

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

Finance Working Paper N° 1024/2024

December 2024

Ferdinand Bratek

New York University

April Klein

New York University and ECGI

Yanting (Crystal) Shi

HEC Paris

© Ferdinand Bratek, April Klein and Yanting (Crystal) Shi 2024. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

This paper can be downloaded without charge from:
http://ssrn.com/abstract_id=5034828

www.ecgi.global/content/working-papers

ECGI Working Paper Series in Finance

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

Working Paper N° 1024/2024

December 2024

Ferdinand Bratek
April Klein
Yanting (Crystal) Shi

We thank Karthik Balakrishnan, Gurpal Sran, and seminar participants at City University of Hong Kong, New York University, USC, and Warwick Business School for their comments and suggestions. We thank Maximilian Muhn for providing us with their list of voluntary disclosers, and Mason Zhang for his RA work on this project.

Abstract

We exploit the release of Type 2 EEO-1 forms by the Department of Labor for over 11,000 public and private U.S. contractors to estimate gender and race/ethnicity pay gaps. These forms contain standardized detailed demographic breakdowns of companies' 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 for all firms, the pay gap increases with firm size. Pay gaps vary dramatically across industries, and they are associated in ways consistent with labor economics theory. We further exploit the public release of EEO-1 forms 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. 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, the IO structure of the firm, 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.

Keywords: Labor Economics, Gender and Race Pay Equity, EEO-1 Form

Ferdinand Bratek
Researcher
New York University
40 West 4th Street
New York, NY 10012, USA
e-mail: ferdinand.bratek@stern.nyu.edu

April Klein*
KPMG Faculty Fellow and Professor of Accounting
New York University
Kaufman Management Center, 44 West Fourth Street
New York, NY 10013, United States
e-mail: ak5@stern.nyu.edu

Yanting (Crystal) Shi
Assistant Professor
HEC Paris
1 rue de la Liberation
Jouy-en-Josas Cedex, 78351, France
e-mail: shi@hec.fr

*Corresponding Author

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

Ferdinand Bratek
Stern School of Business
New York University
Ferdinand.Bratek@stern.nyu.edu

April Klein
Stern School of Business
New York University
Ak5@stern.nyu.edu

Crystal (Yanting) Shi
HEC Paris
Shi@hec.fr

Abstract: We exploit the release of Type 2 EEO-1 forms by the Department of Labor for over 11,000 public and private U.S. contractors to estimate gender and race/ethnicity pay gaps. These forms contain standardized detailed demographic breakdowns of companies' 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 for all firms, the pay gap increases with firm size. Pay gaps vary dramatically across industries, and they are associated in ways consistent with labor economics theory. We further exploit the public release of EEO-1 forms 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. 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, the IO structure of the firm, 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.

We thank Karthik Balakrishnan, Gurpal Sran, and seminar participants at City University of Hong Kong, New York University, USC, and Warwick Business School for their comments and suggestions. We thank Maximilian Muhn for providing us with their list of voluntary disclosers, and Mason Zhang for his RA work on this project.

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 certain minorities in certain occupations and industrial sectors (DOL 2024a).

In this paper, we estimate, document, 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 (George and Livingston 2024), and Blacks and Hispanics/Latinos earned, on average, 77 cents and 73 cents, respectively (DOL 2024b), for every dollar a white worker was paid.

A large and growing literature examines the fundamental 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) as some of the driving forces. Other papers document some of the 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.

Hitherto, a main impediment to systematically measuring 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 EEO-1 filings from 2016 through 2020 for over 19,000 public and private U.S. contractors. EEO-1 filings are mandatory, standardized annual reports 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. The uniqueness of these reports is that they contain information about *10* levels of job categories, including senior-level managers, mid-level managers, technicians, administrative support, and laborers and helpers – thus allowing 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 expand our analyses to cover a large spectrum of companies within the United States.

We exploit the granularity of the EEO-1 form, along with other detailed state/demographic/job category pay data provided by the EEOC, to calculate estimates of the firm’s actual labor costs and a theoretical labor cost in which the firm’s workforce is comprised of white men only.¹ We call the difference between these two calculations “labor costs saved.”² One advantage of our setting is that firms assumed a right of privacy for these forms at the time of submitting them between 2016 and 2020; thus, they would be less inclined to manage their workplace diversity and IO structures to conform to public pressures.

To provide some intuition into how the workforce diversity and job categories play into the determinants of the pay gap, we present, in Figure 1, a nation-wide figure of gender and race/ethnicity pay gaps by job category. The amount and the relative size of the pay inequities differ across job categories. For example, whereas the gender gap is relatively large across all race/ethnicity categories for “Professionals,” there is no substantive pay difference by gender for “Administrative Support” workers. Thus, even if Firm A and Firm B had the same percentage of women in their workforce, they would have different estimated pay gaps if, for example, Firm A’s women employees were more concentrated in “Professional” positions but Firm B’s women were more heavily represented as “Administrative Support” workers.

Our analyses cover 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

¹ We are not the first paper to use other data to estimate labor costs across firms. For example, Belo et al. (2022) uses published industry data to infer the labor costs of firms in their sample. In section IV.D of this paper, we perform several tests to validate our labor costs estimates. We also use labor economics theory to test several hypotheses about the determinants of our pay gap measure. Both the direct validation tests and the determinants analysis are consistent with our variable being a reasonable presentation of the measure we are seeking.

² Section IV.A contains a detailed explanation on how we derive our measure.

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, the 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 (Ragunandan 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 diversity/industrial organization (IO) structures provides insights into these differences. As the EEO-1 forms 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 racial and ethnicity pay gaps. 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 measures. 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 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, or they might be correlated with other labor violations, for example, unpaid overtime or unsafe working conditions (Raghunandan 2021; Cooper and Kroeger 2017). Although Edmans (2011), Green et al. (2019), Boustanifar and Kang (2022) and Edmans et al. (2024) do not explore pay discrimination, they present evidence consistent with overall employee satisfaction or feelings of inclusion being positively related to future long-term shareholder returns and future accounting performance. 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 these forms. Under efficient markets, if the data in these reports provide new information about a firm, and if investors can contextually calibrate these measures within a valuation framework, 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 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 of the net value of a firm's pay gap.

We present strong and consistent evidence that the market reactions around the release of the EEO-1 reports are positively related to the size of a firm's labor cost savings. Our findings are robust to different specifications of how we compute labor cost savings, and to the inclusion of the firm's IO structure, workforce diversity measures, seniority and talent at the managerial level, earnings announcements, and state and industry fixed effects within the regression estimations. 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) empirically demonstrate the importance of labor in understanding the dynamics of the market value of firms. Belo et al. (2022) shows that labor's contribution to firm value has remained constant over the 1950-2016 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, Belo et al. (2022) demonstrates 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 several literatures surrounding diversity, equity, and inclusion (DEI). There is little debate that following the advent of the #MeToo and the Black Lives Matter movements, firms have increased their DEI initiatives and disclosures of these initiatives.³ However, it is unclear whether increased diversity actually benefits women and minorities through higher pay and more opportunities. A case in point is Amazon, which, in 2020, 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 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,

³ On August 26, 2020, the U.S. Securities and Exchange Commission (SEC) issued Release No. 33-10825, titled "Modernization of Regulation S-K Items 101, 103, and 105," mandating that public companies include disclosures about their human capital resources in their annual reports (Form 10-K). These include initiatives related to employee development, diversity and inclusion, and health and safety, thereby encouraging firms to disclose their DEI initiatives.

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.

Our paper contributes to the DEI 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 form 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. We expand on their findings by showing that these job segregation patterns congregate more strongly around the job categories that, on average, pay the least, thus contributing to the persistent wealth inequalities documented in the literature.

Another stream of literature examines whether diversity correlates with higher firm value. Several papers (e.g., Adams and Ferreira 2009; Ahern and Dittmar 2012; Ecbo, Nygaard, and Thornburg 2022; Greene, Intintoli, and Kahle 2020; Allen and Wahid 2021; Fried 2021) concentrate on gender diversity at the board of directors level. Other papers relate current racial and ethnic diversity at the executive level to future firm profits (e.g., McKinsey 2015; 2018; 2020; Green and Hand 2021). The findings of these papers are mixed, thus leaving the economic value of diversity at the board or executive level an open question. Daniels et al. (2024) finds a positive stock market reaction to the percentage of women employees in the overall workforce for 49 U.S. technology firms that voluntarily released their first diversity report between May 2014 and December 2018.⁴ Our paper documents a positive association between firm value and the percentage of Hispanic workers over its entire workforce, but no significant associations for the

⁴ Daniels et al. (2024) also finds a positive mean stock market reaction around April 4, 2017 for the 10 financial firms that had their gender diversity percentage announced in the *Financial Times*.

percentages of women, Black, or Asian workers. Furthermore, after controlling for pay gaps, this positive association becomes insignificantly different from zero.⁵

Finally, our paper contributes to the literature on pay inequities in the U.S.⁶ A large and growing literature examines the fundamental determinants behind the persistence of these gaps, attributing, for example, family obligations (Bertrand et al. 2010) and racial discrimination (Wilson and Darity 2022) as some of the driving forces. Other papers document some of 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). Our paper presents estimates of the size of these pay gaps for both private and public firms. Similar to Kline et al. (2022) and Bourveau et al. (2024), who show that racial and gender job discrimination differs dramatically across industries, we find variations in the labor cost ratio across industries. We also examine some of the economic determinants behind pay gaps, and present results consistent with Becker’s (1957, 1962) theories on wage determinants. Finally, we provide evidence that investors positively incorporate the 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.

⁵ Our findings on women differ from Daniels et al. (2024) for many reasons, including using a much larger, industry-diversified sample, a more sophisticated expected returns model, and the inclusion of industry and state fixed effects in our regression estimations. We also acknowledge that there may be other benefits to having a more diverse workforce beyond labor cost savings. One benefit often cited is that workforce diversity increases creativity, and leads to more innovation and profitability (Dallas 2002; Dezsö and Ross 2012; Rock and Grant 2016; Reynolds and Lewis 2017). A second often cited benefit is that diversity reduces litigation risk related to discrimination and class action suits (Brummer and Strine 2022; Balakrishnan et al. 2023; Daniels et al. 2024). Examining these benefits is beyond the scope and aim of this paper.

⁶ 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; Wallsgog, et al. 2024).

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

A. EEO-1 Reports

Since 1966, firms (U.S. government contractors) with over 100 (50) 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 report is a "consolidated report," which includes all full-time and part-time employees who worked (anytime) in the 50 U.S. states and the District of Columbia within the October 1 through December 31 window of the filing firm (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.

Appendix A presents the Type 2 EEO-1 Report for Netflix in 2022. 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, Netflix has 7,627 employees in total, with 3,858 (50.6%) being male and 3,858 (49.4%) being female. Seven hundred fifty employees are "Black or African-American", which represents 9.8% of Netflix's total workforce; 893 (11.7%) are "Hispanic or Latino" workers. In terms of IO structure, Netflix

is a top-heavy firm, in that 80.6% of its employees fall into the top three categories: “Senior-Level Managers,” “Mid-Level Managers,” and “Professionals.” We also can discern that “Professionals” are tilted towards men, who hold 55% of the positions, whereas “Administrative Support” is dominated by women, who hold 64% 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 EEO-1 Reports in March and April 2023

EEO-1 reports are filed confidentially and are not publicly available⁷ – however, U.S. government contractors are required to share their reports with the U.S. Department of Labor’s Office of Federal Contract Compliance Programs (OFCCP). 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 U.S. contractors. Consistent with the DOL’s disclosure regulations, the OFCCP published multiple notices of the FOIA request in the National Register, giving contractors until March 31, 2023 to object to the release of their data. Over 4,000 contractors contacted the OFCCP with objections to their release; many held that their reports were exempt from disclosure under FOIA Exemption 4, an exemption that protects “trade secrets and commercial or financial information” as being “privileged or confidential.”⁸ Thirty-three firms (see below) allowed the OFCCP to release their forms. Over 19,000 U.S. contractors either did not object or did not respond to the National Register notices.

⁷ Companies are not precluded from voluntarily releasing these documents to the public, and many firms, particularly those in the Fortune 100, place the EEO-1 form or a summary of that form on their company websites.

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

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 forms for the 21 Federal contractors who already voluntarily released their forms. On April 17, 2023, the OFCCP released the EEO-1 forms 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 (19,366).⁹

III. Data and Descriptive Statistics

A. Data Collection

The data source for the workplace demographics is the Type 2 EEO-1 forms provided by the DOL’s website. Compensation data are from the U.S. EEOC website.¹⁰ We obtain stock returns and financial reporting data from CRSP and Capital IQ Compustat (Compustat). Table 1, Panel A shows the sample construction for the private and public firms we use in our analyses.

The DOL database contains all EEO-1 filings from 2016 to 2020, with many firms having multiple filings across this time period. For this paper, we take the latest available Type 2 EEO-1 form of each sample firm in our analyses, thus keeping our initial sample to 19,400 unique firms.¹¹ Of these firms, 18,208 are private and 1,192 are publicly-traded. For private firms, we keep the 10,434 contractors that exhibit a valid NAICS industry classification in the FOIA data set. For the public firms, we do the same match; all public firms in our sample have this data. Dropping public firms without the required Compustat or CRSP data reduces the sample to 969 individual firms.

⁹ The OFCCP still is in litigation over the release of the remaining forms. 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, and to our knowledge, the forms 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>).

¹⁰ 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>

¹¹ In total, there are 56,488 unique firm-year filings from 2016 to 2020.

Removing the five firms with fewer than 50 employees gives us 964 unique firms. We further drop those firms that fundamentally changed between their 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 distribution of the most recently filed EEO-1 forms by year. As the panel shows, the vast majority of our sample consists of firms that filed their latest EEO-1 form in 2020. For public firms, 75.4% of our sample hails from 2020, and for private firms, this percentage blooms to 89.2%.

B. Overall Workforce Diversity

Table 2 presents gender and race/ethnicity distributions for our sample firms. We show, in Panel A, the gender and race/ethnicity for the entire *current* U.S. workforce, as reported by the Bureau of Labor Statistics (BLS). For 2023, women make up 47% of the entire U.S. workforce, compared to men, who account for 53%. In terms of race/ethnicity, the U.S. workforce can be divided into the following categories: “White” 77%; “Black” 13%; “Hispanic” 19%; and “Asian” 7%.¹² 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

¹² 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.”

and ethnic identity, we cannot make comparisons between our sample firms and the national averages. However, we note that whereas both groups have similar percentage of white employees (68% and 67%, respectively), public firms have lower percentages of Black and Hispanic employees, but a larger percentage of Asian workers when compared to private firms.

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

Figure 2 shows the proportion of workers by gender, race/ethnicity and job category. For all workers in our sample, the four most common positions held 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 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.

Weber and Stamm (2024) show that many occupations are tilted towards a particular gender or ethnicity, a tendency known as job segregation. In Figure 2, we present data consistent with this phenomenon. Specifically, using the data from our EEO-1 filings, we divide race/ethnicity groups by gender, with men shown on the left and women on the right. Each bubble represents the percentage of jobs held by workers within that demographic group, with larger (smaller) bubbles reflecting the relative sizes for each group. We highlight the two largest bubbles for each job

category. By doing 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 provides some interesting insights into the U.S. labor market. White men are overweighted as Senior-Level Managers and Mid-Level Managers. Given that Senior-Level Managers and Mid-Level Managers are the two highest paid positions, this helps explain the relatively high average pay for this demographic group. In contrast, Black men and Hispanic men are overweighted as Operatives and Laborers & Helper. Laborers & Helpers is the second lowest paying job, thus contributing to these workers' relatively low average pay. When looking across job categories (untabulated), we find that White men, despite comprising 38.5% of the labor force, hold 61.6% and 47.0% of all Senior-Level and Mid-Level Manager jobs. Black men and Hispanic men, in contrast, comprise 5.3% and 7.3%, respectively, of the labor force; yet they hold just 1.7% and 2.6% of Senior-Level Manager jobs and just 2.9% and 4.7% of Mid-Level Management positions.

Asians (men and women) are extremely overweighted as Professionals, with 44% of men and 40% of women, falling into this one job category. Professionals is the third highest-paid position, thus offering some insight into the relatively high pay averages for Asian workers.

White and Hispanic women are overrepresented as Administrative Support workers, and Black and Hispanic women are overweighted as Service Workers. Service Workers accrue the lowest average pay; Administrative Support is the third lowest paid job. These data offer insights into why Hispanic and Black women fall into the two lowest-paid demographics. White women, however, are slightly overrepresented as Mid-Level Managers, thus raising their average national pay. Finally, looking across job categories (untabulated), Black (Hispanic) women hold just 1.8% (1.7%), 3.6% (3.8%), and 5.5% (4.6%) of all Senior-Level Managers, Mid-Level Managers, and

Professional jobs, respectively. Yet, they comprise 5.7% and 5.8%, respectively, of the entire labor force.

The observations provided in Figure 2 are compatible with Bourveau et al. (2024), who compares all managers (senior-level and middle managers) with lower-level employees (the other eight job categories). Their focus is on the identity of managers, and they demonstrate that women, Black and Hispanic employees are underrepresented vis-à-vis national averages in these two job categories. We add to their study by showing that race and gender job segregation exists in some of the lowest-paid job categories. Thus, the Amazon example discussed in the Introduction of greater diversity coming at the cost of minorities being placed in lower-paid jobs does not appear to be an isolated case.

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

A. Estimation of the Pay Gap

We define the pay gap as the difference between what a White man and a woman/minority worker in the same job category would earn at an individual firm. The EEO-1 form provides us with both the horizontal gender/race/ethnicity and the vertical 10 job category breakdown of a firm's workforce. This gives us a matrix of 140 cells based on diversity and the firm's IO structure. For example, from a firm's EEO-1 form, we may see that 7% of its workforce is comprised of Black women who are Professionals. What we do not have, however, is the income earned by these women in that job.

To estimate these amounts, we turn to other data published by the EEOC. Specifically, we use the "2018 EEO-1 Component 2 Pay Data Collection State Aggregates (NAICS-3) Public Use File" from the EEOC website. This file contains information on the average pay of employees in the same 140 diversity-job categories as shown on the EEO-1 forms broken down by state and by

NAICS three-digit and two-digit industry codes.¹³ Using the same example above, if our firm is in the Retail Trade industry and is headquartered in Colorado, we take the average pay that a Black woman who works as a Professional in Colorado for a Retail Trade firm as our estimate of her average pay. We repeat this process for each of the 140 diversity-job cells throughout the firm.

There are several advantages and disadvantages to our process. One advantage is that the EEOC uses the same gender-racial/ethnicity-job category format for its EEO-1 forms and its Pay Collection database, thus giving us a one-to-one alignment between datasets. A second advantage is that the pay data 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.

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 gender-race/ethnicity-job category within its respective state and two-digit NAICS industry. This may not be valid for larger firms who have more leverage in determining wages. A second disadvantage is that we use the state in which the firm’s company headquarters is located, thus assuming all employee wages are

¹³ According to the EEOC, in 2016, the agency added a pay data collection component, “Component 2,” to its EEO-1 form. The EEOC collected this pay data from private employers and certain federal contractors from 2017 through 2018 only. Employers were instructed to pick a pay period from October through December of the given year (2017 or 2018) to identify employees for reporting purposes, using 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>). In 2017 and 2018, the EEOC made aggregated Component 2 pay data available based on these individual forms to the public through its website EEOC Explore, thereby protecting employer and employee confidentiality. The aggregation is by industry-state-gender-race/ethnicity-job, thus giving us the average pay data for each of the 140 cells in the EEO-1 for any firm in its three-digit NAICS industry code in the state in which its headquarters is domiciled. 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. In addition, to better align our industry classifications with Fama-French industry classifications, we also map these NAICS three-digit codes with Fama French 48 industries and conduct a robustness analysis (Section VIII.B). The results and interpretations are robust to this alternative classification. After 2018, the EEOC discontinued the publication of this data. Thus, we use the latest file from 2018.

determined at the headquarters level. This, too, may not be a valid assumption for larger firms with subsidiaries or factories in multiple states. To address these concerns, we perform robustness tests based on firm size and industry definitions.¹⁴

For each firm in our sample, we multiply the number of employees in each cell (from the EEO-1 form) by the average pay in each cell (from 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 of each firm as if all workers were compensated according to the pay standards of White males within their respective job categories. This involves recalculating total pay as if every worker was paid at the average pay level of White males 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:

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

To control for firm size, we calculate:

$$\text{Labor Costs Savings Ratio} = \text{Labor Cost Savings} / \text{Total Imputed Pay} \quad (2).$$

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

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.

¹⁴ 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.

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 \$6,069 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 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

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."

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 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 monotonic increase in the mean *Labor Cost Savings Ratio* by size for public (nearly) and private firms, 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 (Panel A), 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 forms provides a partial answer. First, we note from Panel B that it is not due to outliers, in that the number of 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 IO 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. First, we examine the degree to which *Total Imputed Pay* is associated with a firm’s actual labor force and labor costs. 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 on the 10-K, on the total number of workers taken from the EEO-1. The coefficient on the *Total Number of Workers* (EEO-1 report) is significantly positive, consistent with the EEO-1 form capturing almost all of a firm’s workforce. In column (2), we regress SG&A expense, as reported on the Form 10-K, 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 turn to a different data source – IRS Form 1120, entitled “U.S. Corporation Income Tax Return” – which delineates firms’ revenues and expenses as reported to the IRS. BrightQuery is the source of these forms, and their database covers 733 firms in our public sample. Using these forms, we add “Compensation of Officers” (line 12) and “Salaries and Wages” (line 13) together, giving us each firm’s tax-based

compensation expense as reported to the IRS. As column (3) shows, the coefficient on *Total Imputed Pay* is highly significant, thus showing a high correlation between our measure of the firm's payroll and the IRS- reported payroll.

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 panel 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, there is a body of papers showing that within-firm pay gaps – differences in pay between top- and bottom-level jobs – are influenced by talent and seniority at the highest levels within a firm's organization (Mueller et al. 2017; Wallsgog et al. 2024). Their findings have implications for our measure of pay gaps, in that the pay gaps for employees in the management levels might be due to factors unrelated to diversity. We examine this issue further in Section VI.B, when correlating market reactions to the *Labor Cost Savings Ratio*.

V. Economic Determinants of the Labor Cost Savings Ratio

In this section, we examine some of the economic determinants behind variations in labor cost savings. Because *Labor Cost Savings* is derived from state data, we exploit differences in

economic variables among states. First, we posit a negative association between the pay gap and the bargaining power of the available labor force (Becker 1957). We use the state's *Minimum Wage*, its *Unemployment Rate*, the percentage of *Union Participation*, and whether the state has a *Right to Work* as our measures of the employees' bargaining power. Jobs that pay the minimum wage place a lower bound on wages paid, thus constricting the band in which employers can pay their workers; in contrast, better paying jobs have no lower bounds, thus providing wider discretion in pay levels. Workers, particularly at lower level jobs, can be replaced easily by unemployed workers, thus lowering their ability to negotiate higher wages. 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 negative cross-sectional associations between the pay gap and *Minimum Wage*, *Unemployment Rate*, and *Union Participation*, and a positive association for companies in states with *Right to Work* laws.

Next, we predict a negative association between education levels and the 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*), and predict a negative relation between it and the firm's pay gap.

Table 6 presents summary statistics for the regressions of the *Labor Cost Savings Ratio* on these six 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 four variables *Minimum Wage*, *Unemployment Rate*, *Union Participation Rate*, and *Right to Work* are reliably different from zero for both public (except *Unemployment Rate*) and private (except for *Minimum Wage*) firms in their predicted directions. These findings are consistent with a negative cross-section association between the pay

gap and the 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, Table 6 presents evidence consistent with the pay gap being determined in ways that are consistent with labor economics theory.

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 the 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. 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, 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 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 associated with employee dissatisfaction. 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

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.

reviews for the year its EEO-1 form 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, its Culture & Values rating, and most tellingly, its Compensation & Benefits rating. In contrast, the coefficients on Work-Life Balance, Career Opportunities, and Senior Leadership, while negative, are not significantly from zero at conventional levels. Thus, we present evidence of a negative association between pay inequities and 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 forms 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.

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). Further, as Figure 3 shows, the ratio varies systematically across industries, with healthcare, beauty parlors and science and technology services sporting percentages of around 40%, while insurance, construction, manufacturing and retail spending around 20% or less on labor costs.

¹⁷ See <https://www.pwc.com/us/en/products/saratoga.html>.

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 value 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 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 find no significant differences in the firms' leverage or CapEx ratios.

We estimate the following OLS regression of the firm's CAR on its Labor Costs Savings Ratio:

$$CAR_{i,t-1,t+2} = \alpha_0 + \beta_1 Labor\ Cost\ Savings\ Ratio_i + \beta_j State_j + \beta_k Industry_k + \beta_2 EA_{i,t-1,t+2} + \varepsilon_{i,t-1,t+2} \quad (3),$$

where $CAR_{i,t-1,t+2}$ is firm i 's FF5-factor CAR over a $[-1, +2]$ window surrounding day 0, the DOL's release of firm i 's EEO-1 form 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 forms 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 from its latest EEO-1 form. We control for the supply of workers by including fixed effects 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. $EA_{i,t-1,t+2}$ 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.

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, presumably through the employee's disaffection with the firm.

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 (untabulated).

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 forms, 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 Consolidated 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 forms 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 (Moreno 2023).

Second, the release dates must be unexpected. 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. In addition, the information in the releases must contain some value-relevant information. Edmans et al. (2024) presents evidence that the market does not fully price in workplace equity and inclusion (as measured through survey data), suggesting that investors may be able to use the EEO-1 forms to glean additional information about the value-relevance of pay inequities from these forms.

Third, the data must be relatively easy to access and process. The DOL made access very easy. On March 2nd, they placed the initial group of EEO-1 forms 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 form, the DOL provided excel spreadsheets that are clear, accessible, and comparable to each other. In addition, investors already had practice 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, McNichols, and Muhn 2024), As for the pay data that we use, the EEOC pay data were made available from 2018 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.¹⁹ The pattern of these CARs is inconsistent, and show 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

Table 7 contains summary statistics for Equation (3). In column (1), we use the Labor Cost Savings Ratio as the independent variable; its coefficient is 11.36, significant at the 0.01 level. In

¹⁹ 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.

economic terms, a one standard deviation increase in the Labor Cost Savings Ratio (5.45%) increases the CAR over the window $[-1, +2]$ by 0.62%.

To gain additional insights into these results, we create an indicator, *Top 25% Savings Ratio*, which is one for firms lying in the top 25% of the *Labor Cost Savings Ratio* distribution, and zero otherwise. These firms have the largest pay gaps and should enjoy the greatest positive market reaction upon the revelation of the EEO-1 forms. As shown in column (2), the coefficient on *Top 25% Savings Ratio* is 1.354, significantly positive at the 0.01 level. In economic terms, firms hailing from the top quarter of the *Labor Costs Savings Ratio* had, on average, a CAR that is 1.354% greater than those firms in the bottom 75% of our pay gap sample.

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

The release of the EEO-1 form provided investors with two new sources of information – detailed information on workplace diversity, but also the firm’s IO 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 IO structures and that the market is reacting positively to these differences, and not to the pay gaps that the firms enjoy. For example, if the market, hypothetically, expected Firm A to have only 4% of its total employees in the highest paying category (Senior-Level Managers), but discovered that Senior-Level Managers comprised 6% of its total workforce, then it might revalue the firm’s market value downwards to adjust for these additional compensation costs.

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 (3) of Table 7 shows, the stock price reaction to the release of the EEO-1 forms is significantly positively related to a firm’s percentage of employees who are Sales Workers. This is among the lowest paid job categories, thereby

supporting the view that the market reacted positively to firms revealing IO structures that are tilted towards lower-paying jobs.²⁰

In columns (4) and (5), we add the job category percentages to *Labor Cost Savings* and *Top 25% Savings Ratio*. The coefficients on *Labor Cost Savings* and *Top 25% Savings Ratio*, though smaller than that shown in columns (1) and (2), remain statistically significant at the 0.05 and 0.01 levels, respectively. The coefficients on the job categories show the same pattern as in column (3). Thus, we conclude that our pay gap variable and the firm's IO structure capture information incremental to each other.

B.4 Are We Just Capturing Diversity? Connecting Diversity and Pay Equity Across Firms

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 (Brummer and Strine 2022; Billings et al. 2022; Daniels et al. 2024; Balakrishnan et al. 2022), allows a firm

²⁰ A firm's IO structure is somewhat determined by its industry. If we remove Industry fixed effects from equation (3), we find significantly positive coefficients on Sales Workers, Administrative Support, and Craft Workers.

to tap and retain a larger pool of talented and dedicated employees, and better attracts and retains customers and clients who value workplace diversity.

Table 8 contains regression results in which we regress CARs on the percentage of women (*%Women*), Black, (*%Black*), Hispanic (*%Hispanic*), Asian (*%Asian*) workers. As columns (1) and (2) show, only the coefficient on *%Hispanic* is significantly positive, suggesting that after controlling for industry and state effects, investors do not, in general, value greater 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 (3) and (4), we add *Labor Cost Savings Ratio* as an additional variable. After including this variable, the coefficients on *Labor Cost Savings* and *%Hispanics* remain statistically significant. Columns (5) and (6) put in the firm's IO structure 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, IO, and industry measures, a finding reflected in *%Hispanics* now becoming insignificantly different from zero. In total, we conclude that our pay gap variable captures information incremental to a firm's level of workplace diversity.

B.5 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, 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 EEO-1 forms on their company websites (Bourveau et al. 2024; Choi et al. 2024). For these firms, the information contained in the EEO-1 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 form. 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 EEO-1 forms 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 already posted their EEO-1 form(s) on their company websites; Non-voluntary disclosers are firms whose EEO-1 form(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 EEO-1 forms 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 Asian workers, but significantly lower 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.

Panel B contains summary statistics for the regressions of CAR on the firm’s pay gaps by group. Consistent with efficient market theory, we find reliably significant coefficients on *Labor Cost Savings Ratio* and *Top 25% Savings Ratio* only for the group of non-voluntary disclosers. Using the Seemingly Unrelated Estimations (SUE) method, there are significant differences in the coefficients for *Labor Cost Savings Ratio* (one-sided significant at the 0.06 level) and *Top 25% Savings Ratio* (one-sided significant at the 0.04 level) between the two groups.

In summary, our findings lend further support for our efficient market theory approach to evaluating how investors value workplace diversity.

B. Robustness Tests

We conduct several robustness tests. Our first set of tests examines 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 (untabulated) are consistent with this truncated sample.

IX. Summary and Initial Conclusions

Using the recent release of Type 2 EEO-1 forms by the Department of Labor for over 19,000 publicly-traded and private U.S. contractors, alongside detailed wage data by the EEOC, we examine the prevalence, determinants, and market valuation of pay gaps between white men and women, and between white men and other workers within the firm across firms and industries.

Thus, our paper offers insights into two lesser-known aspects of pay gaps – variation among firm-types and investor valuation of these inequities.

We document economically significant 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 that they are relatively higher (in percentage terms) for private firms and for larger firms. 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 state of incorporation, industry classification, workforce diversity measures, the firm's IO structure, and other effects, we find a significantly positive abnormal stock price reaction around the release of the EEO-1 forms 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 pernicious. 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.

References

- Adams, R. B., and D. Ferreira. 2009. Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics* 94(2), 291-309.
- Ahern, K., and A. Dittmar. 2012. The changing of the boards: The impact of firm valuation of mandated female board representation. *The Quarterly Journal of Economics* 127(1), 137-197.
- Aliprantis, D., and D. Carroll. 2019. What is behind the persistence of the racial wealth gap? *Economic Commentary*. Federal Reserve Bank of Cleveland. February 28, 2019.
- Allen, A. and A. Wahid. 2021. Regulating Gender Diversity: Evidence from California Senate Bill 826. Working paper.
- Balakrishnan, K., Copat, D. De La Parra, and K. Ramesh. 2023. Racial diversity exposure and firm responses following the murder of George Floyd. *Journal of Accounting Research* 61(3), 737-804.
- Becker, G.S. 1957. *The Economics of Discrimination*. The University of Chicago Press.
- Becker, G.S. 1962. Investments in human capital: A theoretical analysis. *Journal of Political Economy* 70(5), 9-49.
- Belo, F., B.D. Gala, J. Salomao, and M.A. Vitorino. 2022. Decomposing firm value. *Journal of Financial Economics* 143(2), 619-639.
- Bertrand, M., C. Goldin, and L. Katz. 2010. Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics* 2, 228-255.
- Billings, M., Klein, A. and Shi, Y. 2022. Investors' response to the #MeToo Movement: Does corporate culture matter? *Review of Accounting Studies* 27, 897-937.
- Blair, P., and B. Posmanick. 2023. Why did gender wage convergence in the United States stall? Working paper. NBER.
- Blau, F.D., I. Cohen, M.L. Comey, L. Kahn, and N. Boboshko. 2023. The minimum wage and inequality between groups. Working paper. NBER.
- Blau, F.D., and L.M. Kahn. 2017. The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature* 55, 789-865.
- Bleiweis, R., J. Frye, and R. Khattar. 2021. *Women of Color and the Wage Gap*. <https://www.americanprogress.org/article/women-of-color-and-the-wage-gap/>.
- Boustanifar, H. and D. K. Kang. 2022. Employee satisfaction and long-run stock returns, 1984-2020. *Financial Analysts Journal* 78, 129-151.
- Bourveau, T., R.W. Flam, and A. Le. 2024. Behind the curtain of workforce diversity: Evidence from EEO-1 reports. Working paper. Columbia University.

- Brummer, C., and L. E. Strine, Jr. 2022. Duty and Diversity. *Penn Carey Law: Legal Scholarship Repository*. http://scholarship.law.upenn.edu/faculty_scholarship/2255.
- Choi, J.H., M. McNichols, and M. Muhn. 2024. Decoding Social Disclosure Decisions: A Field Experiment with Workforce Diversity Data. Working paper. Stanford University.
- CNBC. 2019. With wages on the rise, Goldman Sachs has a ‘low labor costs’ stock strategy that beats the market. <https://www.cnbc.com/2019/02/12/goldman-sachs-has-a-low-labor-costs-stock-strategy-that-beats-the-market.html>
- Cooper, D. and Kroeger, T. 2017. Employers steal billions from workers’ paychecks each year: Survey data show millions of workers are paid less than the minimum wage, at significant cost to taxpayers and state economies. Working paper. *Economic Policy Institute*.
- Dallas, L. L. 2002. The New Managerialism and Diversity on Corporate Boards of Directors, 76 *Tulane Law Review*, 1363-1391.
- Daniels, D. P., J. Dannals, T. Z. Lys, and M.A. Neale. 2024. Do investors value workforce gender diversity? *Organization Science*. <https://doi.org/10.1287/orsc.2022.17098>.
- Day, Matt. 2021. Amazon’s early pandemic hiring spree mostly people of color. Yahoo Finance. March 22, 2021. <https://finance.yahoo.com/news/amazon-early-pandemic-hiring-spre-212316155.html>
- Dezső, C. L., and D.G. Ross, 2012. Does female representation in top management improve firm performance? A panel data investigation. *Strategic Management Journal*, 33(9), 1072–1089. <https://doi.org/10.1002/smj.1955>
- DOL. 2024a. *What You Need to Know About the Gender Wage Gap*. <https://blog.dol.gov/2024/03/12/what-you-need-to-know-about-the-gender-wage-gap>
- DOL 2024b. Earnings disparities by race and ethnicity. <https://www.dol.gov/agencies/ofccp/about/data/earnings/race-and-ethnicity>
- Ecbo, B. E., K. Nygaard, and K.S. Thornburg. 2022. Does mandatory board gender-balancing reduce firm value? *Harvard Business Law Review*. 12, 407.
- Edmans, A. 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics* 101, 621-640.
- Edmans, A., C. Flammer, and S. Glossner. 2024. (Diversity) equity and inclusion. Working paper. London Business School.
- EEOC. 2018. 2018 EEO-1 Component 2 Pay Data Collection State Aggregates (NAICS-3) Public Use File. <https://www.eeoc.gov/data/2017-and-2018-pay-data-collection>
- EEOC. 2022. *EEO-1 Component 1 Data Collection Instruction Booklet*. U.S. Equal Employment Opportunity Commission. Washington DC.
- Fried, J. 2021. Will Nasdaq’s diversity rules harm investors? *Harvard Business Law Review Online*. 12, 1.

Friedman, M. 1970. A Friedman doctrine – The social responsibility of business is to increase its profits. *New York Time Magazine*, September 13, 1970.

George, Erin and Gretchen Livingston. 2024. What you need to know about the Gender Wage Gap. U.S. Department of Labor Blog, March 12, 2024. <https://blog.dol.gov/2024/03/12/what-you-need-to-know-about-the-gender-wage-gap>

Goldin, C. 2014. A grand gender convergence: Its last chapter. *American Economics Review* 104(4), 1091-1119.

Goldman Sachs. 2019. *US Weekly Kickstart*, December 6, 2019.

Green, J., and J. M. R. Hand. 2021. Diversity matters/delivers/wins revisited in S&P 500 firms. Working paper. Texas A&M.

Green, T. C., R. Huang, Q. Wen, and D. Zhou. 2019. Crowdsourced employee reviews and stock returns. *Journal of Financial Economics* 134, 26-251.

Greene, D., V. J. Intintoli, and K. M. Kahle. 2020. Do Board Gender Quotas Affect Firm Value? Evidence from California Senate Bill No. 826. *Journal of Corporate Finance* 60.

Kline, P., E. K. Rose, and C.R. Walters. 2022. Systematic discrimination among large employers. *Quarterly Journal of Economics* 137, 1963-2036.

McKinsey: Hunt, V., Layton, D., and S. Prince. 2015. *Diversity Matters*. (London: McKinsey & Company, Feb. 2, 2015).

McKinsey: Hunt, V., Prince, S., Dixon-Fyle, S., and L. Yee. 2018. *Delivering through Diversity*. (London: McKinsey & Company, January 2018).

McKinsey: Hunt, V., Prince, S., Dixon-Fyle, S., and K. Dolan. 2020. *Diversity Wins: How Inclusion Matters*. (London: McKinsey & Company, May 2020).

Merz, M., and E. Yashiv. 2007. Labor and the market value of the firm. *American Economics Review* 97(4), 1419-1431.

Milli, J., Y. Huang, H. Hartmann, and J. Hayes. 2017. The impact of equal pay on poverty and the economy. *Institute for Women's Policy Research: Briefing Paper*. April 2017.

Moreno, J. E. 2023. Diversity data for thousands of federal contractors to go public. *Bloomberg Law News*. <https://news.bloomberglaw.com/daily-labor-report/diversity-data-for-thousands-of-federal-contractors-to-go-public>.

Mueller, H. M., P. P. Ouimet, and E. Simintzi. 2017. Within-firm pay inequality. *Review of Financial Studies* 30(10), 3605-3635.

Posner, M. 2024. Why U.S. corporations need to promote greater workplace diversity. *Forbes* September 12, 2024, <https://www.forbes.com/sites/michaelposner/2024/09/12/why-us-corporations-need-to-promote-greater-workplace-diversity/>.

Raghunandan, A. 2021. Financial misconduct and employee mistreatment: Evidence from wage theft. *Review of Accounting Studies* 26(3), 867-905.

Reynolds, A., and D. Lewis. 2017. Teams Solve Problems Faster When They're More Cognitively Diverse, *Harvard Business Review*, (Mar. 30, 2017).

Rock, D., and H. Grant. 2016. Why Diverse Teams Are Smarter *Harvard Business Review*, November 4, 2016.

Wallsgog, M., N. Bloom, S. W. Ohlmacher, C. Tello-Trillo. 2024. Within-firm pay inequality and productivity. NBER Working Paper 32240.

Weber, L., and S. Stamm. 2024. 40% of lawyers are women. 7% are Black: America's workforce in charts. *Wall Street Journal*, February 9, 2024.

Wilson, V., and W. Darity Jr. 2022. Understanding black-white disparities in labor market outcomes requires models that account for persistent discrimination and unequal bargaining power. *Economic Policy Institute*. <https://www.epi.org/unequalpower/publications/understanding-black-white-disparities-in-labor-market-outcomes/>

Appendix A: Netflix's Type 2 EEO-1 Form

U.S. EQUAL EMPLOYMENT OPPORTUNITY COMMISSION (EEOC) 2022 EMPLOYER INFORMATION REPORT (EEO-1 COMPONENT 1)										EEOC Standard Form 100 (SF 100) Revised 08/2023 OMB Control Number: 3046-0049 Expiration Date: 08/31/2024									
SECTION A – TYPE OF REPORT CONSOLIDATED REPORT																			
SECTION B – EMPLOYER IDENTIFICATION																			
OFS COMPANY ID A578005					EMPLOYER NAME NETFLIX INC														
ADDRESS 121 Albright Way										CITY/TOWN LOS GATOS					STATE CA		ZIP CODE 95032		
SECTION C – HEADQUARTERS OR ESTABLISHMENT-LEVEL IDENTIFICATION (if applicable)																			
HQ/ESTABLISHMENT-LEVEL UNIT ID					HEADQUARTERS OR ESTABLISHMENT-LEVEL NAME														
HEADQUARTERS OR ESTABLISHMENT-LEVEL ADDRESS										CITY/TOWN					STATE		ZIP CODE		
SECTION D – EMPLOYER IDENTIFICATION NUMBER (EIN) 770467272																			
SECTION E – EMPLOYER FILING ELIGIBILITY ☒ YES (Employer Is Eligible to File) ☐ NO (Employer Is Not Eligible to File) ☐ EMPLOYER NO LONGER IN BUSINESS																			
SECTION F – FEDERAL CONTRACTOR DESIGNATION (if applicable) Unique Entity ID (UEI): Not Applicable ☐ YES (Single-Establishment Employer is Federal Contractor) ☐ YES (Multi-Establishment Employer is Federal Contractor) ☐ YES (Headquarters is Federal Contractor) ☐ YES (Non-Headquarters Establishment is Federal Contractor) ☐ YES (One or More Non-Headquarters Establishments is Federal Contractor)																			
SECTION G – NAICS INFORMATION 512110 - Motion Picture and Video Production																			
SECTION H – WORKFORCE DEMOGRAPHIC DATA																			
JOB CATEGORIES	Hispanic or Latino		Race/Ethnicity												Row Total				
			Not Hispanic or Latino																
			Male				Female												
	Male	Female	White	Black or African American	Asian	Native Hawaiian or Other Pacific Islander	American Indian or Alaska Native	Two or More Races	White	Black or African American	Asian	Native Hawaiian or Other Pacific Islander	American Indian or Alaska Native	Two or More Races					
Executive/Senior Level Officials and Managers	5	4	45	7	7	0	0	2	44	10	12	0	1	2	141				
First/Mid-Level Officials and Managers	64	85	499	74	145	2	4	25	449	94	204	3	3	33	1684				
Professionals	228	223	1216	169	711	8	12	53	840	185	638	6	5	61	4355				
Technicians	8	1	44	2	27	0	0	1	3	0	8	0	0	1	95				
Sales Workers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
Administrative Support Workers	84	178	217	74	74	6	2	9	339	128	134	4	3	41	1293				
Craft Workers	1	0	14	1	1	0	0	0	8	0	3	0	0	0	28				
Operatives	3	8	5	4	2	0	0	0	1	2	5	0	0	0	31				
Laborers and Helpers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
Service Workers	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
CURRENT 2022 REPORTING YEAR TOTAL	394	499	2042	331	967	16	18	90	1684	419	1004	13	12	138	7627				
PRIOR 2021 REPORTING YEAR TOTAL	503	556	3025	472	1104	14	30	54	2434	553	1236	22	17	91	10111				
SECTION I – WORKFORCE SNAPSHOT PERIOD 12/15/2022 - 12/31/2022																			
SECTION J – HEADQUARTERS OR ESTABLISHMENT-LEVEL COMMENTS (optional) Not Applicable																			

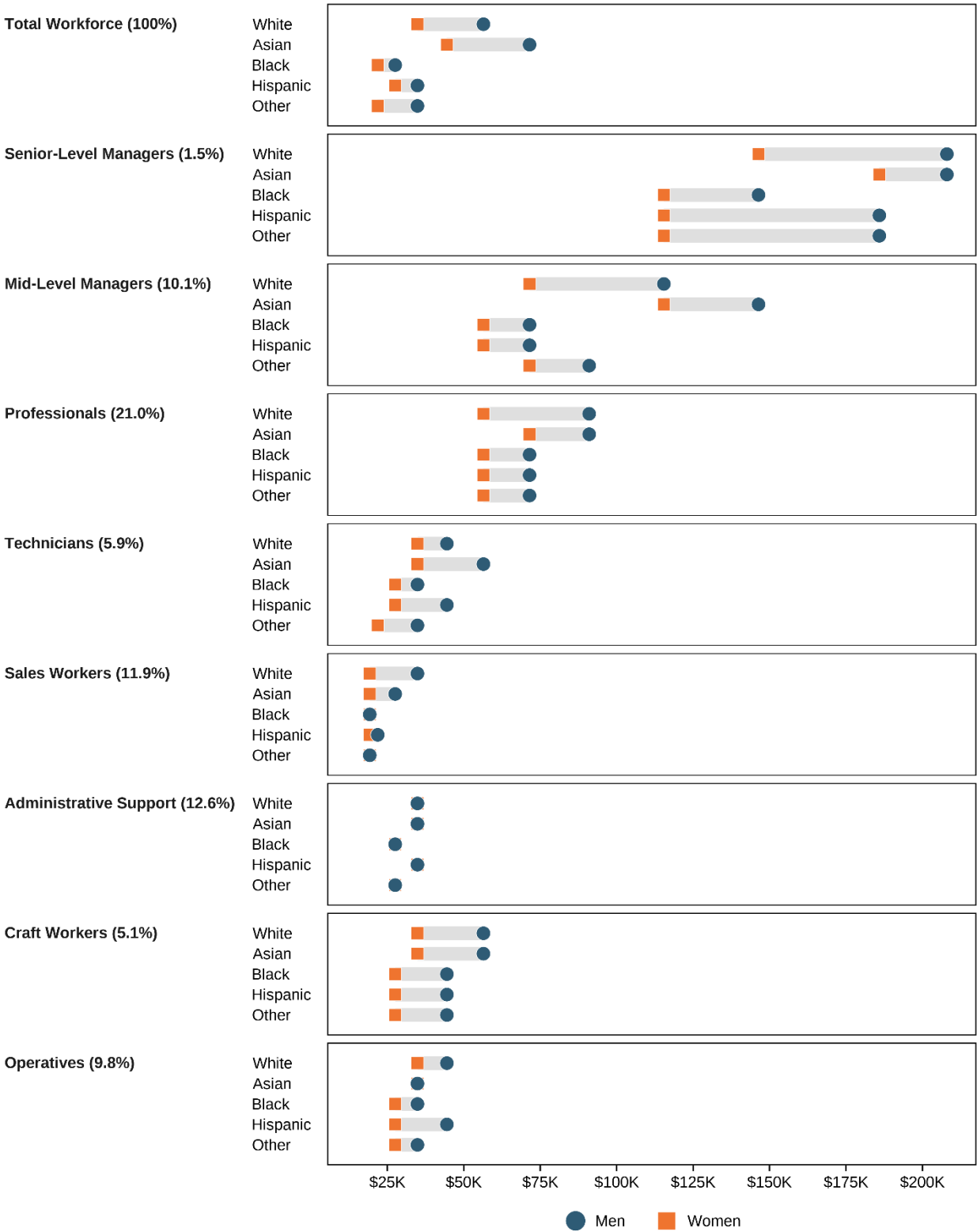
Appendix B: Variable Definitions

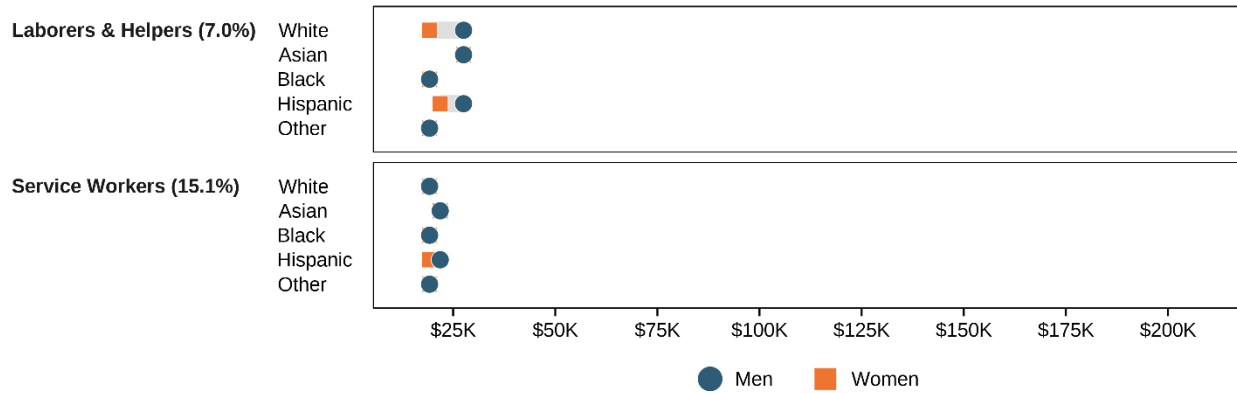
Variable Names	Data Sources	Variable Definitions
AR[0]	CRSP	The difference between the observed return of a stock on the event day and the expected return predicted by the Fama-French 5-factor model. The expected return is based on factor loadings (betas) estimated using all trading days in 2022 (with a minimum requirement of 30 non-missing trading days). Events are FOIA release dates for sample firms, i.e., March 2nd, 2023, for four sample firms and April 17th for 638 sample firms.
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.
ln(Size)	Compustat	The natural logarithm of the book value of total assets of a firm.
Leverage	Compustat	Leverage is calculated as the sum of long-term debt and current debt (DLTT + DLC) divided by the book value of total assets. DLTT and DLC are replaced by zero if missing.
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 dummy variable that equals one if the firm's Return on Assets (ROA) is negative, indicating a financial loss, and zero otherwise.
CapEx	Compustat	A firm's capital expenditures (replaced by 0 if missing) divided by its total assets.
%Men	EEO-1 Forms (FOIA release)	This variable represents the percentage of male workers in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Women	EEO-1 Forms (FOIA release)	This variable represents the percentage of women workers in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%White	EEO-1 Forms (FOIA release)	This variable represents the percentage of White workers in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Black	EEO-1 Forms (FOIA release)	This variable represents the percentage of Black or African American workers in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Hispanic	EEO-1 Forms (FOIA release)	This variable represents the percentage of Hispanic workers in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Asian	EEO-1 Forms (FOIA release)	This variable represents the percentage of Asian workers in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Other	EEO-1 Forms (FOIA release)	This variable represents the combined percentage of workers who identify as Native American or Other Pacific Islander, American Indian or Alaska Native, or Two or More Races in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.

Variable Names	Data Sources	Variable Definitions
%Senior-Level Managers	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Executive/Senior Level Officials and Managers" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Mid-Level Managers	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "First/Mid-Level Officials and Managers" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Professionals	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Professionals" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Technicians	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Technicians" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Sales Workers	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Sales Workers" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Administrative Support	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Administrative Support Workers" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Craft Workers	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Craft Workers" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Operatives	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Operatives" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Laborers & Helpers	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Laborers and Helpers" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
%Service Workers	EEO-1 Forms (FOIA release)	This variable represents the percentage of workers classified as "Service Workers" in a firm's total workforce, as reported in the last EEO-1 form filed during the period from 2016 to 2020.
Total Imputed Pay (in million \$)	EEO-1 forms and EEO-1 Component 2 Pay data	This variable represents 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 forms and EEO-1 Component 2 Pay data	This variable represents 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 forms 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 /SG&A	EEO-1 forms and EEO-1 Component 2 Pay data, Compustat	Total Imputed Pay divided by Selling, General and Administrative (SG&A) expenses.

Variable Names	Data Sources	Variable Definitions
Labor Cost Savings /Total Revenue	EEO-1 forms and EEO-1 Component 2 Pay data, Compustat	Total Imputed Pay divided by total sales revenue.
Labor Cost Savings /Net Income	EEO-1 forms and EEO-1 Component 2 Pay data, Compustat	Total Imputed Pay divided by net income.
Labor Cost Savings /EBIT	EEO-1 forms and EEO-1 Component 2 Pay data, Compustat	Total Imputed Pay divided by operating income after depreciation.
Labor Cost Savings /Total Assets	EEO-1 forms and EEO-1 Component 2 Pay data, Compustat	Total Imputed Pay divided by total assets.
Labor Cost Savings Ratio	EEO-1 forms 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	Self-computed suing EEO-1 forms and EEO-1 Component 2 Pay data	A binary indicator 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.
Per Worker Labor Cost Savings (in \$)	Self-computed suing EEO-1 forms and EEO-1 Component 2 Pay data	This variable is calculated by dividing the firm's Labor Cost Savings by the total number of workers, as reported in the EEO-1 form.
Race/Ethnicity Index	EEO-1 Forms (FOIA release)	Calculated using the Blau Index, this measure of race/ethnicity diversity is determined by 1 minus the sum of the squared White, Black, Hispanic, Asian, and Other in the workforce.
Minimum wage	Federal Reserve Economic Data	State minimum wage rates as of 2018, including federal minimum wage where applicable.
Unemployment	Federal Reserve Economic Data	Unemployment rate as of 2018, which represents the percentage of the labor force that is unemployed but actively seeking employment and willing to work. It is calculated by dividing the number of unemployed individuals by the total labor force (which includes both the employed and unemployed, but excludes individuals who are not actively seeking employment, such as retirees, students, or discouraged workers who have stopped looking for work).
Union Participation	Federal Reserve Economic Data	Union participation as of 2018, which represents the percentage of employed wage and salary workers who were members of unions.
Right to Work	National Right to Work Legal Defense Foundation	List of states with Right to Work laws as of 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.

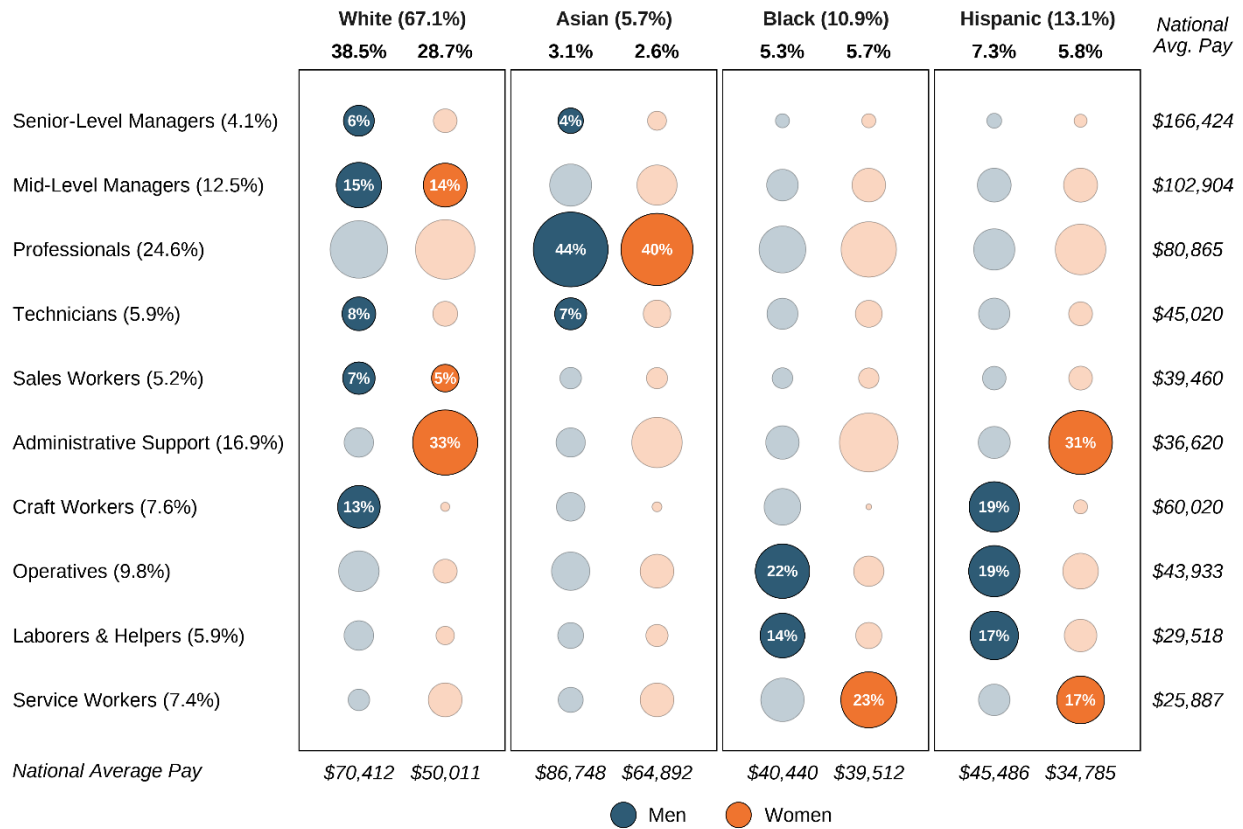
Figure 1: National Comparisons of Pay Gaps by Gender and Job Categories





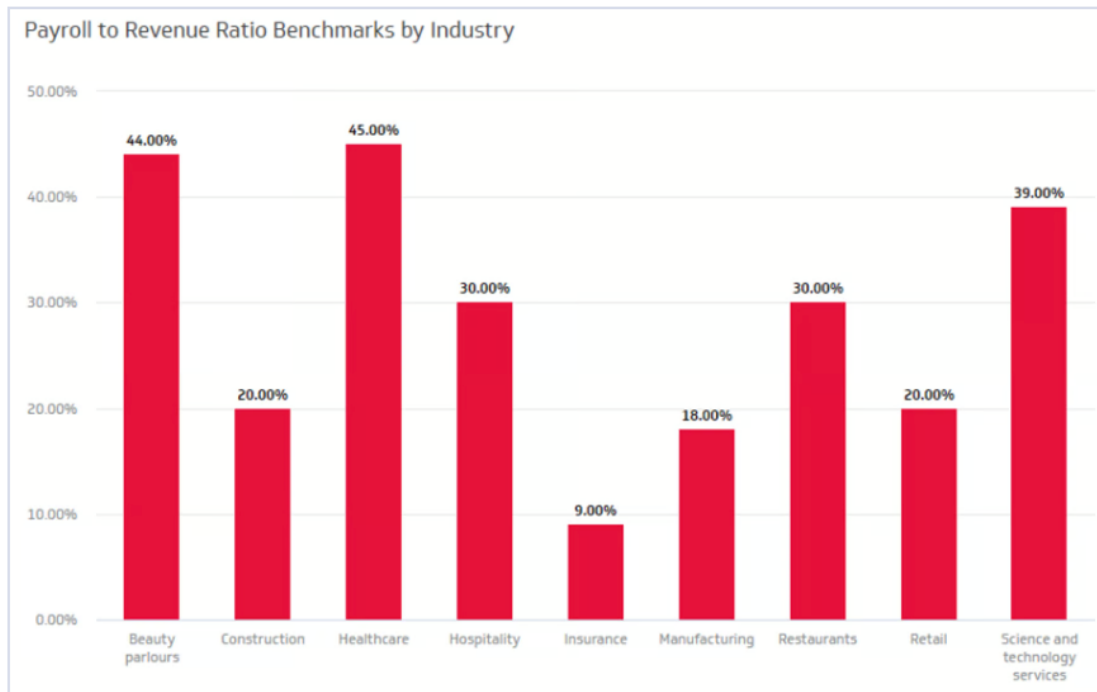
In this figure, we compare the national-level pay gaps across different job categories using data obtained from the EEO-1 Component 2 dataset. The analysis includes various demographic groups (White, Asian, Black, Hispanic, and Other) within each job category, and we compare the average pay between men and women.

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



This figure displays the workforce distribution of our combined private and public firm sample by gender (men in blue and women in orange), race/ethnicity, and job category. Each race/ethnicity and gender column sums to 100%. We highlight the top two race/ethnicity and gender pairs per job category. We do not display the race/ethnicity category “Others” due to the limited number of observations.

Figure 3: Variation in Labor Costs-to-Revenue Ratios by Industry



This figure illustrates differences in payroll-to-revenue ratios across various industries. See <https://www.klipfolio.com/resources/kpi-examples/financial/payroll-to-revenue-ratio>.

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 provides a breakdown of the most recent EEO-1 report for each firm. It is this report that we use in our analyses.

Panel A: Sample Construction

Processing Step	# Distinct 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: Year of the Most Recent Type-2 EEO-1 Form

Year	Public Firms		Private Firms	
	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	6,069	3,879	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%	5.45%	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	10.47%	69.33%	-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

Firm Size	Public Firms' Labor Cost Saving Ratios			Private Firms' Labor Cost Saving Ratios			t-test of the Mean
	Obs.	Mean	Std.	Obs.	Mean	Std.	
50 to 250 Employees	103	7.24%	4.89%	5,318	10.93%	8.69%	3.69%***
251 to 500 Employees	103	8.38%	5.01%	2,121	11.49%	9.03%	3.11%***
501 to 1,000 Employees	131	7.83%	5.33%	1,359	11.89%	8.85%	4.06%***
1,001 to 5,000 Employees	346	8.08%	5.49%	1,315	12.48%	8.69%	4.40%***
>5,001 Employees	244	8.59%	5.85%	321	15.86%	9.16%	7.26%***

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

Fama-French Industries	Public Firms		Compustat-CRSP		Private Firms	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Consumer Non-Durables	38	4.1%	160	3.2%	304	2.9%
Consumer Durables	26	2.8%	106	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%	729	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%	1,057	21.1%	1,358	13.0%
Other	113	12.2%	1,119	22.4%	5,302	50.8%
Total	927	100.0%	5,005	100.0%	10,434	100.0%

Panel B: Imputed Labor Cost Savings

Fama-French Industries	Public Firms			Private Firms		
	# 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 and data from Compustat and the IRS. 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 Expense (Compustat)	Salary and Wages (IRS Form 1120)
	(1)	(2)	(3)
Total Number of Workers (EEO-1 report)	1.547*** (30.711)		
Total Imputed Pay (in million \$)		3.093*** (7.799)	1.678*** (10.513)
EA Control	yes	yes	yes
Industry FE	yes	yes	yes
State FE	yes	yes	yes
Observations	916	835	733
Adj. R2	0.873	0.697	0.690

Table 6: Economic Determinants of the Labor Cost Savings Ratio

This table examines the relationship between our imputed Labor Cost Savings Ratio and state-level labor market 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

	Prediction	Labor Cost Savings Ratio				
		(1)	(2)	(3)	(4)	(5)
Minimum Wage	–	-0.003** (-2.117)				
Unemployment Rate	–		-0.001 (-0.290)			
Union Participation	–			-0.001* (-1.819)		
Right to Work	+				0.011*** (2.988)	
Highschool and Above	–					-0.002*** (-2.981)
Observations		927	927	927	927	927
Adj. R2		0.004	-0.001	0.003	0.009	0.009

Panel B: Private Firms

	Prediction	Labor Cost Savings Ratio				
		(1)	(2)	(3)	(4)	(5)
Minimum Wage	–	0.001 (1.611)				
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)
Observations		10,434	10,434	10,434	10,434	10,434
Adj. R2		0.000	0.001	0.000	0.000	0.011

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 (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	11.358*** (3.219)			8.178** (2.285)	
Top 25% Savings Ratio		1.354*** (3.459)			1.079*** (2.706)
%Senior-Level Managers			-6.576 (-1.258)	-4.795 (-0.928)	-5.123 (-0.994)
%Mid-Level Managers			-0.220 (-0.101)	-0.202 (-0.093)	-0.532 (-0.244)
%Technicians			-0.461 (-0.161)	-0.610 (-0.212)	-0.424 (-0.148)
%Sales Workers			4.131** (2.433)	3.279* (1.862)	3.425** (1.964)
%Administrative Support			-1.214 (-0.654)	-1.173 (-0.634)	-1.237 (-0.669)
%Craft Workers			1.034 (0.702)	1.127 (0.770)	1.265 (0.864)
%Operatives			1.826 (1.389)	1.576 (1.193)	1.665 (1.269)
%Laborers & Helpers			1.014 (0.571)	0.926 (0.511)	1.019 (0.565)
%Service Workers			3.284 (1.244)	2.731 (1.041)	2.244 (0.873)
EA Control	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes
Observations	927	927	927	927	927
Adj. R2	0.097	0.098	0.094	0.098	0.100

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 (5) and (6), 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)	(6)
Labor Cost Savings Ratio			11.547*** (3.024)	9.610** (2.473)	7.305* (1.926)	6.813* (1.735)
%Women	1.656 (1.149)		-0.183 (-0.120)		0.844 (0.479)	
%Black		2.883 (1.184)		1.339 (0.540)		1.315 (0.525)
%Hispanic		5.054*** (2.874)		3.737** (2.098)		3.032 (1.607)
%Asian		1.475 (0.864)		1.531 (0.892)		2.148 (1.140)
%Other		-9.242 (-1.115)		-11.494 (-1.291)		-14.924 (-1.640)
%Senior-Level Managers					-4.911 (-0.949)	-5.365 (-1.034)
%Mid-Level Managers					-0.237 (-0.109)	-0.524 (-0.242)
%Technicians					-0.469 (-0.163)	-0.267 (-0.093)
%Sales Workers					3.251* (1.845)	3.990** (2.181)
%Administrative Support					-1.512 (-0.743)	-0.721 (-0.356)
%Craft Workers					1.379 (0.885)	0.944 (0.602)
%Operatives					1.675 (1.248)	1.323 (0.959)
%Laborers & Helpers					0.953 (0.526)	0.518 (0.266)
%Service Workers					2.497 (0.932)	2.215 (0.789)
EA Control	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
Observations	927	927	927	927	927	927
Adj. R2	0.087	0.094	0.096	0.100	0.098	0.102

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. 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	10.142*** (3.038)	7.527** (2.236)	10.276*** (2.814)	8.475** (2.321)
IO Structure Controls	–	yes	–	–
Gender Controls	–	–	yes	–
Race/Ethnicity Controls	–	–	–	yes
EA Control	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Observations	927	927	927	927
Adj. R2	0.103	0.106	0.102	0.105

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

	CAR[-1,2]			
	(1)	(2)	(3)	(4)
Labor Cost Savings Ratio	8.529*** (3.071)	6.344** (2.252)	8.450*** (2.880)	7.247** (2.472)
IO Structure Controls	–	yes	–	–
Gender Controls	–	–	yes	–
Race/Ethnicity Controls	–	–	–	yes
EA Control	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Observations	919	919	919	919
Adj. R2	0.103	0.105	0.102	0.106

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; Panel B contrasts the relation between market reactions and the firms’ diversity information or imputed labor cost savings variables across the two groups. In Panel B, we perform a Chi-squared (χ^2) test on the coefficients to determine whether the coefficients for each subgroup are significantly different using the Seemingly Unrelated Estimation (SUE) method. 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

Variable	Non-Voluntary Disclosers 687 firms		Voluntary Disclosers 240 firms		t-test of the Mean
	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 \$)	6,083	3,820	6,030	4,051	-53
Total Number of Workers	3,538	10,070	21,185	35,241	17,647***
Labor Cost Savings Ratio	8.36%	5.44%	7.45%	5.46%	-0.91%***

Panel B: Market Reactions to Labor Cost Savings

	CAR[-1,2]			
	Non-VD		VD	
	(1)	(2)	(3)	(4)
Labor Cost Savings Ratio	12.324** (2.444)	1.014 (0.218)		
Top 25% Savings Ratio			1.417*** (2.881)	-0.009 (-0.014)
Test of coefficients (Non-VD>VD)	Prob > chi2 = 0.0588		Prob > chi2 = 0.0396	
IO Structure Controls	yes	yes	yes	yes
EA Control	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Observations	687	240	687	240
Adj. R2	0.084	0.322	0.085	0.322

Internet Appendix

Table IA.1: O*NET Categories

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

EEO-1 Category	EEO-1 Job Category Job Description	O*Net Zone
<i>Category 1</i>	<i>Executive/Senior Level Officials and Managers</i>	
	Chief Executive Officer	5
<i>Category 1.2</i>	<i>First.Mid-Level Officials and Managers</i>	
	Human Resources	5
	Information Systems	4
	Marketing	4
	Operations	4
	Purchasing and Transportation	4
	Storage and Distribution Managers	4
<i>Category 2</i>	<i>Professionals</i>	
	Architects	5
	Lawyers	5
	Librarians	5
	Mathematical Scientists	5
	Dieticians	5
	Physicians	5
	Accountants and Auditors	4
	Airplane Pilots	4
	Chemists	4
	Computer Programmers	4
	Editors	4
	Engineers	4
	Registered Nurses	4
	Teachers	4
	Surveyors	4
<i>Category 3</i>	<i>Technicians</i>	
	Emergency Medical Technicians	3
	Chemical Technicians	3
	Broadcast and Sound Engineering Technicians	3
<i>Category 4</i>	<i>Sales Workers</i>	
	Advertising Sales Agents	4
	Insurance Sales Agents	4
	Real Estate Brokers	3
	Telemarketers	2
	Retail Salespersons	2
	Counter and Rental Clerks	2
	Cashiers	2
<i>Category 5</i>	<i>Administrative Support Workers</i>	
	Proofreaders	4

EEO-1 Category	EEO-1 Job Category Job Description	O*Net Zone
	Bookkeepers	3
	Desktop Publishers	3
	Accounting and Auditing Clerks	3
	Office and Administrative Support	2
	Cargo and Freight Agents	2
	Dispatchers	2
	Couriers	2
	Data Entry Keyers	2
	Computer Operators	2
	Receiving and Traffic Clerks	2
	Word Processors and Typists	2
	General Office Clerks	2
<i>Category 6</i>	<i>Craft Workers</i>	
	Aircraft Mechanics	3
	Electronic Equipment Repairers	3
	Tool and Die Makers	3
	Boilermakers	3
	Electricians	3
	Plumbers	3
	Automotive Mechanics	2
	Brick and Stone Masons	2
	Carpenters	2
	Etchers and Engravers	2
	Millrights	2
	Painters	2
	Glaziers	2
	Pipe Layers	2
	Roofers	2
	Earth Drillers	2
	Gas Rotary Drill Operators	2
	Plasterers	1
	Derrick Operators	1
<i>Category 7</i>	<i>Operatives</i>	
	Textile Machine Workers	2
	Photographic Process Workers	2
	Electronic Equipment Assemblers	2
	Bakers	2
	Bridge and Lock Tenders	2
	Bus or Taxi Drivers	2
	Forklift Operators	2
	Parking Lot Attendants	2
	Sailors	2
	Semiconductor Processors	2

EEO-1 Category	EEO-1 Job Category Job Description	O*Net Zone
	Laundry and Dry-cleaning Workers	1
	Graders and Sorters	1
	Conveyor Operators	1
<i>Category 8</i>	<i>Laborers and Helpers</i>	
	Vehicle and Equipment Cleaners	2
	Stock and Material Movers	2
	Service Station Attendants	2
	Construction Laborers	2
	Refuse and Recyclable Materials Collectors	2
	Septic Tank Servicers	1
	Sewer Pipe Cleaners	1
<i>Category 9</i>	<i>Service Workers</i>	
	Janitors	3
	Private Detectives and Investigators	3
	Bartenders	2
	Medical Assistants	2
	Ushers	2
	Transportation Attendants	2
	Food Service Workers	1
	Cleaners	1

**Table IA.2: Correlations of Economic
Determinants of the Labor Cost Savings Ratio**

This table examines the correlations between state-level labor market 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.

Panel A: Public Firms

	(1)	(2)	(3)	(4)	(5)
(1) Minimum Wage	1.0000	0.1851	0.6971	-0.6704	-0.0470
(2) Unemployment Rate	0.1851	1.0000	0.2903	-0.3135	-0.4113
(3) Union Participation	0.6971	0.2903	1.0000	-0.7929	0.1119
(4) Right to Work	-0.6704	-0.3135	-0.7929	1.0000	-0.2253
(5) Highschool and Above	-0.0470	-0.4113	0.1119	-0.2253	1.0000

Panel B: Private Firms

	(1)	(2)	(3)	(4)	(5)
(1) Minimum Wage	1.0000	0.1851	0.6971	-0.6704	-0.0470
(2) Unemployment Rate	0.1851	1.0000	0.2903	-0.3135	-0.4113
(3) Union Participation	0.6971	0.2903	1.0000	-0.7929	0.1119
(4) Right to Work	-0.6704	-0.3135	-0.7929	1.0000	-0.2253
(5) Highschool and Above	-0.0470	-0.4113	0.1119	-0.2253	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), Leverage, MTB, Cash, R&D, ROA, and earnings announcement) are calculated at the end of 2022. See Appendix B for variable definitions. 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	-1.563** (-2.188)	-1.547** (-2.007)	-0.943 (-1.415)	-1.122* (-1.694)	-1.032 (-1.525)	-0.970 (-1.243)
IO Structure 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	688	681	681	681	681	681
Adj. R2	0.087	0.155	0.146	0.119	0.123	0.085

Table IA.4: Firm Characteristics

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

Variable	Public Firms (year of EEO-1 report)			Public Firms (as of the end of 2022)			Compustat-CRSP (as of the end of 2022)		
	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.
ln(Size)	869	8.273	1.964	927	7.939	1.970	5,491	6.841	2.420
Leverage	869	0.282	0.215	927	0.272	0.210	5,491	0.278	0.262
MTB	868	3.135	6.772	920	4.235	7.386	5,463	2.727	8.169
ROA	869	0.011	0.144	927	−0.002	0.138	5,489	−0.189	0.527
Market Cap	922	15,052	37,339	921	15,067	37,356	5,898	6,934	21,128
I(Loss)	928	0.293	0.455	927	0.292	0.455	5,898	0.442	0.497
CapEx	869	0.031	0.037	927	0.028	0.032	5,491	0.031	0.048

about ECGI

The European Corporate Governance Institute has been established to improve *corporate governance through fostering independent scientific research and related activities*.

The ECGI will produce and disseminate high quality research while remaining close to the concerns and interests of corporate, financial and public policy makers. It will draw on the expertise of scholars from numerous countries and bring together a critical mass of expertise and interest to bear on this important subject.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.

ECGI Working Paper Series in Finance

Editorial Board

Editor	Nadya Malenko, Professor of Finance, Boston College
Consulting Editors	Renée Adams, Professor of Finance, University of Oxford Franklin Allen, Nippon Life Professor of Finance, Professor of Economics, The Wharton School of the University of Pennsylvania Julian Franks, Professor of Finance, London Business School Mireia Giné, Associate Professor, IESE Business School Marco Pagano, Professor of Economics, Facoltà di Economia Università di Napoli Federico II
Editorial Assistant	Asif Malik, Working Paper Series Manager

Electronic Access to the Working Paper Series

The full set of ECGI working papers can be accessed through the Institute's Web-site (www.ecgi.global/content/working-papers) or SSRN:

Finance Paper Series	http://www.ssrn.com/link/ECGI-Fin.html
Law Paper Series	http://www.ssrn.com/link/ECGI-Law.html