and marginal productivity of labor, and an increase in employee-related expenses. A one-standard deviation increase in discrimination severity decreases the ROA by approximately 20% from its baseline level. We contribute a continuous measure of discrimination severity, which contrasts the literature's current measures of discrimination existence.

Keywords: Discrimination, Profitability, Employees
JEL Codes: G34, G40, J16, J71

1. Introduction

The literature abundantly documents the negative impact of workplace discrimination on employees' physiological and mental health, engagement, productivity, and intentions to stay (e.g., Chan et al. 2008; Shields and Price 2002). Further, economic theory shows that discrimination against employees negatively affects firms (Phelps 1972; Arrow 1973 and 1998). It is therefore unsurprising that the literature reports that workplace discrimination has a negative impact on firm performance (e.g., Li and Nagar 2013 Abebe and Dadalar 2019; Au, Dong and Tremblay 2022; Barnes 2022). However, most of the finance and economic literature documents the firm value consequences of the *existence* of discrimination, but is silent regarding whether these consequences augment with the *severity* of workplace discrimination.

In this paper, we contribute to the discrimination literature by proposing a new measure of discrimination severity: the gender discrimination payout gap, which we define as the average difference in payouts received by men and women after they file discrimination suits with the United States Equal Employment Opportunity Commission (EEOC). We first argue that both the absolute count of discrimination lawsuits and the absolute payout to discrimination suits are imprecise proxies of discrimination severity. For instance, using the absolute payout as a proxy for merit fails to control for the underlying number of case issues, which could conjointly determine the payout amount. By the same token, any approach whereby a dependent variable is regressed on a discrimination variable is potentially contaminated with unobserved heterogeneity (Small and Pager 2020). In contrast, our proposed gender discrimination payout gap measures the gender difference in payouts received, while holding all other observable case, employer, and filer characteristics constant. In essence, our severity proxy measures "discrimination within discrimination."

We find that the gender discrimination payout gap exists: using 412,315 individual discrimination filings from the EEOC, we document that on average, women obtain \$440 more than men, even when holding constant the filer's birth year, the employer's public status, size, industry, and state, as well as the nature and number of the underlying case issues. This \$440 differential is economically significant, as it represents 16% of our full sample's average awarded payout of \$2,731. We dismiss the possibilities that the gender discrimination payout gap mirrors the gender wage gap, or that it arises due to EEOC chivalry towards women in determining payout amounts. In short, the evidence supports our interpretation of the gender discrimination payout gap as a measure of discrimination severity.

We document that firms' exposure to the discrimination payout gap affects negatively their operating performance (ROA). Because the EEOC anonymizes cases such that identification of the employers that engage in workplace discrimination is impossible, we transform the industry-level average discrimination payout gap measure into a firm-level variable estimating the firm's exposure to discrimination severity. More specifically, we define the firm-level exposure to the payout gap as the firm's total number of employees (scaled by its total assets), multiplied by its industry's average yearly discrimination payout gap. The exposure measure assumes that firms with more employees are more likely to be exposed to workplace discrimination, which is presumed to be uniformly prevalent within industries (defined at the 6-digit NAICS codes level), and varying in severity across industries. The results show that a one-standard deviation increase in the payout gap leads to a 1.16% decline in ROA (t =-3.41), which represents approximately 20% of the full-sample average baseline ROA.

Consistent with the discrimination literature that documents an array of negative consequences of workplace discrimination for employees, we find that the decline in corporate operating performance following exposure to the discrimination payout gap is driven by a contemporaneous increase in employee-related expenses, as well as a decline in employee efficiency. Although the economic impact of reputational damages and the long-lasting negative consequences due to a working environment's toxicity may have larger dollar impact, the immediate effects of both a decline in employee efficiency and an increase in employee-related expenses are easily traceable, and economically sound, thus supporting our argument of the impact of discrimination severity on ROA.

Our case- and firm-level tests make extensive use of fixed effects, thus reducing the concern that time, firm, case, or filer-invariant characteristics drive the results. In addition, we minimize endogeneity concerns by estimating IV regressions that exploit the 2011 structural break in the number of EEOC suits; we confirm that our operating performance results are robust to this IV approach. As further confirmation, we verify that the coefficients of our variables of interest are stable under Oster's (2019) assumptions of bias due to unobservable variables.

Our main contribution to the discrimination literature is to propose a new measure of discrimination severity. Most of the discrimination literature estimates discrimination prevalence, often through the definition of an indicator variable that flags the existence or absence of discrimination (e.g., Chan et al. 2008; Abebe and Dadanlar 2019; Borelli-Kjaer et al. 2021). Some studies, including Au, Dong and Tremblay (2022) consider the firm-level frequency of discrimination, whereas Dahl and Knepper (2021) estimate a case's merit, using cases' payouts as proxies, which may introduce noise if payouts are determined conjointly with the number of issues or other underlying case characteristics. Dougal, Griffin and Hutton (2022) attempt to classify civil lawsuits according to severity, but their textual analysis returns quasi-uniform results, and is therefore unsuccessful in separating cases along their severity.

Our paper also contributes to the environmental, social, and governance (ESG) literature and more precisely, to the gender, minorities and economics literature. There exists many barriers to female employment, including the resistance to women's leadership (Cortis and Cassar 2005; Eagly and Carli 2007), demands of family life, and underinvestment in social capital (Eagly and Carli 2007). However, discrimination remains "one of the most damaging barriers to career success and satisfaction of women" (Fitzgerald et al. 1988, in Willness et al. 2007, p. 127). Similar barriers to employment and promotion exist for other underrepresented groups (e.g., Cook and Glass 2014). These barriers provide a partial explanation for women and other minorities' underrepresentation in executive or board positions (e.g., Adams and Funk 2012; Cook and Glass 2014; Kirsch 2018); simultaneously, other papers (e.g., Au, Bhagwat and Tremblay 2022; Au, Tremblay and You 2022) argue that board (gender) diversity is an efficient policy to reduce workplace discrimination. This paper contributes to the literature by providing a measure of discrimination severity, which is a first step towards the effective monitoring of workplace discrimination and, eventually, its elimination.

2. Literature Review and Hypotheses Development

2.1. How Should Discrimination Severity Be Measured?

Estimating discrimination prevalence empirically is notoriously difficult. Traditionally, the sociology and health literatures rely on surveys and interviews to quantify the proportion of employees experiencing discrimination. For instance, in their meta-analysis, Chan et al. (2008) lists 49 studies using surveys to appraise workplace sexual harassment.

In finance and accounting, where panel data are required, researchers suggest different methods. For instance, Borelli-Kjaer et al. (2021) and Abebe and Dadanlar (2021) use disclosure of wrongdoing, either in the news or through litigation. While these measures unambiguously identify corporate wrongdoing, such events are rare, possibly underreported (Au, Dong and

Tremblay 2022), and measure the existence of corporate wrongdoing, but not the full extent of its severity.

Estimating discrimination severity adds a layer of complexity, as both the existence and the cruelty or consequences of discrimination incidents must be established. In a departure from merely counting the number of lawsuits, Dougal, Griffin and Hutton (2022) perform textual analysis of civil rights lawsuits and find that filed discrimination cases almost always contain allegations of harassment or retaliation. Therefore, textual analysis of civil rights lawsuits does not offer enough cross-sectional variation to allow for a precise measure of discrimination severity.

Alternatively, other papers (e.g. Au, Dong and Tremblay 2022) use textual analysis of social media posts to quantify the likelihood of an employee experiencing discrimination at work. This method provides a continuous measure of discrimination prevalence, but social media posts typically do not contain enough details to measure discrimination severity in a precise way. In addition, while the frequency of discriminatory incidents may be indicative of the toxicity of the work environment, it is mostly silent regarding the severity of any specific incident.

Lastly, other papers (e.g., Dahl and Knepper 2021) use fines imposed on firms guilty of discrimination as a proxy for the case's legal merit. Using payouts associated with discrimination cases filed with the EEOC ensures that cases have merit, defined by the EEOC as the inherent wrongs or rights of a case, and reduces the noise around the measurement of discrimination existence. In addition , because proportionality to the severity of the crime is an accepted sentencing principle (Roberts 2003), payouts to plaintiffs in employee discrimination cases should in theory be directly proportional to the severity of the committed offense, which represents a significant advantage in estimating discrimination severity.

However, EEOC merit resolutions include negotiated settlements, withdrawals with benefits, and (un)successful conciliations, thus making the absolute dollar payout a noisy proxy for the severity of discrimination. In addition, cases filed with the EEOC are complex, and filers, employers and case characteristics could affect the awarded payout, adding further noise to the proxy. Moreover, cases often include more than a single issue: because no payout breakout is provided, the mapping between payout and the severity of a single issue is problematic.

In this paper, we propose the gender discrimination payout gap as a measure of discrimination severity.[1] We define the gender discrimination payout gap as the average difference in payouts received by men and women who file a discrimination case with the EEOC, after accounting for filer, employer and case observable characteristics. In essence, our proposed measure matches discrimination cases on all observable characteristics, except gender of the filer and awarded payout.

Considering that payouts to discrimination are a function of either moral or lost pay damages (Bachman 2022)[2], any differences in payouts should proxy for differences in the perceived severity of the experienced discrimination, after controlling for case characteristics. Therefore, our proposed gender discrimination payout gap, because it matches cases on all characteristics except gender and payout, is expected to be different from zero only if the perceived severity of the discrimination experienced by women and men differs.

On the other hand, there is a wide variety of research showing that women receive better outcomes in criminal and civil matters than men (e.g., Mustard 2001; Bontrager, Barrick and Stupi 2013; Goulette, Wooldredge, Frank, Travis 2015; Fisher, Rosen-Zvi, Eisenberg 2016; Philippe 2020; Beeby et al. 2021), and that the disparity in sentencing is mostly caused by voluntary

[1] In the remaining of the paper, we use the words "gender" and "sex" interchangeably, for consistency with the conventions from the economics and finance literatures that have adopted the expression "gender diversity" to refer to both concepts.

[2] Bachman, E. "How much money is an employment discrimination case worth?", Forbes, April 26, 2022. Retrieved on August 17, 2022 from https://www.forbes.com/sites/ericbachman/2022/04/26/how-much-money-is-an-employment-discrimination-case-worth/?sh=56ce92fd7507.

departures from the sentencing guidelines (defined under the Sentencing Reform Act of 1984; Mustard 2011). More generally, the legal literature refers to courts' systematic positive bias towards women as the chivalry hypothesis (e.g., Beeby et al. 2021). In the context of EEOC payouts, the chivalry hypothesis predicts that women filing a complaint receive higher payouts than male filers. If this disparity exists among EEOC payouts and the EEOC exerts its discretionary power in determining payouts in a not completely predictable way, considering payouts associated to discrimination cases without controlling for the filer's sex introduces noise in the estimation of discrimination severity.

This leads to the following contrasting hypotheses:

H1a (Severity hypothesis): There exists systematic gender differences in payouts to EEOC employee discrimination cases, and these differences proxy for the severity of experienced discrimination.

H1b (Chivalry hypothesis): There exists systematic gender differences in payouts to EEOC employee discrimination cases, and these differences are due to differential treatment of women by the court system.

Both the severity of discrimination and the chivalry hypotheses predict that payouts to women in EEOC discrimination cases are higher than payouts to men. If payouts are primarily a function of discrimination severity, the discrimination severity hypothesis predicts that women receive higher payouts, resulting in a payout gap in favor of women. Indeed, the literature argues that women are more often victims of discrimination (e.g., Schmitt and Branscombe 2002).[3] Schmitt and Branscombe (2002) also argue that women perceive discrimination incidents more

[3] Daniller, A. "Majorities of Americans see at least some discrimination against Black, Hispanic and Asian people in the U.S." Pew Research Center, March 18, 2021. Retrieved from https://www.pewresearch.org/fact-tank/2021/03/18/majorities-of-americans-see-at-least-some-discrimination-against-black-hispanic-and-asian-people-in-the-u-s/ on September 26, 2022.

severely than men, among others because women, as part of the disadvantaged group, attribute more importance to the experienced prejudice.

To disentangle the severity of discrimination hypothesis from the chivalry hypothesis, we examine other outcomes of the EEOC process. Under both hypotheses, women should be more likely to win their EEOC cases, either because their case has more merit, or because the court is more lenient towards women. However, the two hypotheses make divergent predictions regarding the time discrimination cases remain under review. Under the chivalry hypothesis, given that courts exhibit a systematic favorable bias toward women, women's discrimination cases should spend less time under review, as the EEOC understand how taxing the process may be for the plaintiff.[4] In contrast, under the severity of discrimination hypothesis, we expect women's cases to have more merit, which requires gathering more information and more analysis. This explains why under the severity of discrimination hypothesis, we expect women's EEOC discrimination cases to remain under review for longer periods.

Alternatively, it is possible that the discrimination payout gap mirrors the documented wage gap. If discrimination claims are a function of lost pay (Bachman 2022), and therefore paid as a percentage of salary, and if men earn more on average,[5] then women should have lower litigation payouts (Mueller, Ouimet, and Simintzi 2017; Célérier and Vallée 2019). If the payout gap echoes the wage gap, not only would the direction of the payout gap be contrary to that predicted by both the chivalry and discrimination severity hypotheses, but there should be no gender differences in the probability of winning one's case, or in the time cases remain under review. In short, the three possible interpretations for a gender payout gap make contrasting predictions regarding the

[4] In fact, courts specialized in sexual crimes offer a streamlined judicial process designed to reduce victims' trauma (Walker and Louw 2005).

[5] Barroso, A. and Brown, A. "Gender pay gap in U.S. held steady in 2020". Pew Research Center, May 25, 2021. Retrieved from https://www.pewresearch.org/fact-tank/2021/05/25/gender-pay-gap-facts/ on September 26, 2022.

direction of said gap, or the time cases remain under review. We use these differentiated predictions to disentangle the three hypotheses and interpret the gender discrimination payout gap.

2.2. Does Discrimination Severity Affect Firm Performance?

The discrimination literature unanimously documents negative consequences of workplace discrimination, including stress and lower job satisfaction (Buchanan and Fitzgerald, 2008), intentions to quit (Shields and Price 2002), limited career advancement (Bertrand and Mullanaithan 2004), threats of large-scale discrimination lawsuits (Abebe and Dadanlar 2019), and reputational damages (e.g. Bhagat, Brickley and Coles 1994; Hirsh and Cha 2015; Karpoff and Lott 1993). Discrimination, such as sexual harassment of women, is also associated with large impacts on morale, profitability, and stock returns (Au, Dong, Tremblay 2022; Barnes 2022).

However, while the above studies establish a clear link between the *existence* of workplace discrimination and firm performance, very few studies attempt to relate the *severity* of workplace discrimination to firm performance. Among the exceptions, Au, Dong and Tremblay (2022) find that the impact of workplace sexual harassment on stock returns is non-linear and concentrated in firms with harassment prevalence beyond the 95th percentile of the distribution. In fact, the accumulation of minor incidents (described as "flirt" in their raw data) seem to have no measurable impact on firm value. However, the authors do not attempt to qualify the severity of specific discrimination incidents. More specifically, beyond the two extreme points of benign incidents and extreme discrimination, the authors provide no metric allowing the measure of discrimination severity, thus leaving the question of the economic impact of being exposed to infrequent, but severe discrimination unanswered.[6]

[6] The authors do not make any attempt to separate reviews that view "flirt" positively, from the reviews that associate "flirt" with a discriminatory behavior. This adds noise to their measure of minor discrimination, and increases the need for a more complete measure of discrimination severity.

We build on the literature documenting overwhelming negative firm impact of discrimination, as well as on Au, Dong and Tremblay's (2022) findings that the firm value consequences of workplace sexual harassment increases when moving from benign discrimination to extremely severe discrimination. Therefore, we expect the negative impact of discrimination on firm operating performance to augment with the severity of discrimination. This leads to our second hypothesis:

H2: Firms with high exposure to industry discrimination severity experience lower operating performance than firms with a low employee exposure to industry discrimination severity.

We base our prior of a negative effect between exposure to discrimination and firm operating performance on the literature that documents mostly negative impacts of discrimination. However, some papers (e.g. Hersch 2011) argue that firms have adjusted their response to account for existing discrimination, thus leaving negligible remaining observable effects of discrimination on firm performance. Similarly, if discrimination is statistical (e.g., Phelps 1972; Small & Pager 2020) such that observable, discriminating variables correlate with unobservable productivity characteristics, exposure to discrimination could have an insignificant impact on firm performance. Therefore, whether exposure to discrimination impacts firms' operating performance is ultimately an empirical question.

2.3. Why Does Discrimination Severity Affect Firm Performance?

We examine different plausible economic mechanisms that could explain the impact of exposure to discrimination severity on firms' operating performance. An early theoretical paper by Arrow (1973) notes that taste-based discriminating firms face higher marginal product of labor and consequently, generate lower profits. As discrimination increases and becomes more severe, the model infers a growing gap between discriminatory and non-discriminatory firms' efficient marginal product of labor.

Further, the discrimination literature has shown empirically large effects on firms and employees. The literature abundantly documents the negative impacts of discrimination on employees, from lower job satisfaction (Buchanan and Fitzgerald 2008), intentions to quit (Shields and Price 2002), and physiological and psychological problems (Chan et al. 2008). Employees exposed to severe discrimination are therefore likely to be distracted, which in turn should negatively affect their productivity (e.g. Arrow 1973). Indeed, Avery et al. (2007) and Downey et al. (2015) find that in the absence of discrimination, employees engage more, and employee engagement is a driver of firms' productivity (e.g. Little and Little 2006). Therefore, we expect employees' productivity to decrease following exposure to severe discrimination.

Exposure to discrimination is also likely to increase employee-related expenses. If exposure to discrimination incites employees to quit (Shields and Price 2002), hiring costs will rise. Alternatively, exposure to discrimination may increase absenteeism (Volpone and Avery 2013), which in turn augments employee-related costs. Hiring costs could also increase if the employer's reputation suffers following discrimination allegations (Wang 2013). While these examples do not represent an exhaustive list of the effects of exposure to discrimination on employee-related expenses, they unanimously suggest that holding the number of employees constant, employee-related costs increase following exposure to severe discrimination. This leads to our third hypothesis:

H3: The decline in operating performance of firms exposed to discrimination severity is due to a decline in employee efficiency and/or an increase in employee-related expenses.

Of course, other channels could cause the hypothesized decline in operating performance following exposure to discrimination. For instance, customers and suppliers could disassociate themselves from doing business with a corporation with a poor reputation (Bhagat et al. 1994).

However, reputational indirect effects are drawn-out, and are therefore difficult to capture empirically and to trace back to discrimination exposure unambiguously.

3. Sample and Payout Gaps Measurement

3.1. EEOC Payout Measures

We obtain individual discrimination filings from the U.S. Equal Employment Opportunity Commission (EEOC) through a Freedom of Information Act request. Each filing includes anonymized demographic details on the filer (e.g., gender, birth year), the filer's employer (number of employees and six-digit NAICS code), as well as characteristics regarding the discrimination case: state in which the discrimination case was filed, date the EEOC initiated the litigation process, the nature of the discrimination (underlying issues), the litigation outcome, and in case a payout was made, the amount paid. Additionally, in ethnic/racial discrimination cases, the filer may report his or her self-reported ethnic group. The EEOC protects the anonymity of filers and therefore keeps details about both the filer and his/her employer vague enough to avoid tracing back individual EEOC cases to specific, firm-level employers.

Our full sample includes 412,315 individual filings, filed from January 2011 to September 2017 inclusively. Table 1 shows that 57% of the (self-identifying) filers are female, and the mean birth year is 1968. Regarding the process outcomes, 15% of cases were won by filers, and the mean case spent approximately 8 months under reviews (0.67 years). Although most cases end without a payout, in those cases ending with a payout, the mean payout is $2,644, and the maximum payout is $5,460,000. The average payout may appear small relative to most firms' size, but the reputational damages of being fined by the EEOC could significantly impact the filer's employer (e.g., Karpoff and Lott 1993).

Panel A of Table 2 reports Pearson correlation coefficients among the EEOC variables. We find that most pairwise correlations are positive, which is expected, if cases with more issues represent more severe discrimination and therefore have a higher ex ante probability of winning, and receiving a payout. The correlation coefficients confirm that women file cases with more issues, and that these cases remain longer under review, are more likely to be won, and to receive a larger payout. With the exception of the correlation between *Payout* and *Won*, most correlations are low.

In table IA.2 of the Internet Appendix, we estimate panel regressions of the model

$$Payout_j = \alpha + Female_j + Birth\_Yr_j + N\_Issues_j + Emp\_size_j + Issue\_Type_j + State_j + Institution_j + NAICS_j + \varepsilon_j \quad (1)$$

Where the dollar value of *Payout* associated with case j is regressed on the case's observable characteristics. Consistent with the positive correlation coefficient reported in Table 2, Table IA.2 shows that women filers receive higher payouts, on average. More importantly, Table IA.2 reveals that all case observable characteristics are significantly related to the dollar value of the payout, possibly creating identification and multicollinearity issues. Small and Pager (2020) highlight that this "residual gap" approach is fraught with unobserved heterogeneity. For this reason, among others, we argue that our gender discrimination payout gap is a cleaner measure of discrimination severity.

Panel A of Figure 1 shows the geographical distribution of complaints (scaled by state population) filed over our entire sample period, and reveals there is no severe spatial concentration of complaints, although the Midwest and Southern states appear to receive slightly more complaints than Northeastern or Western states. At a glance, states where employees file the most complaints seem to be on both ends of the political spectrum, thus eliminating political affiliations from the potential drivers of discrimination payout outcomes. Panel B of Figure 1 restricts the sample to complaints filed by women, and shows that female filers concentrate in Southern states, although with enough noise that the amount received by women who file an EEOC discrimination complaint cannot be explained by geographical factors only.

3.2. Other Data Sources

To test Hypotheses 2 and 3, we use data from Compustat. We also require each firm-year to have non-negative and non-missing total assets (*AT*), sales (*SALE*), market equity (*ME*), and common equity (*CEQ*). Additionally, we remove firm-year observations that have less than 15 employees (*EMP*) as these firms are not covered by the EEOC. All accounting ratios and exposure variables are winsorized at the 1% and 99% levels to reduce the impact of potential outliers.

Panel B of Table 1 shows the firm characteristics. In addition, Panel B of Table 2 reports the Pearson correlation coefficients among the accounting variables. The correlation coefficients have the expected signs, and the highly correlated ratios are expected, as these highly-correlated pairs are intimately related to each other (ROA and profitability, for instance). However, since our regressions do not include multiple accounting ratios simultaneously, concerns of multicollinearity are negligible.

4. Results

4.1. Does the EEOC Discrimination Payout Correlate with Discrimination Severity?

Figure 2 presents visual evidence that on average, women receive higher discrimination payouts than men, over the full sample period. The gap in discrimination payout has remained relatively constant over the 2011-2016 period. Our 2017 data cover only the first three quarters of the year, which partially explains the drop in the number of cases and, possibly, a portion of the decrease in the payout gap. All our regressions control for year-specific effects to account for time trends in covariates.

Turning to univariate tests, Table 3 presents evidence regarding the association between payout to EEOC discrimination filings, and the filer’s gender. We find that women receive larger payouts on average than men (difference = \$250.80; t = 3.32), and women win their EEOC case more often than men (difference = 0.01; t = 12.11). Women's cases remain under review for longer periods of time than the cases filed by men (difference = 0.026 years; t = 9.99), and women's cases include more issues than cases filed by men (t = 29.02). In short, the univariate results of Table 3 highlight a discrimination payout gap, and the gender differences in the probability of winning, time under review and number of issues included in the filing align with the predictions that the discrimination payout gap arises because of gender differences in discrimination severity experienced in the workplace.

The discrimination literature identifies several antecedents to workplace discrimination, including among others the industry, characteristics of the victim, and intersectionality (Reskin 2000; Rosette, de Leon, Koval, Harrison 2018). Therefore, to control for various time, age, industry, geography, firm size, and both number and nature of the underlying issues, we run panel regressions of the following form:

$$Outcome_i = Female_i + \gamma_i + \varepsilon_{i,t} \qquad (1)$$

Where $Outcome_i$ is, in turn, the payout (in dollars) received by filer i, a binary indicator that equals 1 if filer i won his or her case, or the time, in years, that case i remained under review. $Female_i$ is an indicator variable set to 1 if the plaintiff in case i is female (and 0 otherwise) and γ are fixed effects for litigation year, which we interact with fixed effects for each of the filer's birth year, public status of the employer, industry (defined at the 6-digit NAICS level) of the employer, state where the claim was filed, size of the employer, and the number of issues listed in the case. Including these fixed effects control for all of the observable and identifiable characteristics of the individual cases, thus essentially matching cases with other, similar ones.[7] Table 4 presents the results.[8]

In Column 1 of Table 4, we find that women filing a discrimination complaint with the EEOC on average receive \$440.05 (t = 5.48) more than male filers, even after accounting for the filer's birth year, the public status, location, industry and size of the employer, and the nature and number of the discrimination issues included in the filed discrimination case. Coupled with the univariate evidence of Table 3, these results support the existence of a gender gap in discrimination payouts. This difference is economically significant: indeed, an additional payout of \$440.05 represents approximately 16% of the full-sample average payout received (\$2,731.40). The economic importance of the payout gap is magnified by the knowledge that payouts are not strictly a function of cases' observable characteristics since these are matched.

Identifying the underlying causes of the gap is essential to establish the payout gap as a measure of discrimination severity. We first reject the possibility that the payout gap is a strict function of lost pay (Bachman 2022), or that the payout gap mirrors the documented wage gaps (Mueller, Ouimet, and Simintzi 2017; Célérier and Vallée 2019). Under this possibility, we should observe a payout gap, but the average payout gap should favor men rather women. Observing a robust payout gap in favor of women allows us to dismiss this hypothesis.

Section 2.1 suggests two other hypotheses for the existence of a payout gap that favors women: the chivalry hypothesis and the discrimination severity hypothesis. Both hypotheses

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[7] We verify that our results are robust to an alternative specification with non-interacted fixed effects for litigation year, filer's birth year, institution, industry (NAICS), state, size, and the number of issues listed in the case. Table IA.1 presents the results.

[8] If the dollar amount of payout correlates with cases merit, it is possible that the subsample of cases with positive payout has fundamentally different characteristics than the subsample where no payout was awarded. To address this potential issue, we drop observations with no payouts, and re-estimate our outcomes regressions (Equation 1). Table IA.3 shows that even though our sample size decreases significantly, all our results remain, thus minimizing possible selection concerns.

predict that women are more likely to win their EEOC discrimination case. To verify this prediction, we estimate a linear probability model where the dependent variable equals 1 if the filer won his or her EEOC discrimination case, and zero otherwise. Column 2 of Table 4 shows that women are more likely to win their EEOC discrimination case, even when matching cases on available filer, employer, and case characteristics. These results are consistent with both the chivalry and discrimination severity hypotheses.

To differentiate the chivalry hypothesis that states that women receive better legal treatment from the hypothesis that the discrimination payout gap arises due to gender differences in the severity of experienced workplace discrimination, we examine the time EEOC cases remain under review. The chivalry hypothesis predicts that women's cases are resolved faster, as women receive preferential court treatment. In contrast, the discrimination severity hypothesis predicts that more severe cases require gathering and analyzing more evidence, resulting in longer time spent under review. Column 3 of Table 4 estimates a fixed effects panel regression where the dependent variable is the time cases spend under review (in years). Column 3 shows that complaints filed by women remain under investigation 0.0298 years (t = 9.79), or approximately 10.9 days, longer than complaints filed by men. Given that the EEOC has 180 days from the day of filing to complete the investigation,[9] this delay is economically significant. In addition, this result contradicts the chivalry hypothesis, but aligns with the discrimination severity hypothesis. The gender discrimination payout gap we document therefore appears to arise due to gender differences in the severity of workplace discrimination: women seem to face more severe workplace discrimination than men, which translates into women being more likely to win their EEOC case, after a longer review period, and a higher dollar payout.

[9] https://www.eeoc.gov/federal-sector/filing-formal-complaint, retrieved on August 15, 2022.

4.2. Is the EEOC Payout Gap Capturing Discrimination Severity?

Measuring discrimination severity is a challenge, among others because judging the severity of individual alleged harassment incidents is subjective and therefore prone to measurement error. Because by construction, the gender discrimination payout gap holds observable case, employer, and filer characteristics constant, we argue it is an effective measure of "discrimination within discrimination", or severity of discrimination. Nonetheless, we perform an array of validation tests to verify this claim.

Given the extant law literature that documents that Black and Latinx people receive more severe punishments for committed crimes (e.g., Steffensmeier et al. 1998; Mitchell 2005), we find a positive and significant correlation between the average state-level EEOC payout gap and the state-level prison population Black-White ratio.[10] Table IA.3 reports the results, and also shows that the ratio of Black to White prisoners is significantly smaller in states with low EEOC payout gap than in states with above-median EEOC payout (4.90 vs 7.02; t = 3.15). Similarly, the ratio of Latinx to White prisoners is significantly lower in states with below-median EEOC payout gap (0.86 vs 1.75; t = 3.88).

To the extent that we consider the racial disproportionality in prisons to be a product of racial discrimination, a possibility suggested by, among others, Blumstein (2015), we could argue that the disproportionality in prison population is a proxy for the severity of racial discrimination. Because it correlates positively with the EEOC payout gap, it supports our interpretation of the EEOC payout gap as a measure of discrimination severity. Moreover, Mitchell (2005) highlights the importance of controlling for crime characteristics when examining sentence gaps; in this context, our EEOC payout gap eliminates unobserved heterogeneity, as it examines the disparity

[10] Data on racial characteristics of the incarcerated population come from Nellis (2021).

in payouts, after controlling for all observable case characteristics (except gender, which defines the gap).

4.3. What is the Impact of the EEOC Payout Gap on Firm Performance?

The literature documents overwhelmingly negative consequences to workplace discrimination (e.g., Bertrand and Mullanaithan 2004; Chan et al. 2008; McDonald 2012; Au, Dong, and Tremblay 2022). In a robustness test, Au, Dong and Tremblay (2022) document undetectable firm value consequences to "benign" discrimination, suggesting that the impact of discrimination on firm performance increases with its severity. Therefore, there are reasons to expect firms' operating performance to worsen with the severity of workplace discrimination.

To test our second hypothesis, we build on our previous findings that the gender EEOC discrimination payout gap seems driven by the severity of the underlying discrimination cases. We first define a firm's exposure to the industry-level discrimination payout gap, since the case-level EEOC payout data include only industry-level identifiers. $Exposure_{i,j,t}$ is defined as the ratio of a firm i's total number of employees to its total assets, multiplied by industry j's (at the six-digit NAICS level) average discrimination payout gap in year t. The exposure measure assumes that prevalence of discrimination is uniform within industries, and that the severity of workplace discrimination varies across industries, in line with the findings from the discrimination literature (Hersch 2011). The rationale of the exposure measure is that firms with more employees are more likely to be exposed to workplace discrimination.

Because we measure firms' exposure to the industry level discrimination gap, our sample for the operating performance tests include all Compustat firms with non-negative assets and book value of equity. We estimate the following fixed effects panel regressions:

$$ROA_{i,t} = Exposure_{i,j,t} + \varphi_i + \omega_{jt} + \theta_{st} + \varepsilon_{i,t} \tag{2}$$

Where *ROA* is the firm's return on assets, *Exposure* is firm *i*'s exposure to the payout gap in industry *j* at time *t*, and ψ, ω and θ are firm, industry interacted with year, and state interacted with year fixed effects, respectively. We standardize the exposure measure (to mean = 0 and standard deviation =1) to facilitate its interpretation. Table 5 reports the results.

We find that firm exposure to the discrimination payout gap is negatively related to *ROA* (coefficient = -0.012; t = 3.41), even after including firm, year interacted with industry (six-digit NAICS), and year interacted with state fixed effects. These results are consistent with the interpretation that firm operating performance worsens with exposure to the discrimination payout gap. Because our interpretation of the payout gap is that it captures discrimination severity, and because the direction of the payout gap is in favor of women, Table 5 suggests that firms exposed to more severe discrimination against women underperform.[11]

Section 2.1 argues that the absolute number of filed cases may be a noisy proxy for the severity of discrimination, as such measure does not control for the underlying number of issues, among others. To verify this intuition, Table 5 repeats the tests, but uses *Exposure_Filing*, which we defined as the ratio of a firm *i*'s total number of employees to its total assets, multiplied by industry *j*'s (at the six-digit NAICS level) average absolute number of discrimination cases filed in year *t*. Again, to facilitate its interpretation, we standardize the *Exposure_Filing* measure. Column 2 of Table 5 shows that *Exposure_Filing* has no significant impact on firms' *ROA*. More importantly, in Column 3, *Exposure_Payout* retains its significance even after including *Exposure_Filing* as an additional independent variable.

[11] Because the average firm in the CRSP/Compustat universe is significantly larger than the average firm in our EEOC payout sample, we estimate the payout gap using only EEOC cases filed against firms with at least 500 employees. We repeat the tests of Table 5, and obtain nearly identical results (results untabulated).

Our interpretation of the results is that the absolute number of discrimination cases is a poor measure of the severity of workplace discrimination, as there are large variations in the underlying characteristics of the filed cases, and these characteristics may correlate with the severity of discrimination itself. In contrast, the discrimination payout gap, by effectively keeping the underlying case's characteristics constant, allows a more precise measure of discrimination severity. It follows that exposure to the expected discrimination severity affects firm operating performance.

4.4. Endogeneity

Our regressions control for an array of unobservable dimensions through firm, year by industry and year by state fixed effects. The possibility that firm exposure to the discrimination payout gap and firm operating performance are conjointly defined is therefore remote. However, to address this unlikely possibility, we follow Charles et al. (2018), Gong and Yannelis (2018), and Kalmenovitz (2021), and estimate instrumented regressions that exploit variation in EEOC regulatory intensity.

First, we identify a structural break in EEOC regulatory intensity, which we define as a year where the number of firms sued by the EEOC changed markedly. Specifically, for each proposed break $t^* \in [2011,2017]$ in our sample, we estimate the following regression:

$$Lawsuits_t = \tau_t + \beta(t - t^*) \tag{3}$$

Lawsuits is equal to the number of lawsuits the EEOC files in year *t*, τ_t is a linear time trend, and β measures the size of the structural break in the number of lawsuits. The difference term $(t - t^*)$ is an indicator variable that equals 1 if year *t* is greater than the year of the tested structural break (t*), and zero otherwise. We estimate this regression with, in turn, each of our sample year as the tested break. We identify the structural break by comparing the explanatory power that each tested break offers over the EEOC regulatory intensity. We find that t* = 2011 maximizes the regression R-Square, which is consistent with the visual evidence (Figure 3): there appears to have been some structural change in the number of EEOC lawsuits filed after 2011. In fact, the identification of 2011 as a structural break is consistent with a significant shift in the EEOC's priorities around that year. Indeed, the EEOC started to focus on systemic discrimination cases around 2011, as part of a strategic plan it passed in 2006.[12] After 2011, the EEOC seems to focus on fewer, but more complex, and more visible cases.

The second step involves predicting the EEOC's regulatory burden, based on Equation (4), and using 2011 as the structural break. The predicted values of the number of lawsuits the EEOC files in a year represent the portion of the regulatory burden driven by idiosyncratic EEOC shocks. Lastly, as shows in Equation (3), we multiply a firm's payout gap exposure by the predicted regulatory burden to create the instrument.

$$Pred\_exp_{i,t} = St\_Exp_{i,t} \times \widehat{Suits}_{i,t} \quad (4)$$

Panel A of Table 6 reports the results of the estimation of the first-stage regressions. There is a significant positive correlation between the predicted exposure (the instrument) and the realized exposure (the endogenous variable), which highlights that the instrument satisfies the relevance condition. We observe this significant and positive correlation for exposure to both payouts (*Exposure_Payout*) and filings (*Exposure_Filing*). In our setting, the exclusion restriction states that EEOC structural breaks impact firm-level outcomes only through their impact on regulatory intensity, and not through any other channel. Since our regressions include firm, year by industry, and year by state fixed effects, only the EEOC's structural break coinciding with firm-specific events, conditional on broad industry, state, and macroeconomic trends, could weaken identification. In other words, the EEOC's resources and focus vary from year to year; years with

[12] https://www.eeoc.gov/strategic-plan-fiscal-years-2007-2012 last accessed September 19, 2022

higher (lower) resources will exogenously increase (decrease) the regulatory burden on firms. In other words, the number of cases the EEOC brings to litigation is exogenous variation for the regulatory burden the agency presents to firms, as it should influence the number of filers and gaps those firms must deal with.

Panel B of Table 6 presents the results of the second-stage regressions, and shows a negative relation between firm-level ROA and exposure to the payout gap, instrumented with the EEOC structural break. A one-standard deviation increase in the instrumented *Exp_Payout* results in a 1.07% decline in ROA, or a loss of approximately 20% of the baseline average full-sample ROA. In addition, Panel B of Table 6 reports that the instrumented exposure to the number of discrimination filings has no significant impact on firm operating performance, consistent with the results of Table 5. Moreover, the second-stage coefficients of the instrumented *Exposure_Payout* are similar to those reported in Table 5, indicating minimal concerns that our main results are affected by the local average treatment effect (Jiang 2017).

To further confirm that endogeneity concerns are minimal, Tables IA.5 and IA.6 present the results of using Oster's (2019) methodology, which assesses the impact of unobservable variables on the treatment effect by considering the contributions of the observable and unobservable variables to the *R*-Square value. We first examine the stability of the *Female* coefficient in our fixed effects panel regressions of the dollar payout amount and time cases remain under review. Table IA.4 reports limits of the bias-adjusted *Female* coefficient under the different assumptions suggested by Oster (2019). None of the intervals reported in Table IA.5 spans zero. Therefore, our results establishing the discrimination payout gap as a measure of discrimination severity appear unaffected by unobservable variables.

We then turn to examining the impact of unobservable variables on the relation between exposure to discrimination payouts and firm performance. Table IA.6 reports the bounds of the bias-adjusted *Exposure_Payout* coefficients under the parameter values recommended by Oster (2019), and shows that none of the intervals include zero, thus assuaging concerns that our results are driven by unobservable variables.

4.5. Why Does Exposure to the EEOC Payout Gap Affect Firm Performance?

To establish that the impact of exposure to the discrimination payout gap on firm operating performance is real, we explore the economic channels through which exposure to discrimination could affect firm performance. Hypothesis 3 poses that loss of employee efficiency and increases in employee-related expenses are two likely channels. To test this hypothesis, we estimate fixed effects panel regressions similar to Equation 2, but use our proxies for the likely channels as the dependent variables. Table 7 Panel A presents the OLS results. Panel B of Table 7 presents the second-stage regressions of the IV results, where the independent variable of interest is the instrumented *Exposure_Payout*, calculated as specified in Section 4.3.

As noted in the hypotheses development, from a theoretical standpoint, higher discrimination associates with a lower marginal productivity of labor (Arrow 1973). We define employee efficiency (*Emp_Efficiency*) as the natural log of the ratio of sales (SALE) to the number of employees (*EMP*); this is our proxy for a firm's marginal productivity of labor. Column 1 of Table 7 shows that *Emp_Efficiency* declines with greater exposure to discrimination. Documenting the motive behind the decline in *Emp_Efficiency* goes beyond the scope of this paper; however, we suggest plausible reasons. For instance, employees experiencing discrimination could have lower morale, resulting in lower engagement and productivity, or more productive employees from the discriminated group may not be hired.

Table 7, Column 2 also reports a positive and significant effect of *Exposure_Payout* on selling, general and administrative (*SGA*) expenses, which include employee-related expenses. As *SGA* includes expenditures on both management and human resources (Eisfeldt and Papanikolaou

2013), finding that these costs increase with exposure to discrimination severity confirms our hypothesized channel. Indeed, we expect firms' employee-related expenses to be proportional to the perceived discrimination threat. For instance, firms' *SGA* could increase with exposure to discrimination severity due to higher employee absenteeism. Alternatively, exposure to discrimination could prompt firms to take preemptive actions such as increased discrimination awareness training, which would in turn increase employee-related expenses.

In untabulated tests, we dismiss alternative explanations for the negative relation between exposure to discrimination and firm operating performance. For instance, we exclude a sharply changing workforce as the driver of the efficiency and SGA effects. Similarly, although discrimination exposure increases employee-related expenses, it has an insignificant impact on gross profitability, which implies that is it unlikely that the relation we document is caused by financially distressed firms cutting back on employee-related initiatives. Instead, the reduction in employee efficiency appears consistent with employees distracted by discrimination issues, therefore reducing efficiency, which in turn is likely to affect negatively firm operating performance.

5. Robustness Tests

5.1. Alternative Econometric Models

We verify that our findings are robust to our editorial decision to select models that are easy to interpret for our main tests. Untabulated tests reveal that the distribution of payouts is heavily skewed. To control for outliers, we estimate Equation 1, but use the natural logarithm of (1+*Payout*) as the dependent variable. Table IA.7 of the Internet Appendix shows that results remain. Similarly, our main tests estimate a linear probability model of the likelihood of winning an EEOC litigation. In Table IA.8, we estimate instead a logit regression, where the dependent variable is equal to 1 if the filer wins his or her case, and zero otherwise. We confirm that our results hold when we estimate logit regressions.

5.2. Discrimination Gap Defined on the Basis of Issue Count

Our motivation for using the difference in EEOC discrimination payouts as a measure of discrimination severity is based on the theoretical works that predict proportionality of sentencing to crime severity (Mustard 2001) and, should a gap occur, that is should mirror the documented wage gap (e.g., Mueller, Ouimet, and Simintzi 2017; Célérier and Vallée 2019; Bachman 2022). Nonetheless, a natural question is whether our conclusions are robust to the definition of an issue-based discrimination gap.

We define the gender discrimination issues gap, as the difference in the number of issues mentioned in discrimination cases filed by men and women. Table 3 shows that on average, women file cases with more underlying issues than men (difference = 0.35; t = 29.02). Since this gap is aligned with the discrimination payout gap, we expect that firms' exposure to the discrimination issues gap also leads to a decline in operating performance.

As a robustness test, we estimate Equation (2), but we use the exposure to the discrimination issues gap (*Exp_Issues*) as the independent variable, which we define as a firm's total number of employees, scaled by its total assets, and multiplied by the six-digit NAICS industry average issues gap. Panel A of Table IA.9 reports the results, and shows that *Exp_Issues* is negative and significant. In Panel B, we repeat our IV tests with the instrumented *Exp_Issues*, using again the 2011 structural break in EEOC filings. Panel B confirms that our results are robust to alternative gap definitions and this favors the interpretation of the difference in payouts as a perceived measure of the severity of discrimination issues.

To verify this last interpretation, we define the ratio of payout to issues (*Payout/Issues*). We find no significant gender differences in *Payout/Issues* (results untabulated). Therefore, the

EEOC's imposed penalties do not appear to be a direct function of the case's number of issues. Rather, the EEOC seems to interpret the charges to determine a payout that is a function of discrimination severity. These findings support our use of the gender discrimination payout gap as a proxy for discrimination severity.

5.3. Alternative Definitions of the Payout Gap

Our measure of discrimination severity relies on the gender discrimination payout gap. A natural question, is whether our measure captures the severity of all types of discrimination, or whether its explanatory power is limited to discrimination on the basis of gender or sex. To examine this issue, we re-estimate the regressions of Table 4, but use two other indicator variables, *Older40* and *Nonwhite,* to measure other dimensions of discrimination. *Nonwhite* is an indicator variable that equals 1 if the filer self-reports to be of non-white racial origin, and *Older40* is an indicator variable that equals 1 if the filer is older than 40 years old. Our choice of 40 years old as the separation point mirrors the EEOC's definition of age discrimination.

Table IA.10 reports the results, and shows that if we measure a nonwhite discrimination payout gap, we reach similar conclusions, of similar direction and magnitude, than when the payout gap is defined on the basis of gender: the disadvantaged group appears to suffer from more severe discrimination, consistent with the qualitative observations from Schmitt and Branscombe (2002). Table IA.11 reveals that firm-level exposure to the nonwhite discrimination payout gap also translates into a decline in ROA, similar to the one observed with the gender payout gap. Results when the payout gap is defined on the basis of age are largely similar: older filers receive higher payouts then younger but otherwise similar filers, and older filers' cases remain longer under review than their matched cases. The direction of the gap reverses when considering the probability of winning the case, however. Still, exposure to the age discrimination gap negatively impacts firm-level operating performance.

The generally similar results we obtain when defining the payout gap along other dimensions reinforce our interpretation of the discrimination payout gap as a measure of discrimination severity. However, we focus on the gender payout gap for several reasons. First, because our dataset always reports gender, but only reports the filer's race in racial discrimination cases, defining a gender payout gap maximizes sample size and reduces concerns of selection bias. Second, biological sex is generally easily observable, and is thus more likely to affect the discrimination incident, its perception and the recognition of its impacts, even if this process is not done purposefully (Bartels and Nordstrom 2013). Third, as mentioned above, there are theoretical arguments for a gender discrimination payout gap, but fewer (if any) for a racial or age discrimination payout gap. Thus, gender is a cleaner metric for evaluating the payout gap.

Lastly, even though defining a payout gap along multiple dimensions simultaneously could appear to capture intersectionality better, we choose to define the payout gap along a single dimension, for both empirical and theoretical reasons. Defining the payout gap along multiple dimensions would result in fewer observations in each category, therefore increasing noise and the influence of potential outliers. Moreover, previous research (e.g., Au, Bhagwat and Tremblay 2022) show that multidimensional diversity indices can be summarized to less than three factors. Therefore, we focus on one of the most salient diversity factor, gender/sex. We strongly believe that defining the discrimination payout gap along this salient dimension improves the information/noise ratio, and ultimately provides a more precise estimation of discrimination severity.

6. Conclusion

This paper expands on the existing economic literature on discrimination by developing a proxy for the severity of discrimination using the men-women gap in payouts allocated to victims of discrimination. Through a "horserace" test, the paper shows that the gap is associated with the severity of discrimination, dismissing alternative explanations for this payout gap. Indeed, the paper documents that female plaintiffs receive higher payouts, and have more complex cases that take longer to investigate and resolve, consistent with the severity of discrimination hypothesis. Through IV regressions and the implementation of Oster's (2019) recommended analysis to assess the impact of unobservable variables bias, we show that the results are robust to identification issues.

The paper also shows that exposure to more severe discrimination results in a larger drop in firm operating performance, measured by the firm's ROA. In fact, a one-standard deviation increase in exposure to severe discrimination results in a 20% decline in ROA, relative to the full-sample average ROA level. To explain this decline in ROA, we root our analysis in the discrimination literature, which predicts ample employee-related costs to workplace discrimination. Indeed, we find that this decline in turn is caused by a drop in employee efficiency (a proxy for the marginal productivity of labor) and an increase in the costs of employee-related expenses, like human resources expenses.

This paper has several applications for future researchers, executives, and policy makers. For future researchers, we develop a measure for severity of discrimination that can add nuance to the research on discrimination. For executives, this paper highlights the importance of constantly reducing discrimination within the firm. Finally for policy makers, this paper shows that while eliminating discrimination should remain the ultimate goal, reducing the severity of discrimination also has very valuable benefits for society as a whole.

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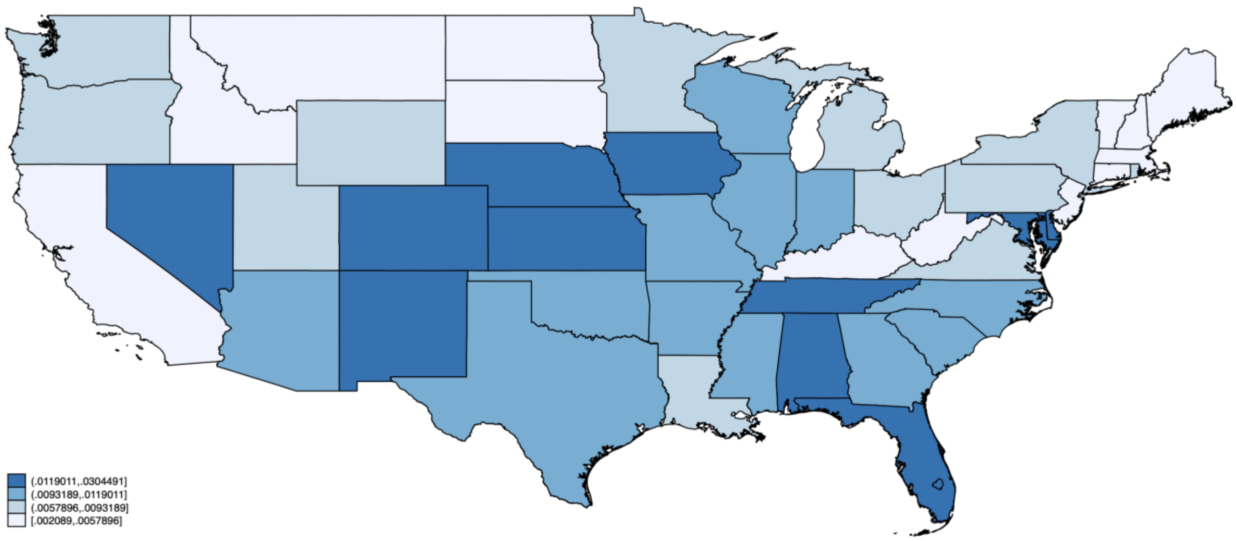
Appendix

Table A.1. Variable Definitions

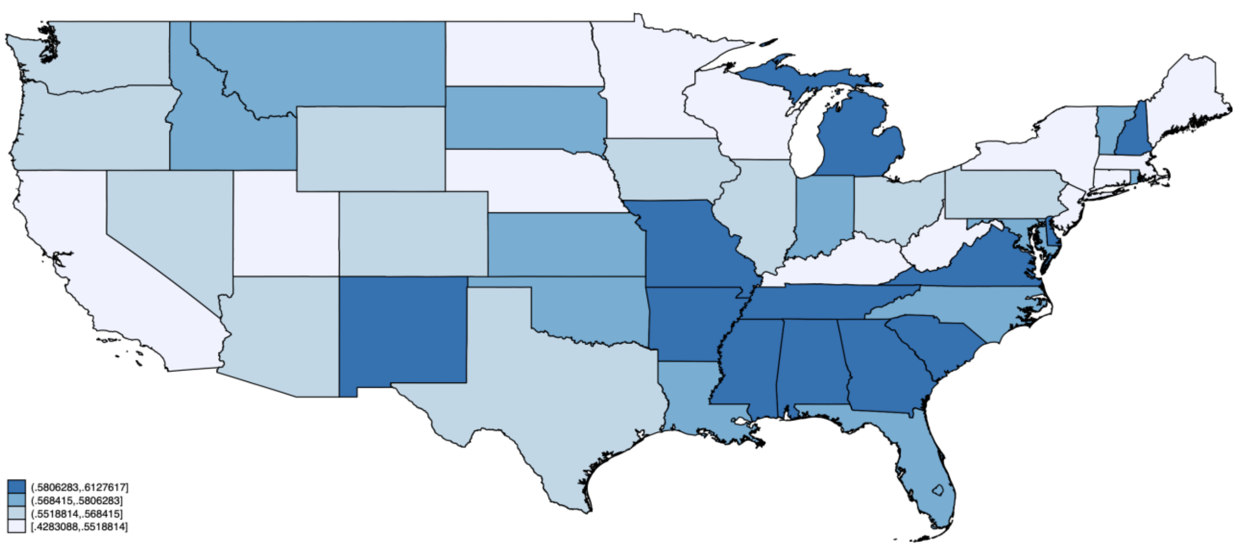
Variable	Definition
Asset_Turn	The ratio of sales (SALE) to total assets (AT).
Emp_Efficiency	The natural log of the ratio of sales (SALE) to the number of employees (EMP).
Emp_Growth	Growth rate (in percentages) in the number of employees, between periods *t* and *t*-1.
Exp_Filing	A firm's total number of employees, divided by its total assets, and multiplied by the six-digit NAICS industry average number of EEOC filings, standardized so that its mean is equal to 0 and its standard deviation is equal to 1.
Exp_Payout	A firm's total number of employees, divided by its total assets, and multiplied by the six-digit NAICS industry average payout gap, standardized so that its mean is equal to 0 and its standard deviation is equal to 1.
Female	An indicator variable that takes the value of one if the EEOC filer is a female, and zero otherwise.
Issue Count	The total number of issues (gender, race, retaliation, etc.) mentioned in an EEOC filing.
NS_Exp_Filing	A firm's total number of employees, divided by its total assets, and multiplied by the six-digit NAICS industry average number of EEOC filings.
NS_Exp_Payout	A firm's total number of employees, divided by its total assets, and multiplied by the six-digit NAICS industry average payout gap.
Older40	An indicator variable that equals 1 if the filer is older than 40 years old at the time of filing, and zero otherwise.
Payout	The total monetary benefit amount, in dollars, from an EEOC filing.
Payout Gap	Six-digit NAICS averages of difference between payouts received by male and female filers.
Profitability	The ratio of net income (NI) to revenues (SALE).
ROA	The ratio of net income (NI) to total assets (AT).
SGA	The ratio of selling, general, and administrative expenses (XSGA) to revenues (SALE).
Won	An indicator variable that takes the value of one if an EEOC filing results in a payout, and zero otherwise.
Years_Review	The time difference, in years, between the time an EEOC filing is closed and the date the same EEOC filing was first submitted.

Figure 1. Geographical Distribution of EEOC Filings for Discrimination

Panel A. Geographical Distribution of EEOC Filings for Discrimination, All Filers

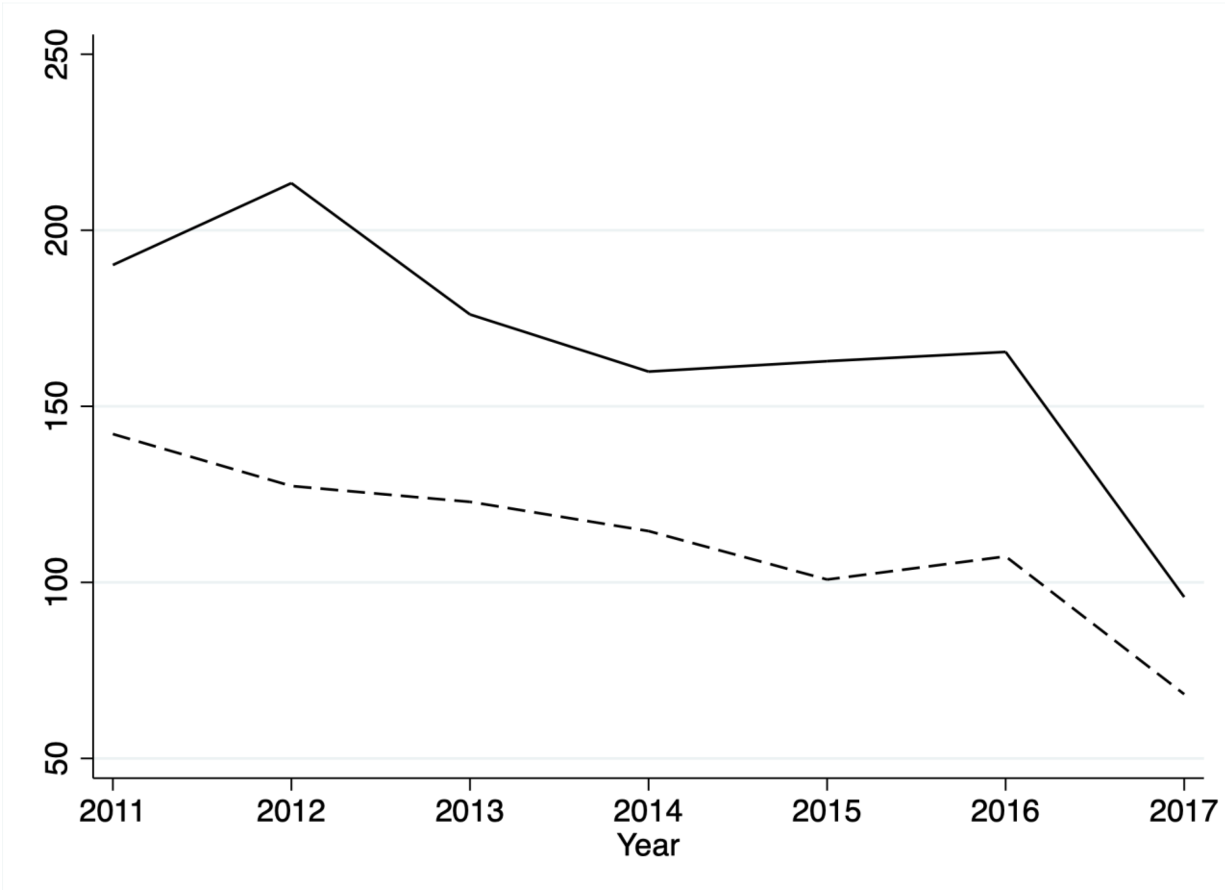


Panel B. Geographical Distribution of EEOC Filings for Discrimination, Women Filers Only



Note. This figure shows the number of EEOC filings per population by state. Panel A shows the distribution for all filings, whereas Panel B shows the distribution for complaints filed by women only. The darkest shade of blue indicates the states with the highest number of filings per population while the lightest shade of blue indicates the state with the lowest number of filings per population. The data is from the EEOC for the years 2011 to 2017.

Figure 2. EEOC Discrimination Payout Gap



Note. The figure shows the dollar payout of an EEOC filing by gender. The solid line plots the sum of EEOC filing payouts by year for female filers. The dashed line plots the sum of EEOC filing payouts by year for male filers. The y-axis reports payout amounts in millions of dollars. The data is from the EEOC for the years 2011 to 2017.

Figure 3. Structural Break in EEOC Lawsuits

Note. The figure shows the total number of suits the EEOC filed in a year. The vertical line marks the year 2011 as the year in which there was rapid change in the EEOC's regulatory trend. The data is from https://www.eeoc.gov/statistics/eeoc-litigation-statistics-fy-1997-through-fy-2021.

Table 1. Summary Statistics

This table reports sample summary statistics. Panel A reports summary statistics for the EEOC filings, whereas Panel B shows firm-level characteristics, calculated using data from Compustat. Variable definitions are in Table A.1 of the appendix. The data are from the EEOC and Compustat for the years 2011 to 2017.

Panel A. EEOC Measures.				
	Obs.	Mean	Std. Dev.	Median
Payout	412,315	2,731.40	24,054.50	0.00
Won	412,315	0.14	0.34	0.00
Years_Review	412,315	0.68	0.82	1.00
Female	412,315	0.57	0.50	1.00
Issue Count	412,315	3.79	3.86	2.00
Panel B. Firm Characteristics.				
	Obs.	Mean	Std. Dev.	Median
ROA	17,526	-0.05	0.25	0.03
Profitability	17,526	-1.57	9.69	0.03
Asset_Turn	17,526	1.00	0.75	0.81
SGA	15,912	0.49	1.19	0.25
Emp_Growth	16,941	0.10	0.30	0.04
Emp_Efficiency	17,526	437.33	616.34	267.93
NS_Exp_Payout	17,526	8.66	52.60	0.00
Exp_Payout	17,526	0.00	1.00	-0.16
NS_Exp_Filing	17,526	3.28	12.39	0.33
Exp_Filing	17,526	0.00	1.00	-0.24

Table 2. Correlations

This table reports Pearson correlations coefficients among variables of interest. Panel A reports correlations among EEOC variables, whereas Panel B shows correlations among firm characteristics. Variable definitions are in Table A.1 of the appendix. The data are from the EEOC and Compustat for the years 2011 to 2017.

Panel A. Correlations Among EEOC Variables

	Payout	*Won*	*Years_Review*	*Female*
Won	0.28	1.00		
Years_Review	0.01	-0.03	1.00	
Female	0.01	0.02	0.02	1.00
Issue Count	0.02	0.01	0.03	0.05

Panel B. Correlations Among Firm Characteristics

	ROA	*Profitability*	*Asset_Turn*	*SGA*	*Emp_Growth*	*Emp_Efficiency*	*Exp_Payout*
Profitability	0.44	1.00					
Asset_Turn	0.23	0.21	1.00				
SGA	-0.53	-0.76	-0.23	1.00			
Emp_Growth	-0.04	-0.09	-0.12	0.09	1.00		
Emp_Efficiency	0.36	0.48	0.18	-0.37	-0.09	1.00	
Exp_Payout	-0.04	0.01	0.03	0.02	0.02	-0.08	1.00
Exp_Filing	0.06	0.04	0.25	-0.05	-0.02	-0.30	0.03

Table 3. Univariate Tests of the EEOC Payout Characteristics as Proxy for Discrimination Severity

This table reports results of univariate tests of the differences in means of the female and male subsamples, for the EEOC filing variables. Columns 1 and 2 report the mean characteristics and number of observations for the female subsample, whereas Columns 3 and 4 report the same statistics, for the male subsample. Column 5 shows the difference between the female and male subsamples (Column 1 – Column 3), and Column 6 reports the t-statistics for the null that the difference is equal to zero. Variable definitions are in Table A.1 of the appendix. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC for the years 2011 to 2017.

	Female		Male			
	Mean	N	Mean	N	Diff.	*t*-stat.
	(1)	(2)	(3)	(4)	(5)	(6)
Payout	2,840.15	233,466	2,589.35	178,849	250.80***	3.32
Won	0.14	233,466	0.13	178,849	0.01***	12.12
Years_Review	0.69	233,466	0.66	178,849	0.03***	9.99
Issue Count	3.94	233,466	3.59	178,849	0.35***	29.02

Table 4. Filer Gender and EEOC Outcomes

This table reports fixed effect regression model results. The dependent variable is the monetary payout of an EEOC filing, whether a filer won their filing, and the number of years under review in columns (1), (2), and (3), respectively. The main independent variable of interest is *Female* which is an indicator variable that takes the value of one if the EEOC filer is a female and zero otherwise. Variable definitions are in Table A.1 of the appendix. Coefficient estimates are shown, and their robust standard errors are displayed in parentheses. ***(**)(*) Significance at the 1%(5%)(10%) two tailed level, respectively. The data is from the EEOC for the years 2011 to 2017.

	Payout	*Won*	*Years_Review*
	(1)	(2)	(3)
Female	440.0453***	0.0161***	0.0298***
	(80.2553)	(0.0011)	(0.0025)
N	412,315	412,315	412,315
R-Square	0.03	0.05	0.18
Year by Birth Year FE	Y	Y	Y
Year by Institution FE	Y	Y	Y
Year by NAICS FE	Y	Y	Y
Year by State FE	Y	Y	Y
Year by Size FE	Y	Y	Y
Year by Issue FE	Y	Y	Y
Year by Number of Issues FE	Y	Y	Y

Table 5. Impact of the Exposure to Payout Gaps on Firm ROA

This table shows fixed effect panel results. The standardized payout exposure (*Exp_Payout*) is defined as a firms' total number of employees divided by its total assets and multiplied by the six-digit NAICS industry average payout gap. The standardized filing exposure (*Exp_Filing*) is defined as a firms' total number of employees divided by its total assets and multiplied by the six-digit NAICS industry average number of EEOC filings. The dependent variable is ROA. NAICS fixed effects (FE) are at the six-digit NAICS industry level. State FE are the state in which a firm is headquartered. Variable definitions are in the Table A.1 of the appendix. Coefficient estimates are shown, and their standard errors are clustered by firm and displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC and Compustat for the years 2011 to 2017.

	ROA	*ROA*	*ROA*
	(1)	(2)	(3)
Exp_Payout	-0.0109***		-0.0108***
	(0.0032)		(0.0032)
Exp_Filing		-0.0105	-0.0094
		(0.0070)	(0.0069)
N	17,526	17,526	17,526
R-Square	0.78	0.78	0.78
Firm FE	Y	Y	Y
Year x NAICS FE	Y	Y	Y
Year x State FE	Y	Y	Y

Table 6. Instrumental Regressions

The table presents the results of estimating a 2SLS IV approach akin to the regressions presented in Table 5. The instrumental variable is a firm's level of payout gap and filing exposure, multiplied by the predicted amount of litigation cases from the EEOC in a given year from the structural break in regulatory intensity that occurs in the data in 2011. The method follows Kalmenovitz (2021). The standardized payout exposure (*Exp_Payout*) is defined as a firms' total number of employees divided by its total assets and multiplied by the six-digit NAICS industry average payout gap. The standardized filing exposure (*Exp_Filing*) is defined as a firms' total number of employees divided by its total assets and multiplied by the six-digit NAICS industry average number of EEOC filings. NAICS fixed effects (FE) are at the six-digit NAICS industry level. State FE are the state in which a firm is headquartered. Variable definitions are in Table A.1 of the appendix. Coefficient estimates are shown, and their standard errors are clustered by firm and displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC and Compustat for the years 2011 to 2017.

Panel A. First-Stage Regressions			
	Exp_Payout	*Exp_Filing*	*Exp_Payout & Exp_Filing*
	(1)	(2)	(3)
Predicted(*Exp_Payout*)	0.0046***		0.0046***
	(0.00005)		(0.00005)
Predicted(Exp_Filing)		0.0031***	-0.0006***
		(0.0003)	(0.0001)
N	17,526	17,526	17,526
F-Stat	7,946	101	53
Firm FE	Y	Y	Y
Year x NAICS FE	Y	Y	Y
Year x State FE	Y	Y	Y
Panel B. Second-Stage Regressions			
	ROA	*ROA*	*ROA*
	(1)	(2)	(3)
Exp_Payout	-0.0102***		-0.0102***
	(0.0032)		(0.0032)
Exp_Filing		-0.0032	0.0006
		(0.0099)	(0.0098)
N	17,526	17,526	17,526
F-Stat	7,946	101	53
Firm FE	Y	Y	Y
Year x NAICS FE	Y	Y	Y
Year x State FE	Y	Y	Y

Table 7. Channel Tests

This table reports results of fixed effect panel regressions of firm-level operating performance on standardized payout exposure (*Exp_Payout*). In Panel A, we estimate the fixed effect panel with OLS. Panel B reports the second-stage results of 2SLS IV regressions results using the same model in Column (1) of Table 6. The standardized payout exposure (Exp_Payout) is defined as a firms' total number of employees divided by its total assets and multiplied by the six-digit NAICS industry average payout gap. The instrumental variable is a firm's level of payout gap and filing exposure, multiplied by the predicted amount of litigation cases from the EEOC in a given year from the structural break in regulatory intensity that occurs in the data in 2011. The method follows Kalmenovitz (2021). NAICS fixed effects (FE) are at the six-digit NAICS industry level. State FE are the state in which a firm is headquartered. Variable definitions are in Table A.1 of the appendix. Coefficient estimates are shown, and their standard errors are clustered by firm and displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC and Compustat for the years 2011 to 2017.

Panel A. OLS Regressions		
	ln(Emp_Efficiency)	*SGA*
	(1)	(2)
Exp_Payout	-0.0134***	0.0216***
	(0.0052)	(0.0074)
N	17,526	15,817
R-Square	0.91	0.83
Firm FE	Y	Y
Year x NAICS FE	Y	Y
Year x State FE	Y	Y
Panel B. Second-Stage Regressions of 2SLS Regressions		
	ln(Emp_Efficiency)	*SGA*
	(1)	(2)
Exp_Payout	-0.0189***	0.0208***
	(0.0055)	(0.0068)
N	17,526	15,817
F-Stat	7,946	7,508
Firm FE	Y	Y
Year x NAICS FE	Y	Y
Year x State FE	Y	Y

Internet Appendix

Table IA.1. Alternative Econometric Specifications

This table reports alternative specifications to Table 4 in the main text. Columns 1, 3 and 5 do not include any fixed effects. Columns 2, 4 and 6 include non-interacted year, filer birth year, institution, six-digit NAICS, state, firm size, issue, and issue count fixed effects. In Columns 1 and 2, the dependent variable is the monetary payout of an EEOC filing, whereas in Columns 3 and 4, the dependent variable is an indicator variable that equals 1 if a filer won their filing, and zero otherwise. In Columns 5 and 6, the dependent variable is the number of years a filing remains under review. The independent variable of interest is *Female*, which is an indicator variable that takes the value of one if the EEOC filer is a female and zero otherwise. Birth Year fixed effects (FE) capture the year in which the filer was born. Institution FE categorize whether the filer works at a private, public, or governmental institution. NAICS FE are the six-digit NAICS industry that the filer worked in for the filing. State FE capture the state in which the filing occurred. Size FE describe the categorical size of the filer's employer, by number of employees. Issue FE are the type of issue the filing falls under such as race, gender, retaliation, etc. Issue Count FE captures the number of issues that are in a single filing. Variable definitions are in Table A.1 of the appendix. Coefficient estimates are shown, and their robust standard errors are displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC for the years 2011 to 2017.

	Payout		*Won*		*Years_Review*	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	250.8005***	439.3940***	0.0131***	0.0161***	0.0256***	0.0340***
	(74.9745)	(78.2179)	(0.0011)	(0.0011)	(0.0025)	(0.0025)
N	412,315	412,315	412,315	412,315	412,315	412,315
R-Square	0.001	0.01	0.001	0.03	0.001	0.13
Year FE	N	Y	N	Y	N	Y
Birth Year FE	N	Y	N	Y	N	Y
Institution FE	N	Y	N	Y	N	Y
NAICS FE	N	Y	N	Y	N	Y
State FE	N	Y	N	Y	N	Y
Size FE	N	Y	N	Y	N	Y
Issue FE	N	Y	N	Y	N	Y
Issue Count FE	N	Y	N	Y	N	Y

Table IA.2. Determinants of the Absolute Discrimination Payout

This table shows the results of the estimation of the model: $Payout_j = \alpha + Female_j + Birth\_Yr_j + N\_Issues_j + Emp\_size_j + Issue\_Type_j + State_j + Institution_j + NAICS_j + \varepsilon_j$.
The dependent variable is the absolute payout (in dollars) received by filers.

Female is an indicator variable that equals 1 if the filer identifies as a woman, and zero otherwise. Birth year is the filer's birth year. Issue count is the number of issues in the filed complaint. Issue type is a categorical variable that describes the nature of the issues included in the complaint. N_employees is a categorical variable to describe the size of the employer, as defined by the EEOC. State_code is a vector of indicator variable that equal 1 if the filer filed in state s, and zero otherwise. Institution_type is a categorical variable that describes the filer's employer's type. Industry is a vector of indicator variable that equals 1 if the filer's employer is in employee i, and zero otherwise.

Coefficient estimates are shown, and robust standard errors are displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC and Compustat for the years 2011 to 2017.

	Total_Amount (1)	Total_Amount (2)	Total_Amount (3)
Female	275.727***		438.446***
	(-74.131)		(-75.992)
Birth_year	-27.710***		-30.872***
	(-2.095)		(-2.189)
Issue_count	117.329***		115.143***
	(-11.539)		(-11.538)
Issue_type	-21.029***		-20.423***
	(-2.851)		(-2.842)
N_employees		174.428***	162.483***
		(-29.332)	(-29.299)
State_code		8.783***	9.089***
		(-2.727)	(-2.728)
Institution_type		-62.194***	-104.669***
		(-16.577)	(-17.422)
Industry		-1.574***	-1.638***
		(-0.201)	(-0.204)
Intercept	56800.000***	3845.842***	64200.000***
	(-4136.110)	(-256.154)	(-4323.700)
N	412315	412315	412315
R-Square	0.001	0.001	0.001
Fixed effects	None	None	None

Table IA.3. Correlation and Univariate Differences of the EEOC Payout Gap with Racial Disproportionality of Incarcerated Population

Panel A. Correlation Matrix.

	EEOC Payout Gap (1)	*BW_Prison_Ratio* (2)	*LW_Prison_Ratio* (3)
EEOC Payout Gap	1.000	0.299	0.294
		(0.035)	(0.041)
BW_Prison_Ratio	0.299	1.000	0.544
	(0.035)		(<.0001)
LW_Prison_Ratio	0.294	0.544	1.000
	(0.041)	(<.0001)	

Panel B. Univariate Tests.

	Below-Median EEOC Payout Gap (1)	*Above-Median EEOC Payout Gap* (2)	*Difference* (3)
BW_Prison_Ratio	4.896	7.012	-2.116
			(0.003)
LW_Prison_Ratio	0.8583	1.784	-0.9257
			(<.0001)

This table shows how the EEOC Payout Gap covaries with racial disproportionality in prisons. *BW_Prison_Ratio* refers to the state-level ratio of Black to White prisoners, whereas *LW_Prison_Ratio* is the state-level ratio of Latinx to White prisoners. For this analysis, we aggregate the EEOC discrimination payout gap at the state level. Panel A reports the Pearson correlation coefficients and their associated *p*-value (in parentheses). Panel B shows the mean racial disparity ratios in states with below-median EEOC payout gap (Column 1) and states with above-median EEOC payout gap (Column 2), as well as the results of *t*-tests for the difference in mean racial disparity ratios (Column 3). *P*-values are reported in parentheses.

Table IA.4. Outcomes Regressions Excluding Observations with No Payout

This table reports fixed effect regression model results from Table 4 in the main text but excludes observations with no payout from the sample. The dependent variable is the natural log of the monetary payout of an EEOC filing, and the number of years under review in columns (1) and (2), respectively. The main independent variable of interest is *Female* which is an indicator variable that takes the value of one if the EEOC filer is a female and zero otherwise. Variable definitions are in Table A.1 of the appendix. Coefficient estimates are shown, and their robust standard errors are displayed in parentheses. ***(**)(*) Significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC for the years 2011 to 2017.

	Ln(Payout)	*Years_Review*
	(1)	(2)
Female	0.0779***	0.0136*
	(0.0156)	(0.0075)
N	44,476	44,476
R-Square	0.23	0.20
Year by Birth Year FE	Y	Y
Year by Institution FE	Y	Y
Year by NAICS FE	Y	Y
Year by State FE	Y	Y
Year by Size FE	Y	Y
Year by Issue FE	Y	Y
Year by Number of Issues FE	Y	Y

Table IA.5. Stability of the *Female* Coefficient: Potential Effects of the Unobservable Variables

This table reports the robustness of the *Female* coefficient in the payout and time under review regressions of Table 2, estimated under different assumptions as per Oster (2019). The first two columns report the *Female* coefficients and R-squared for the baseline (e.g., $Payout_i = \beta_1 Female_i + \varepsilon_{it}$) and the controlled regressions ($Payout_i = \beta_1 Female_i + \varphi_i + \psi_j + \omega_t + \varepsilon_{it}$), where φ_i, ψ_j, and ω_t are fixed effects specified in Table 2. Columns 4 to 6 report the identified *Female* coefficient sets. The sets are bounded by $\tilde{\beta}$, the coefficient from the regressions with controls, and $\beta*$, the bias-adjusted coefficient after accounting for the bias from the unobservable variables, calculated using Oster's (2019) methodology. $R_{\max}$ is the theoretical upper bound on *R*-squared, which is the *R*-squared value from a (hypothetical) regression of the dependent variable on *Female* and both observed and unobserved controls. Column 4 to 6 progressively relax the value of $R_{\max}$. $\tilde{R}$ is the *R*-squared from the regression with controls. The parameter δ quantifies the selection relationship: $\delta = 1$ implies that the unobservable and observables are equally related to the treatment, and $\delta = 2$ implies that the unobservables are twice as important as the observables. Since none of the identified coefficient sets includes zero, the *Female* effect is not influenced by unobservable variables.

Panel A: Dependent Variable = Payout

(1)	(2)	(3)	(4)	(5)	(6)
Baseline Effect, [R^2]	Controlled Effect, [R^2]		$R_{\max} = \min(2\tilde{R}; 1)$	$R_{\max} = \min(1.5\tilde{R}; 1)$	$R_{\max} = \min(1.25\tilde{R}; 1)$
281.48, [0.001]	440.04, [0.03]	1	[440.04, 604.07]	[440.04, 522.05]	[440.04, 481.04]
281.48, [0.001]	440.04, [0.03]	2	[440.04, 768.10]	[440.04, 604.07]	[440.04, 522.05]
281.48, [0.001]	440.04, [0.03]	3	[440.04, 932.12]	[440.04, 686.08]	[440.04, 563.06]

Panel B: Dependent Variable = Years_Review

(1)	(2)	(3)	(4)	(5)	(6)
Baseline Effect, [R^2]	Controlled Effect, [R^2]		$R_{\max} = \min(2\tilde{R}; 1)$	$R_{\max} = \min(1.5\tilde{R}; 1)$	$R_{\max} = \min(1.25\tilde{R}; 1)$
0.0201, [0.01]	0.0298, [0.18]	1	[0.0298, 0.0401]	[0.0298, 0.0349]	[0.0298, 0.0323]
0.0201, [0.01]	0.0298, [0.18]	2	[0.0298, 0.0503]	[0.0298, 0.0401]	[0.0298, 0.0349]
0.0201, [0.01]]	0.0298, [0.18]	3	[0.0298, 0.0606]	[0.0298, 0.0452]	[0.0298, 0.0375]

Table IA.6. Stability of the *Exp_Payout* Coefficient: Potential Effects of the Unobservable Variables

This table reports the robustness of the *Exp_Payout* coefficient in the operating performance regressions of Table 5, estimated under different assumptions as per Oster (2019). The first two columns report the *Exp_St* coefficients and R-squared for the baseline (e.g., $Operating\_Performance_{i,t} = \beta_1 Exp\_St_{i,t} + \varepsilon_{it}$) and the controlled regressions ($Operating\_Performance_{i,t} = \beta_1 Exp\_St_{i,t} + \varphi_i + \psi_j + \omega_t + \varepsilon_{it}$), where φ_i, ψ_j, and ω_t are fixed effects specified in Table 5. Columns 4 to 6 report the identified *Exp_St* coefficient sets. The sets are bounded by $\tilde{\beta}$, the coefficient from the regressions with controls, and $\beta*$, the bias-adjusted coefficient after accounting for the bias from the unobservable variables, calculated using Oster's (2019) methodology. $R_{\max}$ is the theoretical upper bound on R-squared, which is the R-squared value from a (hypothetical) regression of the dependent variable on *Exp_St* and both observed and unobserved controls. Column 4 to 6 progressively relax the value of $R_{\max}$. $\tilde{R}$ is the R-squared from the regression with controls. The parameter δ quantifies the selection relationship: $\delta = 1$ implies that the unobservable and observables are equally related to the treatment, and $\delta = 2$ implies that the unobservables are twice as important as the observables. † indicates the identified sets that include zero.

Dependent Variable = ROA					
(1)	(2)	(3)	(4)	(5)	(6)
Baseline Effect, [R^2]	Controlled Effect, [R^2]		$R_{\max} = \min(2\tilde{R}; 1)$	$R_{\max} = \min(1.5\tilde{R}; 1)$	$R_{\max} = \min(1.25\tilde{R}; 1)$
-0.0108, [0.002]	-0.0116, [0.003]	1	[-0.0118, -0.0116]	[-0.0118, -0.0116]	[-0.0118, -0.0116]
-0.0108, [0.002]	-0.0116, [0.003]	2	[-0.0121, -0.0116]	[-0.0121, -0.0116]	[-0.0120, -0.0116]
-0.0108, [0.002]	-0.0116, [0.003]	3	[-0.0123, -0.0116]	[-0.0123, -0.0116]	[-0.0122, -0.0116]

Table IA.7. Natural Log of Payout

The table repeats the same analysis as Table 4 in the main text but uses ln(Payout+1) as the dependent variable. The dependent variable is the natural log of 1 plus the monetary payout of an EEOC filing. The main independent variable of interest is *Female* which is an indicator variable that takes the value of one if the EEOC filer is a female and zero otherwise. Variable definitions are in Table A.1. of the appendix. Coefficient estimates are shown, and their robust standard errors are displayed in parentheses. ***(**)(*) Significance at the 1%(5%)(10%) two tailed level, respectively. The data is from the EEOC for the years 2011 to 2017.

	(1) ln(*Payout*+1)
Female	0.1392***
	(0.0095)
N	412,315
R-Square	0.05
Year by Birth Year FE	Y
Year by Institution FE	Y
Year by NAICS FE	Y
Year by State FE	Y
Year by Size FE	Y
Year by Issue FE	Y
Year by Number of Issues FE	Y

Table IA.8. Logit Regression of the Probability of Winning an EEOC Discrimination Claim

The table reports the results of the estimation of a logit model to estimate the probability of winning an EEOC Discrimination Claim. The independent variable of interest is *Female* which is an indicator variable that takes the value of one if the EEOC filer is a female and zero otherwise. Variable definitions are in Table A.1 of the appendix. Coefficient estimates are shown, and their standard errors are displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC for the years 2011 to 2017.

	Won (1)	*Won* (2)
Female	0.0132*** (0.0011)	0.0163*** (0.0011)
N	412,315	412,315
R-Square	0.05	0.05
Year FE		Y
Birth Year FE		Y
Institution FE		Y
One-Digit NAICS FE		Y
State FE		Y
Firm Size FE		Y
Issue Type FE		Y
Number of Issues FE		Y

Table IA.9. Impact of the Exposure to the Discrimination Issue Gap on Firm ROA

This table shows fixed effect panel results. The standardized issues exposure (*Exp_Issues*) is defined as a firms' total number of employees divided by its total assets, and multiplied by the six-digit NAICS industry average issues count gap. Panel A presents the OLS results, whereas Panel B presents the results of the IV regressions. NAICS fixed effects (FE) are at the six-digit NAICS industry level. State FE are the state in which a firm is headquartered. Variable definitions are in the Table A.1 of the appendix. Coefficient estimates are shown, and their standard errors are clustered by firm and displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC and Compustat for the years 2011 to 2017.

	Panel A: OLS	*Panel B: IV Regressions*	
		First Stage	*Second Stage*
	Dep. Var.: ROA	*Dep. Var.: Exp_Issues*	*Dep. Var.: ROA*
	(1)	(2)	(3)
Exp_Issues	-0.0068**		
	(0.0031)		
Predicted*(Exp_Issues)*		0.0049***	
		(0.00005)	
Exp_Issues(IV)			-0.0070**
			(0.0031)
N	17,526	17,526	17,526
R-Square	0.78		
F-Stat		7,811	7,811
Firm FE	Y	Y	Y
Year x NAICS FE	Y	Y	Y
Year x State FE	Y	Y	Y

Table IA.10. Filer Racial Origin and Age and EEOC Outcomes

This table reports fixed effect regression model results. The dependent variable is the monetary payout of an EEOC filing, whether a filer won their filing, and the number of years under review in columns (1), (2), and (3), respectively. In Panel A, the main independent variable of interest is *Nonwhite* which is an indicator variable that takes the value of one if the EEOC filer is of non-white racial origin and zero otherwise. In Panel B, the main independent variable is *Older40*, which is an indicator variable that equals one for filers older than 40 years old, and zero otherwise. Variable definitions are in Table A.1 of the appendix. Coefficient estimates are shown, and their robust standard errors are displayed in parentheses. ***(**)(*) Significance at the 1%(5%)(10%) two tailed level, respectively. The data is from the EEOC for the years 2011 to 2017.

Panel A. Non-white Origin			
	(1)	(2)	(3)
	Payout	*Won*	*Years_Review*
Nonwhite	339.0385***	0.0108***	0.0310***
	(121.9489)	(0.0026)	(0.0062)
N	141,589	141,589	141,589
R-Square	0.06	0.08	0.19
Year by Birth Year FE	Y	Y	Y
Year by Institution FE	Y	Y	Y
Year by NAICS FE	Y	Y	Y
Year by State FE	Y	Y	Y
Year by Size FE	Y	Y	Y
Year by Issue FE	Y	Y	Y
Year by Number of Issues FE	Y	Y	Y
Panel B. Older Than 40 Years Old			
	(1)	(2)	(3)
	Payout	*Won*	*Years_Review*
Older40	780.7577***	-0.0071***	0.0058**
	(68.4268)	(0.0012)	(0.0025)
N	412,315	412,315	412,315
R-Square	0.03	0.05	0.18
Year by Birth Year FE	Y	Y	Y
Year by Institution FE	Y	Y	Y
Year by NAICS FE	Y	Y	Y
Year by State FE	Y	Y	Y
Year by Size FE	Y	Y	Y
Year by Issue FE	Y	Y	Y
Year by Number of Issues FE	Y	Y	Y

Table IA.11. Impact of the Exposure to Nonwhite and Age Payout Gaps on Firm ROA

This table shows fixed effect panel results. The standardized payout exposure (*Exp_Payout*) is defined as a firms' total number of employees divided by its total assets, and multiplied by the six-digit NAICS industry average payout gap. The standardized filing exposure (*Exp_Filing*) is defined as a firms' total number of employees divided by its total assets, and multiplied by the six-digit NAICS industry average number of EEOC filings. In Panel A, the exposure is defined relative to the *Nonwhite* discrimination gap. In Panel B, the exposure is defined relative to the *Older40* discrimination gap. The dependent variable is ROA. NAICS fixed effects (FE) are at the six-digit NAICS industry level. State FE are the state in which a firm is headquartered. Variable definitions are in the Table A.1 of the appendix. Coefficient estimates are shown, and their standard errors are clustered by firm and displayed in parentheses. ***(**)(*) indicates significance at the 1%(5%)(10%) two tailed level, respectively. The data are from the EEOC and Compustat for the years 2011 to 2017.

Panel A. Nonwhite Discrimination Gap			
	ROA	*ROA*	*ROA*
	(1)	(2)	(3)
Exp_Payout	-0.0109***		-0.0104***
	(0.0032)		(0.0038)
Exp_Issues		-0.0132***	-0.0122***
		(0.0032)	(0.0032)
N	17,526	17,526	17,526
R-Square	0.78	0.78	0.78
Firm FE	Y	Y	Y
Year x NAICS FE	Y	Y	Y
Year x State FE	Y	Y	Y
Panel B. Age Discrimination Gap			
	ROA	*ROA*	*ROA*
	(1)	(2)	(3)
Exp_Payout	-0.0097***		-0.0090**
	(0.0037)		(0.0036)
Exp_Issues		-0.0086***	-0.0077***
		(0.0030)	(0.0030)
N	17,526	17,526	17,526
R-Square	0.78	0.78	0.78
Firm FE	Y	Y	Y
Year x NAICS FE	Y	Y	Y
Year x State FE	Y	Y	Y