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

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Abstract: We exploit the release of Type 2 EEO-1 Reports by the Department of Labor for over 11,000 public and private U.S. contractors to estimate gender and race/ethnicity pay gaps. These reports are standardized forms containing detailed demographic breakdowns of companies' full workforces by ten job categories. Using EEOC pay data alongside these forms, we estimate that public firms save, on average, over $49 million a year by including women and minorities in their workforce. Private firms, which generally are smaller, save almost $6 million a year. In relative terms, private firms have larger pay gaps than public firms, and within both the private and public sectors, the pay gap increases with firm size. Pay gaps vary dramatically across industries, and they are associated with labor economics theory and political factors. We further exploit the public release of these EEO-1 reports by examining the market reaction to this release, conditional on the size of the firm's pay gap. Pay gaps lower labor costs, thus increasing net income, and potentially firm value. They also have been extensively documented to be persistent over time, suggesting a somewhat permanent nature to these savings. On the other hand, systematic pay inequities can lower employee satisfaction, potentially hurting firm value. We present strong and consistent evidence that investors view pay gaps as net value-enhancing. Our results hold after controlling for workplace diversity, job categories, state, industry and other effects. Our findings should inform stakeholders about the size, determinants, and perceived value of pay gaps. They also suggest that capital markets may not be the appropriate avenue to address systematic pay inequities in the U.S.

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I. Introduction

One of the defining social issues of our time is the persistent earnings inequality 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). Many factors contribute towards these inequalities, but two explanations stand out: (1) pay gaps, i.e., the difference in pay earned by men and women, or by white and non-white workers working in the same job category, and (2) job segregation, i.e., the overrepresentation or underrepresentation of women and minorities in certain occupations and industrial sectors (BLS 2024).

In this paper, we estimate and examine variations in pay gaps across firms and industries for a large sample of publicly-traded and private U.S. firms. Title VII of the Civil Rights Act of 1964 prohibits pay discrimination by race, color, religion, and national origin, and The Equal Pay Act of 1963 proscribes wage discrimination based on sex. Yet, 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, 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).

In this paper, we turn our lens towards two lesser-known aspects of pay gaps: (1) the extent of variation across companies and industries, and (2) whether investors view these pay gaps as net value-enhancing or -diminishing to individual firms. By understanding the first issue, firms, social-minded activists, and regulatory bodies can turn their attention to tackling wage inequality in a more studied and efficient way. Kline, Rose, and Walters (2022), for example, finds that racial discrimination is concentrated in firms in the top quintile of their sample, and that industry accounts for almost one-half of the cross-firm variation in gender and racial discriminatory practices. If pay gaps concentrate more highly in certain industries, then closer attention can be paid to firms in these industries. By understanding the second issue, solutions for remediating gender and racial/ethnic pay inequities 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 pay gap as the difference in earnings between white men and women/minority workers in the same job category within an individual firm. At the firm level, we measure its pay gap as the difference between a theoretical labor cost in which the firm's workforce is comprised of white men only and our estimation of the firm's total labor costs. We refer to this estimated measure as a firm's "labor costs savings."

Hitherto, a main impediment to systematically measuring firm-wide pay gaps is the lack of publicly available, standardized information about the demographic makeup of U.S. companies' workforces beyond their boards of directors and limited data about top-level executives. This impediment was lifted in 2023 when, in response to a federal lawsuit, the Office of Federal Contract Compliance Programs (OFCCP) publicly released 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 Commission (EEOC), detailing the numerical breakdown of a company's entire workforce into 140 distinct gender/race-ethnicity/job categories based on 14 gender, race or ethnicity categories and 10 job categories for each firm in our sample (see Appendix A for Amazon's 2020 EEO-1 Report). The uniqueness of these reports is that they allow us to have an accurate 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. Further, because the data consist of both private and publicly-traded firms, we can cover a large spectrum of companies within the United States.

Our average pay data are from the EEOC. Specifically, in 2017 and 2018, the EEOC required filing firms to simultaneously report detailed pay information for the same 140 cells, thus providing the EEOC with granular data on the pay structure of a firm by the same demographic and job categories as those used in their EEO-1 reports.[1] In 2020, the EEOC published the 2018 pay data on its website, but to retain confidentiality, they aggregated the data by the state and two- and three-digit NAICS code of the filing firm. Their aggregation consists of 12 bands of pay for each of the 140 cells; we take the weighted average by number of employees in each band to estimate the "average" pay for each of the cells. We use these weighted averages alongside demographic data from the EEO-1 form to estimate each firm's pay gap.[2]

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

[2] See section IV.Afor a more detailed description of the EEOC data.

One advantage of using the EEOC pay data is that they mirror perfectly the demographic and job categories of the firms within our sample, thus minimizing errors based on fuzzy job specifications or definitions of race or ethnicity. For example, the Bureau of Labor Statistics allows a person to identify as both White and Hispanic, whereas the EEOC separates these categories out in their filings. Further, as Figure 1 shows, pay gaps vary greatly across the 10 job categories, with senior managers, mid-level managers and professionals showing larger gender, race and ethnicity gaps, and administrators, laborers and helpers, and service workers displaying the smallest pay gaps, thus giving us granular data on job categories as well as the demographics of a firm's workforce.

Although our paper is not the first to use industry data to infer a firm's labor costs, e.g., see Belo et al. (2022), we acknowledge that using aggregated measures of pay per cell in lieu of precise data is not without its drawbacks. Using state and industry averages carries the implicit assumption that firms pay their wages at the market average, thus relating their pay gaps to the market pay gap environment in which they operate. We partially overcome this criticism by using 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. We also conduct some validation tests on the reliability of our labor costs measure, and present evidence consistent with it capturing both the size of the workforce and the overall compensation paid to a firm's workforce.

We further note that several papers show that wages tend to converge within a region or within an industry (Zhou and Bloch 2019; Silva 2021). However, this convergence may be more valid for smaller firms in our sample, and therefore, may not hold for larger firms with greater market power in determining their wages. To address this concern, we re-do our market analyses after removing the largest firms, by employees, from our samples. Our investor-based findings hold after these exclusions. As such, the pay gaps we present for these analyses should be reasonable approximations.

Our sample covers 927 publicly-traded and over 10,000 private firms. We estimate that public firms save, on average, \$49.41 million a year by including women and minorities in their workforce. This translates to an average savings of 6.96% in a firm's total selling, general, and administrative (SG&A) costs. It also accounts for an average savings equal to 1.44% of its total revenues. Private firms are smaller and, therefore, have smaller payrolls. Nevertheless, we estimate that their labor cost savings average $5.86 million a year.

When we scale these raw numbers as a percentage of the firm's total imputed pay, we find that public firms save 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, this labor cost savings ratio for private firms exceeds those of public firms. Thus, we present evidence that private firms may be exploiting gender and race/ethnicity pay gaps to a larger degree than publicly-traded firms. Second, there is an almost monotonic increase in the labor cost savings ratio as firm size increases, suggesting that larger firms benefit more from pay inequities than smaller firms. Our estimations of labor costs saved do not include other types of pay discrimination that have been shown to affect minorities more vividly, such as wage theft (Raghunandan 2021; Cooper and Kroeger 2017), and therefore might be understated.

Using Fama-French 12 industry classifications, we document large variations in labor cost savings ratios across industries, with Consumer Non-Durable Goods and Finance displaying the highest ratios, and Chemicals having the smallest pay gap. Looking into their overall demographic/job category structures provides insights into these differences. As the EEO-1 reports reveal, Consumer Non-Durable Goods employ relatively high percentages of Blacks and Hispanics, who disproportionately work as "Sales Workers." As Figure 1 shows, this job category has large pay gaps for minority workers. Finance, on the other hand, has many workers in the top three job categories – "Senior-Level Managers," "Mid-Level Managers," and "Professionals," with a large number of these workers being white women. From Figure 1, these three job categories have large gender pay gaps. Chemicals, on the other, have a large percentage of white men in all job categories, thus limiting their pay gaps through a lack of diversity. We examine this seemingly disconnect between diversity and pay equity throughout the paper.

We also examine some of the determinants behind the variations in our pay gap measure. Using labor economics theory, we posit that pay gaps are 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. We find evidence consistent with both hypotheses, thus providing more insights into the causes of pay gaps. Our findings hold for both public and private firms.

Having documented variations in estimated pay gaps, and some of the determinants behind these variations, we turn to our second research question: Are pay gaps value enhancing or decreasing? There are strong reasons in support of either view. Pay gaps reduce operating costs and they persist over time (Blau and Khan 2017; Blair and Posmanick 2023; Blau et al. 2023), which suggest a somewhat permanent nature to these savings. Under this cost savings view, investors would view pay gaps as a value-enhancing cost-saving measure, not unlike firms saving taxes in a tax haven or outsourcing their labor to countries with weaker labor laws. 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 pay inequities throughout the workplace engender lower employee satisfaction, then investors may view pay gaps in a negative light, thus reducing the value of the firm.

We examine this research question 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 about a firm, then the cumulative abnormal return around the release date will inform us on how the market values this new information. We then regress these CARs on the firm's *Labor Cost Savings Ratio.* A positive coefficient is consistent with investors placing a net positive valuation on a firm's pay gap; a negative coefficient suggests an opposite interpretation.

Our findings consistently support the view that market reactions around the release of the EEO-1 reports are positively related to the size of a firm's labor cost savings. These findings hold regardless of our approach to computing labor cost savings, for example using different industry categorizations. However, our results may be an artifact of alternative explanations that are unattributable to the market pricing the firm's labor costs savings.

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 10 other randomly-elected 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 *Labor Cost Savings* 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.

We also pursue the possibility that the market is reacting to non-pay information provided by the EEO-1 forms, and not to the pay gap measure that we estimate using these forms. To examine if investors are reacting to the revelation of the percentages of women or minorities implicit in our labor cost savings ratio we include different demographic measures in our regressions. To explore the alternative explanation that the market is reacting to the job structure array that the EEO-1 forms describe, and not to the labor cost saving, we add the percentages of workers in each of the jobs. Our results are robust to the inclusion of these variables.

Finally, we examine the possibility that our findings are related to differences in worker productivity, and not to the pay gap itself – that is, we posit the view that more productive workers are paid higher and that these differences in productivity may cluster among different job categories (Mueller et al. 2017) . Our tests are robust to the inclusion of productivity variables and to the exclusion of subsamples of the workforce in which seniority or ability factors into pay discrepancies. We therefore conclude that, at least partially, investors place a positive value on the amount of labor costs saved due to pay inequities between genders and among races and ethnicities.

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 importance of labor in understanding the dynamics of the market value of firms. Using structural estimation methods, Belo et al. (2022) shows that labor's contribution to firm value has remained constant over the 1975-2016 period, but that the market differentiates between industries primarily with low-skill labor and high-skill workforces, with higher market values placed on firms in high-skill labor industries. Thus, they demonstrate that the market pays attention to the composition of a firm's workforce. 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). 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 lowering their labor costs through pay inequities. From a social standpoint, we note that these savings are congruent with many firms outsourcing their labor, or moving their manufacturing facilities to countries with weaker labor protection standards than those found in the U.S.

Our paper contributes to the literature on gender and minority pay inequities within the U.S. on several dimensions.[3] First, we estimate and examine pay gaps over a large sample of public and private firms. Our estimates are consistent with pay gaps being relatively larger for private firms, and with the relative size of the pay gap increasing with firm size. We also find variations in our *Labor Cost Ratio* across industries, a result parallel to Kline et al. (2022) and Bourveau et al. (2024), who show that gender and minority job discrimination differs dramatically across industries.

Next, we examine some of the economic determinants behind pay gaps, and present results consistent with Becker's (1957, 1962) theories on wage determinants. Thus, we contribute to the large and growing literature that addresses the fundamental determinants behind the persistence of these gaps, for example, family obligations (Bertrand et al. 2010) and racial discrimination (Wilson and Darity 2022). We also add to papers documenting the economic consequences of these pay gaps, for example, their detrimental effect on overall GDP (Milli et al. 2017) or individual wealth accumulation (Aliprantis and Carroll 2019; Bleiweis, Frye, and Khattar 2021). We provide evidence consistent with investors positively incorporating labor costs saved from these structural pay gaps into the firm's stock market price, thus adding to our understanding of the socio-economic determinants behind the persistence of pay gaps throughout the United States.

Although not the focus our paper, we also contribute to the literature that documents job segregation by gender and race. Bourveau et al. (2024), using the same data as us, divides a firm's workforce into managers (senior and middle managers) and lower-level workers (the remaining eight EEO-1 report job categories). They show that women and underrepresented minorities (i.e., Blacks and Hispanics) are under- (over)-represented at the manager (lower), and that white men are overrepresented at the management level. Rigel Hines (2020) shows similar findings with aggregated EEO-1 data. We expand on their findings by showing that job segregation patterns exist in some of the lowest-paid job categories, thus contributing to the persistent wealth inequalities documented in the literature.

[3] A different literature examines pay inequality within firms, i.e., the differences in pay between executives and lower level employees (e.g., Mueller, Ouimet, and Siminti 2017; Pan et al. 2022; Wallsgog, et al. 2024).

A related, but intriguing, literature examines how firms and employees react to gender pay gap transparency.[4] Cullen and Pakzad-Hurson (2023) and Burn and Kettler (2019) present evidence that U.S. employees rarely discuss their pay with their coworkers, which may contribute to demographic disparities in pay levels through a lack of transparency. In contrast, several countries have passed new laws requiring public and private-sector firms to disclose salary data by gender. 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. Several papers show a reduction of the gender pay gap after the enactment of the new laws – however, Bennedsen et al. (2022) finds that this narrowing is due to a reduction in the growth of wages paid to men, and not to women enjoying higher pay levels. Their findings are for firms in Denmark. An interesting exercise would be to see if a similar trend occurs for U.S. firms used in our paper.

II. EEO-1 Reports and the Legal Background Behind Their Release in 2023

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. 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. The Type 2 EEO-1 report 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). 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.

[4] See Duchini, Simion and Turell (2024) for a comprehensive review of this literature.

Appendix A presents Amazon's 2020 Type 2 EEO-1 Report. Consistent with the form's requirements, race and ethnicity are separated by gender, and each individual cell represents the number of employees by their gender/race /ethnicity/job category. 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.

B. Release of the Type 2 EEO-1 Reports in March and April 2023

EEO-1 reports are filed confidentially with the EEOC. 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).[5] In June 2022, Will Evans from the Center for Investigative Reporting (CIR) filed a Freedom of Information Act (FOIA) request 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."[6] Thirty-three firms (see below) 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 OFCCP to release all requested data. On March 2, 2023, the OFCCP released the Type 2 EEO-1 reports for the 21 federal contractors who had already voluntarily released their forms. On April 17, 2023, the OFCCP

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5 These reports are 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.

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

released the Type 2 EEO-1 reports for those contractors and sub-contractors that either affirmatively agreed to the release (12 contractors) or did not object or respond to the National Register notices (19,367).[7]

III. Data and Descriptive Statistics

A. Data Collection

The data source for the workplace demographics are the Type 2 EEO-1 reports provided by the DOL's website. Compensation data are from the EEOC website.[8] We obtain stock returns and financial reporting data from CRSP and Capital IQ Compustat (Compustat).

A firm is required to file its EEO-1 with the DOL only if it is a covered federal contractor for that year. As such, even though all firms in our sample will have filed their EEO-1 reports annually with the EEOC, the DOL has EEO-1 filings only for those years in which an individual firm is designated as a covered federal contractor. 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.

Table 1, Panel A shows the sample construction for the private and public firms we use in our analyses. We begin with the 56,761 firm-year filings from 2016 through 2020 from the DOL's website. So as not to use multiple filings for any firm, we take the latest available Type 2 EEO-1 report of each sample firm in our analyses, thus keeping our 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 data reduces the sample to 969 individual firms. Removing five firms with fewer than 50 employees gives us 964 unique firms. We further drop

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[7] The OFCCP still is in litigation over the release of the remaining reports. On December 22, 2023, the U.S. District Court held that FOIA requests for the remaining EEO-1 reports may not be withheld under a FOIA Exemption 4. The OFCCP was given until February 20, 2024, to release the remaining reports. However, this deadline was extended by the courts, with oral arguments now being scheduled for February 14, 2025. As of the date of this paper, the remaining reports have not been released yet by the OFCCP, and therefore are not publicly available. See the OFCCP Submitter Notice Response Portal for a full description of the OFCCP's position on the litigation (https://www.dol.gov/agencies/ofccp/submitter-notice-response-portal).

[8] 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

those firms that fundamentally changed between their latest EEO-1 filing date and the 2023 DOL release date. In total, we have 927 publicly-traded firms, a number similar to Bourveau et al. (2024). Table 1, Panel B shows the number of firms by the year of its most recent filing with the DOL. The vast majority of our public and private firm samples consist of EEO-1 forms from 2020.

How representative is our sample? Given that the EEO-1 forms are designed by EEOC to primarily prevent employment discrimination based on sex, race, or ethnicity (see https://www.eeoc.gov/overview and https://www.eeoc.gov/data/eeo-1-employer-information-report-statistics), using EEO-1 forms for our sample could introduce a bias in terms of workforce diversity representation in our samples. For example, if federal contractors were more heavily scrutinized by the DOL, they might increase their diversity to gain or retain their status as government contractors. Further, the DOL posted Type 2 EEO-1 forms only for firms that did not object to the CIR FOIA request, thus excluding the 4,000 firms that asked for an exclusion from the request.[9] Economic theory suggests that voluntary disclosers have less to hide or better news to share than non-disclosers (Grossman 1981; Milgrom 1981; Verrechia 1983). Choi et al. (2024) and Bourveau et al. (2024) present evidence that firms that uploaded their EEO-1 forms on their company websites have a more diverse workplace. However, it is unclear whether firms with more diverse workplaces are more likely to have lower pay gaps. Edmans et al. (2024) presents evidence that greater workplace diversity does not translate into higher employee satisfaction with respect to feelings of inclusion within the firm, suggesting that any possible bias in workplace diversity within our sample may not transfer over to a similar bias in the size of a firm' pay gap. Further, although it is possible that more diverse firms internally track their pay gaps for minority and women workers, Downing et al. (2015) finds that only one-third of the firms in their UK sample actually do so. Lastly, federal contractors are not required to disclose compensation data to the DOL, suggesting that pay gaps may not play an important role in determining whether a firm can gain access to federal contracts.

Table 2 presents demographic distributions for our sample firms. We show, in Panel A, the entire *current* 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

[9] A January 2025 FOIA request by us to the DOL for the names of the firms requesting exclusion was denied by the DOL. Their explanation was that the matter was still in litigation.

following categories: “White” 77%; “Black” 13%; “Hispanic” 19%; and “Asian” 7%.[10] 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.

B. Workforce Diversity, Job Categories, and National Pay Averages

Figure 2 shows the proportion of workers by demographic and job categories. For all workers in our sample, 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%). We also present two national averages of pay using data released by the EEOC in 2018 – the average national pay for each job category and the average national pay for each demographic group. 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. Black and Hispanic women and Black men fall into the three lowest average national pay groups.

We further divide our race and ethnicity data into men (the blue bubble on the left) and women (the orange bubble on the right). Each bubble represents the percentage of jobs held by workers

[10] 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.”

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 this, we can provide comparisons between the percentage of the workforce within each job category and the percentage 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 presents a clear picture of how job segregation impacts income inequality, as reflected by the average demographic pay data shown in the bottom row.

The upper left triangle parallels the findings presented in Bourveau et al. (2024), who shows that women, Blacks and Hispanics are underrepresented vis-à-vis national averages as senior-level and middle managers. We add to their paper by showing that race and gender job segregation exists in some of the lowest-paying job categories. Our figure also weighs in on the question of whether workplace initiatives aimed at increasing diversity actually benefit minorities through higher pay and more opportunities. For example, in 2020, Amazon publicized that it significantly increased its workplace diversity by hiring large numbers of non-white workers in response to the Covid 19 crisis. A deeper dig into these hirings, however, found that 61% of these new workers were classified by the Equal Employment Opportunity Commission (EEOC) as "Laborers & Helpers," one of the two lowest paid jobs within the EEOC taxonomy of job categories (EEOC, 2018; Day, 2021). Thus, while Amazon improved its *diversity* within the overall firm (i.e., supplying jobs to underrepresented minorities), many of those hired found themselves in low-paying jobs.

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

A. Estimation of a Firm's Pay Gap

Following standard definitions, we define a pay gap as the difference between what a White man and a woman/minority worker earns in the same job category at an individual firm. To calculate this gap for an entire firm, we need to have data on the demographic breakdown of workers by job categories as well as the average compensation paid to each subgroup of workers.

The EEO-1 report has the demographic data by job category, which allows us to construct a matrix of 140 cells based on gender-race-or-ethnicity and job category for each firm in our sample. For example, from a firm's EEO-1 report, we may see that 7% of its workforce is comprised of Black women who are Professionals.

We use the 2018 "EEO-1 Component 2 Pay Data Collection State Aggregates (NAICS-3) Public Use File" (Pay Data File) from the EEOC's website to estimate workers' pay. In 2017 and 2018, firms were required to add a "Component 2" pay data collection component to its EEO-1 Report, thus providing the EEOC with pay information for the same 140 demographic/job category cells.[11] 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 the 12 bands as our measure workforce pay for that cell. Using the same example above, if our firm is in the Retail Trade industry and is headquartered in Colorado, our estimate of the dollar amount paid to all Black Women Professionals in that firm is the weighted average of the midpoints of the 11 pay bands for Black Women Professions, as provided by the Pay Data File. We repeat this calculation for each of the 140 cells and call the sum of these calculations a firm's estimated total labor costs.[12]

There are several advantages and disadvantages to our process. One advantage is that the EEOC uses the identical 140-cell format for its EEO-1 report and for its Pay Collection database, thus giving us a one-to-one alignment between datasets. A second advantage is that the pay data

[11] 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.

[12] 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 VIII.B). The results and interpretations are robust to this alternative classification.

are collected by the EEOC from employers and “certain” federal contractors only. Our sample is comprised of federal contractors only, thus adding a further alignment between datasets.[13]

One disadvantage is that our estimate assumes that 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, who have more leverage in determining wages. Further, by taking data from the state in which the firm’s company headquarters is located assumes that all U.S. employee wages are determined at the headquarters level. This, too, may not be a valid assumption for larger firms with subsidiaries or factories in multiple states.[14] To address these concerns, we re-do our market analyses after removing the largest firms, by employees, from our samples of firms.

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:

$$\textit{Labor Cost Savings} = \textit{Total Imputed Pay All White Men} - \textit{Total Imputed Pay} \qquad (1)$$

To control for firm size, we calculate:

$$\textit{Labor Costs Savings Ratio} = \textit{Labor Cost Savings} \,/\, \textit{Total Imputed Pay} \qquad (2).$$

As such, the *Labor Cost Savings Ratio* effectively reflects the overall gender and race pay gaps within each firm.

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[13] 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.

[14] 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.

B. Descriptive Statistics: Public and Private Firms

Table 3 contains summary statistics pertaining to the *Labor Cost Savings Ratio* 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 *Labor Cost Savings* (pay gap) of $49.41 million per firm or $6,067 per worker.[15]

How significant are these savings to the firm? In relative terms, the mean *Labor Cost Savings 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 labor cost savings 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 savings over revenues is 1.44%, and the average ratio over total assets is 0.83%.

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 *Labor Cost Savings* (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 *Labor Cost Savings Ratio* for private firms is 11.52%, which is larger than the 8.12% for public firms. Thus, private firms benefit more from pay inequities per employee and per dollar spent on labor costs than 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 3 Panel C presents summary statistics on the *Labor Cost Ratio* by size for the

[15] 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 "Labor Cost Savings."

public and private firms. Two observations can be made. First, for all 5 buckets, the mean *Labor Cost Savings 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 more pernicious in the private sector. Second, there is a nearly monotonic increase in the mean *Labor Cost Savings 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 4, 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 labor cost savings ratio by industry. As the table shows, there are stark differences in the magnitude of the pay gaps across industries. For public firms, Finance (12.1%) and Consumer Non-Durables (11.4%) have the greatest labor cost savings. In contrast, Chemicals (3.8%), Utilities (4.5%), and Oil, Coal & Gas (4.8%) display the smallest pay gaps. For private firms, Healthcare (21.5%), Finance (12.6%), and Consumer Non-Durables (10.4%) have the highest pay gaps; Utilities (3.6%) has the smallest pay gap.

A natural question to ask is why the healthcare ratio for private firms is so large. A perusal of the firms' EEO-1 reports provides a partial answer. First, we note from Panel B that it is not due to outliers, in that the number or workers and firms in the Healthcare are very high. What we do ascertain, however, is that private Healthcare firms have a very high percentage of women in their workforce – the average percentage being 75%. Further, the private Healthcare industry has a large proportion of all workers (men, women, White, Black, Hispanic, Asian) as Professionals. As Figure 1 shows, the pay gaps between men and women for Professionals is very high, and it encompasses all races and ethnicities. Thus, we see evidence of how an industry's job category structure and its workforce diversity work together to create a large average pay gap.

D. Validation Tests on Imputed Labor Costs

Is the *Labor Cost Savings 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 5 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. The coefficient on the *Total Number of Workers (EEO-1 Report)* is significantly positive, consistent with the EEO-1 report capturing almost all 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 the significantly positive coefficient on *Total Imputed Pay*. In column (3), we use a different data source, BrightQuery, to regress *Salary and Wages* on *Total Imputed Pay*. Compustat reports these expenses for only 211 firms in our sample (of which 166 are finance firms). In contrast, BrightQuery has this information for 733 firms. As column (3) shows, the coefficient on *Total Imputed Pay* is significantly positive, consistent with our measure of total pay capturing salary and wage costs.

We next turn to another possible criticism, which is that our *Labor Cost Savings* measure might be capturing pay differentials related to firms employing workers with varying skills instead of different genders/races/ethnicities. To address this concern, we compare jobs within each EEO-1 category as delineated in their handbook with the level of skillsets and educational background needed for the same job as delineated by O*NET. Internet Appendix Table IA.1 contains overlapping job titles for those jobs contained in the EEO-1 instruction booklet and those contained on the O*Net website. 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. As the table shows, the EEO-1 job categories generally align to one or two adjacent O*NET skillsets, thus mitigating the possibility that our labor cost savings measure is capturing differences in skills across firms and not the wage gap we seek to measure.

However, differences in skillsets may not be uniform across all categories. For example, 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 have implications for our measure of pay gaps, in that the pay gaps for employees at the management levels might be due to factors unrelated to diversity. We examine this issue further in Section VII.B.6, when correlating market reactions to the *Labor Cost Savings Ratio*.

V. Economic and Political Determinants of the Labor Cost Savings Ratio

In this section, we examine some of the economic and political determinants behind variations in labor cost savings. Because *Labor Cost Savings* 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* as our measures of the employees' bargaining power. A higher unemployment 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 cross-sectional associations between the pay gap and *Unemployment Rate* and *Right to Work,* and a negative association for companies in states with *Union Participation.* We also predict a negative association between education levels and 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 6 presents summary statistics for the regressions of the *Labor Cost Savings Ratio* on these four variables. As Internet Appendix Table IA.2 shows, some of these state variables are highly correlated, and therefore, we estimate our regressions separately for each variable.

Consistent with our first prediction, all three variables *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 and workers' bargaining power. With respect to our second prediction, we find a negative relation between the pay gap 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 inequities for their workforce (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 6 present summary statistics for the regression of the *Labor Cost Savings 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.

VII. How Do Investors Value the Labor Costs Savings 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. Systematic pay gaps reduce labor costs in ways not dissimilar to firms outsourcing their labor, placing workers on part-time or temporary status, or moving their factories to countries with weaker labor laws. Further, pay gaps historically have persisted over time (Blau and Khan 2017; Blair and Posmanick 2023; Blau et al. 2023), which suggests a somewhat permanent nature to these savings. If these cost savings are seen as a means to increase net income without a loss to productivity, then investors will view pay gaps in a positive way. On the other hand, Pan et al. (2022) finds an average negative stock price reaction around the first-time disclosure of CEO-median worker pay ratios, consistent with investors taking a negative view of within-firm pay gaps. Pan et al. (2022) interpret their findings as being reflective of investors' social values. From an accounting standpoint, Edmans (2011), Green et al. (2019), Boustanifar and Kang (2022), and Edmans et al. (2024) present evidence consistent with job satisfaction or worker inclusion being positively correlated to a firm's future earnings. If persistent wage gaps provide incremental evidence to the surveys used in these papers, then investors may view pay gaps in a negative way, thus reducing the value of the firm.

In Internet Appendix Table IA.3, we present some data consistent with pay gaps being negatively associated with employee satisfaction. Our employee job satisfaction data are sourced from Glassdoor, a widely used platform where employees can anonymously review their workplace experiences.[16] For our analysis, we calculate the average of these employee ratings across all reviews for the year its EEO-1 report is included in our public-firm sample. We then regress the *Labor Cost Savings Ratio* on these Glassdoor ratings. As the panel shows, the *Labor Cost Savings Ratio* is significantly negatively related to Glassdoor's Overall Rating, Culture & Values, and weakly to Compensation & Benefits, as well as Career Opportunities. In contrast, the coefficients on Work-Life Balance and Senior Leadership, while negative, are not significantly different from zero at conventional levels. Thus, we present evidence of a negative association between pay inequities and some measures of employee satisfaction. These findings are consistent with Green et al. (2019), who use Glassdoor ratings to predict future stock returns, and with Edmans (2011), Boustanifar and Kang (2022) and Edmans et al. (2024) who use other surveys of employee satisfaction to predict future stock returns and accounting performance. The small R-square values on our equations, along with the results found in the above four papers, suggest that there is not one extant measure that captures employee (dis)satisfaction; and therefore, supports the view that the release of the EEO-1 reports could provide investors with a measure of employee satisfaction that is incremental to Glassdoor, Best Companies to Work For or other survey data used in the economics literature.

[16] Each Glassdoor review includes a mandatory overall job satisfaction rating on a scale of one to five, with five indicating the highest satisfaction. Reviewers can also provide optional ratings for subcategories like compensation, work-life balance, culture, career opportunities, and management. All these review ratings reflect the employees' job satisfaction with different aspects of the firm.

A. Labor Costs and Firm Value

Labor costs comprise a significant portion of a firm's overall expenses. PWC's 2023 Saratoga Workforce Index reports a 2022 national average ratio of labor costs to revenues of 22%;[17] Goldman Sachs estimates a 2019 median ratio of 12% for all S&P 500 firms (Goldman Sachs 2019). That labor contributes to a firm's overall market value is without controversy. Belo et al. (2022) estimates that labor is responsible for 14% to 22% of a firm's market value, with low-skill (high-skill) industries appearing in the lower (upper) ranges of the distribution. They also show that these ratios remain relatively stable from 1975 through 2016, whereas the contribution of physical capital and knowledge to market value have dropped and risen, respectively, over the same period.

There is some limited evidence showing that containing labor costs can produce higher stock returns. In 2019, it was reported that Goldman Sachs had created a synthetic portfolio of stocks consisting of the 50 S&P 500 firms with the lowest ratio of labor costs to revenues (CNBC 2019). Specifically, over the "early 2016-mid 2018" time period, these 50 companies had an average 6% labor cost-to-revenue ratio, compared to the 14% average for the entire S&P 500. According to Goldman Sachs, this basket of stocks outperformed the S&P 500 by more than 20 percentage points over the same 2016 to 2018 time period, thus lending credence to the view that investors place positive market values on firms that can limit their overall labor costs.

B. How Do Investors Value Pay Gaps?

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.4 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 Labor Costs Savings Ratio:

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

[17] See https://workforce.pwc.com/saratoga-benchmarking-survey-results-2023-ty.

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 some 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.[18] *Labor Cost Savings Ratio* is firm i's labor cost savings ratio. We control for the supply of workers by including a fixed effect for the state in which firm i's headquarters is located ($State_j$). The ability to diversify a firm's workforce may be influenced by the state's gender and race/ethnicity demographics – for example, New Mexico has the highest percentage of Hispanic population in the United States at 50.2%, while Vermont has the lowest at 1.5%. 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 may capture 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 measures to control for omitted variables that may be correlated with the *Labor Cost Savings Ratio*. *Firm Controls* are calculated at the end of 2022. Larger firms (*Firm 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* in equation (3). Finally, *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 to account for possible heteroskedasticity in standard errors.[19]

[18] 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.

[19] Our control variables indirectly address a "corner solution" question – if firms can benfit 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 2 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

A positive coefficient on the *Labor Costs Savings Ratio* is consistent with investors viewing the pay gap as a net benefit, presumably through the firm achieving cost savings without sacrificing employee productivity. A negative coefficient is consistent with investors viewing a firm's pay gap as a net cost, possibly through the employee's disaffection with the firm.

B.1 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, five underlying assumptions of the methodology must be satisfied. Our setting appears to satisfy each of these assumptions.

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 inequities, 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

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).

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. 2024; 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 two placebo tests. In the first test, we calculate FF5-factor CARs using ten randomly-selected "pseudo-events" days outside of the March 2nd and April 17th release dates.[20] The pattern of these CARs is inconsistent, and shows no systematic bias in sign. Second, we use these placebo CARs to re-estimate equation (3), and find no systematic pattern of coefficients on the *Labor Cost Savings Ratio* for these regressions.

Fifth, investors need a contextual basis to evaluate the value relevance of pay gap data. As discussed above, there is little debate about the value relevance of labor costs across firms.

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

B.2 Empirical Results: Baseline Model

Table 7 contains summary statistics for Equation (3). In column (1), the coefficient on *Labor Cost Savings Ratio* is 10.43, significant at the 0.01 level. In economic terms, a one standard deviation increase in the *Labor Cost Savings Ratio* (5.45%) increases the CAR over the window [-1, +2] by 0.57%. Our findings hold after controlling for state, industry, firm-specific characteristics, and earnings announcements over the [-1, +2] window.

B.3 Are We Just Capturing Differences in Pay Across Job Categories?

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 *Labor Cost Savings 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 that the firms enjoy. For

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[20] Specifically, we start with a time period encompassing 60 calendar days before March 2nd (January 2nd, 2023), and ending 60 calendar date after April 17th (June 16th, 2023). We then exclude the 14 days before and after March 2nd and April 17th, respectively.

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.

To examine this possibility, we first regress each firm's CAR on its percentage of employees in each of the ten job category levels. As column (2) of Table 7 shows, the stock price reaction to the release of the EEO-1 reports is significantly positively related to a firm's percentage of employees who are Sales Workers and Operatives. Sales Workers is one of the lowest paid job categories, thereby supporting the view that the market reacted positively to firms revealing job category structures that are tilted towards lower-paying jobs.[21]

In column (3), we add the job category percentages to the regression on *Labor Cost Savings*. The coefficient on *Labor Cost Savings*, though smaller than that shown in column (1), is statistically significant at the 0.05 level. The coefficients on the job categories show the same pattern as in column (2). Thus, we conclude that our pay gap variable and the firm's job category structure capture information incremental to each other.

B.4 Other Measures of the Firm's Pay Gap

To gain additional insights into how investors value pay gaps, we create an indicator, *Top 25% Savings Ratio,* for firms lying in the top 25% of the *Labor Cost Savings 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 (4) of Table 7, the coefficient on *Top 25% Savings Ratio* is 1.02 significantly positive at the 0.05 level. In economic terms, firms hailing from the top quarter of the *Labor Costs Savings Ratio* distribution had, on average, a CAR that is 1.02% greater than those firms in the bottom 75% of our pay gap sample.

In lieu of including industry effects, we construct *Within-Industry Savings Ratio*, which measures a firm's labor cost savings relative to its industry mean. As column (5) shows, the coefficient on *Within-Industry Savings Ratio* is 8.23, significant at the 0.05 level. In economic terms, a one standard deviation increase in the savings ratio (4.3%) increases the CAR over the window [-1, +2] by 0.35%.

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[21] A firm's job category structure is somewhat determined by its industry. If we remove Industry fixed effects from equation (3), we find significantly positive coefficients on Sales Workers, Craft Workers, Operatives, Laborers & Helpers, and Service Workers.

B.5 Are We Just Capturing Workplace Diversity?

An alternative explanation to our findings is that the *Labor Cost Savings Ratio* captures pay differentials across firms primarily through the firms' workforce diversity. As such, the positive stock price reaction is through more workplace diversity and not to the pay gaps that the firms enjoy. 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 et al. 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), suggesting that their findings may not generalize to other industries.

Table 8 contains regression results in which we regress CARs on the percentage of women *(%Women*), Black, (*%Black*), Hispanic (%*Hispanic*), and Asian *(%Asian*) workers. As columns (1) and (5) show, only the coefficient on *%Hispanic* is significantly positive, suggesting that after controlling for industry, state, and firm effects, investors do not, in general, value greater workplace diversity. 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.

In columns (2) and (5), we add *Labor Cost Savings Ratio* as an additional variable. The coefficients on *Labor Cost Savings* and *%Hispanics* remain statistically significant. Columns (3) and (6) include job categories as additional variables. Again, we note a positive coefficient on *Labor Cost Savings* after the inclusion of these variables. For these two regressions, we remove the Industry fixed effect due to high correlations among the diversity, job categories, and industry measures, a finding reflected in *%Hispanics* now becoming insignificantly different from zero in column (6). In total, we conclude that our pay gap variable captures information incremental to a firm's level of workplace overall diversity.

We next examine if the positive coefficient on *Labor Cost* Savings is due to the market reacting positively to the EEO-1's disclosure of the percentages of minority workers in senior management positions. 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, we replace the five demographic percentages in our regressions with 10 variables representing the percentages of senior managers by gender and race/ethnicity. For brevity, we show the coefficients only for the 4 minority worker categories. As the column shows, none of the coefficients on the demographic-based senior manager percentages are significantly different from zero, whereas the coefficient on *Labor Cost Savings* remains significantly positive[22]. We therefore conclude that the information contained in the pay gap variable is incremental to diversity variables.

B.6 Are We Just Capturing Differences in Talent and Seniority at the Managerial Levels?

Mueller et al. (2017) and Wallsgog et al. (2024) examine determinants of within-firm pay inequalities. These inequalities measure pay gaps between employees who are paid the most and those paid the least. There are two important findings from these papers that are germane to our paper. The first is that differences in managerial talent and seniority account for large portions of the within-firm pay gaps. The second is that these factors do not explain much of the pay gaps between lower-level positions (non-managerial) and those who are paid the least. Thus, a key takeaway from these papers is that the *Labor Cost Savings Ratio* for Senior-Level Management,

[22] Including the four demographic senior management percentages only produces nearly identical coefficients and standard errors.

and perhaps for Mid-Level Management as well, may be a reflection of both diversity and non-diversity factors. As such, by using the full spectrum of job categories, we might be including these non-diversity factors in our measure of pay inequities across gender, race, and ethnicity.

To address this concern, we sequentially remove Senior-Level Managers and Senior-and-Mid-Level Managers from our measure of *Labor Cost Savings Ratio*. This gives us samples of employees in the lower 8 or 9 job categories, i.e., employees who are less likely to be rewarded for their star abilities or for their seniority. We then re-do our analyses with these truncated samples. Table 9 contains summary statistics for our regression estimations. As the table shows, the coefficient on *Labor Cost Savings Ratio* remains significantly positive across these subsamples of employees. Because these employees give us a "cleaner" sample of diversity-based pay gaps, they provide concurring evidence that the market views pay gaps as net value-enhancing.

VIII. Additional Analyses

A. 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. 2024; Choi et al. 2024). For these firms, the information contained in these filings has already been revealed to the market. 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.

Table 10, Panel A presents workforce demographics by group. Bourveau et al. (2024) finds that contractors with higher percentages of "under-represented minorities" in management positions were more likely to post their Type 2 EEO-1 reports online over the years 2016-2020. Consistent with their findings, our sample of voluntary disclosers has a smaller percentage of

White employees than the involuntary disclosers. When we disaggregate by race and ethnicity, we find that voluntary disclosers have substantively higher percentages of Black and Asian workers, but no meaningful differences in the percentages of Hispanic workers. We also find evidence that voluntary disclosures have significantly lower percentages of women in their workplace when compared to the group of non-voluntary disclosers, a finding contrary to a voluntary disclosure framework.

To examine whether the market reaction surrounding the DOL release of the EEO-1 forms is muted for voluntary disclosures, we estimate the following regression:

$$\begin{aligned} CAR_{i,t\text{-}1,t+2} &= \alpha_0 + \beta_1\ \textit{Labor Cost Savings Ratio}_i + \beta_2\ \textit{Voluntary}_i \\ &+ \beta_3\ (\textit{Labor Cost Savings Ratio*Voluntary})_i + \beta_j\ \textit{State}_j + \beta_k\ \textit{Industry}_k \\ &+ \beta_l\ \textit{Firm Controls}_i + \varepsilon_{i,t\text{-}1,t+1} \qquad (4), \end{aligned}$$

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 the pay gaps for voluntary disclosures over the DOL release of their EEO-1 reports.

Panel B contains summary statistics for equation (4). Consistent with finance theory, the coefficient on $(\beta_1 + \beta_3)$ is insignificantly different from zero. When we substitute *Top 25% Savings Ratio* or *Within-Industry Savings Ratio* for the *Labor Cost Savings Ratio*, we find similar results. In summary, our findings lend further support for our event study approach to evaluating how investors value workplace diversity.

B. Robustness Tests

We conduct several robustness tests. Our first set of tests examine the robustness of how we use the EEOC pay data in calculating our measures of *Labor Cost Savings.* Recall that we use the average gender/race-ethnicity/job category cell for the two-digit NAICS industry in the state where the firm's headquarters are domiciled. To examine the sensitivity of how we define industry, we re-calculate *Labor Cost Savings* by (1) collapsing the NAICS classifications to mimic the Fama French 48 industry category levels, (2) using demographic/job category averages at the national level to impute average salaries, and (3) treating the 96 subsectors/three-digit codes as separate industries. Our results (untabulated) are consistent with all aggregation methods.

Next, by using data from the state in which the firm is incorporated, we are assuming that the firm is paying all its employees as if they lived in the state, an assumption that may be violated for firms with operations outside their headquarters' state. Further, 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 Table IA.5, are consistent with this truncated sample.

IX. Summary and Initial Conclusions

Using the recent release of Type 2 EEO-1 reports by the Department of Labor for over 19,000 publicly-traded and private U.S. contractors, alongside detailed employee compensation data by the EEOC, we examine the prevalence, determinants, and market valuation of firm-specific pay gaps across firms and industries. 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 inequities.

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. We also show that these gaps vary significantly across industries, and they are relatively higher (in percentage terms) for private firms, and for 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 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. One surprising finding is that the largest publicly-traded firms have the largest pay gaps, suggesting that diversity initiatives taken by these firms may not spill over to the equity portion of a firm's DEI program. 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 inequities. This latter observation is consistent with Friedman's (1970) doctrine, which is that investors should 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.
Labor Cost Savings (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.
Labor Cost Savings Ratio	EEO-1 Reports and EEO-1 Component 2 Pay data	This variable is calculated by dividing a firm's Labor Cost Savings by its Total Imputed Pay.
Top 25% Savings 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 Labor Cost Savings Ratio distribution and zero for all other firms.
Within-Industry Savings Ratio	EEO-1 Reports and EEO-1 Component 2 Pay data	The difference between a firm's Labor Cost Savings Ratio and the corresponding average Labor Cost Savings Ratio of a firm's Fama-French 48 industry.
Per Worker Labor Cost Savings (in $)	EEO-1 Reports and EEO-1 Component 2 Pay data	The firm's Labor Cost Savings divided by the total number of workers, as reported in the most recent Type 2 EEO-1 report.

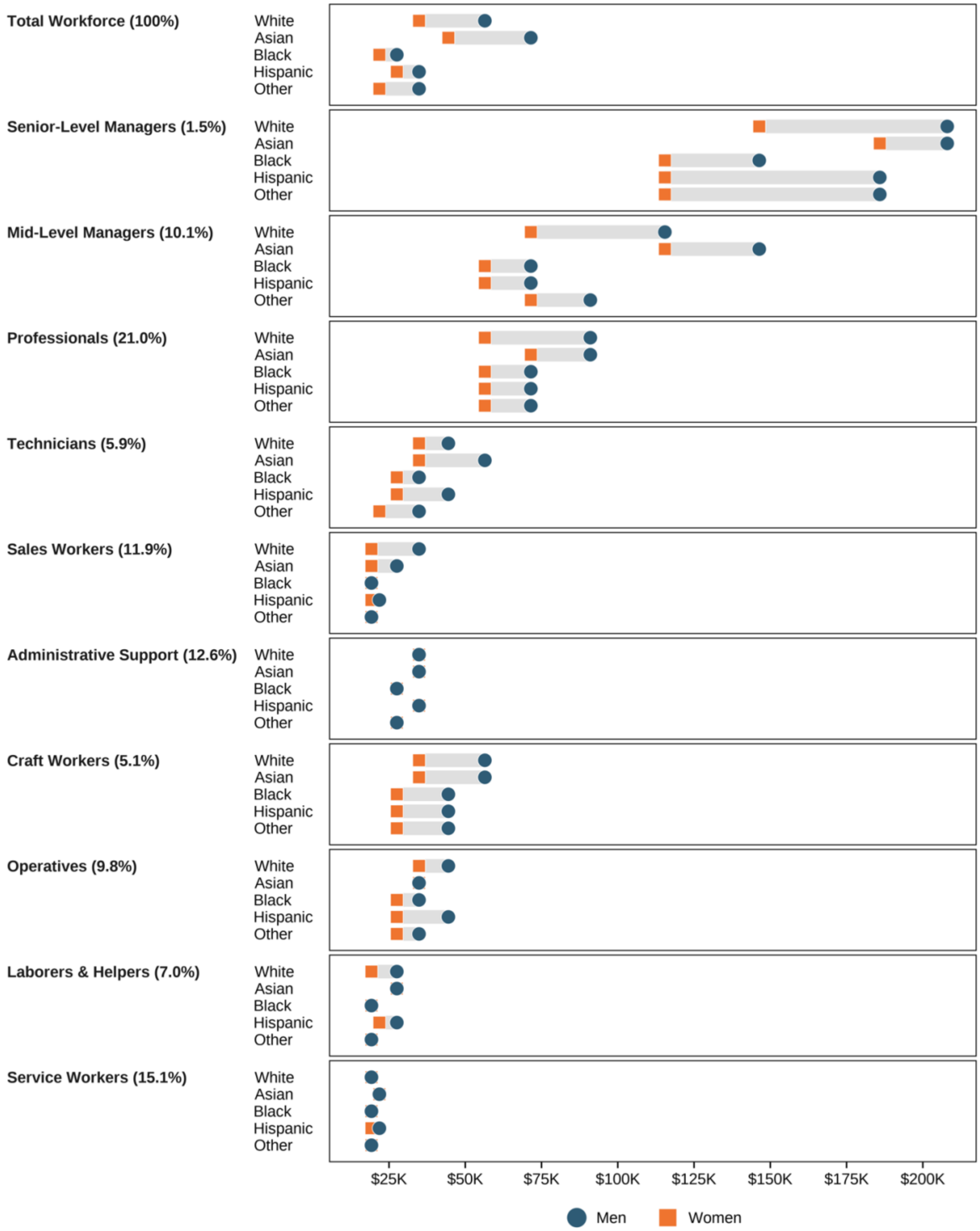
Variable Names	Data Sources	Variable Definitions
Total Number of Worker (EEO-1 report)	EEO-1 Reports (FOIA release)	Total number of workers from the most recent Type 2 EEO-1 report.
Total Number of Worker (Compustat)	Compustat	Total number of workers from a firm's annual report (10-K), originally presented in thousands of workers.
SG&A	Compustat	Selling, General and Administrative (SG&A) expenses at the end of 2022.
Salary and Wages	BrightQuery	Salary and Wages expenses at the end of 2022.
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.
ln(Size)	Compustat	The natural logarithm 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.
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
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.
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.

Rating Overall	Glassdoor	A firm's average Overall Rating on Glassdoor for our EEO-1 sample report year.
Culture and Values	Glassdoor	A firm's average Culture and Values Rating for our EEO-1 sample report year.
Work-Life Balance	Glassdoor	A firm's average Work-Life Balance Rating for our sample report year.
Compensation and Benefits	Glassdoor	A firm's average Compensation and Benefits Rating for our EEO-1 sample report year.
Career Opportunities	Glassdoor	A firm's average Career Opportunities Rating for our EEO-1 sample report year.
Senior Leadership	Glassdoor	A firm's average Senior Leadership Rating for our EEO-1 sample report year.

Figure 1: National Comparisons of Pay Gaps by Gender and Job Categories



This figure compares the national-level pay gaps across different job categories using data obtained from the EEO-1 Component 2 dataset. 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.

Table 1: Sample Construction

This table reports our sample construction process. Panel A outlines the number of public and private sample firms after each processing steps. 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: 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 3: Summary Statistics for the Labor Cost Savings 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 the Labor Cost Savings Ratio 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
Labor Cost Savings (in million $)	927	49.41	146.52	2.57	9.08	29.37
Per Worker Labor Cost Savings (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
Labor Cost Savings Ratio	927	8.12%	5.46%	4.56%	7.02%	10.22%
Labor Cost Savings/SG&A	835	6.96%	10.83%	1.86%	3.73%	7.16%
Labor Cost Savings/Total Revenue	927	1.44%	1.54%	0.41%	0.92%	1.96%
Labor Cost Savings/Net Income	927	10.31%	69.90%	−0.93%	4.56%	13.40%
Labor Cost Savings/EBIT	927	16.11%	68.50%	0.78%	4.15%	10.81%
Labor Cost Savings/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
Labor Cost Savings (in million $)	10,434	5.86	16.04	0.59	1.41	3.72
Per Worker Labor Cost Savings (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
Labor Cost Savings 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' Labor Cost Saving Ratios			**Private Firms' Labor Cost Saving 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 4: Comparisons Across Fama-French Industries

This table compares the samples of 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 labor cost savings 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: Imputed Labor Cost Savings

	Public Firms			**Private Firms**		
Fama-French Industries	**# Firms**	**# Workers**	**Mean Savings**	**# Firms**	**# Workers**	**Mean Savings**
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 5: 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 and BrightQuery. All variables are winsorized at the 1% and 99% levels. See Appendix B for variable definitions. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Total Number of Workers (Compustat)	**SG&A (Compustat)**	**Salary and Wages (BrightQuery)**
	(1)	**(2)**	**(3)**
Total Number of Workers (EEO-1 report)	1.481***		
	(27.259)		
Total Imputed Pay (in million $)		2.098***	1.626***
		(13.116)	(9.363)
Firm Controls	yes	yes	yes
Industry FE	yes	yes	yes
State FE	yes	yes	yes
Observations	916	835	733
Adj. R2	0.879	0.808	0.691

Table 6: Economic and Political Determinants of the Labor Cost Savings Ratio

This table examines the relationship between our imputed Labor Cost Savings 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

		Labor Cost Savings Ratio					
	Prediction	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Unemployment Rate	+	-0.001					
		(-0.294)					
Union Participation	–		-0.001*				
			(-1.820)				
Right to Work	+			0.011***			
				(2.986)			
Highschool and Above	–				-0.002***		
					(-2.980)		
Minimum Wage	–					-0.003**	
						(-2.118)	
Democratic Governor	–						-0.006
							(-1.638)
Observations		927	927	927	927	927	927
Adj. R2		-0.001	0.003	0.009	0.009	0.004	0.002

Panel B: Private Firms

		Labor Cost Savings Ratio					
	Prediction	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Unemployment Rate	+	0.005***					
		(3.326)					
Union Participation	–		0.000**				
			(-2.525)				
Right to Work	+			0.003**			
				(2.013)			
Highschool and Above	–				-0.003***		
					(-11.081)		
Minimum Wage	–					0.001	
						(1.611)	
Democratic Governor	–						-0.007***
							(-3.966)
Observations		10,434	10,434	10,434	10,434	10,434	10,434
Adj. R2		0.001	0.000	0.000	0.011	0.000	0.001

Table 7: Investor Reactions to the Labor Cost Savings Ratio

This table presents the results of regression analyses examining the relation between CAR[-1,2] and imputed labor cost savings variables. In columns (2), (3), (4), and (5), we omit the job category with the highest representation, % Professionals, to avoid perfect collinearity. See Appendix B for variable definitions. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Labor Cost Savings Ratio	10.428***		7.968**		
	(2.898)		(2.161)		
Top 25% Savings Ratio				1.019**	
				(2.512)	
Within-Industry Savings Ratio					8.230**
					(2.180)
ln(Size)	0.206**	0.240**	0.229**	0.227**	0.254***
	(2.313)	(2.456)	(2.331)	(2.330)	(2.862)
Firm Profitability	0.761	0.630	0.663	0.650	0.913
	(0.967)	(0.802)	(0.846)	(0.831)	(1.183)
Asset Efficiency	-0.198	-0.195	-0.261	-0.234	-0.314
	(-0.494)	(-0.487)	(-0.640)	(-0.580)	(-1.075)
Firm Leverage	0.217	0.094	0.126	0.093	0.147
	(0.268)	(0.115)	(0.155)	(0.114)	(0.197)
Earnings Announcement	1.516*	1.434*	1.545*	1.484*	1.955**
	(1.905)	(1.801)	(1.946)	(1.880)	(2.366)
%Senior-Level Managers		-0.203	1.297	0.886	4.627
		(-0.036)	(0.233)	(0.159)	(0.855)
%Mid-Level Managers		0.194	0.184	-0.118	1.855
		(0.090)	(0.085)	(-0.055)	(0.880)
%Technicians		0.534	0.353	0.521	-0.252
		(0.189)	(0.125)	(0.184)	(-0.095)
%Sales Workers		4.678***	3.845**	4.001**	6.424***
		(2.787)	(2.211)	(2.325)	(4.179)
%Administrative Support		0.303	0.313	0.229	3.320**
		(0.157)	(0.162)	(0.119)	(2.539)
%Craft Workers		1.636	1.704	1.828	3.396***
		(1.110)	(1.168)	(1.252)	(2.643)
%Operatives		2.437*	2.190*	2.266*	2.724***
		(1.854)	(1.656)	(1.726)	(2.590)
%Laborers & Helpers		1.536	1.446	1.528	3.928**
		(0.875)	(0.805)	(0.857)	(2.418)
%Service Workers		4.370*	3.778	3.336	4.305***
		(1.658)	(1.444)	(1.299)	(2.976)
Industry FE	yes	yes	yes	yes	--
State FE	yes	yes	yes	yes	yes
Observations	927	927	927	927	927
Adj. R2	0.111	0.107	0.111	0.112	0.068

Table 8: Workforce Diversity and the Labor Cost Savings Ratio

This table presents the results of regression analyses examining the relation between CAR[-1,2] and imputed labor cost savings variables after controlling for workforce diversity measures. In columns (3) and (6), we omit the job category with the highest representation, % Professionals, to avoid perfect collinearity. Similarly, in columns (4) to (6), we omit the race with the highest representation, % White, to avoid perfect collinearity. See Appendix B for variable definitions. Robust t-statistics 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)**
Labor Cost Savings Ratio		10.075***	8.892**		8.818**	9.069**	9.367**
		(2.598)	(2.493)		(2.260)	(2.558)	(2.446)
%Women	1.954	0.334	0.797				
	(1.393)	(0.225)	(0.516)				
%Black				1.698	0.371	1.140	
				(0.726)	(0.155)	(0.496)	
%Hispanic				5.195***	4.002**	1.737	
				(3.004)	(2.295)	(0.972)	
%Asian				0.562	0.665	0.522	
				(0.318)	(0.376)	(0.312)	
%Other				-9.597	-11.571	-13.625	
				(-1.140)	(-1.288)	(-1.359)	
%Black Women Senior Mgrs.							259.877
							(1.392)
%Black Men Senior Mgrs.							-67.780
							(-0.379)
%Hispanic Women Senior Mgrs.							-190.043
							(-1.097)
%Hispanic Men Senior Mgrs.							-149.431
							(-1.066)
%Senior-Level Managers			4.523			4.179	
			(0.839)			(0.771)	
%Mid-Level Managers			2.020			1.775	0.245
			(0.964)			(0.838)	(0.112)
%Technicians			0.388			0.350	0.489
			(0.149)			(0.133)	(0.171)
%Sales Workers			5.618***			6.009***	3.636**
			(3.586)			(3.723)	(2.083)
%Administrative Support			2.028			2.452	0.679
			(1.297)			(1.641)	(0.348)
%Craft Workers			4.090***			3.573**	1.663
			(2.773)			(2.441)	(1.148)
%Operatives			3.116***			2.638**	2.075
			(2.858)			(2.213)	(1.575)
%Laborers & Helpers			3.561**			3.158*	1.390
			(2.172)			(1.758)	(0.776)
%Service Workers			3.834**			3.827**	4.003
			(2.553)			(2.221)	(1.515)
Firm Controls	yes	yes	yes	yes	yes	yes	yes
Remaining Senior Mgrs. Cells	--	--	--	--	--	--	yes
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	0.103	0.110	0.073	0.108	0.114	0.073	0.114

Table 9: Talent and Seniority at the Managerial Levels and the Labor Cost Savings Ratio

This table presents the results of regression analyses examining the relation between CAR[-1,2] and two variations of the imputed labor cost savings ratio. Panel A excludes Senior-Level Managers from the calculation of pay gaps, and Panel B excludes both Senior-Level and Mid-Level Managers. In column (2), we omit the job category with the highest representation, % Professionals, to avoid perfect collinearity. In columns (4), we omit the race with the highest representation, % White, to avoid perfect collinearity. 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: Labor Cost Savings Ratio without Senior-Level Managers

	CAR[-1,2]			
	(1)	**(2)**	**(3)**	**(4)**
Labor Cost Savings Ratio	9.677***	7.382**	9.310**	8.009**
	(2.827)	(2.115)	(2.530)	(2.187)
Job Category Controls	--	yes	--	--
Gender Controls	--	--	yes	--
Race/Ethnicity Controls	--	--	--	yes
Firm Controls	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Observations	927	927	927	927
Adj. R2	0.111	0.111	0.110	0.113

Panel B: Labor Cost Savings Ratio without Senior-and-Mid-Level Managers

	CAR[-1,2]			
	(1)	**(2)**	**(3)**	**(4)**
Labor Cost Savings Ratio	8.262***	6.568**	7.856***	6.972**
	(2.921)	(2.255)	(2.661)	(2.383)
Job Category Controls	--	yes	--	--
Gender Controls	--	--	yes	--
Race/Ethnicity Controls	--	--	--	yes
Firm Controls	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Observations	927	927	927	927
Adj. R2	0.111	0.111	0.110	0.114

Table 10: 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"). Panel A presents descriptive statistics for both subgroups. In Panel B, we examine the partial effects of $\frac{\partial CAR}{\partial \text{Labor Cost Savings Ratio}}$ when the "Voluntary" variable is set to one. The test determines whether the capital market reacts significantly to the voluntary disclosure group, whose EEO-1 information had been released previously. We omit the job category with the highest representation, % Professionals, to avoid perfect collinearity. 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: Descriptive Statistics

	Non-Voluntary Disclosers 687 firms		**Voluntary Disclosers 240 firms**		**t-test of the Mean**
Variable	**Mean**	**Std.**	**Mean**	**Std.**	
%Men	59.58%	19.65%	64.48%	15.01%	4.89%***
%Women	40.42%	19.65%	35.52%	15.01%	−4.89%***
%White	69.23%	16.54%	64.32%	14.30%	−4.91%***
%Black	8.01%	7.33%	8.94%	6.20%	0.93%**
%Hispanic	10.95%	9.79%	10.67%	7.80%	−0.28%
%Asian	9.06%	11.26%	13.15%	13.62%	4.09%***
%Other	2.75%	2.77%	2.92%	2.29%	0.17%
Total Imputed Pay (in million $)	215.19	546.64	1,604.68	2,458.90	1,389.49***
Total Imputed Pay All White Men (in million $)	235.51	607.66	1,745.63	2,705.73	1,510.12***
Labor Cost Savings (in million $)	20.33	65.36	132.64	248.05	112.31***
Per Worker Labor Cost Savings (in $)	6,082	3,822	6,025	4,061	−57
Total Number of Workers	3,538	10,070	21,185	35,241	17,647***
Labor Cost Savings Ratio	8.35%	5.44%	7.44%	5.47%	−0.92%***

Panel B: Market Reactions to Labor Cost Savings

	CAR[-1,2]		
	(1)	**(2)**	**(3)**
Voluntary	0.674	0.292	-0.171
	(1.112)	(0.655)	(-0.440)
Labor Cost Savings Ratio	10.418**		
	(2.330)		
Labor Cost Savings Ratio x Voluntary	-7.706		
	(-1.369)		
Top 25% Savings Ratio		1.291***	
		(2.738)	
Top 25% Savings Ratio x Voluntary		-1.029	
		(-1.495)	
Within-Industry Savings Ratio			10.077**
			(2.045)
Within-Industry Savings Ratio x Voluntary			-6.315
			(-0.948)
Job Category Controls	yes	yes	yes
Firm Controls	yes	yes	yes
Savings Ratio + Interaction Term = 0?	p=0.549	p=0.658	p=0.422
Industry FE	yes	yes	--
State FE	yes	yes	yes
Observations	927	927	927
Adj. R2	0.111	0.112	0.067

Internet Appendices

Table IA.1: 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.2: Correlations of Economic and Political Determinants of the Labor Cost Savings 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)
Unemployment Rate	1.0000	0.2903	−0.3135	−0.4113	0.1851	0.3098
Union Participation	0.2903	1.0000	−0.7929	0.1119	0.6971	0.5416
Right to Work	−0.3135	−0.7929	1.0000	−0.2253	−0.6704	−0.5098
Highschool and Above	−0.4113	0.1119	−0.2253	1.0000	−0.0470	0.0069
Minimum Wage	0.1851	0.6971	−0.6704	−0.0470	1.0000	0.3892
Democratic Governor	0.3098	0.5416	−0.5098	0.0069	0.3892	1.0000

Panel B: Private Firms

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

Table IA.3: Employee Satisfaction

This table examines the association between the Labor Cost Savings Ratio and Glassdoor ratings. All firm control variables (ln(Size), Firm Profitability, Asset Efficiency, and Firm Leverage) are calculated at the end of 2022; earnings announcements are [t-1,t+2] days around the FOIA release data. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Rating Overall	**Culture and Values**	**Work-Life Balance**	**Compensation and Benefits**	**Career Opportunities**	**Senior Leadership**
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Cost Savings Ratio	-1.626**	-1.714**	-0.884	-1.148*	-1.150*	-1.112
	(-2.247)	(-2.229)	(-1.320)	(-1.713)	(-1.699)	(-1.438)
Job Category Controls	yes	yes	yes	yes	yes	yes
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	689	682	682	682	682	682
Adj. R2	0.084	0.160	0.142	0.126	0.116	0.086

Table IA.4: 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.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 are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	CAR[-1,2]			
	(1)	**(2)**	**(3)**	**(4)**
Labor Cost Savings Ratio	13.243***	11.839**	13.912**	12.687**
	(2.700)	(2.223)	(2.577)	(2.372)
Job Category Controls	--	yes	--	--
Gender Controls	--	--	yes	--
Race/Ethnicity Controls	--	--	--	yes
Firm Controls	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Observations	683	683	683	683
Adj. R2	0.099	0.094	0.097	0.109