The Market Value of Pay Gaps: Evidence from EEO-1 Disclosures

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Abstract: Although demographic pay gaps have been widely examined at the individual and macroeconomic levels, firm-level pay gaps, defined as the difference in labor costs between a hypothetical all-White male workforce and the firm's actual workforce, have historically been difficult to estimate in the absence of required disclosure. We combine firm-specific demographic and job category information from the recent release of EEO-1 reports with previously available aggregated EEOC pay data to systematically estimate firm-level pay gaps for more than 11,000 U.S. public and private firms. We document substantial variation in pay gaps across industries, show that pay gaps increase with firm size, and find patterns consistent with established labor-economics theory as well as political factors. We further show that private firms exhibit larger average pay gaps than public firms of similar size. Treating the EEO-1 data release as an information event regarding firm-specific pay gaps, we examine stock-market reactions and find that cumulative abnormal returns are positively associated with the incremental component of pay gaps, but not the previously known component. Our results remain robust after controlling for firms' diversity metrics, job categories, state, industry, and other firm characteristics. Our paper informs stakeholders about the magnitude, determinants, and perceived economic value of firm-level pay gaps.

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I. Introduction

One of the defining social issues of our time is the persistent pay gaps in the U.S. between men and women, and between White and minority workers (Blau and Khan 2017; Blair and Posmanick 2023; Blau et al. 2023). In 2024, women earned, on average, 84 cents for every dollar a man earns (Mitchell 2024), and Blacks and Hispanics/Latinos earned, on average, 76 cents and 73 cents, respectively, for every dollar a White worker was paid (DOL 2023).

A large and growing literature examines determinants behind the persistence of these pay gaps, attributing, for example, occupational segregation (Blau and Kahn 2017), family obligations (Bertrand, Goldin, and Katz 2010), age and flexible work conditions (Goldin 2014), education (Becker 1962), and racial discrimination (Wilson and Darity 2022). Other papers document some macroeconomic consequences of these pay gaps, for example, their detrimental effect on overall GDP (Milli et al. 2017).

We turn our lens towards two lesser-known aspects of pay gaps: (1) the extent of variation across companies, and (2) whether investors view these pay gaps as enhancing or diminishing firm value. By understanding variations in pay gaps across firms, social-minded activists, and regulatory bodies can turn their attention to tackling wage inequality in a more studied and efficient way. By understanding the second issue, solutions for remediating gender and racial/ethnic pay gaps may become more apparent. For example, if pay gaps are perceived by investors to enhance firm value, then we should not turn to capital markets to redress this problem.

Following standard definitions, we define a firm's pay gap as the difference between its hypothetical labor cost under an all-White male workforce and its actual total labor costs. Estimating these two parameters, however, is difficult due to a lack of publicly available information. U.S. accounting standards do not require companies to disclose information about their labor costs in its financial filings, and in fact, very few firms provide this data. For our sample of publicly listed firms, only 6.2% of non-financial institutions report their total compensation or labor costs, and no firm discloses its pay (or pay gaps) by race and ethnicity.[1] Using survey data on 1,000 large U.S. firms, Just Capital reports that less than one-third of large U.S. firms conduct an analysis of their gender pay gap (Nestler, Radeva and Sanders 2023). Of these firms, less than one-half voluntarily disclosed the size of this gap, with the bulk of the disclosures coming from firms with relatively small gender pay gaps (Nestler et al. 2023). Further, Cullen and Pakzad-Hurson (2023) and Burn and Kettler (2019) present evidence that U.S. employees rarely discuss their pay with their coworkers, thus contributing to non-transparency within firms.

Instead, stakeholders must rely on aggregated earnings measures. For example, the U.S. Census Bureau, through its Current Population Survey (CPS) and the American Community Survey (ACS), reports earnings by gender, race/ethnicity, and occupation on the national level, and the Equal Employment Opportunity Commission (EEOC) publishes earnings by demographic and occupation at the state and industry level. Thus, while pay gaps can be calculated at an industry or national level, they cannot be estimated at the firm level.

This changed somewhat in 2023, when a federal lawsuit prompted the Office of Federal Contract Compliance Programs (OFCCP) to publicly release Type 2 EEO-1 Reports (EEO-1 reports) from 2016 through 2020 for over 19,000 public and private U.S. federal contractors. These reports are mandatory, standardized annual forms filed with the Equal Employment Opportunity

[1] Private firms are not required to publicly disclose their financial reports, thus limiting any publicly available financial filings to publicly traded firms. As for financial institutions, bank holding companies (BHC) and securities holding companies (SHC) with assets over $3 billion are required to file FR Y-9C forms with the Federal Reserve. This form contains a detailed consolidated income statement, with line 7a requiring the disclosure of "salaries and employee benefits." This form is publicly available for most banks and security holding companies. Our sample encompasses 145 banks and 15 trading companies with information on their labor costs. We use these firms to validate our measures within the paper.

Commission (EEOC), detailing the numerical breakdown of a company's entire workforce into a matrix of 14 distinct gender/race-ethnicity and 10 job categories. (See Appendix A for Amazon's 2020 EEO-1 Report). The uniqueness of these reports is that they contain a fuller picture of a firm's *entire* workforce, and not just its top executives, or those included in online databases, such as LinkedIn, or through employee surveys. As such, these reports can be integrated with the aggregated data to provide a clearer picture of each firm's earnings, given its unique job structure and demographic composition. Further, because the data consist of both private and publicly traded firms, it covers a large spectrum of companies within the United States.

We conduct our main analyses by combining the newly released EEO-1 forms with the previously released EEO-1 Component 2 Pay Data (hereafter referred to as EEOC Pay Data). For 2017 and 2018, the EEOC required firms to submit a supplemental report to their EEO-1 filings that provided detailed pay information for the same 140 demographic-by–job-category cells used in the EEO-1[2] To protect confidentiality, the EEOC aggregated the pay data at the state-industry level. However, each cell is divided into 12 separate pay bands, providing a large degree of granularity. Using the number of employees in each band as weights, we compute a weighted average to estimate the "average pay" for each demographic and job-category cell.[3]

We then merge each firm's individual EEO-1 form with its corresponding industry-and-state level weighted averages, allowing us to estimate (1) the firm's labor costs under a hypothetical all-White male workforce, and (2) its actual labor costs given its demographic and job-category composition. The difference between these two estimates yields the firm-specific pay gap. Because both datasets are based on the same 140 demographic and job-category cells, our measure

[2] In 2019, this requirement was suspended, resulting in this being the latest pay data.

[3] See section II.B for a more detailed description of the EEOC data and how we use it in our paper.

minimizes errors based on inconsistent job definitions or racial and ethnic categorizations. For instance, while the Bureau of Labor Statistics allows individuals to identify as both White and Hispanic, the EEOC treats these as distinct categories in its filings.

Our sample consists of 927 publicly traded companies and over 10,000 private firms. For public firms we derive a mean estimated pay gap of $49.41 million a year. This gap, on average, is equal to 6.96% of a firm's total selling, general, and administrative (SG&A) costs, and 1.44% of its total revenues. Private firms are smaller and, therefore, have smaller payrolls. Nevertheless, we estimate their average pay gap to be $5.86 million a year.

When we scale these raw numbers as a percentage of the firm's total imputed pay (*Pay Gap Ratio*), we find that public firms save, on average, 8.12% of total pay vis-à-vis 11.52% for private firms. Dividing firms into five buckets based on the number of employees produces two interesting observations. First, for all firm sizes, the *Pay Gap Ratio* for private firms exceeds those of public firms. Thus, we present evidence that pay gaps may be more pronounced for private firms than for publicly traded firms. Second, there is an almost monotonic increase in the *Pay Gap Ratio* as firm size increases, suggesting that larger firms are more likely to have greater pay gaps than smaller firms.

We also examine some of the determinants behind the variations in our *Pay Gap Ratio* measure. Using labor economics theory, we find that the *Pay Gap Ratio* is lower when workers have more bargaining power (Becker 1957) or have higher levels of education (Becker 1962). For this analysis, we pinpoint the firm's corporate headquarters and exploit differences across U.S. states in education attainment, minimum wage, unions, and labor laws. Our findings hold for both public and private firms. We also present evidence consistent with the *Pay Gap Ratio* being lower in states that have more sympathetic political leanings towards day-to-day workers.

Having documented variations in estimated pay gaps, and some of the determinants behind these variations, we turn to our second research question: Did investors use the incremental data to revalue firms? We examine this by calculating Fama-French 5-factor (FF5) cumulative abnormal returns (CARs) surrounding the public release of the EEO-1 forms. Finance theory predicts that if the data in these reports provide investors with new value-relevant information, then the cumulative abnormal return around the release date reflects this information. We then regress these CARs on the already known pay gap component based on the firm's state and industry averages (*Known EEOC Pay Gap*) and an incremental component based on the new information gleaned from the firm's EEO-1 report (*Incremental Differential*). We expect the coefficient on *Known EEOC Pay Gap* to be statistically indistinguishable from zero. If, however, investors adjust their valuations based on the size of the updated estimate of a firm's pay gap, then a significantly positive coefficient on *Incremental Differential* would be consistent with investors assigning a net positive value to the pay gap; conversely, a negative coefficient would imply the opposite.

There are strong reasons in support of either view. Structural pay gaps reduce operating costs; they also have been shown to be persistent over time (Blau and Khan 2017; Blair and Posmanick 2023; Blau et al. 2023). A persistent increase in earnings could be viewed by investors as value-enhancing. On the other hand, structural wage gaps can be demoralizing to workers (Card et al. 2012), or they might be correlated with other labor violations, for example, unpaid overtime or unsafe working conditions (Raghunandan 2021; Cooper and Kroeger 2017). If workplace inequities reduce employee satisfaction, then investors may see pay gaps in a negative light, thus reducing the value of the firm. Consistent with this view, Pan et al. (2022) finds an average negative stock price reaction around the initial revelation of the income gap between a company's

CEO and its average worker's pay. They interpret this finding as investors displaying an aversion towards high within-firm pay dispersions.

We find a positive association between stock market returns and the size of a firm's incremental pay gap around the release of the EEO-1 reports. This finding is robust across alternative ways of computing the pay gap, for example, using different industry classifications. It also is robust to the incremental component being relative to the firm's industry-and-state averages, to national averages, and to whether a firm already voluntarily disclosed its EEO-1 report on its website.

However, alternative explanations may account for our findings. To address whether other information is flowing into the market during our time period, we use a relatively short window around the release of the EEO-1 data – four days – and also control for earnings announcements over that time frame. To examine whether the positive coefficient is related to some unobserved factors, we replace the EEO-1 release date with all 109 pseudo-dates within 60 days of the EEO-1 release date, and re-estimate our regression using these alternative dates. We find no consistent patterns of coefficients on *Incremental Differential* for these regressions, thus minimizing this possible explanation. To control for idiosyncrasies among states or industries, we include state and industry fixed effects in all of our specifications. To control for the possibility that our regressions are picking up differences in productivity among workers, we include firm performance, efficiency and leverage ratios as additional control variables. However, we cannot definitively rule out the possibility that measurement error implicit in our pay gap estimates is correlated systematically with omitted variables.

Our market tests are based on investors using the release of the EEO-1 reports in the same manner as us, that is, to better refine their measure of a firm's pay gap over and above its already-known state and industry average. However, an alternative explanation to our findings is that investors reacted to the information in the EEO-1 form alone without putting it in the context of pay gaps. To test this hypothesis, we regress the CARs on different demographic measures, both separately and after including our disaggregated pay gap ratio variables. We also re-estimate our equations after including the percentages of workers in each of the 10 job categories, both on their own and with their disaggregated pay gap ratio. Our results and interpretations are robust to the inclusion of these variables, and hold for whether we use raw or incremental demographic or job-category measures.

Lastly, we perform some analyses to assess whether measurement error or omitted correlated variables influence our findings. To account for measurement error due to job categories lumping together occupations with dissimilar education or professional backgrounds, we recalculate the pay gap ratio for each firm after removing workers from each of the 10 job categories, respectively. To see whether any one industry might be unduly influencing our results, we sequentially drop firms by industry. Our findings and inferences remain the same.

Our paper contributes to the literature on gender and minority pay gaps in the U.S. on several dimensions. First, we provide more precise, firm-level estimates of pay gaps that go beyond the information available from aggregated data. Second, we add to a large and growing literature addressing the underlying determinants of the persistence in pay gaps, for example, family obligations (Bertrand et al. 2010) and racial discrimination (Wilson and Darity 2022), by examining additional economic and political factors associated with these gaps.

Our paper contributes to the literature on the market value of labor. Merz and Yashiv (2007) and Belo et al. (2022) present evidence on the contribution of labor in determining a firm's market value. In 2019, Goldman Sachs claimed that holding a synthetic basket of stocks consisting of the

50 S&P 500 firms with the lowest ratio of labor costs to revenues outperformed the S&P 500 by more than 20 percentage points over the 2016 to 2018 period (CNBC 2019; Goldman Sachs 2019). Although not a peer-reviewed study, their trading strategy is consistent with firms being able to reduce their labor costs without compromising their workforce's productivity, and with the market recognizing this through higher market values. Our paper shows that many investors place a positive value on firms' pay gaps, a finding consistent with Goldman's trading strategy.

Although not the focus of our paper, our input data adds to the literature depicting occupational segregation in the U.S. By connecting the EEO-1 forms to published pay data, we find that occupational segregation by race or ethnicity exists at the lowest-paid job categories, and not just at the management level as shown by Rigel Hines (2020) and Bourveau et al. (2025). Specifically, we show that Black and Hispanic workers fall disproportionately into the lowest paying job categories and that White and Asian employees are disproportionately represented at the highest paying job categories.

Should firms be required to disclose their pay gaps by gender, race, ethnicity, and job category? While there are no U.S. regulations requiring individual firms to reveal this information, several countries have passed new laws requiring public and private-sector firms to disclose salary data by gender.[4] The purpose of these new laws is to provide transparency on gender pay gaps with the hope that it will result in the narrowing of these gaps. Consistent with this goal, Bennedsen et al (2022) and Baker et al. (2023) found a narrowing of the gender pay gap after the initiation of

[4] Austria requires companies with more than 150 employees to provide their employees with anonymized wage reports disaggregated by gender. Germany's Transparency in Wage Structures Act grants employees the right to obtain information about the pay of colleagues in comparable positions. In the UK, organizations with over 250 employees must annually report gender pay gap statistics. The European Union's Pay Transparency Directive (2023/970), expected to be implemented by 2026, also requires firms across member states to disclose salary information and gender pay gaps. See Duchini, Simion and Turell (2024) for a comprehensive review of this literature.

these regulations for Danish firms and Canadian public schools, respectively. However, this narrowing was attributed to a slowed growth of wages paid to men, and not to women enjoying higher pay levels. In contrast, recent evidence shows that salary-history bans, i.e., employers not being allowed to ask about applicants' prior pay, reduced gender pay disparities due to firms no longer being able to anchor their offers on women's historically lower wages (Sinha, 2022; Khanna, 2020).

Our paper contains several caveats. First, our pay gap calculations, while an improvement on the aggregated data, are estimates and not precise measures. To partially overcome this limitation, we use a large sample of firms drawn from a wide array of industries and states, thus averaging out the idiosyncrasies associated with particular geographic areas, industries, or firm policies on pay. Second, we predicate our market tests on investors using the release of the EEO-1 forms to improve their estimates of individual firm pay gaps. We do not, however, rule out the possibility that investors gleaned other value-relevant information from the release of these forms, for example, the percentage of minorities within the workforce or the number of workers in each job category. We examine this possibility by estimating regressions of CAR on the newly-released demographic and job category information from these forms, both separately and after including the disaggregated pay gap rations. Our findings are consistent with investors gaining information on both the firm's pay gaps and its workforce composition. Third, as stated earlier, we cannot rule out the possibility that some of our findings are related to measurement errors or other omitted correlated variables within each job category due to a lumping together of disparate jobs within each category. To partially limit this criticism, we re-do our market analyses after excluding each job category. We also examine via O*NET the educational and professional qualifications needed for jobs within each category and find that our results hold after deleting the job categories with the most disparate qualifications.

II. Data Sources and Sample Construction

The data source for the workplace demographics is the Type 2 EEO-1 reports provided by the DOL's website. Compensation data are from the EEOC website.[5] We obtain stock returns and financial reporting data from CRSP and Capital IQ Compustat.

A. EEO-1 Reports

Since 1966, all private U.S. firms (all U.S. private and public federal contractors) subject to Title VII with 100 (50) or more employees have a legal obligation to file annually a report with the EEOC detailing the numerical breakdown of their U.S. workforce by gender/ethnicity/job title. In addition, covered federal contractors are required to share their reports with the U.S. Department of Labor's Office of Federal Contract Compliance Programs (OFCCP).[6] Unlike voluntary disclosures, for example, those contained in a firm's sustainability report, the structure and layout of these reports are standardized, thus enhancing comparability among firms.

Appendix A presents Amazon's 2020 Type 2 EEO-1 Report. This is a "consolidated report," which includes all full-time and part-time employees who worked in the 50 U.S. states and the District of Columbia during October, November, or December (EEOC 2022). Consistent with the form's requirements, race and ethnicity are separated by gender, and each individual cell represents

[5] Specifically, we downloaded the "2018 EEO-1 Component 2 Pay Data Collection State Aggregates (NAICS-3) Public Use File" from https://www.eeoc.gov/data/2017-and-2018-pay-data-collection

[6] These reports are confidential and not publicly available. However, companies are not precluded from voluntarily releasing these documents to the public, and many firms, particularly those in the Fortune 100, place their Type 2 EEO-1 report or a summary of that report on their company websites.

the number of employees by their gender/race/ethnicity/job category.[7] As the report shows, Amazon has 918,261 employees in total, with 492,272 (53.6%) being male and 425,989 (46.4%) being female. There are 237,783 "Black or African-American" employees, which represent 25.9% of Amazon's total workforce; 209,298 (22.8%) employees are "Hispanic or Latino." In terms of job structure, 67.7% of the workforce is classified as "Laborers & Helpers." We also can discern that Senior and Mid-level Managers (the first two rows) are tilted towards men, who hold 70.8% of the positions, whereas "Administrative Support" is dominated by women, who hold 62.6% of the total positions. It is this granularity of gender and race/ethnicity by job category that we exploit in our analyses.

Our data emanates from a June 2022 Freedom of Information Act (FOIA) request from Will Evans from the Center for Investigative Reporting (CIR) to the OFCCP asking for the release of its Type 2 EEO-1 reports from 2016 to 2020 for all federal contractors. Consistent with the DOL's disclosure regulations, the OFCCP published multiple notices of the FOIA request in the National Register, giving contractors until March 31, 2023 to object to the release of their data. Over 4,000 contractors contacted the OFCCP with objections to their release; many held that their reports were exempt from disclosure under FOIA Exemption 4, an exemption that protects "trade secrets and commercial or financial information" as being "privileged or confidential."[8] Thirty-three firms

[7] Employees self-identify their ethnicity; those who decline to do so are classified by the company through employment records or "observer identification." (EEOC 2022). The EEOC provides six race and ethnicity categories, with a seventh being someone of "two or more races" (EEOC 2022). The EEOC provides a binary option for gender (male or female), but it allows employers to include non-binary employees as part of a comments section. Firms place each employee in one of ten job categories. The EEOC manual (EEOC 2022) contains a detailed description and examples of each race and ethnic category, and equally detailed descriptions and examples pertaining to each job category.

[8] See the Department of Justice Guide to the Freedom of Information Act, p. 263, https://www.justice.gov/archive/oip/foia_guide09/exemption4.pdf.

allowed the OFCCP to release their forms. Over 19,000 federal contractors either did not object or did not respond to the National Register notices.

In November 2022, the CIR sued the OFCCP to compel the release of all requested data. On March 2, 2023, the OFCCP furnished the Type 2 EEO-1 reports for the 21 federal contractors who had already voluntarily released their forms. On April 17, 2023, the OFCCP released the remaining 19,367 Type 2 EEO-1 reports for those contractors and sub-contractors that did not object to their release.

B. EEOC Pay Data

Because firms do not provide disaggregated information about their earnings, we rely on the aggregated 2018 "EEO-1 Component 2 Pay Data Collection State Aggregates (NAICS-3) Public Use File" (Pay Data File) from the EEOC's website as our main source of earnings. In 2017 and 2018, the EEOC required firms to add a "Component 2" pay data collection component to their EEO-1 Reports, thus providing them with pay information for the same 140 demographic/job category cells.[9] However, to protect employer and employee confidentiality, the EEOC aggregated each of the 140 cells by state and NACIS three-digit and two-digit industry codes. More precisely, the Pay Data File shows state-and-industry aggregated data for 12 pay bands and the number of workers within each pay band for each of the 140 cells.

We take each cell's weighted average of the midpoints of up to 12 bands as our workforce pay measure for that cell. The bands are set by the EEOC and are the same across all cells. For example, if our firm is in the Retail Trade industry and is headquartered in Colorado, we calculate the dollar

[9] In 2017 and 2018, employers were instructed to pick a one-month pay period from October through December of the given year and to use their employees' annual pay as reported on form W-2. The W-2 Box 1 earnings definition includes all Occupational Employment Survey (OES) earnings components, plus bonuses, overtime, and shift-differential pay. (see https://nap.nationalacademies.org/read/26581/ chapter/4). On July 2019 and Feb 2020, the EEOC made the 2017 and 2018 data, respectively available (see https://www.eeoc.gov/data/2017-and-2018-pay-data-collection). This requirement was discontinued from 2019 onwards.

amount paid to all Black Women Professionals as the weighted average of the midpoints of the 11 available pay bands for Black Women Professionals, as provided by the Pay Data File.[10] We repeat this calculation for each of the 140 cells and call the sum of these calculations a firm's estimated total labor costs.[11] Because these data are known to the market prior to the release of the EEO-1 data in 2023, we use these averages to calculate the known part of our pay gaps.

There are several advantages to using the EEOC Pay Collection data as our starting point. The 140-cell format used for its Pay Collection database gives us a one-to-one alignment with the demographics and reported job structures in each firm's EEO-1 report. Second, the EEOC collected its pay data from employers and "certain" federal contractors only. Because our sample consists of federal contractors only, this provides a further alignment between datasets.[12] Further, by taking the weighted average of the midpoints of the 12 pay bands for each cell, we eliminate outliers within a pay category. For example, a highly-successful "White Male" bond trader for Goldman Sachs would not overly influence our estimated pay level for senior level White men as we would be using the midpoint of all 12 bands for this pay cell.

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[10] Specifically, we compute the average pay for each race/ethnicity–gender–job category combination by calculating the weighted average based on the distribution of workers for a particular race/ethnicity-gender-job category in a particular industry-state pair across the 12 salary bands. For each of the ten close-ended pay bands, we take the midpoint value; for the two open-ended bottom ("$19,239 and under") and top ("$208,000 and over") bands, we use the ceiling and floor values ($19,239 and $208,000, respectively) for the computation. While this approach is tractable, it may introduce measurement error by understating the pay gaps. In particular, if certain demographic groups (e.g., White males) are disproportionately represented in the top pay band and others (e.g., racial minorities or women) in the bottom pay band, this method may lead to an underestimation of pay gaps.

[11] Using NAICS three-digit codes at the state level results in non-representative pay averages due to the low or even zero frequencies of pay observations. To resolve this, we use NAICS two-digit codes at the state level to compute pay averages for each of the 140 cells, categorized by industry and state. For missing cells, we use the national two-digit NAICS industry average in its stead. In addition, to better align our industry classifications with Fama-French industry classifications, we map these NAICS three-digit codes into Fama French 48 industries and conduct a robustness analysis (Section VII.B.2). The results and interpretations are robust to this alternative classification.

[12] An alternative data source we considered but do not use is from Revelio Labs, which provides *estimated* salary data by firm by job, gender, and race. However, Revelio's depiction of gender, race, and ethnicity is done by an employee's name only, and its job salaries are based on a prediction model that uses information from visa applications, publicly available self-reported data, job postings, and salary data from other "closely-related" companies. These assumptions are fraught with errors; in particular, we are most concerned with Revelio not depicting a firm's workplace diversity accurately.

However, despite the detailed breakdown provided by the EEOC for each of its 140 cells, there are drawbacks to using aggregated measures of pay per cell in lieu of precise data. Using state and industry averages assumes each firm operates as a price taker in the labor market, and that it accepts the prevailing market wage for each demographic/job category within its respective state and two-digit NAICS industry. Whereas several papers show that wages tend to converge within a region or within an industry (Zhou and Bloch 2019; Silva 2021), this convergence may not hold for larger firms, which have more leverage in determining wages. Further, taking data from the state in which the firm's company headquarters is located assumes employee wages are determined at the headquarters level. This, too, may not be a valid assumption for firms with subsidiaries or factories in multiple states.[13] By using a large sample of firms from different states and industries, we average out many of these idiosyncrasies. We also repeat our analyses using alternative definitions of industry, for example the 96 three-digit NAIC code or Fama-French 48 industry categories. As a further robust check, we repeat our tests using the BLS 2021 and 2022 national surveys as alternative sources of pay-differential data.

C. Sample Construction

Table 1, Panel A shows the sample construction for the private and public firms we use in our analyses. Even though all firms in our sample filed their EEO-1 reports annually from 2016 through 2020, the DOL website has EEO-1 filings only for 56,761 firm-years in which an individual firm is designated as a covered federal contractor.[14] To avoid using multiple filings for any firm, we take the latest available Type 2 EEO-1 report for each sample firm, thus keeping our

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[13] The EEO-1 filing also contains reports on employees at the firm's headquarters (Type 3 EEO-1 Report) and by establishment (Type 4 EEO-1 Report). However, the FOIA request was for Type 2 Reports only, and therefore we do not have data from these forms.

[14] The OFCCP defines a covered federal contractor as a prime or first-tier subcontractor with 50 or more employees that has a contract, subcontract purchase order of at least $50,000, or serves as a depository of government funds of any amount, or issues U.S. savings bonds.

initial sample to 19,400 unique firms. Of these firms, 18,208 are private and 1,192 are publicly traded. For private firms, we keep the 10,434 federal contractors that exhibit a valid North American Industry Classification System (NAICS) code. All public firms have this code and thus all remain in our sample. Dropping public firms without the required Compustat or CRSP, as well as firms with fewer than 50 employees, reduces the sample to 964 unique firms. Removing firms that fundamentally changed between their latest EEO-1 filing date and the 2023 DOL release date gives us a final sample of 927 publicly traded firms, similar to the sample size used by Bourveau et al. (2025). Table 1, Panel B shows the number of firms by year of their most recent filing with the DOL. The vast majority of our public and private firm samples consist of EEO-1 forms from 2020.

II. Descriptive Statistics

A. Evidence of Pay Gaps: Total Workforce and Across Job Categories

Figure 1 presents pay levels by gender across each of the 10 different job categories, and the total workforce, using data from the 2018 EEOC Pay Data File. For the full sample (including other ethnicities), the four most commonly-held positions are "Professionals" (24.6%), "Administrative Support" (16.9%), "Mid-Level Managers" (12.5%), and "Operatives" (9.8%). In contrast, the four least common job categories are "Senior-Level Managers" (4.1%), "Sales Workers" (5.2%), Technicians (5.9%), and "Laborers & Helpers" (5.9%).

Within each frame, we show the pay levels by race or ethnicity (White, Asian, Black and Hispanic). We omit the "Other" category due to the limited number of observations. As the figure shows, pay differentials vary by gender depending on the job category, but also on the race or gender of the worker. To place dollar amounts on these differences, we regress the pay for White male workers separately on each demographic group's pay using all state × 2-digit NAICS × job-category × gender × race level observations from the EEOC pay data, excluding observations with zero demographic presence. Our regressions add controls for state and 2-digit NAICS industry fixed effects.

Table 2 contains these results, with Column (1) reporting summary statistics over all job categories, and Columns (2) – (11) presenting findings within each job category. In general, after controlling for state and industry effects, there are large, systematic pay differentials for Women and for non-White workers relative to White men. In Panel A, Women earn, on average, $9,047 less than White men, with significant pay differentials in every job group. The largest differentials are at the top of the hierarchy ($20,247 for senior managers), and the smallest at the bottom ($2,059 among service workers). In Panel B, Black workers earn $7,159 less and Hispanic workers earn $6,101 less overall, with sizable differentials across occupations, especially in managerial and professional roles. In contrast. Asian workers show a small overall premium (i.e., negative pay differentials relative to White male) of $2,125, driven by large premiums in senior management ($17,446) and mid-level management ($12,144), but experience positive pay differentials in sales, administrative support, and several blue-collar categories. The results in Table 2 show that, overall, gender pay differentials widen in higher-status occupations, and race/ethnicity pay differentials vary significantly across occupations.

B. Demographic Statistics

Table 3 presents gender and race/ethnicity distributions for our EEO-1 data. To facilitate comparisons, we show, in Panel A, the entire U.S. workforce by gender and race/ethnicity as reported by the Bureau of Labor Statistics (BLS). For 2023, women make up 47% of the entire U.S. workforce, compared to men, who account for 53%. In terms of race/ethnicity, the U.S.

workforce can be divided into the following categories: "White" 77%; "Black" 13%; "Hispanic" 19%; and "Asian" 7%.[15] Further, the percentages for the U.S. labor force have been relatively stable, with a slight increase in the representation of non-White workers from 2020 to 2023, and no change in gender make-up over time.

Panels B and C present the distributions of gender and race/ethnicity for the 927 public firms and 10,434 private firms, respectively, in our sample. In terms of gender, public firms are more skewed towards men as compared to the national level, whereas private firms more closely resemble the national average. Because the BLS and the EEOC use different definitions of racial and ethnic identity, we cannot make comparisons between our sample firms and the national averages. However, we note that whereas both groups have similar percentages of White employees (68% and 67%, respectively), public firms have lower percentages of Black and Hispanic employees, but a larger percentage of Asian workers when compared to private firms.

C. Evidence of Occupational Segregation

In Figure 2, we combine the EEO-1 forms with 2018 national EEOC pay data to further examine the occupational segregation that was suggested in Table 2. Occupational segregation refers to the uneven distribution of racial, ethnic and gender groups across occupations (Weeden, 2019). It is one of the major drivers of wage inequality, and has been shown to be persistent over time (Blau and Kahn 2017; Weeden 2019; Derenoncourt and Montialoux 2021).

We begin by presenting two national averages – the average national pay for each job category (right of the figure) and the average national pay for each demographic group (bottom of the

[15] We note that these percentages, as reported by the Bureau of Labor Statistics, add up to more than 100%. This is because the BLS identifies Hispanic or Latino origins as an ethnicity that is not mutually exclusive with a race. For example, a White American worker can also identify as having a Hispanic ethnicity. We also note that the percentages reported by the BLS do not include three categories in the EEO-1 reports – "Native American or Pacific Islander", "American Indian or Alaskan Native", and "Two or More Races."

figure). As expected, the top three job categories (Senior-Level Managers, Mid-Level Managers, and Professionals) have the highest average pay, whereas the bottom two job categories (Laborers & Helpers, and Service Workers) are at the bottom of the pay scale. In terms of demographics, Asian men, on average, comprise the highest pay group, followed by White men and Asian women. Hispanic and Black women and Black men fall into the three lowest average national pay groups.

We next divide our race and ethnicity data from the EEO-1 forms into men (the blue bubble on the left) and women (the orange bubble on the right) by occupation. Each bubble represents the percentage of jobs held by workers within that demographic group, with larger (smaller) bubbles reflecting the relative sizes for each group. We highlight the two largest bubbles for each job category. By doing so, we can provide comparisons between the percentages of the workforce within each job category with the percentages of workers within a specific demographic group.

This snapshot of our data presents a clear picture of the existence of job segregation by race or ethnicity in the U.S. workforce. As the two triangles in Figure 2 show, White and Asian workers are clustered primarily in the upper left corner, whereas minority workers, particularly Black and Hispanic workers are highly represented in the lower right corner. Because the upper left corner contains the highest paying jobs and the lower right corner has the lowest paying jobs, Figure 2 illustrates how job segregation impacts income inequality, as reflected by the average demographic pay data shown in the bottom row.

Whereas the upper left triangle parallels the findings presented in Rigel Hines (2020) and Bourveau et al. (2025), our paper adds to their findings by showing that race and gender job segregation exists in some of the lowest-paying job categories.

III. Pay Gaps: Measurement, Descriptive Statistics and Validation Tests

A. Estimation of a Firm's Pay Gap

For each firm in our sample, we multiply the number of employees in each cell (from the EEO-1 report) by the weighted average pay in each cell (using the EEOC Pay Database). Adding up these cells gives us the total estimated pay for the company, which we name *Total Imputed Pay*. Next, we quantify the hypothetical pay for each firm as if all its workers were compensated according to the pay standards of White men within their respective job categories. This involves recalculating total pay as if every worker was paid at the average pay level of White men in their job category, state, and two-digit NAICS industry. We call this the *Total Imputed Pay All White Men*. We calculate the dollar value of the firm-level gender-race pay gap as:

Pay Gap = Total Imputed Pay All White Men – Total Imputed Pay

$$=\sum_{j=1}^{10} N_j\,\bar{y}(j, WM) - \sum_{j=1}^{10} \sum_{h\in H} N_{j,h}\bar{y}(j,h) = \sum_{j=1}^{10} \sum_{h\in H} N_{j,h}[\bar{y}(j, WM) - \bar{y}(j,h)] \quad (1)$$

Where:

$N_j = \sum_{h\in H} N_{j,h}$, the total number of workers in job category *j*,

j=1st, 2nd,…,10th job categories,

h=one of the 14 demographic groups, e.g., White Men (WM), White Women (WW),

$\bar{y}(j, WM)$ = the average pay of White Men in job category *j*, and,

$\bar{y}(j,h)$ = the average pay of demographic group *h* in job category *j.*

According to Equation (1), firm-specific pay gaps are determined by two components. First, $N_{j,h}$ reflects the number of each firm's workers for job category *j* from demographic group *h*. This data is historically unobservable but became available when the EEO-1 forms were released. Second, $[\bar{y}(j, WM) - \bar{y}(j,h)]$ measures the average pay-gaps between each demographic group and White Men workers in the same job category *j*. These job-specific average pay gaps, though not observable at the individual firm level, are already known to the public at the state and industry level via previous EEOC Pay Data releases and alternative data sources such as annual BLS CPS data releases. As such, the incremental information gained by the market is mainly through $N_{j,h}$.

To control for firm size, we calculate:

$$\textit{Pay Gap Ratio} = \textit{Pay Gap} \,/\, \textit{Total Imputed Pay} = \frac{\sum_{j=1}^{n}\sum_{h\in H} N_{j,h}\,\bar{y}(j,WM)}{\sum_{j=1}^{n}\sum_{h\in H} N_{j,h}\bar{y}(j,h)} - 1 \qquad (2).$$

Accordingly, the *Pay Gap Ratio* effectively reflects the firm-level aggregate pay disparities across gender and racial groups relative to White Men's pay.

B. Descriptive Statistics: Public and Private Firms

Table 4 contains descriptive statistics for our sample. All data are winsorized at the 1% and 99% levels. Panel A describes our public firms, and Panel B reports on our private firms.

For publicly traded firms, the average *Total Imputed Pay* is \$574.93 million per firm. Assuming a workforce comprising solely of White men yields a theoretical average *Total Imputed Pay All White Men* of \$626.48 million per firm. These calculations yield an estimated *Pay Gap* of \$49.41 million per firm or \$6,067 per worker.[16]

How significant is the *Pay Gap Ratio* to the firm? In relative terms, the mean *Pay Gap Ratio* is 8.12%, suggesting that a firm saves over 8% of its total labor costs through its pay gap. Using financial accounting data as reported on the firm's Form 10-K, the mean pay gap is 6.96% of total selling, general, and administrative expenses (SG&A), implying that the average firm in our sample saves almost 7 percent of its operating costs by having a more diverse workforce. In terms of revenues and assets, the mean ratio of the pay gap over revenues is 1.44%, and the average pay gap over total assets is 0.83%.

[16] The unwinsorized means are \$674.4 million for *Total Imputed Pay All White Men*, \$610.4 million for *Total Imputed Pay,* and \$64.0 million for "Pay Gap."

As measured by the total number of employees, private firms are, on average, much smaller than public firms. The mean *Total Imputed Pay* for private firms is \$47.04 million; its average *Total Imputed Pay All White Men* is \$53.14 million. These numbers yield an average pay gap of \$5.86 million. However, in relative terms, the average pay gap for private firms surpasses those for public firms in two dimensions. First, the average per-worker pay gap for private firms is \$6,928, which exceeds the average for public firms by 14%. Second, the mean *Pay Gap Ratio* for private firms is 11.52%, which is larger than the 8.12% for public firms.

One of the reasons behind the difference in ratios may be that private firms are smaller on average and, therefore, face different supply and demand environments when hiring and paying their workforce. To explore this possibility, we divide our samples of firms into 5 buckets based on the number of their employees: 50-250; 251-500; 501-1,000; 1,001-5000; and 5000+ employees. Table 4, Panel C presents summary statistics on the *Pay Gap Ratio* by size for the public and private firms. Two observations can be made. First, for all 5 buckets, the mean *Pay Gap Ratio* is larger for private firms vis-à-vis public firms; testing for differences between means produces t-statistics significantly different from zero at the .01 level for all size levels. Thus, regardless of firm size, pay gaps appear to be larger for the private sector. Second, there is a nearly monotonic increase in the mean *Pay Gap Ratio* by size for public and private firms, respectively, with the largest firms experiencing the greatest wage gaps. Although we do not explore this phenomenon further, this finding is consistent with larger firms having more power in the workplace when setting pay levels.

C. Descriptive Statistics – Industry Breakdown

Table 5, Panel A presents the Fama-French 12 (FF12) industry breakdown of our sample firms. Compared with the Compustat-CRSP merged universe, our sample firms hail more frequently from Manufacturing; in contrast, we have fewer firms from Healthcare.

Panel B aggregates the *Pay Gap Ratio* by industry. As the table shows, there are stark differences in the magnitude of pay gaps across industries. For public firms, Finance (12.1%) and Consumer Non-Durables (11.4%) have the greatest *Pay Gap Ratios*. In contrast, Chemicals (3.8%), Utilities (4.5%), and Oil, Coal & Gas (4.8%) display the smallest ratio. For private firms, Healthcare (21.5%), Finance (12.6%), and Consumer Non-Durables (10.4%) have the largest ratios; Utilities (3.6%) has the smallest ratio.

D. Validation Tests on Imputed Labor Costs

Is the *Pay Gap Ratio* a reliable estimate? To address this question, we conduct several validation tests. We conduct these tests over public firms only, as the data we use are not available for private firms.

Table 6 contains summary statistics from three regressions. In column (1), we regress the total number of workers, as reported by Compustat, on the total number of workers taken from the EEO-1 report.[17] The coefficient on the *Total Number of Workers (EEO-1 Report)* is significantly positive, consistent with the EEO-1 report capturing a large portion of a firm's workforce. In column (2), we regress SG&A expense, as reported by Compustat, on *Total Imputed Pay*. SG&A captures many discretionary costs of the firm, including its compensation expenses. Our regression is consistent with our estimated labor cost variable capturing actual labor costs, as evidenced by

[17] The EEO-1 report is for U.S. employees only, whereas Compustat has a field for all employees, including those within and outside the U.S.

the significantly positive coefficient on *Total Imputed Pay*. In column (3), we use a different publicly available data source, the Federal Reserve FR Y-9C form. The Federal Reserve requires bank holding companies (BHC) and securities holding companies (SHC) with assets over $3 billion to file this form with the Federal Reserve. This form includes a detailed consolidated income statement, with line 7a requiring the disclosure of "salaries and employee benefits." Our sample encompasses 145 banks and 15 trading companies with information on their labor costs. As column (3) shows, regressing *Salaries and Benefits* on *Total Imputed Pay* yield a significantly positive coefficient. Thus, for the subsample of financial firms, we find evidence consistent with our measure capturing a firm's total compensation costs.[18]

IV. Economic and Political Determinants of the Pay Gap Ratio

In this section, we examine some of the economic and political determinants behind variations in the *Pay Gap Ratio*. Because the ratio is derived from state data, we exploit differences in economic and political variables across states.

A. Economic Determinants

We posit a negative association between a firm's pay gap and the bargaining power of its available labor force (Becker 1957). We use the state's *Unemployment Rate*, its percentage of *Union Participation*, and whether the state has a *Right to Work* law as our measures of the employees' bargaining power. A higher unemployment rate gives employers an advantage in hiring and compensation decisions. Belonging to a union and Right to Work laws are the flip sides of workers using collective bargaining to monitor and increase their pay levels. We predict positive

[18] As noted earlier, the EEOC pay data are drawn from W-2 Box 1, which reports taxable wages and other pay-related income; however, non-pay benefits, such as employer Social Security contributions, health insurance, and other benefits, are not included in these data, even though such benefits are typically captured in the Salaries & Benefits account reported on the FR Y-9C.

cross-sectional associations between the *Pay Gap Ratio* and *Unemployment Rate* and *Right to Work,* and a negative association with *Union Participation.* We also predict a negative association between education levels and a firm's pay gap due to education enhancing a worker's human capital (Becker 1962). We use the percentage of the state's population aged 25 years and over with at least a high school diploma (*Highschool and Above*) as our measure of education attainment, and predict a negative relation between it and the firm's pay gap.

Columns (1) through (4) of Table 7 presents summary statistics for the regressions of pay gap ratio on these four variables. As Internet Appendix Table IA.1 shows, some of these state variables are highly correlated, and therefore, we estimate our regressions separately for each variable.

Consistent with our first prediction, *Unemployment Rate*, *Union Participation Rate*, and *Right to Work* are reliably different from zero for both public (except *Unemployment Rate*) and private firms in their predicted directions. These findings are consistent with a negative cross-section association between the *Pay Gap Ratio* and workers' bargaining power. With respect to our second prediction, we find a negative relation between the *Pay Gap Ratio* and the education level of a state's adult population, a result consistent with human capital theory (Becker 1962). Thus, we present evidence of pay gaps being determined in ways consistent with labor economics theory.

B. Political Determinants

We predict systematic associations between the political environment of a state and the pay gaps for firms whose headquarters are domiciled within that state. First, we propose that states with higher minimum wages (*Minimum Wage*) have political environments more disposed to alleviating income inequality for their workforce (Derenoncourt and Montialoux 2021; Pan et al. 2022), and therefore predict a negative association between a firm's pay gap and *Minimum Wage*. Next, the Democratic party is perceived to be more protective of their workers as compared to the

Republican party's emphasis on market forces determining the wages and working conditions of workers. State governors reflect both the sentiment of their constituents and are the proponents and guardians of any state laws meant to protect workers within their state borders. We therefore propose a negative relation between a state having a *Democratic Governor* and a firm's pay gap.

Columns (5) and (6) of Table 7 present summary statistics for the regression of the *Pay Gap Ratio* on these two variables. As the table shows, there is some empirical evidence in support of pay gaps being associated with the political environment of a firm's headquarters state. For public firms, the coefficient on *Minimum Wage* is significantly negative at the 0.05 level; for private firms, the coefficient on *Democratic Governor* is reliably negative at the 0.01 level.

V. Do Investors Value the Pay Gaps Inherent in a Firm's Workforce Diversity?

In this section, we turn to our second research question, which is whether a firm's pay gap is viewed by investors as being net value-enhancing or value-decreasing.

A. Methodology

We use a market-based setting to evaluate how investors value pay gaps. Because we require market data, our analyses are limited to the 927 publicly traded firms with required data only. Internet Appendix Table IA.2 shows some firm characteristics for the sample firms. When comparing our sample of government contractors to the Compustat-CRSP universe, we find the former group is significantly larger, more profitable (in terms of ROA and the incidence of a Net Loss), and has higher growth opportunities (in terms of the MTB ratio).

We estimate the following OLS regression of the firm's CAR on its *Pay Gap Ratio*:

$$CAR_{i,t-1,t+2} = \alpha_0 + \beta_1\, Pay\ Gap\ Ratio_i + \beta_j\, State_j + \beta_k\, Industry_k + \beta_l\, Firm\ Controls_i + \varepsilon_{i,\,t-1,t+2} \quad (3),$$

where $CAR_{i,t-1,t+2}$ is firm i's FF5-factor CAR over a [-1, +2] window surrounding day 0, the DOL's release of firm i's EEO-1 report on either March 2 or April 17, 2023. We use the [-1 +2] window as a trade-off between investors needing time after the immediate release of the EEO-1 reports to process the release of the data with other value-relevant information being disclosed around the EEO-1 release dates.[19]

We further disaggregate the *Pay Gap Ratio* into an already-known (*Known EEOC Pay Gap)* based on the EEOC state and industry pay data and an incremental piece (*Incremental Differential)* based on the release of the EEO-1 report. The *Known EEOC Pay Gap* is calculated using Equation (2), where we substitute $N_{j,h}$ with the state-industry wide demographic-job distribution. This proxy may be coarse, but investors likely have updated their beliefs about a firm's pay gap ratio when the EEOC state-industry level pay data were released, since even imperfect information can be informative. We do not expect the market to respond to this previously inferable estimate. *Incremental Differential* is defined as the difference between the firm's pay gap computed from its own EEO-1 data and the *Known EEOC Pay Gap*. We expect the market to react only to the *Incremental Differential*. That is, we estimate:

$$CAR_{i,t-1,t+2} = \alpha_0 + \beta_1 \, Known\ EEOC\ Pay\ Gap_i + \beta_2 \, Incremental\ Differential_i + \beta_j \, State_j$$

$$+ \beta_k \, Industry_k + \beta_l \, Firm\ Controls_i + \varepsilon_{i,\ t-1,t+2} \qquad (4).$$

We control for state effects by including a fixed effect variable for the state in which firm i's headquarters is located (*State*$_j$). One state effect might be a firm's ability to diversify its workforce due to the state's gender and race/ethnicity demographics – for example, New Mexico has the

[19] The average CAR over the [-1, +2] window for the 927 firms is -0.55% (t-statistic = -4.63, p-value < 0.01). Alternatively, we calculate CARs ranging from [-1,0] through [-1,+4] windows. Repeating our analyses with these alternative windows produces similar findings as those reported in the paper.

highest percentage of Hispanic population in the United States at 50.2%, while Vermont has the lowest at 1.5%. Other effects might be due to political or economic factors, for example, Right to Work Laws or the state's unemployment rate. We control for industry-specific information that may come out over the [-1,+2] timeframe by including *Industry*$_k$, an integer based on firm i's FF-48 industry classification. *Industry*$_k$ also captures differences in worker productivity due to structural workforce differences across industries, for example, men being able to work longer or less flexible hours than women (Goldin, 2014).

Although the FF5-factor model controls for size and firm performance, we include several firm-specific measures to control for omitted variables that may be correlated with pay gap ratio. Firm controls are calculated at the end of 2022. Larger firms (*Ln(Size)*) have greater market power and might be able to exploit pay gaps to a larger extent. To control for possible differences in worker productivity among workers, we disaggregate ROE using a three-component Dupont equation and include *Firm Profitability*, *Asset Efficiency*, and *Firm Leverage*. *Earnings Announcement* is an integer variable for firms that had an earnings announcement over the [t-1, t+2] window. All data are winsorized at the .01 and .99 levels. We cluster robust standard errors by industry and state to account for possible heteroskedasticity in standard errors.[20]

[20] Our control variables indirectly address a "corner solution" question – if firms can benefit economically from gender and race-ethnic pay gaps, then why don't all firm hire only minority women, or only women, or only minority workers? Although we do not specifically examine this question, we offer several plausible reasons for why we do not see this phenomenon. First, the supply of minority workers in the U.S., and in many states, would not be sufficient to allow all firms to hire only minority workers. As Table 3 shows, Black and Hispanic workers make up less than one-third of the entire U.S. workforce. Second, U.S. and state labor laws prohibit firms from discriminating against hires based on gender, race, or ethnicity. As such, White and Asian men would be able to sue firms for discrimination under these laws if the firm systematically excludes them from their workplace. This would apply particularly to large U.S. firms. Third, managers are not without their perceptions and prejudices about the productivity of workers, a factor consistent with job segregation (Duchini et al. 2024).

A positive coefficient on *Pay Gap Ratio* or on *Incremental Differential* is consistent with investors viewing the pay gap as a net benefit. A negative coefficient is consistent with investors viewing a firm's pay gap as a net cost.

B. Is Our Methodology Appropriate for Our Setting?

In order for an event study to be an appropriate methodology to evaluate investors' overall reaction to the release of the EEO-1 reports, five underlying assumptions of the methodology must be satisfied. As Appendix C shows, our setting appears to satisfy each of these assumptions.

C. Empirical Results

C.1 Baseline Model

Table 8 contains summary statistics for Equation (3). In column (1), we regress *CAR* on the state and industry fixed effects only to calibrate the degree to which these two factors capture differences across firms. The R^2 value for this regression is 0.085, suggesting that 8.5% of the variation in CARs around the release of the EEO-1 reports was captured by state and industry effects. In column (2), we include *Pay Gap Ratio* as an additional variable, along with the firm control variables. The coefficient on *Pay Gap Ratio* is 7.22, significant at the 0.10 level. In economic terms, a one standard deviation increase in the pay gap ratio (5.46%) is associated with an increase in CAR of 0.39% over the window. Larger firms have higher market reactions, and earnings announcements made within the time frame are associated with abnormal stock returns. Our findings hold after controlling for state, industry, and other firm-specific characteristics.

C.2 Other Measures of the Firm's Pay Gap

To gain additional insights into how investors value pay gaps, we create an indicator, *Top 25% Pay Gap Ratio,* for firms lying in the top 25% of the *Pay Gap Ratio* distribution. These firms have the largest pay gaps and should enjoy the greatest positive market reaction upon the revelation of the EEO-1 reports. As shown in column (3) of Table 8, the coefficient on *Top 25% Pay Gap Ratio* is 1.11, significantly positive at the 0.01 level. In economic terms, firms hailing from the top quarter of the *Pay Gap Ratio* distribution had, on average, a CAR that is 1.11% greater than those firms in the bottom 75% of our pay gap sample.

In lieu of including industry effects, we construct *Within-Industry Pay Gap Ratio*, which measures a firm's *Pay Gap Ratio* relative to its industry mean. If we think of the industry mean as being an expectation of what a firm's pay gap is, then this measure measures a deviation from that expectation. As column (3) shows, the coefficient on *Within-Industry Pay Gap Ratio* is 9.87, significant at the 0.01 level. In economic terms, a one standard deviation increase in the pay gap ratio (4.3%) increases the CAR over the window [-1, +2] by 0.42%.

B.3 Incremental Information

We divide the three pay gap variables into an already-known pay gap (*Known EEOC Pay Gap)* based on the EEOC state and industry pay data and an incremental piece (*Incremental Differential)* based on the release of the EEO-1 report. The mean of the *Known EEOC Pay Gap* variable is 0.087 (the median is 0.075), with a standard deviation of 0.048. The variable's range is from a minimum of -0.021 to a maximum of 0.348. The 1% and 99% percentiles are 0.002 and 0.247, respectively. Figure 3 shows the distribution of the *Incremental Differential*. The variable has a mean of -0.005 (the median is -0.008), with a standard deviation of 0.050. Its range is from a minimum of -0.256 to a maximum of 0.401, and its 1% and 99% percentiles are -0.117 and 0.155, respectively. As the figure shows, EEO-1 forms provide a consequential degree of new information about firms' pay gaps.

Columns (5) – (7) of Table 8 present summary statistics for equation (4). To regulate the effect of outliers, we winsorize *Known EEOC Pay Gap* and *Incremental Differential* in our regression analysis at the 1% and 99% levels. Consistent with our prediction, the coefficients on *Known EEOC Pay Gap* are not reliably different from zero in any of the three regressions. This finding is consistent with investors not reacting to the known component of our estimated *Pay Gap* Ratio. In contrast, the coefficients on *Incremental Differential* are statistically different from zero at the 0.01 level for each of the three regressions. Our overall findings are consistent with the market reacting positively only to the incremental component of pay gaps.

C.3 Placebo Tests

Our methodology hinges on the assumption that the abnormal market reaction over the event windows is due to the newly-released information. However, systematic risk factors not captured by the FF5-factor expectation model or correlated idiosyncratic events within the time frame associated with pay gap ratio could produce similar findings to those reported in Table 8. To address these concerns, we perform two placebo tests.

In the first test, we calculate FF5-factor CARs around all of the 109 "pseudo-events" days outside of the March 2nd and April 17th release dates.[21] We then use these placebo CARs to re-estimate equation (4). Figure 4 presents the distribution of the placebo coefficients on *Incremental Differential*; we observe no systematic pattern of coefficients. Further, our coefficient from Table 8 (12.46) exceeds 99% of the pseudo-event placebo coefficients, suggesting that the observed market reaction is unlikely to be driven by random chance. These findings are consistent with our

[21] Specifically, we use a time period encompassing 60 calendar days before March 2nd (January 2nd, 2023), and ending 60 calendar date after April 17th (June 15th, 2023). To avoid having the pseudo windows overlapping with our event days, we exclude the 3 days before and after March 2nd and April 17th, respectively.

methodology picking up the effects of the new information, and not to other systematic risk factors or correlated idiosyncratic events reported around March 2nd or April 17th.

In the second test, we examine whether the observed effect is unique to the disclosure event rather to the underlying firm characteristics. Using the full Compustat dataset, we match our sample of EEO-1 firms lying in the top 25% of the *Pay Gap Ratio* by industry, firm size, firm profitability, asset efficiency and firm leverage. Our treatment firms are the actual filers from our sample. Using entropy balancing on the mean, variance and skewness of these variables, we construct a group of non-EEO-1 filing firms that are similar in these underlying firm characteristics. Table 9, Panel A shows the covariate distributions of the respective EEO-1 subsamples. In Panel B, we present coefficients for equation (3), in which we regress the CAR on the EEO-1 filer indicator, *Top 25% Pay Gap Ratio*, using the balanced control group as the benchmark. As the panel illustrates, the coefficient on the indicator is significantly positive, thus supporting the view that our observed effect in Table 8 is unique to the disclosure event and not to the disclosing firms' underlying firm characteristics.

VI. Alternative Explanation – The Release of the EEO-1 Report as a Stand-Alone Document

Our interpretation of the findings in Table 8 assumes that investors used the release of the EEO-1 reports to derive more precise estimates of firm-specific pay gaps. However, an alternative explanation is that investors used the data provided within these reports in ways unrelated to updating their estimates of a firm's pay gap.

A. Are We Just Capturing Workplace Diversity?

An alternative explanation to our findings is that the *Pay Gap Ratio* primarily captures the firms' workforce diversity as revealed in the firm's EEO-1 Form. As such, the positive stock price reaction to *Incremental Differential* is through more workplace diversity and not to our measure of pay gaps. There are several arguments in favor of expecting a positive market reaction to firms with greater representations of women, Blacks, and Hispanic workers. One common assertion is that heterogeneous groups lead to better decision-making, which generates more innovation and superior problem-solving skills (e.g., Dallas 2002; Dezsö and Ross 2012; Rock and Grant 2016; Reynolds and Lewis 2017; Posner 2024). A second proposition is that the presence of under-represented minorities and women is indicative of a more open and inclusive company culture. This, in turn, reduces the risks associated with employment discrimination violations, allows a firm to tap and retain a larger pool of talented and dedicated employees, and better attracts and retains customers and clients who value workplace diversity (Brummer and Strine 2022; Billings, Klein and Shi 2022; Daniels et al. 2024; Balakrishnan et al. 2023).

The empirical literature on whether workplace diversity enhances firm performance is mixed. McKinsey (2015; 2018; 2021) present evidence consistent with racial and ethnic diversity at the executive level being positively associated to future firm profits, whereas Green and Hand (2021) find no association. Daniels et al. (2024) finds a positive stock market reaction to the initial revelation of the percentage of women employees in the overall workforce for U.S. technology firms and financial firms, but their sample sizes are small (49 and 10 firms, respectively), thus limiting the generalization of their findings across industries.

Table 10 contains summary statistics for the regressions of *CAR* on different diversity measures: *%Women*; *%Black*; *%Hispanic; %Asian;* and *%Other*. In column (1), we regress the *CAR* on the percentage of women in the firm; the coefficient is significantly positive at the 0.10 level, consistent with the market rewarding firms with higher percentages of women in their workforce. However, after including *Known EEOC Pay Gap* and *Incremental Differential* as additional regressors (column 2), the coefficient on *Incremental Differential* remains significantly positive, whereas the magnitude and significance level of the coefficient on *%Women* decline dramatically.

In column (3), we disaggregate *%Women* into two components: *Known %Women* and %Women_*Incremental Difference*. *Known %Women* is taken from the EEOC pay data base. Specifically, we aggregate the number of women across the 70 racial, ethnicity and job categories for each firm's state and industry and divide that number by the total number of workers in the same state and industry. *%Women-Incremental Differential* is the actual percentage of women from the firm's EEO-1 form minus *Known %Women*. As shown in Column (3), when disaggregating the percentage of women into its known and incremental components, only the coefficient on the incremental part of the pay gap ratio is significantly positive. Our findings are consistent with *Incremental Differential* providing new information to the market after controlling for the gender balance of the firm's workforce.

We next examine the influence of race and ethnicity on our regression results. Column (4) shows summary statistics on the regressions with these demographic variables alone; column (5) adds the disaggregated *Pay Gap Ratio* variables; and column (6) includes both the known and incremental parts of the percentages of the four racial and ethnicity variables.[22] Whereas the coefficients on the raw and incremental percentages of Black or Asian workers do not reliably load in any of the estimations, the coefficients on the percent of Hispanic workers are significantly positive in all three specifications. However, including the raw (column 5) or incremental (column

[22] Alternatively, we define diversity using a Blau Index, which views diversity holistically, instead of through the percentages of different demographic groups (McKinsey 2015; 2018; 2020; Green and Hand 2021). Our findings (untabulated) with this measure are consistent with those reported in Table 8, in that the coefficient on the overall diversity measure is not significantly different from zero at conventional significance levels.

6) percentages of workers by their racial or ethnicity backgrounds do not dampen the positive association between *CAR* and *Incremental Differential*.

In sum, we conclude that although the market reaction to the release of the EEO-1 forms is positively related to the percentage of women and certain minorities within the firm's total workforce, these diversity measures do not supplant the strong market effect associated with the size of the estimated pay gap, as reflected by the coefficient on *Incremental Differential*.

B. Are We Just Capturing the Firm's Job Distribution?

The release of the EEO-1 report provided investors with two new sources of information – detailed information on workplace diversity, but also the firm's job category structure. As such, one alternative explanation to our findings is that the *Pay Gap Ratio* captures pay differentials across firms primarily through the firms' differing job category structures, and that the market is reacting positively to these differences, and not to the pay gaps themselves. For example, if the market, hypothetically, expected Firm A to have only 4% of its total employees in the highest paying category (Senior-Level Managers), but discovered that Senior-Level Managers comprised 6% of its total workforce, then it might revalue the firm's market value downwards to adjust for these additional compensation costs. Or the job categories may be capturing omitted correlated variables to *Incremental Differential*.

We begin by regressing each firm's *CAR* on its percentage of employees on the nine separate EEOC job category levels with the tenth category, *%Professionals*, being subsumed in the coefficient. As column (1) of Table 11 shows, none of the coefficients are significantly different from zero. In column (2), we add the disaggregated pay gap ratio variables to the regression. The coefficient on *Incremental Differential*, though smaller than that shown in column (5) of Table 8, is statistically significant at the 0.05 level. The coefficients on the job categories show a similar pattern as in column (1) of the current table. We therefore conclude that our pay gap variable and the firm's job category structure capture information incremental to each other.

VII. Additional Analyses

A. Measurement Error in the Estimation of the Pay Gap Ratio

Because we estimate a firm's pay gap, by definition, it contains some measurement error. If this measurement error is correlated with some omitted variable that also is correlated with market returns, then the coefficients on *Pay Gap Ratio*, and consequently, *Known EEOC Pay Gap*, and *Incremental Differential* would be biased in the direction of the correlation. In addition, the standard error would be affected, with a positive correlation increasing the standard error, but a negative correlation reducing its magnitude.

We consider two sources of measurement error: (1) job categories and (2) industry designation.

Mueller et al.(2017) and Wallsgog et al. (2024) present evidence that pay differentials between top- and bottom-level jobs are influenced by talent and seniority at the highest levels within a firm's organization. Their findings are consistent with pay gaps being related to factors other than demographic pay inequality and occupational segregation, and thus may introduce a correlated omitted variable into our analyses.

We examine this possibility by recalculating the pay gap ratio for each firm after separately removing all senior and middle management workers from the firm's total workforce. We then re-run equation (4) using the subset of employees that are not in the senior or middle management ranks, respectively. Table 12, Panel A contains summary statistics for these regressions. In column (1), we remove all senior-level managers; in column (2), we drop all middle-level managers. The coefficient on *Incremental Differential* remains significantly positive at the 0.01 level for both regressions. Dropping both senior and mid-level managers yields similar results and inferences (untabulated). Thus, we conclude that our baseline findings are not unduly influenced by differences in pay due to differences in productivity for a firm's senior and middle managers.

Mueller et al. (2024) find evidence that pay differentials below the management level are *not* systematically related to seniority or disparate talents among workers. Nevertheless, the coarseness of the job categories could be reflective of these categories lumping together occupations requiring different levels of education and professional skills, resulting in differences in earnings within each job categories. If these factors are correlated with pay gap ratio (for example gender or race/ethnicity occupation segregation within each category), then our findings and interpretations may be due to this coarseness, and not to the pay gap per se.

To assess the degree of heterogeneity within job categories, we compare occupations within each EEO-1 category as depicted in their handbook by the level of skillsets and educational background needed for the same job as delineated by O*NET. The O*NET website ranks its job descriptions from 1 through 5, with 1 being jobs with the lowest level of skillsets/educational background and 5 being jobs with the highest level. We find overlapping job titles for over 100 different jobs. As Internet Appendix Table IA.3 shows, the EEO-1 job categories generally align to one or two adjacent O*NET skillsets. For example, Operatives contain 13 overlapping job titles, with 11 occupations requiring an O*NET qualification background of "2" and 2 other jobs requiring an O*NET background of 1. Three of the categories have three levels of skillsets – Sales Workers, Administrative Support Workers, and Service Workers – suggesting more heterogeneity among jobs. Some of the overlaps are woefully incomplete, for example, the only overlap between senior level executives from the EEO-1 handbook and the O*NET website is the chief executive.

As such, we recalculate the *Pay Gap Ratio* for each firm after separately removing all workers from each of the remaining 8 job categories within the EEO-1 report from its workforce.

Regression results with each group of workers removed, respectively, are presented in columns (3) through (10) of Panel A. As the panel shows, we find no evidence that any one category of workers is unduly influencing our results.

Another source of measurement error could be associated with industry representation. We use the industry and state average pay gap between White men and other workers within a job category as our measure of the firm's pay gap for that group of workers. However, within any industry, there might be omitted variables correlated with how firms pay their employees. We examine this possibility by first re-running equation (4) after removing all firms in the FF12 Consumer Non-Durables industry. We repeat this analysis 11 more times, once for each additional FF12 industry. Panel B of Table 12 shows the coefficients and t-statistics for the 12 regressions. As the panel shows, no one industry overly influences our findings.

B. Alternative Benchmarks for Known Information

B1. Voluntary vs. Non-Voluntary Disclosers

Prior to April 17, 2023, many firms voluntarily disclosed their Type 2 EEO-1 reports on their company websites (Bourveau et al. 2025; Choi et al. 2024). As such, the demographic breakdown of their workforces were already known to investors. From an efficient market perspective, this should mute the market reaction to the DOL's disclosure of its EEO-1 report. However, this may not necessarily be true. For example, when searching for voluntary disclosures, we found some of these forms to be well-hidden within the firm's website, thus increasing search costs for investors. Further, by releasing over 19,000 Type 2 EEO-1 reports together on April 17th, investors may be able to calibrate better how an individual firm compares to other firms in its industry or local area.

We separate our publicly traded sample into 240 voluntary and 687 non-voluntary disclosures. Voluntary disclosers are those firms that had already posted their Type 2 EEO-1 report(s) on their company websites; non-voluntary disclosers are firms whose Type 2 EEO-1 report(s) were revealed for the first time on the DOL release date.

We estimate the following regression:

$$CAR_{i,t\text{-}1,t+2} = \alpha_0 + \beta_1\ \textit{Incremental Differential}_i + \beta_2\ \textit{Voluntary}_i$$

$$+ \beta_3\ (\textit{Incremental Differential*Voluntary})_i + \beta_4\ \textit{Known EEOC Pay Gap}_i$$

$$+ \beta_5\ (\textit{Known EEOC Pay Gap*Voluntary})_i + \beta_j\ \textit{State}_j + \beta_k\ \textit{Industry}_k$$

$$+ \beta_l\ \textit{Firm Controls}_i + \varepsilon_{i,t\text{-}1,t+2} \qquad (5),$$

where *Voluntary*$_i$ is an integer for firms that voluntarily disclosed their EEO-1 forms prior to the DOL release dates. A significantly positive (or negative) coefficient on $(\beta_1 + \beta_3)$ is consistent with the market pricing pay gaps for voluntary disclosures over the DOL release of their EEO-1 reports.

Table 13 contains summary statistics for equation (5). Consistent with the prior disclosure of the EEO-1 form being already priced by the market, the coefficient on $(\beta_1 + \beta_3)$ is insignificantly different from zero. When we substitute *Top 25% Incremental Differential* or *Within-Industry Incremental Differential* for *Incremental Differential*, we find similar results. These findings are similar to those found when we disaggregated the *Pay Gap Ratio* into its known and incremental parts – that is, only the coefficient on the unknown (incremental) part was found to be statistically different from zero. In summary, our findings lend further support for our event study approach to evaluating how investors value workplace diversity.

B2. U.S. Census Bureau Data

Our main analyses use the EEOC pay data as our source of known information to investors. The market, however, could form expectations by using alternative sources of U.S. pay data. For example, the U.S. Census Bureau's Current Population Survey (CPS) provides publicly available data on earnings by gender, race/ethnicity, and occupation at the national level.

We replicate our tests in Table 8 Column (1) using national BLS CPS data for 2021 and 2022.[23] The data consist of weekly national medians of full-time wages and salary by gender (Male or Female) by race, or ethnicity (White, Black, Asian Hispanic or Latino ethnicity) by occupation. Using annualized data, we compute a BLS pay-differential for each job category j, which is the difference between the average annual pay of White men and the average annual pay of demographic group h in that same job category, based on the national BLS survey data. In other words, the CPS provides an alternative way to calculate $\bar{y}(j, WM) - \bar{y}(j, h)$ that does not rely on the EEOC Pay Data.[24] Using the data, we apply Equation (1) with the same set of $N_{j,h}$ from EEO-1 to estimate the pay gaps of each sample firm. The estimated average pay gaps are $49.1 million (2021 BLS) and $49.9 million (2022 BLS), very close to the estimates based on EEOC pay data. Because the BLS CPS data are collected from households/individuals rather than firms, we cannot infer a "Known" firm-level average pay gap from them.

In untabulated specifications, the coefficient on *BLS Pay Gap Ratio* is 13.73 (2021) and 14.64 (2022), both significant at the 1% level. This additional analysis shows that our inferences do not depend on investors having direct access to EEOC pay data; they need only a comparable context for pay gaps when interpreting the EEO-1 reports.

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[23] See (https://www.bls.gov/opub/reports/race-and-ethnicity/2021/) for the 2021 data and (https://www.bls.gov/opub/reports/race-and-ethnicity/2022/) for the 2022 data.

[24] We acknowledge that this match is not as precise as using the EEOC Pay data. The BLS CPS uses different definitions of job categories and demographic groups from those in the EEO-1 forms. For example, in the CPS, individuals identified as Hispanic or Latino may be of any race. Therefore, the match is relatively coarse and is intended only as a robustness check for our main method.

C. Is the Market Reacting to the Disclosure of the Percentage of Minority Workers in Senior Management Position?

In Table 10, we include gender, race and ethnicity as additional variables to assess how the market calibrated workplace diversity from the release of the EEO-1 forms. We found that the coefficient on *Incremental Differential* was relatively unaffected by the inclusion of these demographic variables. However, investors might be reacting to a more nuanced form of diversity – the disclosure of minority workers in senior management positions, which could be imbedded in our measurement of known and incremental pay gaps. For example, Balakrishnan et al. (2023) documents a positive average abnormal return around the appointments of Black directors over the time period immediately following the Black Lives Matters movement. Their results are consistent with investors viewing diversity at the highest managerial levels in a positive light.

To examine this possibility, we replace the five demographic percentages in Table 10 with 10 variables representing the percentages of senior-level managers by gender (Men and Women) and race/ethnicity (White, Black, Hispanic, Asian, and Other). We note, however, that the percentages for each of the categories, particularly those for Black, Hispanic, and Other senior managers, are relatively small (see Figure 1), thus diminishing the power of the regression results. Summary statistics for these regressions are shown in Internet Table IA.4. For brevity, we show only the coefficients for 4 minority worker categories (*%Black Women Senior Mgrs*; *%Black Men Senior Mgrs; % Hispanic Women Senior Mgrs; %Hispanic Men Senior Mgrs*), since these are the demographic groups most likely to be on investors' radar screens. As the table shows, including the percentages of diversity within a firm's senior ranks does not absorb the effect that the incremental pay gap ratio has on our regression results.

D. Robustness Tests

We conduct several robustness tests. First, to examine the sensitivity of how we define industry, we re-calculate the pay gap by (1) collapsing the NAICS classifications to mimic the Fama French 48 industry category levels and (2) treating the 96 subsectors/three-digit codes as separate industries. Our results (untabulated) are consistent with all aggregation methods.

Next, using data from the state in which the firm is incorporated assumes that the firm pays all its employees as if they lived in the state, an assumption that may be violated for firms with operations outside their headquarters' state. Taking the average pay by industry-state assumes that the firm is a price taker at the industry-state level when paying their workers. Both assumptions most likely would be violated by larger firms, which are more likely to have operations across the country, and have the most market power in determining their wages. To address these concerns, we exclude the 244 largest firms from our publicly traded sample – those with 5,001+ employees – and re-estimate our market return regressions with this smaller sample. Our results, shown in Internet Appendix Table IA.5, are consistent with this truncated sample.

VIII. Summary and Initial Conclusions

Using the recent release of Type 2 EEO-1 reports by the Department of Labor for over 11,000 publicly traded and private U.S. contractors with previously-released detailed employee compensation data by the EEOC, we examine the prevalence, determinants, and market valuation of firm-specific pay gaps across firms. Our paper adds to the literature on pay gaps by offering insights into two lesser-known aspects of pay gaps – how they vary across firms and investor valuation of these pay gaps.

We document economically significant estimated pay gaps, averaging about $49 million a year for publicly traded firms, and about $6 million a year for private firms. These gaps vary significantly across industries. They also are relatively higher (in percentage terms) for private, and larger firms, respectively. We further use labor economics theory to make predictions about some of the determinants behind variations in pay gaps across firms. Consistent with Becker's 1957 and 1962 seminal papers, we find evidence that pay gaps are related negatively to the bargaining power of employees and to their human capital.

We exploit the release of these forms by the Department of Labor by measuring the immediate market reaction to these pay gaps for a sample of 927 publicly traded firms. Pay gaps, *ceteris paribus*, reduce labor costs, which increases net income. If investors view this in a positive light, then we expect a net positive association between market returns and the relative size of the pay gap. Conversely, if pay gaps correlate negatively with employee satisfaction, then the net market reaction may go in the opposite direction. Our results support the first view – after controlling for the firm's state of incorporation, industry classification, workforce diversity measures, job categories, and other firm-specific characteristics, we find a significantly positive abnormal stock price reaction around the release of the EEO-1 reports conditional on the size of a firm's incremental pay gap.

Our paper provides new insights into the persistence of pay gaps. By detailing the variations in pay gaps by industry, firm size, and whether a firm is publicly or privately held, we provide a partial roadmap as to where these pay gaps are most prevalent. By presenting large sample and robust evidence that investors reward firms with larger pay gaps, we make the observation that a capital markets solution may not be the most fruitful or effective path to addressing these systematic and persistent pay gaps. This latter observation is consistent with Friedman's (1970) doctrine, which is that investors view the firm's duty to maximize its earnings, and not to engage in social engineering.

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Appendix A: Amazon's 2020 Type 2 Consolidated EEO-1 Report

COMPID = T036832
UNITID = T036832

EQUAL EMPLOYMENT OPPORTUNITY
2020 EMPLOYER INFORMATION REPORT EEO-1
Consolidated Report

SECTION B – COMPANY IDENTIFICATION

1. Amazon.com, Inc.
410 TERRY AVE N
SEATTLE, WA 98109

2.a. Amazon.com, Inc.
410 TERRY AVE N
SEATTLE, WA 98109

c. EIN= 911646860

SECTION C – TEST FOR FILING REQUIREMENT

1-Y 2-Y 3-Y DUNS=

SECTION E – ESTABLISHMENT INFORMATION
NAICS: 454110 - Electronic Shopping and Mail-Order Houses

SECTION D – EMPLOYMENT DATA

JOB CATEGORIES	Hispanic or Latino		Non-Hispanic or Latino														Overall Totals
			********** Male **********						********** Female **********						
	Male	Female	White	Black or African American	Native Hawaiian Or Pacific Islander	Asian	American Indian or Alaska Native	Two or More Races	White	Black or African American	Native Hawaiian Or Pacific Islander	Asian	American Indian or Alaska Native	Two or More Races	
Exec/Sr. Officials & Mgrs	83	26	1396	56	0	416	2	28	454	37	1	93	5	13	2610
First/Mid Officials & Mgrs	3669	1654	19593	3414	100	5809	144	863	7835	1931	52	1944	86	540	47634
Professionals	3703	1810	30608	2230	99	31643	117	1600	13262	1737	63	14039	85	969	101965
Technicians	859	267	3206	736	19	564	54	245	748	170	3	148	28	53	7100
Sales Workers	8628	7772	17460	5709	180	2363	256	1195	16602	6105	174	2356	271	1236	70307
Administrative Support	1387	1825	4218	1069	48	602	71	386	6482	2809	65	1019	114	699	20794
Craft Workers	120	5	575	59	5	30	7	28	11	1	0	0	0	2	843
Operatives	5451	3118	10520	5015	139	1483	180	940	5641	3619	114	672	130	652	37674
Laborers & Helpers	79236	87211	90357	90815	2206	31828	2944	10709	74309	110729	2180	25317	3079	11157	622077
Service Workers	1553	921	1677	1030	32	345	35	125	744	512	19	182	18	64	7257
Total	104689	104609	179610	110133	2828	75083	3810	16119	126088	127650	2671	45770	3816	15385	918261
Previous Year Total	52765	51307	117202	62396	1745	47647	2080	9695	80466	74958	1569	26446	2024	9255	539555

Appendix B: Variable Definitions

Variable Names	Data Sources	Variable Definitions
CAR[-1,2]	CRSP	The Cumulative Abnormal Return (CAR) for the event window from day -1 to day 2. It is calculated by summing the abnormal returns (AR) for day -1 to day 2, where each abnormal return is the difference between the observed return and the expected return as predicted by the Fama-French 5-factor model, using factor loadings estimated from all trading days in 2022.
%Women	EEO-1 Reports (FOIA release)	The percentage of women workers in a firm's total workforce, as reported in the most recent Type 2 EEO-1 report filed during the period from 2016 to 2020.
%White, %Black, %Hispanic, %Asian %Other	EEO-1 Reports (FOIA release)	The percentage of White, Black or African American, Hispanic, Asian, and Other (Native American or Other Pacific Islander, American Indian or Alaska Native, or Two or More Races) workers in a firm's total workforce, as reported in the most recent Type 2 EEO-1 report filed during the period from 2016 to 2020.
%Senior-Level Managers, %Mid-Level Managers, %Professionals, %Technicians, %Sales Workers, %Administrative Support, %Craft Workers, %Operatives, %Laborers & Helpers, %Service Workers	EEO-1 Reports (FOIA release)	The percentage of workers in a given job category in a firm's total workforce, as reported in the most recent Type 2 EEO-1 report filed during the period from 2016 to 2020.
Total Imputed Pay (in million $)	EEO-1 Reports and EEO-1 Component 2 Pay data	The sum of a company's labor costs across all gender-race/ethnicity/job category cells, calculated using state-level average pay for each gender-race-job category group within its respective NAICS two-digit code, as derived from the 2018 EEO-1 Component 2 Pay Data.
Total Imputed Pay All White Men (in million $)	EEO-1 Reports and EEO-1 Component 2 Pay data	The hypothetical total labor cost of a firm if all employees were compensated at the average pay level of White males within their respective job categories. It is calculated by summing the recalculated pay for each gender-race/ethnicity/job category cell, using the state-level average pay of White males in the same job category, state, and NAICS two-digit code, as derived from the 2018 EEO-1 Component 2 Pay Data.
Pay Gap (in million $)	EEO-1 Reports and EEO-1 Component 2 Pay data	The difference between a firm's Total Imputed White Male Pay and its Total Imputed Pay.
Pay Gap Ratio	EEO-1 Reports and EEO-1 Component 2 Pay data	This variable is calculated by dividing a firm's Pay Gap by its Total Imputed Pay.
Top 25% Pay Gap Ratio	EEO-1 Reports and EEO-1 Component 2 Pay data	A binary variable that equals one for firms that are in the top 25% of the Pay Gap Ratio distribution and zero for all other firms.
Within-Industry Pay Gap Ratio	EEO-1 Reports and EEO-1 Component 2 Pay data	The difference between a firm's Pay Gap Ratio and the corresponding average Pay Gap Ratio of a firm's Fama-French 48 industry.
Per Worker Pay Gap (in $)	EEO-1 Reports and EEO-1 Component 2 Pay data	The firm's Pay Gap divided by the total number of workers, as reported in the most recent Type 2 EEO-1 report.

Variable Names	Data Sources	Variable Definitions
Known EEOC Pay Gap	EEO-1 Component 2 Pay data	The *Known EEOC Pay Gap* follows the same construction as the *Pay Gap Ratio*, but replaces firm-level employment counts with state–industry–level demographic–job distributions and aggregates the implied pay differences across demographic groups.
Incremental Differential	EEO-1 Reports and EEO-1 Component 2 Pay Data	The difference between the firm's *Pay Gap Ratio* computed from its own EEO-1 data and the *Known EEOC Pay Gap* from the state-industry level component 2 data.
Top 25% Incremental Differential	EEO-1 Reports and EEO-1 Component 2 Pay Data	A binary variable that equals one for firms that are in the top 25% of the *Incremental Differential* distribution and zero for all other firms.
Within- Industry Incremental Differential	EEO-1 Reports and EEO-1 Component 2 Pay Data	The difference between a firm's Pay Gap Ratio and the corresponding average *Incremental Differential* of a firm's Fama-French 48 industry.
Known %Women	EEO-1 Component 2 Pay data	Percentage of women constructed using state–industry–level gender distributions.
%Women Incremental Diff	EEO-1 Reports and EEO-1 Component 2 Pay Data	The difference between the firm's *%Women* computed from its own EEO-1 data and the *Known % Women* from the state-industry level component 2 data.
Known %Black (%Hispanic, %Asian, %Other)	EEO-1 Component 2 Pay data	Percentage of different demographic distribution constructed using state–industry–level data.
%Black(%Hispanic, %Asian, %Other) Incremental Diff	EEO-1 Reports and EEO-1 Component 2 Pay Data	The difference between the firm's *%Black* (%Hispanic, %Asian,%Other*)* computed from its own EEO-1 data and the *Known %Black* (%Hispanic, %Asian,%Other) from the state-industry level component 2 data.
Total Number of Worker (EEO-1 report)	EEO-1 Reports (FOIA release)	Total number of workers from the most recent Type 2 EEO-1 report.
Total Number of Worker (Compustat)	Compustat	Total number of workers from a firm's annual report (10-K), originally presented in thousands of workers.
SG&A	Compustat	Selling, General and Administrative (SG&A) expenses at the end of 2022.
Salaries & Benefits	FR Y-	Salaries and Employment Benefits as shown on line 7A of the FR Y-9C form for financial institutions
Total Revenue	Compustat	Total Revenue at the end of 2022.
Net Income	Compustat	Net Income at the end of 2022.
EBIT	Compustat	Operating income after depreciation and amortization at the end of 2022.
Total Assets	Compustat	Total Assets at the end of 2022.
Market Cap	Compustat	Total market value of equity. If missing, substituted by multiplying the year-end closing price of a company's stock by its total number of common shares outstanding.
ln(Size)	Compustat	The natural logarithm of Total Assets at the end of 2022.
Firm Profitability	Compustat	Net Income divided by Total Revenue at the end of 2022.
Firm Leverage	Compustat	Total Liabilities divided by Total Assets at the end of 2022.
Asset Efficiency	Compustat	Total Revenue divided by Total Assets at the end of 2022.
Earnings Announcement	Compustat	A binary variable that is set to one for firm a that had an earnings announcement over the [t-1, t+2] window, and zero otherwise.

Variable Names	Data Sources	Variable Definitions
Unemployment Rate	Federal Reserve Economic Data	State unemployment rate in 2018, which represents the percentage of the labor force that is unemployed but actively seeking employment and willing to work.
Union Participation	Federal Reserve Economic Data	The state's percentage of employed wage and salary workers who were members of unions in 2018.
Right to Work	National Right to Work Legal Defense Foundation	A binary variable for each state's Right to Work laws in 2018. These laws prohibit union security agreements between companies and workers' unions, meaning employees are not required to pay union dues or fees as a condition of employment.
Highschool and Above	Federal Reserve Economic Data	Percentage of the state population aged 25 years and over with at least a high school diploma in 2018.
Minimum Wage	Federal Reserve Economic Data	State minimum wage rates as of 2018, including federal minimum wage where applicable.
Democratic Governor	State Government Websites	Hand-collected list of the governor's party affiliation by state at the end of 2020.
Voluntary	Choi et al. (2024) and manual collection	A binary variable that is set to one for firms that voluntarily disclosed their EEO-1 forms prior to the DOL release dates, and zero otherwise.

Additional Variable Definitions for Internet Appendices

Variable Names	Data Sources	Variable Definitions
MTB	Compustat	The market value of equity over the book value of common shareholders' equity.
ROA	Compustat	The ratio of net income to the book value of total assets.
I(Loss)	Compustat	A binary variable that equals one if the firm's Return on Assets (ROA) is negative, indicating a financial loss, and zero otherwise.

Appendix C: Is an Event Study an Appropriate Methodology for Our Setting?

In order for an event study to be an appropriate methodology to evaluate investors' overall reaction to the release of the EEO-1 reports, four underlying assumptions of the methodology must be satisfied.

The first assumption is that the market must be aware of the event dates. There was much forewarning from the OFCCP about the FOIA request. On August 19, 2022, the OFCCP filed a notice on the Federal Register that it had received a request for the Federal Contractors' Type 2 EEO-1 Report Data. The OFCCP followed this up with several notices in the National Register, giving contractors the right to object to the FOIA request. On March 2, 2023, the DOL published the EEO-1 reports for 21 firms on its official website, along with a letter to Will Evans about its compliance with his FOIA request. On April 17, 2023, the DOL published the additional reports and a second letter to Will Evans. Several news outlets and law firms provided information about these releases, including Bloomberg Law News.

Second, the release dates must be unexpected and contain new value-relevant information. An examination of news reports prior to the individual releases reveals no indication that investors had advanced notice about when the DOL would release these reports. Edmans et al. (2024) presents evidence that the market does not fully price in workplace equity and inclusion as measured through survey data. Thus, investors may be able to use the EEO-1 reports alongside already published EEOC data on gender and minority pay inequalities, providing information over and above those presented in surveys or other sources.

Third, the data must be relatively easy to access and to process. The DOL made access very easy. On March 2nd, they placed the initial group of EEO-1 reports on its website, and on April 17th, they created a newly formed webpage called "Employee Information Reports" containing both the March and April reports. With respect to ease of processing these forms, the DOL provided Excel spreadsheets that are clear, accessible, and comparable to each other. In addition, investors already had experience with reading and using this form due to many firms voluntarily posting their EEO-1 reports on their company websites prior to 2023 (Bourveau et al. 2025; Choi, et al. 2024). The EEOC pay data were collected for 2017 and 2018 only, and were made available July 2019 and February 2020, respectively, and onwards.

Fourth, there should be no other systematic risk factors not captured by the FF5-factor model, or correlated idiosyncratic events within the time frame that might be associated with the pay gaps. To address these concerns, we perform several placebo tests within the paper (Section B.3). Our findings support this assumption.

Overall, we conclude that our setting is well suited for an analysis using an event study approach.

Figure 1: Pay Gaps by Gender and Job Categories

This figure compares pay gaps across different job categories of our combined private and public firm sample using data from the 2018 EEOC Pay Data File. We do not display the race/ethnicity category "Others" due to the limited number of observations.

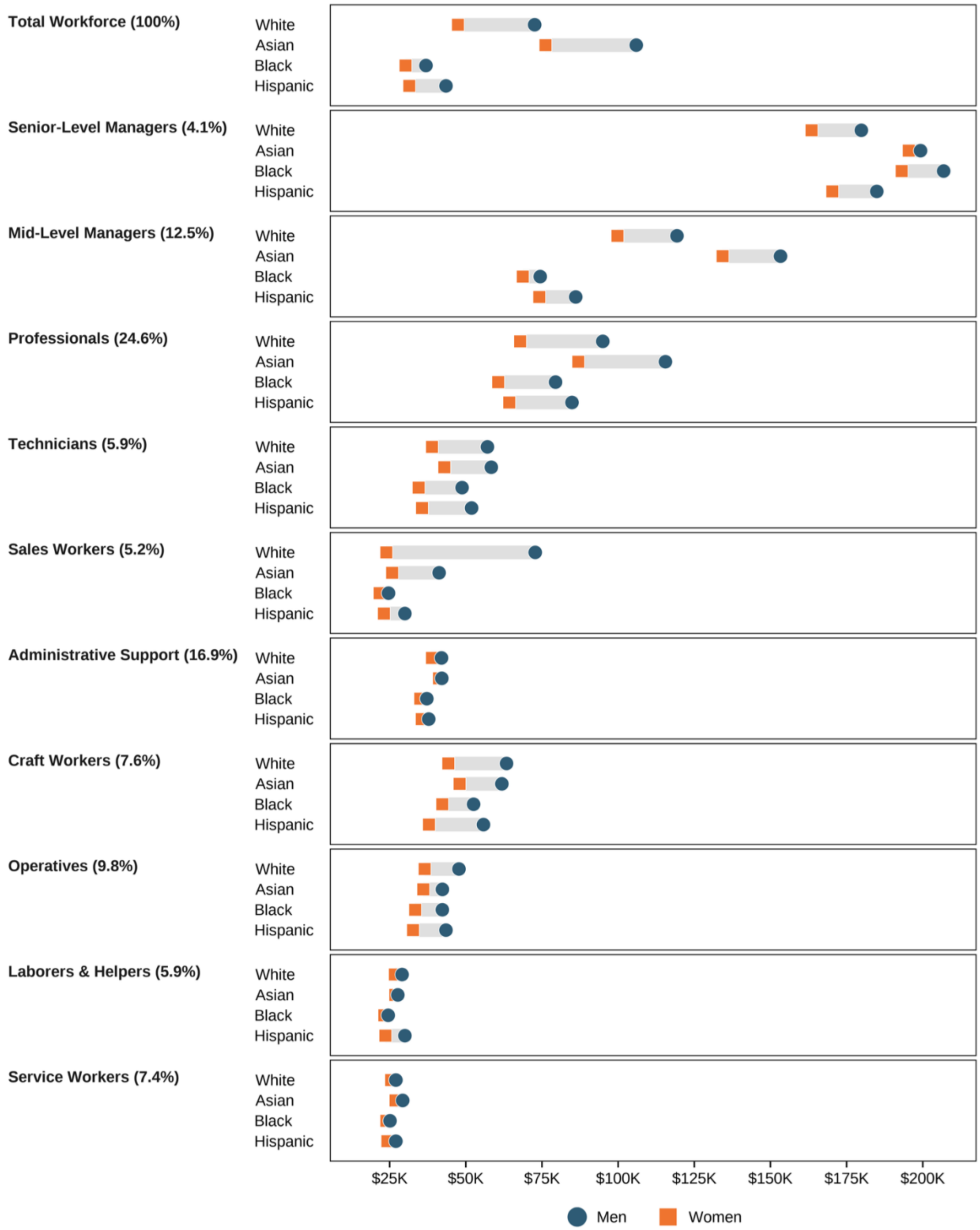

Figure 2: Workforce Distribution by Gender, Race/Ethnicity, and Job Category

This figure displays the workforce distribution of our combined private and public firm sample by gender (men in blue and women in orange), race/ethnicity, and job category. Each race/ethnicity and gender column sums to 100%. We highlight the top two race/ethnicity and gender pairs per job category. We do not display the race/ethnicity category "Others" due to the limited number of observations. Demographic data are sourced from the most recent EEO-1 report for each firm, and national average pay data are from the Bureau of Labor Statistics.

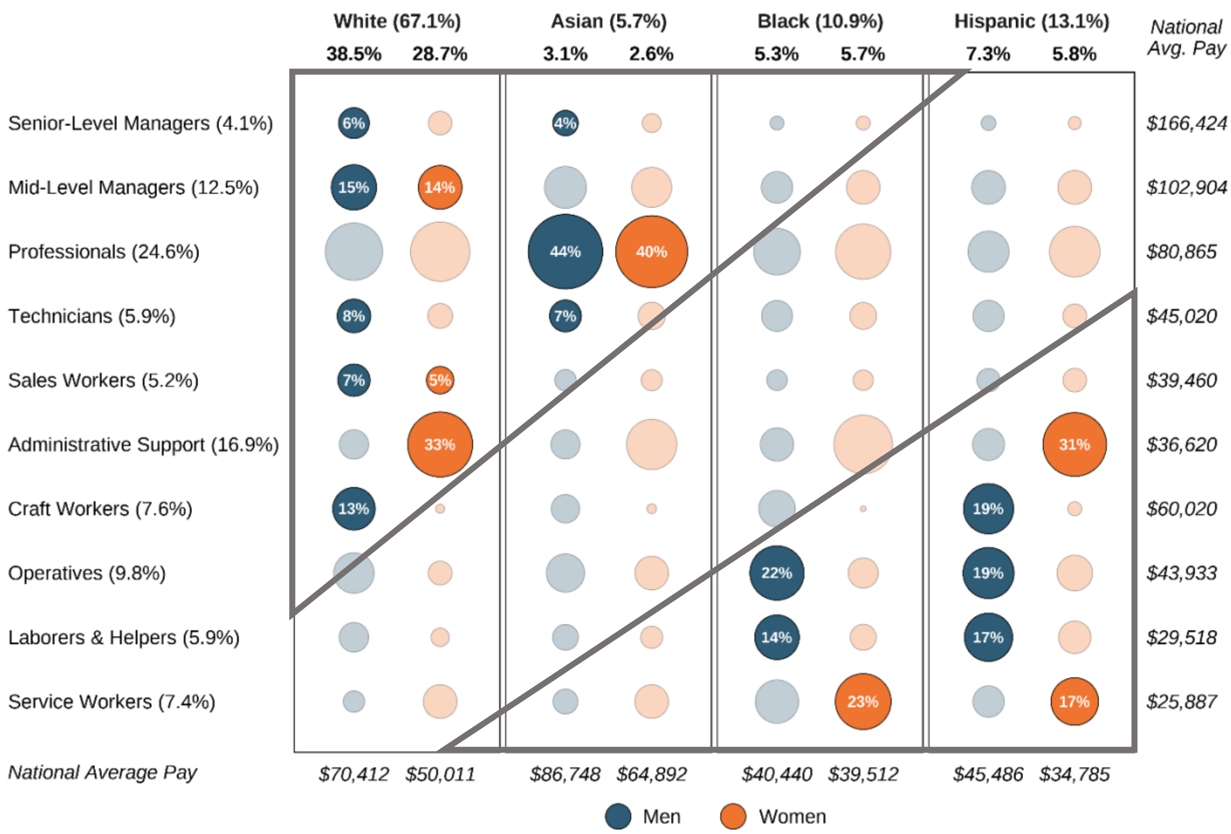

Figure 3: Distribution of the Incremental Differential after Disaggregating the Pay Gap Ratio its Known and Incremental Parts

This figure presents the distribution of *Incremental Differential* defined as the firm-specific *Pay Gap Ratio* from the combines EEOC Pay Data and EEO-1 reports minus the *Known EEOC Pay Gap* at the state × 2-digit NAICS level derived from the EEOC pay data. A positive value indicates that the firm's EEO-1 report provides information resulting in a larger estimated pay gap than its corresponding state-industry average.

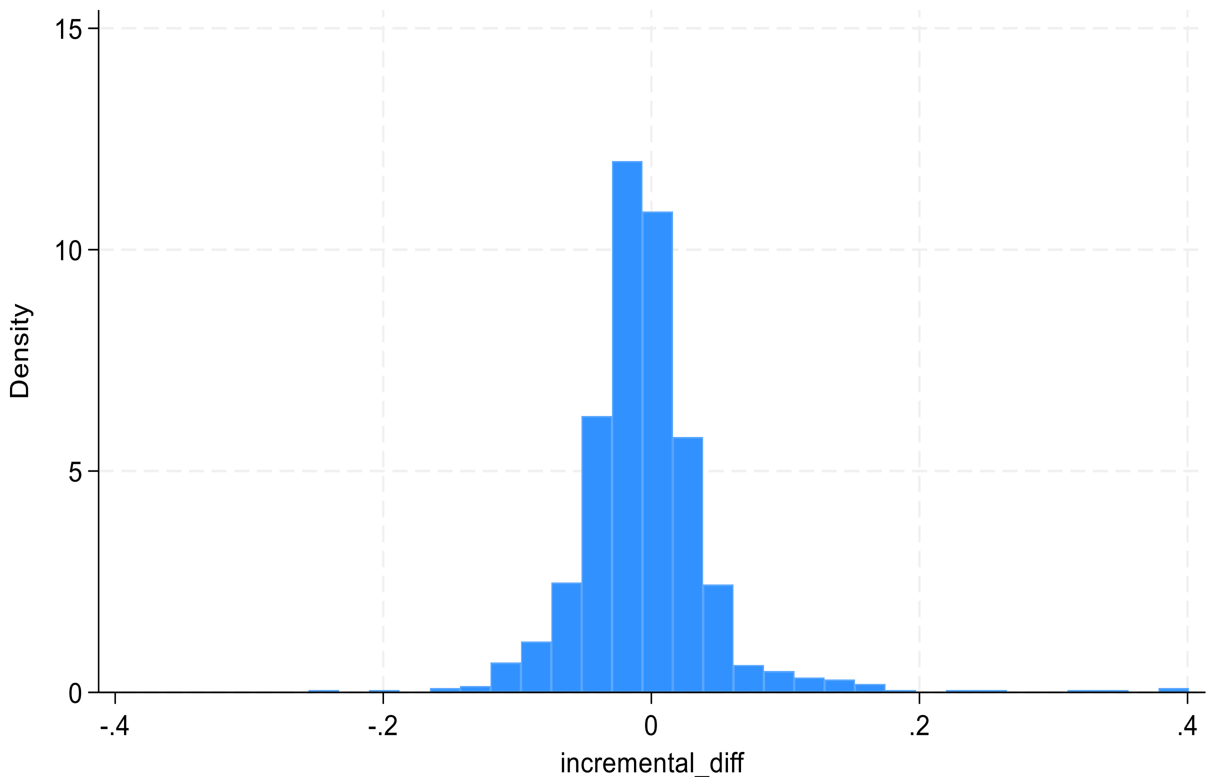

Figure 4: Distribution of Placebo Coefficients

This figure presents the distribution of the placebo test's coefficients on *Incremental Differential* for all possible (109) pseudo-event dates between January 2, 2023 and June 15, 2023, excluding the [-3,+3] windows surrounding the actual events of March 2 and April 17, 2023.

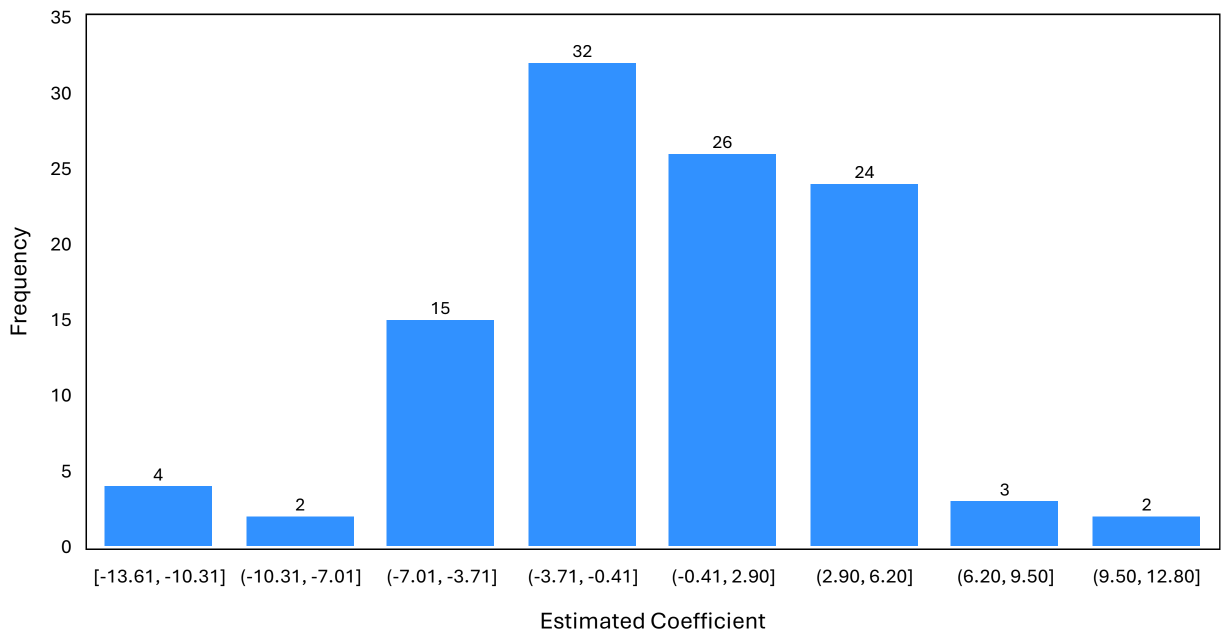

Table 1: Sample Construction

This table reports our sample construction process. Panel A presents the number of public and private sample firms after each processing step. Panel B has a breakdown of the most recent EEO-1 report for each firm we use in our analyses.

Panel A: Sample Construction

Processing Step	**Distinct # of Filings**
All Released EEO-1 forms	56,761
Processing Step	**Distinct # of Firms**
Government contractors in the FOIA release of March 2nd	21
Government contractors in the FOIA release of April 17th	19,379
Subtotal of all public and private federal government contractors	**19,400**
Private firms (no name and address match to Compustat/GVKEY possible)	18,208
After dropping private firms without industry classification	**10,434**
Public firms (valid GVKEY based on name and address matching)	1,192
After dropping firms with insufficient CRSP and Compustat data	969
After dropping firms with less than 50 employees	964
After dropping firms with mergers and acquisitions or fundamental change in operations	**927**

Panel B: Latest Available Type-2 EEO-1 Report for Each Firm

	Public Firms Sample (Most Recent EEO-1 Form)		**Private Firms Sample (Most Recent EEO-1 Form)**	
Year	**Frequency**	**Percentage**	**Frequency**	**Percentage**
2016	17	1.8%	—	—
2017	28	3.0%	1	0.0%
2018	147	15.9%	2	0.0%
2019	36	3.9%	1,128	10.8%
2020	699	75.4%	9,303	89.2%
Total	927	100.0%	10,434	100.0%

Table 2: Systematic Pay Differentials by Gender and Race/Ethnicity

This table shows pay differentials by gender in Panel A and race/ethnicity in Panel B relative to White male workers for the U.S. workforce using the 2018 EEOC Pay Data, after controlling for state and industry fixed effects. Column (1) of both panels uses all workers, while Columns (2) to (11) show the differential by job category.

Panel A: By Gender

	Pay Differential										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sample	**Full**	**Sr.-Level Managers**	**Mid-Level Managers**	**Professional**	**Technicians**	**Sales Workers**	**Admin. Support**	**Craft Workers**	**Operatives**	**Laborers & Helpers**	**Service Workers**
Women	9,046.9***	20,246.7***	11,960.1***	16,048.3***	10,054.2***	12,689.3***	1,656.0***	12,702.8***	7,457.6***	3,138.7***	2,058.8***
	(61.45)	(11.38)	(20.85)	(34.34)	(25.93)	(29.09)	(6.79)	(21.54)	(22.27)	(14.21)	(11.66)
State + Industry FE	Yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	74,188	3,877	8,016	8,819	6,501	7,456	8,873	6,137	8,134	8,194	8,181
Adj. R2	0.082	0.147	0.129	0.190	0.172	0.267	0.091	0.222	0.199	0.148	0.105

Panel B: By Race/Ethnicity

	Pay Differential										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sample	**Full**	**Sr.-Level Managers**	**Mid-Level Managers**	**Professional**	**Technicians**	**Sales Workers**	**Admin. Support**	**Craft Workers**	**Operatives**	**Laborers & Helpers**	**Service Workers**
Asian	-2,125.2***	-17,446.8***	-12,143.7***	-6,247.0***	-153.4	9,399.8***	3,590.8***	876.8	2,295.7***	744.2**	1,268.0***
	(-6.30)	(-7.16)	(-10.42)	(-7.99)	(-0.20)	(10.41)	(10.81)	(1.28)	(5.84)	(2.12)	(4.05)
Black	7,159.1***	6,320.5**	16,690.8***	9,498.3***	6,412.2***	21,160.5***	4,707.5***	5,084.2***	3,107.5***	2,209.3***	2,181.1***
	(22.73)	(2.26)	(19.90)	(16.79)	(14.60)	(23.97)	(19.90)	(9.12)	(10.02)	(9.56)	(9.11)
Hispanic	6,101.3***	5,718.4*	14,629.3***	8,218.4***	6,009.7***	17,922.0***	4,657.1***	4,795.0***	2,903.9***	715.2**	1,506.8***
	(14.10)	(1.76)	(14.71)	(10.74)	(13.46)	(20.70)	(18.66)	(10.16)	(8.34)	(2.64)	(6.42)
American Indian	3,331.2***	-13,659.5*	10,329.7***	2,525.1**	5,677.2***	15,968.7***	5,576.5***	-1,812.0*	1,741.6***	2,774.0***	3,377.8***
	(9.88)	(-1.92)	(5.80)	(2.49)	(5.67)	(14.24)	(10.37)	(-1.75)	(3.23)	(6.58)	(11.01)
Hawaiian	4,429.3***	34.2	11,108.3***	2,225.6	5,016.9***	18,014.0***	6,051.6***	1,422.9	5,125.0***	3,621.0***	3,981.4***
	(7.73)	(0.00)	(4.60)	(1.07)	(3.90)	(18.42)	(8.74)	(0.80)	(8.35)	(10.01)	(10.32)
Two or more	8,220.2***	-3,056.7	14,471.8***	9,243.6***	8,954.4***	20,396.7***	7,242.4***	6,971.6***	7,846.1***	5,222.0***	3,688.1***
	(28.38)	(-0.71)	(18.28)	(14.11)	(15.59)	(20.09)	(21.79)	(10.89)	(19.86)	(17.10)	(14.04)
State + Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	74,188	3,877	8,016	8,819	6,501	7,456	8,873	6,137	8,134	8,194	8,181
Adj. R2	0.064	0.113	0.242	0.122	0.113	0.310	0.149	0.114	0.138	0.152	0.115

Table 3: Gender and Race/Ethnicity Distributions

This table reports firms' gender and race/ethnicity compositions. Panel A reports the national-level demographics for the U.S. employed workforce from 2020 to 2023. The data are obtained from the U.S. Bureau of Labor Statistics. Panels B and C show the demographics of our public and private sample firms, respectively.

Panel A: National Aggregate of U.S. Workforce Diversity

Variable	2020	2021	2022	2023
BLS Men%	53%	53%	53%	53%
BLS Women%	47%	47%	47%	47%
BLS White%	78%	78%	77%	77%
BLS Black%	12%	12%	13%	13%
BLS Hispanic%	18%	18%	19%	19%
BLS Asian%	6%	7%	7%	7%

Panel B: Overall Diversity of Public Firms

Variable	Obs.	Mean	Std.	Min	Q25	Median	Q75	Max
%Men	927	61%	19%	6%	47%	64%	76%	97%
%Women	927	39%	19%	3%	24%	36%	53%	94%
%White	927	68%	16%	2%	59%	70%	79%	99%
%Black	927	8%	7%	0%	3%	6%	11%	70%
%Hispanic	927	11%	9%	0%	5%	8%	14%	87%
%Asian	927	10%	12%	0%	2%	6%	13%	92%
%Other	927	3%	3%	0%	2%	2%	3%	41%

Panel C: Overall Diversity of Private Firms

Variable	Obs.	Mean	Std.	Min	Q25	Median	Q75	Max
%Men	10,434	55%	26%	0%	31%	60%	79%	100%
%Women	10,434	45%	26%	0%	21%	40%	69%	100%
%White	10,434	67%	23%	0%	53%	72%	86%	100%
%Black	10,434	11%	14%	0%	2%	6%	14%	99%
%Hispanic	10,434	13%	17%	0%	3%	7%	17%	100%
%Asian	10,434	5%	9%	0%	1%	2%	6%	100%
%Other	10,434	3%	5%	0%	1%	2%	4%	80%

Table 4: Summary Statistics for the Pay Gap Ratio

This table provides descriptive statistics for our imputed pay variables across the sample firms. Panel A contains the breakdown for public firms and Panel B for private firms, respectively. Panel C compares *Pay Gap Ratios* across public and private firms for different employee size thresholds. All variables are winsorized at the 1% and 99% levels. See Appendix B for variable definitions.

Panel A: Public Firms

Variable	**Obs.**	**Mean**	**Std.**	**Q25**	**Median**	**Q75**
Total Imputed Pay (in million $)	927	574.93	1,467.22	45.49	132.37	390.82
Total Imputed Pay All White Men (in million $)	927	626.48	1,612.79	48.84	143.90	421.54
Pay Gap (in million $)	927	49.41	146.52	2.57	9.08	29.37
Per Worker Pay Gap (in $)	927	6,067	3,883	3,380	5,301	8,048
Total Number of Workers	927	8,107	21,342	572	1,772	5,317
Pay Gap Ratio	927	8.12%	5.46%	4.56%	7.02%	10.22%
Pay Gap/SG&A	835	6.96%	10.83%	1.86%	3.73%	7.16%
Pay Gap/Total Revenue	927	1.44%	1.54%	0.41%	0.92%	1.96%
Pay Gap/Net Income	927	10.31%	69.90%	−0.93%	4.56%	13.40%
Pay Gap/EBIT	927	16.11%	68.50%	0.78%	4.15%	10.81%
Pay Gap/Total Assets	927	0.83%	1.33%	0.12%	0.35%	0.94%

Panel B: Private Firms

Variable	**Obs.**	**Mean**	**Std.**	**Q25**	**Median**	**Q75**
Total Imputed Pay (in million $)	10,434	47.04	105.39	7.83	15.17	35.97
Total Imputed Pay All White Men (in million $)	10,434	53.14	121.46	8.66	16.75	39.80
Pay Gap (in million $)	10,434	5.86	16.04	0.59	1.41	3.72
Per Worker Pay Gap (in $)	10,434	6,928	4,868	3,452	5,822	9,230
Total Number of Workers	10,434	788	1,826	124	244	591
Pay Gap Ratio	10,434	11.52%	8.84%	5.38%	9.03%	15.15%

Panel C: Within Firm Size Comparisons of the Labor Cost Saving Ratio

	Public Firms' Pay Gap Ratios			**Private Firms' Pay Gap Ratios**			**t-test of the Mean**
Firm Size	**Obs.**	**Mean**	**Std.**	**Obs.**	**Mean**	**Std.**	
50 to 250 Employees	103	7.43%	5.96%	5,318	11.02%	9.46%	3.59%***
251 to 500 Employees	103	8.38%	5.01%	2,121	11.54%	9.58%	3.16%***
501 to 1,000 Employees	131	7.97%	6.02%	1,359	11.96%	9.36%	3.99%***
1,001 to 5,000 Employees	346	8.04%	5.68%	1,315	12.57%	9.25%	4.53%***
>5,001 Employees	244	8.84%	7.27%	321	15.80%	9.34%	6.96%***

Table 5: Pay Gap Ratios Across Fama-French 12 Industry Classifications

This table shows the industry composition and *Pay Gap Ratios* for public and private firms by their Fama-French 12 industry classifications. Panel A lists the number of unique firms by industry for our sample firms (public and private) and the Compustat-CRSP universe. Panel B shows information on the number of total workers and the average *Pay Gap Ratio* by industry. Both variables are winsorized at the 1% and 99% levels.

Panel A: Industry Composition

	Public Firms		Compustat-CRSP		Private Firms	
Fama-French Industries	**Frequency**	**Percentage**	**Frequency**	**Percentage**	**Frequency**	**Percentage**
Consumer Non-Durables	38	4.1%	159	3.2%	304	2.9%
Consumer Durables	26	2.8%	105	2.1%	68	0.7%
Manufacturing	122	13.2%	339	6.8%	839	8.0%
Oil, Gas & Coal	35	3.8%	148	3.0%	42	0.4%
Chemicals	23	2.5%	94	1.9%	85	0.8%
Business Equipment	172	18.6%	731	14.6%	580	5.6%
Telephone & TV Transmission	14	1.5%	68	1.4%	15	0.1%
Utilities	34	3.7%	75	1.5%	142	1.4%
Wholesale & Retail	48	5.2%	329	6.6%	789	7.6%
Healthcare	89	9.6%	781	15.6%	910	8.7%
Finance	213	23.0%	1,050	21.0%	1,358	13.0%
Other	113	12.2%	1,122	22.4%	5,302	50.8%
Total	927	100.0%	5,001	100.0%	10,434	100.0%

Panel B: Pay Gap Ratios

	Public Firms			Private Firms		
Fama-French Industries	**# Firms**	**# Workers**	**Mean Pay Gap Ratio**	**# Firms**	**# Workers**	**Mean Pay Gap Ratio**
Consumer Non-Durables	38	196,052	11.4%	304	233,268	10.4%
Consumer Durables	26	173,769	7.4%	68	105,978	7.7%
Manufacturing	122	812,334	5.6%	839	518,274	6.3%
Oil, Gas & Coal	35	113,248	4.8%	42	27,402	6.9%
Chemicals	23	143,646	3.8%	85	86,470	5.9%
Business Equipment	172	878,980	5.7%	580	340,639	7.5%
Telephone & TV Transmission	14	304,446	6.9%	15	4,948	8.1%
Utilities	34	262,371	4.5%	142	91,376	3.6%
Wholesale & Retail	48	1,455,116	9.1%	789	510,166	8.5%
Healthcare	89	339,242	7.3%	910	1,689,101	21.5%
Finance	213	1,245,188	12.1%	1,358	768,546	12.6%
Other	113	1,590,646	9.4%	5,302	3,848,306	11.7%

Table 6: Validation Tests on Imputed Labor Costs

This table presents the results of regression analyses comparing the data we use in constructing our variables with data from Compustat. Firm controls consist of *ln(Size)*, *Firm Profitability*, *Asset Efficiency*, *Firm Leverage*, and an indicator for firms that had an earnings announcement over the [t-1, t+2] window. All variables are winsorized at the 1% and 99% levels. See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Total Number of Workers (Compustat)	**SG&A (Compustat)**	**Salaries & Benefits (FR Y-9C)**
	(1)	**(2)**	**(3)**
Total Number of Workers (EEO-1 report)	1.48***		
	(34.70)		
Total Imputed Pay (in million $)		2.10***	1.83***
		(8.10)	(11.37)
Firm Controls	yes	yes	yes
Industry FE	yes	yes	--
State FE	yes	yes	yes
Observations	916	835	160
Adj. R2	0.88	0.81	0.93

Table 7: Economic and Political Determinants of the Pay Gap Ratio

This table examines the relationship between our imputed Pay Gap Ratio and state-level labor market and political characteristics. Panel A presents the results for our sample of public firms, and Panel B for our sample of private firms, respectively. See Appendix B for variable definitions. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Public Firms

		Pay Gap Ratio					
	Prediction	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Unemployment Rate	+	-0.00					
		(-0.29)					
Union Participation	–		-0.00*				
			(-1.82)				
Right to Work	+			0.01***			
				(2.99)			
Highschool and Above	–				-0.00***		
					(-2.98)		
Minimum Wage	–					-0.00**	
						(-2.12)	
Democratic Governor	–						-0.01
							(-1.64)
Observations		927	927	927	927	927	927
Adj. R2		0.00	0.00	0.01	0.01	0.00	0.00

Panel B: Private Firms

		Pay Gap Ratio					
	Prediction	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Unemployment Rate	+	0.00***					
		(3.33)					
Union Participation	–		-0.00**				
			(-2.52)				
Right to Work	+			-0.00**			
				(2.01)			
Highschool and Above	–				-0.00***		
					(-11.08)		
Minimum Wage	–					0.00	
						(1.61)	
Democratic Governor	–						-0.01***
							(-3.97)
Observations		10,434	10,434	10,434	10,434	10,434	10,434
Adj. R2		0.00	0.00	0.00	0.01	0.00	0.00

Table 8: Investor Reactions to the Pay Gap Ratio

This table presents the results of regression analyses examining the relation between CAR[-1,2] and imputed Pay Gap variables. See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Pay Gap Ratio		7.22*					
		(1.93)					
Top 25% Pay Gap Ratio			1.11***				
			(3.02)				
Within-Industry Pay Gap Ratio				9.87***			
				(3.39)			
Incremental Differential					12.46***		
					(3.12)		
Top 25% Incremental Differential						0.87***	
						(3.54)	
Within-Industry Incremental Differential							14.57***
							(4.71)
Known EEOC Pay Gap					2.79	-0.20	7.99
					(0.56)	(-0.04)	(1.66)
ln(Size)		0.30**	0.30**	0.32***	0.28**	0.30**	0.31***
		(2.30)	(2.35)	(3.06)	(2.09)	(2.33)	(2.83)
Firm Profitability		0.66	0.67	0.77	0.72	0.63	0.82
		(0.53)	(0.54)	(0.62)	(0.58)	(0.52)	(0.67)
Asset Efficiency		0.02	0.04	0.23	-0.04	0.00	0.19
		(0.03)	(0.07)	(0.59)	(-0.06)	(0.00)	(0.48)
Firm Leverage		-0.15	-0.18	-0.24	-0.12	-0.16	-0.22
		(-0.21)	(-0.24)	(-0.36)	(-0.18)	(-0.23)	(-0.29)
Earnings Announcement		1.28***	1.22***	1.61***	1.34***	1.24***	1.66***
		(4.74)	(3.84)	(5.71)	(4.76)	(3.89)	(5.18)
Industry FE	yes	yes	yes	--	yes	yes	--
State FE	yes	yes	yes	yes	yes	yes	yes
Observations	927	927	927	927	927	927	927
Adj. R2	0.085	0.116	0.118	0.058	0.120	0.115	0.060

Table 9: Placebo Test: Controlling for Fundamental Characteristics

This table presents the placebo test in which placebo tests in which we use entropy balancing to construct control groups of non-EEO-1 firms in terms of their fundamental characteristics. Panel A shows the entropy-balanced treatment and control groups. Panel B presents regression results using the balanced control group as the benchmark. See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Covariate Balances of EEO-1 Top 25% Pay Gap Ratio Firms and Non-EEO-1 Firms

Variable	**Group**	**Mean (Before)**	**Variance (Before)**	**Skewness (Before)**	**Mean (After)**	**Variance (After)**	**Skewness (After)**
ln(Size)	Top 25% Pay Gap Ratio (EEO-1)	8.532	3.627	0.147	8.532	3.627	0.147
	Non EEO-1 firms (Control)	7.075	5.561	-0.024	8.532	3.627	0.147
Firm Profitability	Top 25% Pay Gap Ratio (EEO-1)	0.060	0.080	-4.663	0.060	0.080	-4.663
	Non EEO-1 firms (Control)	-3.790	375.6	-6.661	0.060	0.080	-4.847
Asset Efficiency	Top 25% Pay Gap Ratio (EEO-1)	0.568	0.509	1.801	0.568	0.509	1.801
	Non EEO-1 firms (Control)	0.636	0.416	1.881	0.568	0.509	1.801
Firm Leverage	Top 25% Pay Gap Ratio (EEO-1)	0.708	0.056	-0.243	0.708	0.056	-0.243
	Non EEO-1 firms (Control)	0.608	0.107	1.060	0.708	0.056	-0.243

Panel B: Treatment Effect

	CAR[-1,+2]
Top 25% Pay Gap Ratio	0.60***
	(2.91)
Observations	4,086
Adjusted R-squared	0.16
Industry FE	yes
State FE	yes

Table 10: Workforce Diversity and the Disaggregated Pay Gap Ratio

This table presents the results of regression analyses examining the relation between CAR[-1,2] and the Known and Incremental Differential portions of the disaggregated *Pay Gap Ratio*, after controlling for the firm's workforce diversity. We examine gender in columns (1) to (3) and race/ethnicity in columns (4) to (6). See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]					
	(1)	(2)	(3)	(4)	(5)	(6)
Incremental Differential		12.59**	12.27**		11.06**	10.84**
		(2.66)	(2.54)		(2.27)	(2.19)
Known EEOC Pay Gap		2.84	3.29		2.12	3.42
		(0.54)	(0.70)		(0.42)	(0.54)
%Women	1.80*	-0.11				
	(1.88)	(-0.10)				
%Women Incremental Diff			0.09			
			(0.07)			
Known %Women			-0.65			
			(-0.52)			
%Black				1.13	0.03	
				(0.47)	(0.01)	
%Hispanic				4.91***	3.57**	
				(3.50)	(2.34)	
%Asian				-0.18	0.05	
				(-0.09)	(0.03)	
%Other				-11.61*	-13.63*	
				(-1.83)	(-1.93)	
%Black Incremental Diff						-0.35
						(-0.12)
%Hispanic Incremental Diff						4.19**
						(2.67)
%Asian Incremental Diff						-0.67
						(-0.25)
%Other Incremental Diff						-20.48**
						(-2.350)
Known %Black						1.73
						(0.31)
Known %Hispanic						7.08
						(1.53)
Known %Asian						5.87
						(1.10)
Known %Other						-27.38
						(-1.27)
Firm Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
Observations	927	927	927	927	927	927
Adj. R2	0.111	0.119	0.118	0.116	0.122	0.122

Table 11: Job Categories and the Disaggregated Pay Gap Ratio

This table presents the results of regression analyses examining the relation between CAR[-1,2] and the Known and Incremental Differential parts of the disaggregated *Pay Gap Ratio*, after controlling for the firm's job categories. We omit the job category with the highest representation, % Professionals, to avoid perfect collinearity. See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]	
	(1)	**(2)**
Incremental Differential		9.34**
		(2.23)
Known EEOC Pay Gap		2.33
		(0.45)
%Senior-Level Managers	1.63	3.11
	(0.23)	(0.43)
%Mid-Level Managers	-0.27	-0.15
	(-0.09)	(-0.05)
%Technicians	0.66	0.58
	(0.13)	(0.12)
%Sales Workers	4.66	3.63
	(1.31)	(1.07)
%Administrative Support	-0.09	0.10
	(-0.03)	(0.03)
%Craft Workers	1.29	1.37
	(0.39)	(0.43)
%Operatives	1.99	1.83
	(0.66)	(0.63)
%Laborers & Helpers	1.01	0.98
	(0.34)	(0.35)
%Service Workers	4.35	3.78
	(1.15)	(1.03)
Firm Controls	yes	yes
Industry FE	yes	yes
State FE	yes	yes
Observations	920	920
Adj. R2	0.116	0.119

Table 12: Robustness of the Pay Gap Ratio to Different Job Categories and Industries

This table presents summary statistics from the regressions of CAR[-1,2] on the Known and Incremental Differential parts of the disaggregated *Pay Gap Ratio*. In Panel A, we recalculate the *Pay Gap Ratio* for each firm after sequentially omitting the indicated job category. In Panel B, we replicate our main results after sequentially omitting each of the 12 Fama-French industries. See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Omitting Different Job Categories

	CAR [-1,+2]									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Omitted Job Category	**Sr.-Level Managers**	**Mid-Level Managers**	**Professional**	**Technicians**	**Sales Workers**	**Admin. Support**	**Craft Workers**	**Operatives**	**Laborers & Helpers**	**Service Workers**
Incremental Differential	11.74***	9.63***	9.40**	12.51***	18.29***	11.55***	12.89***	11.89***	13.42***	12.17***
	(3.31)	(2.83)	(2.61)	(3.29)	(3.75)	(2.73)	(3.17)	(2.77)	(3.32)	(3.14)
Known EEOC Pay Gap	2.91	2.55	6.21*	2.00	5.17	1.97	2.19	1.98	0.95	3.44
	(0.61)	(0.48)	(1.76)	(0.39)	(1.00)	(0.36)	(0.46)	(0.45)	(0.17)	(0.68)
Firm Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry + State FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	927	927	927	927	927	927	927	927	927	927
Adj. R2	0.118	0.117	0.115	0.119	0.122	0.118	0.120	0.118	0.121	0.119

Panel B: Omitting Different Fama-French Industries

	CAR [-1,+2]											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Omitted Industry	**Consumer Non-Dur.**	**Consumer Durables**	**Manufact.**	**Oil, Gas & Coal**	**Chemicals**	**Business Equip.**	**Phone & TV Trans.**	**Utilities**	**Wholesale & Retail**	**Health**	**Finance**	**Other**
Incremental Differential	13.90***	13.00***	12.63***	12.98***	11.87***	13.04**	11.03***	12.62***	13.51***	10.26***	15.43***	9.93**
	(3.45)	(2.88)	(3.02)	(3.09)	(2.86)	(2.69)	(2.99)	(3.13)	(3.10)	(2.74)	(3.42)	(2.26)
Known EEOC Pay Gap	3.58	3.23	1.58	3.22	2.88	2.24	0.99	2.87	8.17*	4.05	2.00	0.25
	(0.64)	(0.68)	(0.27)	(0.59)	(0.55)	(0.45)	(0.18)	(0.54)	(1.87)	(0.81)	(0.47)	(0.04)
Firm Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry + State FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	889	901	805	892	904	755	913	893	879	838	714	814
Adj. R2	0.120	0.125	0.128	0.091	0.117	0.099	0.123	0.119	0.127	0.174	0.088	0.110

Table 13: Voluntary vs. Non-Voluntary Disclosure of EEO-1 Reports

This table divides our sample of public firms into two subsamples: firms that voluntarily disclosed their EEO-1 reports before the FOIA release ("Voluntary Disclosers") and firms that did not disclose these reports ("Non-Voluntary Disclosers"). We examine the partial effects of $\frac{\partial CAR}{\partial Pay\ Gap\ Variable}$ when the "Voluntary" variable is set to one. The regressions determine whether the capital market calibrated the incremental pay gap ratio against the already known information from the previously disclosed EEO-1 reports. See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]		
	(1)	**(2)**	**(3)**
Incremental Differential	14.84***		
	(2.77)		
Top 25% Incremental Differential		0.92**	
		(2.58)	
Within-Industry Incremental Differential			14.57**
			(2.64)
Voluntary	0.37	0.10	0.34
	(1.07)	(0.31)	(0.97)
Incremental Differential × Voluntary	-8.48		
	(-0.98)		
Top 25% Incremental Differential × Voluntary		-0.19	
		(-0.26)	
Within-Industry Incremental Differential × Voluntary			-7.79
			(-0.84)
Known EEOC Pay Gap	5.33	1.10	5.02
	(1.14)	(0.21)	(1.05)
Known EEOC Pay Gap × Voluntary	-7.93	-4.60	-6.86
	(-1.58)	(-0.80)	(-1.24)
Pay Gap variables + Interaction term = 0	p=0.300	p=0.170	p=0.288
Firm Controls	yes	yes	yes
Industry FE	yes	yes	yes
State FE	yes	yes	yes
Observations	927	927	927
Adj. R2	0.119	0.113	0.119

Internet Appendices

Table IA.1: Correlations of Economic and Political Determinants of the Pay Gap Ratio

This table examines the correlations between state-level labor market and political factors. Panel A presents the results for our sample of public firms, and Panel B for our sample of private firms, respectively. See Appendix B for variable definitions.

Panel A: Public Firms

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Unemployment Rate	1.0000	0.2903	−0.3135	−0.4113	0.1851	0.3098
(2) Union Participation	0.2903	1.0000	−0.7929	0.1119	0.6971	0.5416
(3) Right to Work	−0.3135	−0.7929	1.0000	−0.2253	−0.6704	−0.5098
(4) Highschool and Above	−0.4113	0.1119	−0.2253	1.0000	−0.0470	0.0069
(5) Minimum Wage	0.1851	0.6971	−0.6704	−0.0470	1.0000	0.3892
(6) Democratic Governor	0.3098	0.5416	−0.5098	0.0069	0.3892	1.0000

Panel B: Private Firms

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Unemployment Rate	1.0000	0.2903	−0.3135	−0.4113	0.1851	0.3098
(2) Union Participation	0.2903	1.0000	−0.7929	0.1119	0.6971	0.5416
(3) Right to Work	−0.3135	−0.7929	1.0000	−0.2253	−0.6704	−0.5098
(4) Highschool and Above	−0.4113	0.1119	−0.2253	1.0000	−0.0470	0.0069
(5) Minimum Wage	0.1851	0.6971	−0.6704	−0.0470	1.0000	0.3892
(6) Democratic Governor	0.3098	0.5416	−0.5098	0.0069	0.3892	1.0000

Table IA.2: Firm Characteristics

This table presents the firm characteristics of the sample of public firms. See Appendix B for variable definitions.

	Public Firms (as of the end of 2022)			Compustat-CRSP (as of the end of 2022)			t-test of the Mean
Variable	**Obs.**	**Mean**	**Std.**	**Obs.**	**Mean**	**Std.**	
ln(Size)	927	7.939	1.970	5,491	6.841	2.420	1.098***
Firm Leverage	927	0.272	0.210	5,491	0.278	0.262	−0.006
MTB	920	4.235	7.386	5,463	2.727	8.169	1.508***
ROA	927	−0.002	0.138	5,489	−0.189	0.527	0.187***
Market Cap	927	14,970	37,255	5,898	6,934	21,128	8,036***
I(Loss)	927	0.292	0.455	5,898	0.442	0.497	−0.150***

Table IA.3: O*NET Categories

This table compares how each job category listed in the EEOC instruction booklet (EEOC, 2022) compares with O*NET's job examples by skillsets and educational backgrounds, as defined by O*NET.

EEO-1 Label	EEO-1 Job Category Job Description	O*Net Zone
Category 1	*Executive/Senior Level Officials and Managers*	
	Chief Executive Officer	5
Category 1.2	*First- and Mid-Level Officials and Managers*	
	Human Resources	5
	Information Systems, Marketing, Operations, Purchasing and Transportation, Storage and Distribution Managers	4
Category 2	*Professionals*	
	Architects, Lawyers, Librarians, Mathematical Scientists, Dieticians, Physicians,	5
	Accountants and Auditors, Airplane Pilots, Chemists, Computer Programmers, Editors, Engineers, Registered Nurses, Teachers, Surveyors	4
Category 3	*Technicians*	
	Emergency Medical Technicians, Chemical Technicians, Broadcast and Sound Engineering Technicians	3
Category 4	*Sales Workers*	
	Advertising Sales Agents, Insurance Sales Agents	4
	Real Estate Brokers	3
	Telemarketers, Retail Salespersons, Counter and Rental Clerks, Cashiers	2
Category 5	*Administrative Support Workers*	
	Proofreaders	4
	Bookkeepers, Desktop Publishers, Accounting and Auditing Clerks	3
	Office and Administrative Support, Cargo and Freight Agents, Dispatchers, Couriers, Data Entry Keyers, Computer Operators, Receiving and Traffic Clerks, Word Processors and Typists, General Office Clerks	2
Category 6	*Craft Workers*	
	Aircraft Mechanics, Electronic Equipment Repairers, Tool and Die Makers, Boilermakers, Electricians, Plumbers	3
	Automotive Mechanics, Brick and Stone Masons, Carpenters, Etchers and Engravers, Millwrights, Painters, Glaziers, Pipe Layers, Roofers, Earth Drillers, Gas Rotary Drill Operators	2
	Plasterers, Derrick Operators	1
Category 7	*Operatives*	
	Textile Machine Workers, Photographic Process Workers, Electronic Equipment Assemblers, Bakers, Bridge and Lock Tenders, Bus or Taxi Drivers, Forklift Operators, Parking Lot Attendants, Sailors, Semiconductor Processors	2
	Laundry and Dry-cleaning Workers, Graders and Sorters, Conveyor Operators	1
Category 8	*Laborers and Helpers*	
	Vehicle and Equipment Cleaners, Stock and Material Movers, Service Station Attendants, Construction Laborers, Refuse and Recyclable Materials Collectors	2
	Septic Tank Servicers, Sewer Pipe Cleaners	1
Category 9	*Service Workers*	
	Janitors, Private Detectives and Investigators	3
	Bartenders, Medical Assistants, Ushers, Transportation Attendants	2
	Food Service Workers, Cleaners	1

Table IA.4: Robustness Test for Disclosure of the Percentage of Minority Workers in Senior Management Positions

This table presents robustness tests of the main market reaction results in Table 10 by controlling for the demographic composition of senior management. See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]
Incremental Differential	12.73***
	(3.14)
Known EEOC Pay Gap	3.37
	(0.63)
%Black Women Senior Mgrs.	221.79*
	(1.77)
%Black Men Senior Mgrs.	-15.39
	(-0.11)
%Hispanic Women Senior Mgrs.	-130.25
	(-0.69)
%Hispanic Men Senior Mgrs.	-132.98
	(-0.99)
Remaining Senior Mgr. Controls	yes
Firm Controls	yes
Industry FE	yes
State FE	yes
Observations	927
Adj. R2	0.12

Table IA.5: Validation Test with a Subsample of Small to Medium-Sized Firms

This table presents the results of the main analysis for a subsample that excludes large firms (firms with more than 5,000 employees). See Appendix B for variable definitions. Robust t-statistics using standard errors clustered by industry and state are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]
Pay Gap Ratio	13.24***
	(4.17)
Firm Controls	yes
Industry FE	yes
State FE	yes
Observations	683
Adj. R2	0.10