Human Capital Disclosure and Labor Market Outcomes: Evidence from Regulation S-K

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Abstract: We examine the labor market consequences of the 2020 Regulation S-K requiring human capital disclosure in 10K filings. Using large-sample job-level data, we observe that public firms subject to the regulation increase their disclosure of diversity, equity, and inclusion (DEI) information in job postings relative to a matched sample of large private firms. The increase in job-posting disclosure is more pronounced among firms with greater external pressure and lower internal coordination needs. These findings suggest a shift in demand for diverse candidates by public firms following the regulation. Yet, consistent with short-term inelastic labor supply, this demand shift lengthens the recruitment period and results in only slight improvements in workforce diversity for public firms, partly due to poaching among these firms. Limited improvements in diversity are observable in firms that exhibit a stronger demand for diverse candidates and a credible commitment to DEI. Our study documents how securities regulations can impact labor market disclosure and underscores the significant constraints involved in improving workforce diversity in the short run.

Keywords: Securities Regulation, Labor Market, Disclosure, ESG, DEI

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1 Introduction

Securities regulations, such as those established by the Securities and Exchange Commission (SEC), are developed to protect investors and maintain the fair and efficient functioning of financial markets. Since the Dodd-Frank Act of 2010, the SEC has begun imposing environmental and social disclosure requirements, with notable consequences for firm behavior (e.g., Christensen et al., 2017; Baik et al., 2024). One salient example is the 2020 Regulation S-K, which requires public companies to provide human capital disclosure (HCD) in 10K filings.[1] Regulation S-K confirms a significant move by the SEC towards matters that could influence not only public firms and their investors (e.g., Arif et al., 2024) but also other stakeholders (Christensen et al., 2021). We contribute to the research on the effects of such disclosure requirements by studying the labor market consequences of human capital disclosure in 10Ks.

Prior to Regulation S-K, firms disclosed almost nothing about their human capital, even though some investors considered this information important for their investment decisions (Heath et al., 2023). To fill this disclosure gap, these investors petitioned the SEC to require firms to disclose information about their human capital management policies (e.g., HCMC, 2017; Sheehan, 2017). In 2020, the SEC amended Regulation S-K, providing a clear signal that it considers HCD important for market participants. Including HCD in 10Ks would make such information more credible, given auditor oversight and the risk of SEC enforcement actions, and would reduce information acquisition costs for investors (Blankespoor et al., 2020).

The regulation was conceived as a principles-based disclosure mandate that gives firms discretion over which material human capital metrics to disclose. This raised concerns about the efficacy of the rule (e.g., Crenshaw, 2020; Lee, 2020). However, Bourveau et al. (2024) document

[1] Another recent example is the climate-related disclosure requirement passed by the SEC in March 2024.

a dramatic increase in HCD in the first 10Ks after Regulation S-K, particularly with respect to workforce Diversity, Equity, and Inclusion (DEI) disclosure, which went from almost zero to 57% for S&P500 firms.[2] In light of these results, and given that DEI is linked to distinct labor market outcomes that we can precisely measure, we focus our examination on DEI.

The labor market consequences of including DEI information in 10Ks are not obvious. On the one hand, firms with lower levels of workforce diversity may anticipate that they will be exposed to greater external pressure after Regulation S-K. This would happen whether such firms chose to be forthcoming and include DEI information in their 10Ks, thereby revealing their status, or chose to omit such information, implicitly signaling their type (e.g., Milgrom, 1981). It follows that Regulation S-K would provide an incentive for these firms to try to improve their actual workforce diversity in the short term. To do so, they would include more DEI information in their job postings to signal their commitment to a diverse and inclusive workplace culture, and thereby attract and recruit diverse candidates (Choi et al., 2023a).

On the other hand, Regulation S-K could also have no impact on DEI information in job postings or workforce diversity, for several reasons. Certain firms might have a weak commitment to increasing workforce diversity despite their claims about DEI (Bailey et al., 2024; Baker et al., 2024). Furthermore, DEI is a politically contentious matter since it addresses issues related to race, ethnicity, gender, and other social identities historically subject to discrimination. Some individuals may view efforts to promote DEI as a sign that the company gives less weight to meritocratic promotion or rewards (Castilla and Benard, 2010). Hence, firms might avoid including DEI information in job postings. Even if firms did choose to provide information about

[2] Bourveau et al. (2024) show that the clear jump in HCD in 10Ks is difficult to reconcile with external forces other than Regulation S-K. For example, investor pressure started as early as 2017 (and remained constant over the time period examined; see Heath et al. (2023)), but until 2020, HCD in 10Ks was basically non-existent.

their DEI policies in job postings, this might not necessarily lead to increased workforce diversity if job seekers do not perceive such disclosures as credible. More fundamentally, structural labor market conditions, such as limited or inelastic labor supply, may hinder improvements in diversity.

We begin our analysis by examining the short-term effects of Regulation S-K on the extent and length of DEI disclosure in a sample of 5,169,408 job postings. We implement a difference-in-differences research design where the treatment group is comprised of U.S. public firms, which are subject to the regulation. The control group is comprised of U.S. private firms of similar size, which are not subject to the regulation. To measure the extent and length of DEI disclosure in job postings, we use Named Entity Recognition technology provided by RavenPack. We obtain job posting data from LinkUp, which enables us to analyze a large sample of job vacancies and descriptions, providing valuable insights into the dynamics of the U.S. labor market. We aggregate job posting data at the firm–job-type–year-month level and create a panel dataset spanning 11 months and centered on the amendment of Regulation S-K. Our sample includes job postings from 1,891 public and 347 private firms.

We find that public firms increase the extent and length of DEI disclosure in their job postings following the regulation. The dynamic analysis reveals no pre-trends, but after the amendment of Regulation S-K, we observe that public firms increase the length of DEI information in their job postings and include DEI information in approximately 41,000 additional job postings, or an average of 22 additional job postings per firm (extensive margin). We also use artificial intelligence (AI) to systematically evaluate our sample of job postings for the credibility of DEI disclosure. We carefully design prompts that position the AI as a minority job seeker and find that the job postings that include DEI information show credible commitments and inclusive culture.

We conduct four cross-sectional tests to shed light on the mechanisms through which Regulation S-K affects DEI disclosure in job postings. We observe substantial variation in the treatment effect, which indicates heterogeneous incentives to respond to Regulation S-K. First, consistent with certain firms anticipating greater *external* pressure after the regulation, we find that the average effect of Regulation S-K is significantly larger for firms that prior to the regulation have (i) low levels of gender diversity, (ii) high levels of ownership by environmental, social, and governance (ESG) funds, and (iii) high pressure from analysts on DEI issues during conference calls. Second, we explore the role of *internal* coordination needs by examining human resources (HR) management (e.g., Bloom and Van Reenen, 2011). Managing DEI policies presents several challenges when firms have greater organizational complexity and coordination needs, like those related to their dispersed geographical presence (e.g., Gallemore and Labro, 2015). Hence, we expect and find a stronger increase in DEI disclosure in job postings when employees and HR are less geographically dispersed, and when intranet systems are well-established.

The increased DEI disclosure in job postings suggests a growing demand for diverse candidates. However, job postings are only the first step in the hiring process. Even though our findings shows that job seekers perceive these disclosures as credible, the hiring of diverse candidates might not increase if the labor supply is inelastic. When we examine the average effect of Regulation S-K on a firm's workforce composition, we indeed do not observe any statistically or economically significant change in workforce gender or ethnic/racial diversity for treated firms following the regulation.[3] A further analysis reveals that the average effect is partly muted by

[3] To confirm this result, we also decompose ethnic/racial diversity into its sub-components—namely, Black, Hispanic, and Asian/Pacific Islander groups. Additionally, we examine both overall workforce diversity and diversity within senior positions. We continue to find no changes.

poaching, as we find an increase in the percentage of minorities moving among public firms, rather than moving from private to public firms.

We conduct two sets of tests to confirm that the absence of an average effect is consistent with limited or inelastic labor supply in the short term (e.g., Chetty et al., 2011; Welch, 1997). First, we explore variation in labor supply by looking at geographic and industry heterogeneity in workforce diversity. We find that gender diversity marginally increases in U.S. states and industries with a larger presence of women candidates, indicating that supply-side structural differences play a salient role. Second, we examine the length of the recruitment period, which can proxy for labor market tightness due to inelastic labor supply (Muehlemann and Leiser, 2018). We find that public firms take more time to recruit candidates and conduct more interviews following the regulation, consistent with an inelastic supply of labor.

Finally, we explore demand-side variation by examining whether there is an increase in workforce diversity among firms that exhibit a stronger demand for diverse candidates or a more credible commitment to DEI through the presence of a DEI officer. We observe that firms with a DEI officer and those that substantially increased DEI disclosure in job postings after the regulation marginally improve the gender diversity of their workforce.

A possible threat to the validity of our identification strategy is that concurrent events could change hiring incentives for public firms (but not for private firms) in a way that is consistent with our findings but inconsistent with Regulation S-K playing a prominent role. We address this concern in several ways. First, we choose a narrow window around the amendment of the regulation, since measuring long-term effects and connecting them to a single event is inherently challenging and would exacerbate this concern. Our identification strategy requires reliable measurement of effects within short intervals, such as job-posting disclosure and hiring outcomes,

which change on a monthly basis. Second, we do not observe any differential trends between public and private firms in the pre-regulation period, so any confounding events have to line up precisely with the regulation amendment and affect only public firms. Some might argue that the death of George Floyd in May 2020 might influence the labor market outcomes for public firms, given their greater visibility relative to private firms. If that were the case, social movements rather than Regulation S-K would drive our results. However, we observe meaningful results for gender diversity but not for ethnic/racial diversity, which is inconsistent with this concern. Most importantly, we conduct a falsification test by studying a state of the world characterized by strong social movements but no changes in securities regulations: the emergence of the #MeToo movement in October 2017. We find that public firms' job-posting DEI disclosures do not change relative to those of private firms following the #MeToo movement, which is inconsistent with the concern that social movements, rather than Regulation S-K, are causing our results.

Taken together, our findings show that certain firms responded to Regulation S-K by changing their labor market disclosure strategies in order to attract diverse candidates. However, improving workforce diversity in the short term is challenging. A limited labor supply of diverse candidates for certain jobs and the time required to train candidates for different occupations make it difficult to significantly increase diversity. Indeed, we observe only slight improvements.

From a big-picture perspective, these findings contribute to the literature by documenting how securities regulations can reach beyond capital markets, potentially shaping labor market outcomes through disclosure.[4] While the capital market effects of securities regulations have been widely studied (Leuz and Wysocki, 2016), research on non-capital market outcomes has only

[4] In a similar spirit, recent papers also examine the effects of financial reporting on employee job search (Choi et al., 2023b; deHaan et al., 2023) and the effects of transparency regulation on environmental externalities (Bonetti et al., 2023).

recently emerged. Two recent examples are Christensen et al. (2017) and Baik et al. (2024), who study the real effects of securities regulation related to mine safety and conflict minerals disclosure. Christensen et al. (2017) estimate the incremental effect of including in financial reports information that is already publicly available, whereas Baik et al. (2024) study the effect of disclosing information not previously released elsewhere. In contrast, we examine a principles-based regulation that gives firms discretion over which material human capital metrics to disclose in their 10Ks. While this could prevent unraveling, Bourveau et al. (2024) and Haslag et al. (2022) document a sharp increase in 10K disclosure regarding a firm's workforce diversity following the regulation. This indicates that the rule provides an incentive for firms to meet investors' demand for greater transparency. Our paper goes one step further and documents how Regulation S-K changes firms' incentives in the labor market. Put differently, we examine the real effects of securities regulation on organizational practices, which is increasingly important given the recent global trend towards more ESG reporting (Christensen et al., 2021).

Our paper also contributes to recent studies on labor market disclosure such as Choi et al. (2023a), who show that job seekers highly value workforce diversity information and are more inclined to apply to employers with diverse teams once they are aware of their diversity efforts; Pacelli et al. (2022), who show that including information on workplace culture in job postings helps firms attract and retain employees; and Sran (2023), who examines how firms balance disclosure in job postings, weighing the benefits in the labor market against the costs in product market competition. We document that Regulation S-K has real effects in terms of labor market disclosure but more limited effects on workforce diversity. This emphasizes the costs associated with enhancing workforce diversity, an issue also underscored in Sutherland et al. (2024).

Finally, our paper relates to recent studies about firms' responses to racial and gender diversity issues (e.g., Balakrishnan et al., 2023; Billings et al., 2022; Lins et al., 2024). These studies focus on specific events (George Floyd's death and the #MeToo movement), whereas we focus on the role of securities regulations in shaping firms' social behavior and examine the broader labor market consequences.

2 Institutional Setting and Conceptual Framework

The emergence of a human capital–driven economy in the 20th century has launched an ongoing discussion among academics, practitioners, and policymakers regarding the importance of human capital disclosure (e.g., Zingales, 2000). However, human capital disclosure in the U.S. has remained relatively scarce until recently (Honigsberg and Rajgopal, 2022). In 2005, public companies were mandated to disclose the number of employees in their 10K filings, and starting in 2017, they were also required to disclose the ratio of CEO-to-employee pay. Apart from these two reporting requirements, there was considerable information asymmetry between investors, who demanded more human capital information (e.g., HCMC, 2017; Sheehan, 2017), and companies, who did not voluntarily disclose it.[5] Market forces did not lead to voluntary unraveling (e.g., Grossman and Hart, 1980), possibly because firms were uncertain about investors' responses to HCD (Nagar, 1999; Suijs, 2007) or did not gauge whether HCD was value relevant.

In 2020, the SEC updated its guidelines for business descriptions in Regulation S-K Item 101. This regulation now requires a description of the firm's human capital resources, including disclosure of the number of employees and any human capital measures or objectives that the firm

[5] Choi et al. (2024a) document that workforce diversity information in 10Ks and the public availability of EEO-1 were rare before Regulation S-K (see also Bourveau et al., 2023). This is despite the fact that companies with more than 100 employees have been required to file confidentially an EEO-1 report to the Equal Employment Opportunity Commission annually since 1967.

focuses on in managing its business, such as those that address the attraction, development, and retention of employees (SEC, 2020).

On the one hand, this provides a clear signal to firms that the SEC considers human capital disclosure important for market participants. Moreover, including HCD in 10Ks would make such information more credible, given auditor oversight and the risk of SEC enforcement actions, and it would reduce information acquisition costs for investors (Blankespoor et al., 2020).[6] On the other hand, Regulation S-K does not provide a clear definition of human capital, nor does it mandate specific human capital management policies and metrics to be disclosed. This allows companies the flexibility to select the topics and metrics they consider materially relevant to the business.

Despite this lack of specific guidance by the SEC, Bourveau et al. (2024) document that firms responded unequivocally to Regulation S-K. Before the regulation, less than 1% of firms had a section dedicated to the discussion of human capital issues. In their first 10Ks after the regulation, more than 85% of firms included such a section. Perhaps related to the SEC's reference in the final rule to measures or objectives that address the attraction, development, and retention of personnel (SEC, 2020), the effect is particularly evident in disclosures related to workforce diversity metrics, which increased by 30% on average and up to 57% for S&P500 firms (see the Online Appendix Section IV for examples of DEI disclosure in 10Ks).

In light of these findings, we study the labor market consequences of more DEI information in 10Ks. On the one hand, we expect that, following Regulation S-K, firms with lower levels of

[6] The PCAOB requires external auditors to review and assess whether other information (e.g., HCD) in documents containing audited financial statements (e.g., Form 10Ks) is materially inconsistent with the audited statements. If they find such inconsistencies, auditors must ask management to correct them. If management refuses, auditors must notify the audit committee. Auditors may also take further actions, such as adding an explanatory paragraph to the audit report, withholding the report, or resigning from the engagement (PCAOB, 2002).

workforce diversity may anticipate greater external pressure from investors, analysts, and other stakeholders. This would happen whether such firms chose to be forthcoming and include DEI information in 10Ks, thereby revealing their status, or chose to omit such information, implicitly signaling their type (e.g., Milgrom, 1981). It follows that Regulation S-K would provide an incentive for these firms to try to improve their actual workforce diversity in the short term. Enhancing workforce diversity, even marginally, would enable them to highlight these improvements in the 10K and potentially reduce some pressure. To improve their workforce diversity, firms would begin by including more DEI information in their job postings to signal their commitment to promoting a diverse and inclusive workplace culture, and thereby attract and recruit diverse candidates (Choi et al., 2023a; Cai et al., 2024). Consistent with these arguments, Regulation S-K should result in more DEI disclosure in job postings and, possibly, more workforce diversity (Figure 1).

On the other hand, Regulation S-K could also have no impact on DEI information in job postings or workforce diversity, for several reasons. First, certain firms might have a weak commitment to increasing workforce diversity despite their claims about DEI in the 10K (Baker et al., 2024). Second, firms might avoid including DEI information in job postings and focus on other less controversial human capital issues. This could happen if, for example, some individuals and groups view efforts to promote diversity as a sign that the company gives less weight to meritocratic promotion or rewards (Castilla and Benard, 2010; Castilla and Rho, 2023). Furthermore, the costs associated with developing unified DEI communication policies within a company can limit the inclusion of DEI narratives in job postings, especially when firms have greater organizational complexity and coordination needs, like those related to their dispersed geographical presence (e.g., Gallemore and Labro, 2015).

Even if firms do provide information about their DEI policies in job postings, it remains unclear whether this would lead to increased workforce diversity. Job seekers might not apply to firms if they do not find the DEI disclosures credible. More fundamentally, structural labor market conditions, such as limited or inelastic labor supply, may hinder improvements in diversity. Recruiting diverse talent can be challenging because the pool of diverse candidates in the economy remains fixed in the short term, and training candidates for different occupations takes time.[7] Furthermore, if there is heterogeneity in public firms' demand for diverse candidates, as previously discussed, diverse candidates may move among public firms—from those with less need to those with more need—rather than transitioning from private to public firms. This phenomenon, known as poaching, may attenuate the average effect of Regulation S-K on workforce diversity in public firms.

In sum, the interactions among capital market pressures, internal coordination needs, and labor market dynamics make the ex-ante prediction about the labor market effects of Regulation S-K less clear. Limited workforce diversity information and costly job search processes from both supply and demand further suggest that the labor market outcomes are far from obvious and are likely to be heterogeneous, depending on labor market conditions and companies' recruiting policies. We take advantage of our extensive data on public and private firms to map the lay of the land when it comes to labor market consequences of Regulation S-K.

3 Data and Sample Selection

We measure labor market outcomes using novel micro-level data from two large-sample datasets, LinkUp and Revelio Labs. First, we obtain job posting data from LinkUp, a platform

[7] Li et al. (2020) highlight a further issue in hiring diverse candidates. They argue that diverse candidates belong to numerically smaller groups, so information about them is less accurate (i.e., the conditional variance of their abilities is larger). This can potentially hinder diversity improvements.

specializing in aggregating job listings directly from corporate websites. Campello et al. (2023) show that LinkUp data reliably predict job gains from the U.S. Census Bureau's Quarterly Workforce Indicators (QWI). Furthermore, they highlight a strong correlation between the volume of job postings on LinkUp and the number of total private-sector hires as reported in the Bureau of Labor Statistics' Job Openings and Labor Turnover Survey (JOLTS). The dataset has several additional advantages. First, it is unique in the absence of duplicate entries, as it excludes third-party job listings often found on platforms like Indeed or LinkedIn. Second, LinkUp matches each job posting to a specific O*NET code—a standardized classification system for job roles. This allows us to conduct a within-job-type analysis, comparing labor market outcomes for similar occupations. Third, LinkUp provides information about how quickly job positions are filled, which we use when studying the length of the recruitment period of diverse candidates.[8] Finally, the data are available for both public and private firms, which allows us to use private firms as a control group in our analyses.

Next, we gather resume data from Revelio Labs, which offers coverage of nearly all LinkedIn profiles starting from 2007 (with some individual profiles containing job histories dating back to the 1970s). This dataset allows us to measure workforce diversity in terms of employees' race, ethnicity, and gender.

We match job posting data from LinkUp and individual resume data from Revelio Labs with public firms in COMPUSTAT based on their GVKEYs and with private firms in FactSet using FactSet ID. For private firms, we start from the sample of firms with sales data available in FactSet. We keep only private firms with more than 100 million in sales (in US dollars), because firm size

[8] We complement the analysis of the length of the recruitment period of diverse candidates by examining interview data from GlassDoor. Specifically, we measure the monthly total of the inverse hyperbolic sine of the number of interviews for each firm job type.

is a major determinant of disclosure (both financial and ESG disclosures; see Dhaliwal et al., 2011). Our final sample consists of 5.2 million job postings that can be matched to 1,891 public firms and 347 large private firms, within [-5, +5] months centered on the amendment of Regulation S-K. In Table 1, we summarize the sample construction process.

To measure DEI disclosure in job postings, we use RavenPack's NLP engine, which classifies words related to DEI and equal employment opportunities (EEO). Specifically, the RavenPack algorithm detects all meaningful entities in a job description (i.e., words or word phrases) and provides an entity taxonomy covering four different categories: Benefit and Compensation, Duties and Responsibilities, Qualifications, and Employment Policies. We focus on the two sub-categories of Employment Policies that are relevant to our research question: Diversity, Equity, and Inclusion and Equal Employment Opportunity. We calculate the total number of entities belonging to the two sub-categories to measure the extent and length of DEI-related disclosure for each job posting.

In Figure 2, we report the word cloud of our DEI measure. In Panel A, we observe that job postings include terminology such as Diversity, Equity, and Inclusion, alongside Equal Employment Opportunity and Affirmative Action, similar to the language firms use in delineating DEI policies within 10K filings (see Figure 2 Panel B and Choi et al., 2023a). Our DEI measure represents a conservative estimate for the length of DEI disclosure, as firms generally add a paragraph discussing DEI, and RavenPack only targets the terms that are most relevant to DEI. In the Online Appendix Section I, we develop an AI model to further examine the content of our sample of 5.2 million job postings and assess the credibility of DEI commitments.

In our cross-sectional analyses, we examine the role of socially responsible investors and analysts. To measure firm ownership by socially responsible investors, we follow Choi et al.

(2024b) and obtain mutual funds and exchange-traded funds (ETFs) portfolio holdings data from the Center for Research in Security Prices (CRSP) US Mutual Fund Holdings Database. Within the CRSP universe of funds, we identify socially responsible investors using data on ESG funds from Morningstar's annual Sustainable Funds U.S. Landscape Report. We scale the institutions' reported shares owned by the total number of shares outstanding (from CRSP). To prevent our ownership measures from being confounded by the effect of Regulation S-K on institutional investors' portfolio strategies, we measure holdings for socially responsible funds at the end of June 2020, which is the last quarter before the amendment of Regulation S-K. To measure pressure from analysts, we obtain conference calls transcripts from Capital IQ and examine the content of conference calls during the five-year period preceding Regulation S-K. We categorize firms into those that received DEI-related questions from analysts and those that did not.

Finally, to examine a firm's organizational complexity and coordination needs, we measure the geographical dispersion of employees and HR personnel using LinkUp data. Further, we gather data from the Harte-Hanks Ci Technology database, which surveys companies globally to understand their investment in hardware and software at the firm-division level. These data are commonly used to measure information and communication technology investment (e.g., Bloom et al., 2014; Azarmsa et al., 2023). Following these studies, we measure information and communication technology by calculating the proportion of divisions within a firm that adopt intranet technology. Superior intranet technology should reduce within-firm communication and coordination costs.

4 Regulation S-K and Labor Market Disclosure

4.1 DEI Disclosure in Job Postings

Our first empirical analysis focuses on examining DEI disclosure in job postings following Regulation S-K. We use a difference-in-differences research design centered on the amendment of Regulation S-K and estimate the following ordinary least squared (OLS) regression model:

$$DEI_{ijt} = Treatment_i \times POST_t + Month\ FE_t + Firm \times Job\ Type\ FE_{ij} + \varepsilon_{ijt}. \quad (1)$$

We examine two dependent variables—$d(DEI)$ and $IHS(DEI\ Length)$—that measure job-posting disclosure at the firm *i*, job type *j*, year-month *t* level to mitigate the impact of monthly fluctuations in certain types of jobs. In particular, $d(DEI)$ measures the monthly proportion of job postings with DEI information for each firm–job-type; $IHS(DEI\ Length)$ measures the monthly average of the inverse hyperbolic sine of the number of DEI entities used in job postings for each firm–job-type.[9] We report descriptive statistics for our dependent variables in Table 2.

$POST_t$ is an indicator variable equal to 1 for the months from August 2020 to January 2021, and equal to zero for the months from March 2020 to July 2020.[10] $Treatment$ is an indicator variable equal to 1 for public firms, and equal to zero for private firms. Our identification strategy exploits regulatory differences between public firms, which are subject to Regulation S-K, and large private firms, which are not. There are several advantages to using big private firms as a benchmark group. First, some concurrent events might affect labor market dynamics, such as the

[9] For example, if firm *i* in month *t* has 3 job postings for job type *j*, one with 6 DEI entities, one with 3 DEI entities, and one with 0 DEI entities, *d(DEI)* is equal to 0.67 [=2/3], and *IHS(DEI Length)* is equal to 1.44 [=(IHS(6)+IHS(3)+IHS(0))/3]. We use the inverse hyperbolic sine (Burbidge et al., 1988), rather than the logarithm of 1 plus DEI entities, acknowledging that Cohn et al. (2022) document that using the log of 1 plus the outcome can produce estimates with the wrong sign in expectation. In untabulated analyses, we check our results using log of 1 plus DEI entities and retrieve very similar results (coefficient 0.034, t-stat 6.33). Furthermore, results are robust to examining disclosure at the disaggregated job-postings level.

[10] We use the amendment of Regulation S-K (August 2020), rather than the date when it took effect (November 2020), because firms tend to react to a new regulation as soon as the rule is passed, in order to be prepared by the adoption deadline (e.g., Fiechter et al., 2022; Khrakovsky, 2024). Our dynamic analysis presented in Figure 3 provides visual evidence consistent with this notion.

outbreak of COVID-19 and the death of George Floyd (e.g., Balakrishnan et al., 2023; see also the Online Appendix Section II). This makes the use of an interrupted time-series (ITT) design, which would compare the behavior of public firms before and after Regulation S-K, less desirable in our setting. In contrast, to the extent that those events affect both public and private firms similarly, then using large private firms as a counterfactual helps alleviate concerns that our analyses are confounded by those concurrent events. Second, large private firms have good coverage by LinkUp and Revelio Labs, which allows us to examine both labor market disclosure and hiring outcomes across a larger spectrum of the U.S. economy. To ensure comparability between public and private firms, we keep only private firms with more than 100 million in sales (in US dollars), and we employ entropy balancing to reweight firms based on sales.[11]

Finally, we employ high-dimensional fixed effects to control for potential endogeneity related to omitted variable bias. Specifically, $Firm \times Job\ Type\ FE_{ij}$ sweep out firm- and occupation-specific job-posting strategies, mitigating potential biases stemming from differences in occupational composition within firms and job type, and allowing us to compare private and public firms for the same job type. Additionally, $Month\ FE_t$ control for any temporal variations in DEI disclosures attributable to broader labor market dynamics or shocks, including variation in labor supply and demand, and the spread of the COVID-19 pandemic. It follows that the coefficient on $Treatment_i \times POST_t$ retrieves the difference in job-postings DEI disclosure between public and private firms from the pre-regulation period to the post-regulation period.

[11] Another dimension along which we could balance public and private firms is industry. Unfortunately, FactSet does not provide industry classifications for private firms consistent with those generally employed to classify public firms (e.g., SIC codes). In a robustness test (untabulated), we try to overcome this data limitation by using ChatGPT to assign SIC-4 industry classification to our sample of private firms, and then repeat the entropy balancing with public firms based on both sales and industry. Comparing these findings to those in Table 3, we observe that results are unchanged for *IHS(DEI Length)* and stronger for *d(DEI)*. See Table OA 4 in the Online Appendix.

We report the results for Eq. (1) in Table 3. In column 1, we examine $IHS(DEI\ Length)$ and observe a statistically significant increase in the length of job-postings DEI disclosure for public firms following Regulation S-K. Next, in column 2 we examine $d(DEI)$ and continue to find an increase in job-postings DEI disclosure for public firms following the regulation. In particular, after the amendment of Regulation S-K, we observe that public firms, as compared to private firms, include DEI information in 41,000 additional job postings, or an average of 22 additional job postings per firm (which corresponds to a 2.3% increase in job postings with DEI information).

Given the arguments presented in Section 2, we expect this average effect to vary substantially, depending on public firms' diversity levels prior to the regulation, as well as important external and internal factors. We will examine the heterogeneity in the treatment effect in Section 4.2. Before that, we aim to further unpack our main results by examining the credibility of these DEI disclosures and assessing the validity of our main test.

4.1.1 Analysis of Job Postings DEI Credibility

Job postings represent the first step in the hiring process (Figure 1). To attract and recruit diverse candidates effectively, the DEI information conveyed in job postings must be credible. Diverse candidates are more likely to apply for positions at companies that demonstrate a clear commitment to DEI, do not discriminate based on factors beyond job-related skills, and foster an inclusive culture. They may also prefer companies that offer specific benefits supporting minorities, such as flexible hours, parental leave, and childcare.

We examine whether our sample of job postings with DEI disclosures conveys a credible commitment to DEI. To systematically analyze 5.2 million job postings, we utilize OpenAI's ChatGPT Batch API. This is one of the first studies in Accounting to use this tool for a parsimonious content analysis over a very large job-posting dataset, following de Kok (2024) and

Kim at el. (2024).[12] The analysis involved scoring job postings on four DEI-related criteria: 1) DEI commitment, 2) non-discriminatory job requirements, 3) corporate culture, and 4) benefits. The model was prompted to assume the perspectives of a minority job seeker. We conducted several validation steps, including human review, comparison with benchmark classifications, and human ratings, which revealed that ChatGPT's scores are closely aligned with human evaluations. Furthermore, the examination highlighted the model's ability to incorporate nuanced interpretations and reduce human bias, demonstrating the potential of generative large language models in systematic and context-aware text analysis.

The results reported in Table OA 1 show that job postings including DEI information score 83% in terms of credible commitment to DEI and 62% in terms of inclusive corporate culture. Both estimates are statistically and economically larger than the scores for job postings without DEI information, which are 16% and 32%, respectively. We also observe that benefits that could support minorities (e.g., flexible hours, parental leave, and childcare) are more likely to be discussed in job postings with DEI disclosure (47% compared to 34% in job postings without DEI disclosure, a difference that is statistically significant). Finally, the difference in non-discriminatory job requirements is statistically significant but modest (100% for job postings with DEI disclosure vs. 97% for those without). It is not surprising to see that almost all job postings are written in a non-discriminatory manner, as any form of discrimination beyond job-related skills is against the law. Taken together, this analysis reveals that job postings with DEI disclosures largely convey a credible commitment to DEI and inclusive culture.

[12] A detailed description of the process is provided in the Online Appendix Section I.

4.1.2 Threat to Validity and Falsification Test

The identifying assumption in the difference-in-differences design is parallel trends, meaning that the change in the control group mirrors what the change in the treatment group would have been in the absence of treatment. We indirectly test for this by examining whether there are differential pre-trends in the job-postings DEI disclosure of treatment and control firms. In columns 3 and 4 of Table 3, we replace $POST_t$ in Eq. (1) with distinct indicators for each month [-5, +5] around Regulation S-K. Furthermore, in Figure 3, we report the results of Table 3 in event time. Both Table 3 and Figure 3 indicate the absence of statistically significant differential pre-trends, which provides reassurance about the validity of our research design.

Further, our identification strategy relies on the assumption that the observed changes in DEI disclosures in job postings by public firms immediately following the amendment of Regulation S-K are attributable to the regulation. A possible threat to the validity of our identification strategy is the existence of concurrent events that could change hiring incentives for public firms (but not for private firms) in a way that is consistent with our findings but inconsistent with Regulation S-K playing a prominent role. We choose to examine a narrow window around the amendment of Regulation S-K to alleviate this concern. Measuring long-term effects and connecting them to a single event is inherently challenging and would exacerbate this concern. Our identification strategy requires reliable measurement of effects within short intervals, such as job-posting disclosure and hiring outcomes, which can change rapidly.

However, some might argue that the death of George Floyd in May 2020 (three months before the regulation amendment) and the subsequent surge in the Black Lives Matter movement have the potential to influence the labor market outcomes for public firms, given their greater

visibility relative to private firms.[13] We note that the coefficient for *Pre 3* in Table 3 and Figure 3 (which corresponds to May 2020) indicates no differential trend in job-postings DEI disclosure between public and private firms. Moreover, Figure 3 shows a notable uptick in job-postings DEI disclosures among public companies only in October 2020, five months after Floyd's death and two months after the regulation amendment. These findings provide reassurance regarding the validity of our research design as it is difficult to conceive why any effect related to Floyd's death would manifest during that time period rather than prior to the regulation's amendment. Yet if for some reason firms started responding to these social movements with a 5-month lag, then we would not be able to conclude that Regulation S-K, rather than social movements, impacts job-postings disclosure.

One limitation of our setting is that we only observe one state of the world where both regulatory changes and social movements happen within a few months from each other (even if the SEC started working on the regulation more than a year before).[14] However, we can address the above concern by studying a state of the world characterized by strong social movements but no changes in securities regulations. The idea is that if social movements, rather than regulatory changes, affect public firms' DEI disclosure in job postings, we should observe an increase in DEI disclosures in job postings by public firms (but not by private firms) following the surge of such social movements. In contrast, if Regulation S-K played a prominent role, we should not observe any changes in job-postings DEI disclosures following the surge of social movements.

[13] Balakrishnan et al. (2023) highlight that *some* public firms responded to this shock by improving DEI, specifically with respect to racial/ethnic workforce diversity. Unfortunately, they do not examine the reaction by private firms.
[14] The petition to the SEC to adopt HCD rules was submitted in 2017 (HCMC, 2017), and the new rule was proposed in August 2019 (SEC, 2019). Both of these events preceded the death of George Floyd. Furthermore, none of the comment letters submitted to the SEC mentioned the Black Lives Matter movement or the death of Floyd. This suggests a lack of connection between the event and Regulation S-K (see link). Hence, it is improbable that Floyd's death influenced the *timing* or *outcome* of Regulation S-K.

Accordingly, we conduct a falsification test that examines the emergence of the #MeToo movement in October 2017. This movement changed investors' perceptions of the economic risks linked to gender diversity in the workplace, such as difficulties in hiring and retaining qualified women due to pay inequities, limited advancement opportunities, or inhospitable working conditions (Billings et al., 2022; Lins et al., 2024). Put simply, this setting represents an even stronger confounder than the surge of the Black Lives Matter movement.

We use the regression model of Eq. (1) but examine changes in job-postings DEI disclosure for public and private firms around 5 months from the emergence of the #MeToo movement in October 2017. Results are reported in Table 4. We find that public firms' job-posting DEI disclosures do not change compared to private firms following the #MeToo movement. Results are both statistically and economically insignificant, which is inconsistent with the concern that social movements, rather than Regulation S-K, are likely causing our results.

Finally, it is worth noting that in our analysis of changes in workforce diversity following Regulation S-K, we observe meaningful results for gender diversity but not for ethnic/racial diversity. This finding is inconsistent with the concern that social movements related to race, such as the Black Lives Matter movement, could confound our results.

4.2 External Pressure and Internal Coordination Needs

As we argue in Section 2, the human capital disclosure mandate in Regulation S-K, in expectation, has the potential to increase incentives to enhance workforce diversity, particularly for firms already under intense external scrutiny regarding DEI issues. Thus, certain firms are likely to incorporate DEI information into their job postings with the intent to attract and recruit candidates from diverse backgrounds. In Section 2, we also argue that organizational complexity and internal coordination needs may play a salient role when HR needs to manage DEI policies, which can be controversial across regions and departments. This, in turn, may hinder coherent DEI

disclosure in job postings. In what follows, we examine the cross-sectional variation in pre-regulation levels of *external* pressure and *internal* coordination needs to clarify the mechanisms underlying our results.

4.2.1 Pre-regulation Levels of Workforce Diversity, Institutional Investors Ownership, and Pressure from Analysts

We examine three proxies for external pressure: pre-existing levels of workforce diversity, ownership by socially responsible investors, and pressure from analysts on DEI issues. First, *ceteris paribus* firms with low pre-regulation levels of workforce diversity could *anticipate* greater pressure to increase their workforce diversity (see Section 2). Second, firms with high pre-regulation levels of ownership by socially responsible investors could anticipate greater pressure from these investors to increase their workforce diversity. Those firms could also have greater incentives to increase workforce diversity in order to keep (or cater to) those investors. This is consistent with Heath et al. (2023), who show that socially responsible investors prefer firms with greater workforce diversity, greater equity (e.g., career opportunities, work-life balance), and better corporate culture.[15] Third, firms might feel more compelled to increase workforce diversity when DEI issues are brought up by analysts during conference calls.

In Table 5, Panel A, we split our entire sample of public and private firms based on the pre-regulation sample median of workforce diversity. We examine workforce diversity in terms of gender and ethnicity/race. *Gender Diversity* measures the proportion of women employees in a given firm–year-month, and *Ethnic/Racial Diversity* measures the proportion of non-white employees in a given firm–year-month. The median gender workforce diversity is 39.63%, while the median ethnic/racial workforce diversity is 23.85% (see Table 2). In column 1 of Table 5, we

[15] This is also consistent with experimental evidence from Choi et al. (2024a), which shows that firms are more likely to respond to investors' workforce diversity informational needs rather than those of other constituencies.

find that public firms with pre-regulation levels of gender diversity below the sample median increase the proportion of job postings with DEI disclosure by 2.5 percentage points, a figure statistically larger than the 0.7-percentage-point increase (statistically insignificant) observed in column 2 for companies with pre-regulation levels of gender diversity above the sample median. It's worth noting that the coefficient in column 1 is about 80% larger than the average treatment effect estimated in Table 3 (column 2). This indicates substantial heterogeneity in the effect of Regulation S-K on job-postings DEI disclosure, as we argue in Section 2.

A similar pattern to that observed for workforce gender diversity can be detected for ethnic/racial diversity. In Table 5 column 3, we find that public firms with pre-regulation levels of ethnic/racial diversity below the sample median increase the proportion of job postings with DEI disclosure by 1.8 percentage points, whereas public firms above the sample median increase the proportion of job postings with DEI disclosure by only 1.2 percentage points. This time, the difference between the coefficients is not statistically significant. These results are consistent with a slightly higher number of companies disclosing a numerical gender diversity metric (17%) than an ethnic/racial diversity metric (13%) in 2020 annual reports (Choi et al., 2023a). It is also consistent with the findings in Heath et al. (2023), who show that socially responsible funds are more likely to select firms based on gender than racial diversity, and with the findings in Gow et al. (2023), who show that investors are more likely to support gender-diverse board candidates than racially diverse candidates.

Next, in Panel B, we examine the cross-sectional variation in levels of pre-regulation ownership by institutional investors and the pressure from analysts. We examine pre-regulation levels of both measures to prevent our results from being confounded by contemporaneous increases in pressure from investors and analysts resulting from the regulation.

First, we split our sample of public firms based on the pre-regulation sample median of ownership by ESG funds. In column 1, we find that public firms with pre-regulation levels of ownership by ESG funds above the sample median increase the proportion of job postings with DEI disclosure by 3.1 percentage points, more than double the average treatment effect in Table 3. In column 2, we find that public firms with pre-regulation levels of ownership by ESG funds below the sample median increase the proportion of job postings with DEI disclosure by only 1 percentage point, a figure statistically smaller than that observed in column 1.

Second, we split our sample of public firms based on whether analysts asked DEI-related questions during the conference calls in the five-year period preceding the regulation.[16] In column 3, we find that public firms with high pre-regulation pressure from analysts increase the proportion of job postings with DEI disclosure by 6.6 percentage points. In column 4, we find that public firms with no pressure from analysts on DEI issues increase the proportion of job postings with DEI disclosure by only 1.3 percentage points, a figure statistically smaller than that observed in column 3. We note that analysts rarely bring up DEI issues during these calls. This suggests that when DEI topics are discussed by analysts, it likely indicates serious issues, thereby exerting significant pressure on management.

Taken together, the results in Table 5 Panels A and B provide evidence consistent with firms changing their labor market disclosure policies following Regulation S-K in *anticipation* of significant external pressure after the regulation, given their pre-existing levels of diversity. The evidence also suggests that the *net benefits* of improving workforce diversity vary depending on the social preferences of shareholders (assuming that analysts questions on DEI and ESG fund ownership proxy for shareholders' social preferences). In the next subsection, we explore the costs.

[16] For robustness, we also checked a one-year window and results are consistent with those reported in Table 6.

4.2.2 Organizational Complexity and Coordination Needs

We investigate whether organizational complexity and internal coordination needs interact with the firm's decision to disclose DEI information in job postings following Regulation S-K. We use three measures that aim to capture (albeit imperfectly) coordination needs: geographical dispersion of employees, geographical dispersion of HR personnel, and intranet. When employees are located in diverse geographical regions, companies may need to employ varied rhetoric to effectively communicate with them. Hence, the extent of a uniform DEI disclosure in job postings can be attenuated. Similarly, if HR departments are dispersed across different regions, these HR personnel may have localized knowledge that could be integrated into job postings in a diverse manner (Deller and Sandino, 2020), thereby reducing the need for uniform DEI disclosure in job postings. Furthermore, the establishment of an intranet might facilitate communication between headquarters and subsidiaries, and even across different subsidiaries. Previous studies examine how intranet establishment influences local managers' incentives for information acquisition (Azarmsa et al., 2024). We argue that better-established intranet systems facilitate within-firm communications, thereby resulting in more DEI disclosure in job postings.

Consistent with our predictions, in Table 5 Panel C we find that public firms with less geographically dispersed workforces and HR departments increase the proportion of job postings with DEI disclosure by 3 and 2.6 percentage points, respectively. Similarly, public firms with better-established intranet systems increase the number of job postings with DEI disclosure by 3 percentage points. In contrast, we do not observe a statistically significant increase in DEI disclosures in job postings for public firms with a widely geographically dispersed workforce or low intranet systems. Taken together, findings in Table 5 Panel C show how HR management interacts with the effect of Regulation S-K on labor market disclosure.

5 Regulation S-K and Workforce Dynamics

In the second part of our analysis, we study whether firms affected by Regulation S-K not only increase DEI disclosure in job postings but are also able to increase their workforce diversity. Even though we document that these disclosures represent a credible commitment to DEI, this may not necessarily lead to an increase in the hiring of diverse candidates, as a limited or inelastic labor supply could hinder significant changes in workforce composition.

Since labor market outcomes are measured at the firm–year-month level, for the following analyses we estimate the OLS regression model in Eq. (2):

$$Y_{it} = Treatment_i \times POST_t + Firm\ FE_i + Month\ FE_t + \varepsilon_{it}, \qquad (2)$$

The dependent variable measures either a firm's monthly workforce diversity (in Tables 6, 8, 10-11) or poaching (Table 7). We consider both gender diversity and ethnic/racial diversity, measured as the proportion of employees who are women or non-white, respectively. We also decompose ethnic/racial diversity into its three sub-components: Black, Hispanic, and Asian/Pacific Islander groups. Poaching, instead, represents the number of employees hired from another public firm each month, scaled by the total number of new hires that month.[17] We examine both diversity and poaching for the overall workforce and within senior positions. $Treatment$ and $Post_t$ are defined as in Eq. (1). We include firm fixed effects to control for non-time-varying firm characteristics, and year-month fixed effects to control for labor market trends. It follows that the coefficient on $Treatment_i \times POST_t$ retrieves the difference in workforce diversity or poaching between public and private firms, from the pre-regulation period to the post-regulation period.

[17] For private firms, poaching represents the number of employees hired by another private firm each month, scaled by the total number of new hires that month.

5.1 Regulation S-K and Changes in Workforce Diversity

In Table 6, we examine the average effect of Regulation S-K on workforce diversity. In Panel A, we examine the overall workforce diversity, whereas in Panel B we examine workforce diversity for senior positions. Across the 10 measures examined, we find no change in a firm's workforce diversity following Regulation S-K. The results are both statistically and economically insignificant.

As an alternative measure of diversity, we also examine the monthly number of diverse candidates (i.e., women or non-white individuals) hired by the firm, scaled by the total monthly number of new hires. This analysis addresses the concern that firm-level workforce diversity changes slowly. The results are reported in Table OA 2 (see Online Appendix Section V), and we continue to find no changes following Regulation S-K.

Results in Tables 6 and OA 2 are not surprising, as labor supply is inelastic in the short-term: Recruiting diverse talent is costly, as the pool of diverse candidates in the economy remains fixed in the short term, and training candidates for different occupations requires time. Furthermore, our prior analyses revealed substantial heterogeneity in public firms' demand for diverse candidates, which suggests that diverse candidates may move among public firms—from those with less need to those with more need—rather than transitioning from private to public firms. This phenomenon, known as poaching, may attenuate the average effect of Regulation S-K on workforce diversity in public firms. Consequently, our follow-up analyses focus on the examination of poaching and demand elasticity.

5.2 Regulation S-K and Poaching

We begin by examining poaching. This analysis is conducted using the regression model described in Eq. (2), and the results are reported in Table 7. We define poaching for both gender diversity (columns 1-2) and ethnic/racial diversity (columns 3-4), and consistent with prior

analyses, we examine poaching for all levels of employees (columns 1 and 3) and for senior positions (columns 2 and 4).

Across the board, we find that poaching increases for public firms following the regulation, especially for senior positions. In particular, poaching based on gender increases by 1.0 percentage point, which is 25% above the unconditional mean. If we consider only senior positions, the increase is 1.8 percentage points or 45% above the unconditional mean. Poaching based on ethnic/racial diversity also increases substantially: 0.8 percentage points (27% above the unconditional mean) across all positions and up to 1.6 percentage points (53% above the unconditional mean) when we only consider senior positions.

The results underscore the importance of examining labor market dynamics across firms to provide a complete picture of the labor market consequences of a securities regulation. They suggest that the average effect of Regulation S-K is partly muted by poaching.

5.3 Inelastic Labor Supply

The absence of an average effect of Regulation S-K on public firms' workforce diversity (Table 6) and hiring (Table OA 2) is not surprising given the evidence of poaching (Table 7) and, especially, the limited or inelastic labor supply in the short-term (e.g., Chetty et al., 2011, Welch, 1997). We explore such supply-side constraints by looking at (i) variation in the supply of diverse candidates, and (ii) the length of the recruitment period. With respect to (i), we expect that hiring challenges increase when there is a limited pool of diverse candidates available in a particular region and industry. With respect to (ii), we expect that the recruitment period lengthens when firms face more challenges in finding their ideal candidates, which is consistent with labor market tightness due to inelastic labor supply (Muehlemann and Leiser, 2018).

We begin in Table 8 by studying how variation in the supply of diverse candidates interacts with the relation between Regulation S-K and workforce diversity. The pattern we observe is clear:

the separation of labor markets across regions and industries poses challenges to recruiting diverse candidates. Specifically, we find that gender diversity increases by 0.2 percentage points in U.S. states and industries with a larger presence of women candidates relative to U.S. states and industries with a lower presence of women candidates. We also observe that ethnic/racial diversity increases by 0.13 percentage points in U.S. states and industries with a larger presence of minority candidates relative to U.S. states and industries with a lower presence of minority candidates.[18] The results fall short of statistical significance levels, so interpreting them requires caution. But their direction and magnitude suggest that supply-side constraints play a role in our setting. Put differently, these findings are consistent with the notion that a limited labor supply of diverse candidates for certain jobs might contribute to the limited increase in workforce diversity we observe. Given that training candidates for different occupations takes time, it seems unreasonable to expect larger changes in the workforce in the short term.

Next, we examine the *length* of the recruitment period by looking at how long a job remains vacant and the number of interviews a firm conducts. Considering an additional element when determining whether a candidate is a good match for the position can require interviewing more people and, at the margin, lengthen the recruitment period. Observing prolonged recruitment periods after the regulation would suggest that firms are facing more challenges in finding their ideal candidates.

For this analysis, we use our firm–job-type–year-month panel, consistent with Eq. (1). One notable advantage of the Linkup dataset is that it includes the date of a job posting and the date of its removal. The interval between these two dates corresponds to the recruitment period, which is indicative of a firm's recruitment efforts and hiring challenges. We measure recruiting length in

[18] We also examined senior positions and find similar, but weaker, results. See Online Appendix Section V.

two ways: the firm's monthly average of the inverse hyperbolic sine of the number of filling days for each job type, *IHS(N Filling Days)*, and the firm's monthly proportion of job positions filled within 90 days for each job type (*Filled in 90 Days*). We also examine interviews data from GlassDoor and measure the firm's monthly total of the inverse hyperbolic sine of the number of interviews conducted for each job type, *IHS(N Interviews)*.[19]

Results are reported in Table 9. Consistent with Eq. (1), this analysis includes year-month fixed effects to control for temporal trends in the labor force, and firm–job-type fixed effects that account for firm–job-type–specific hiring policies, recognizing that filling different positions entails varying durations due to firm-specific interview processes, among other factors. In Panel A, column 1, we find that compared to private firms, public companies subject to Regulation S-K increase their average number of filling days. We also find that public companies decrease the likelihood of hiring someone within 90 days by 2.1 percentage points (column 2). In Panel B, we find that the number of candidates firms interview following Regulation S-K increases by approximately 4%.

These findings are consistent with the notion that changing workforce diversity requires greater effort. An alternative possibility could be the lack of interest in hiring diverse candidates (Baker et al., 2024). While this is a plausible alternative, we find that certain firms subject to Regulation S-K do increase DEI disclosure in job postings, and our analysis of the content of these job postings reveals that they incorporate credible DEI commitments. Hence, our analyses suggest that certain firms are indeed serious about their DEI commitments (as in Goldman and Zhang, 2024). Yet our findings highlight the considerable constraints associated with changing a firm's workforce diversity.

[19] The scope of the GlassDoor interviews data is more limited, and therefore results should be interpreted with caution.

5.4 Demand Side

Having examined the supply side, we complete our study of the labor dynamics of Regulation S-K by exploring the demand side. Specifically, we examine whether there is an increase in workforce diversity among firms that show a stronger demand for diverse candidates or a more credible commitment to DEI through the presence of a DEI officer.

5.4.1 The Disclosure Channel

We begin by examining heterogeneity in a firm's demand for diverse candidates. We split firms into those that had an above-median increase in job-posting DEI disclosure following the regulation and those that had a below-median increase. The advantage of this split is that it allows us to capture the demand-side heterogeneity documented in the cross-sectional tests of Table 5 within a single test. Additionally, it enables us to see whether DEI disclosure in job postings is a channel through which Regulation S-K could lead to more workforce diversity. The downside is that the results are not causal and can only suggest a potential pattern in the data since the variable we are partitioning on and the outcome we are examining are both influenced by Regulation S-K.

In Table 10 Panel A, we examine overall workforce diversity, whereas in Panel B we examine diversity among senior positions. In columns 1 and 2 of both panels, we examine gender diversity and find that the difference between the coefficients is statistically significant (t=3.06 in Panel A), indicating a small increase in gender diversity (0.25 percentage points) for firms with an above-median increase in job-postings DEI disclosure following the regulation relative to firms with a below-median increase. [20]

[20] The negative coefficient in column 2 Panel A is consistent with poaching (see Table 7). Furthermore, in columns 3 and 4 of both panels, we examine ethnic/racial diversity and continue to find no changes in the workforce composition.

5.4.2 The Role of DEI Officers

Finally, we examine whether credible commitment to DEI through the support and expertise of the top management team can help increase workforce diversity. Byker et al. (2024) highlight that an increase in women board members contributes to improved gender workforce balance, while Balakrishnan et al. (2023) argue that hiring a DEI officer shows a company's commitment to enhancing workforce diversity. Similarly, we examine whether the presence of a DEI officer facilitates an increase in workforce diversity following Regulation S-K.

In Table 11, we partition our sample between firms with and without a DEI officer. As in the prior tests, in Panel A we study overall workforce diversity, whereas in Panel B we study diversity among senior positions. Table 11 highlights a few important findings. First, the effect on gender diversity among senior positions for firms with a DEI officer (column 1, Panel B) is statistically and economically significant. It indicates a 0.7-percentage-point increase in gender diversity, which corresponds to a 2% increase relative to the sample mean. Given that we are examining the short-term effect of Regulation S-K, the effect is not trivial as it corresponds to approximately 13% of employee turnover over the time period examined (Choi et al., 2023c). Second, when we examine the difference between coefficients, we observe that firms with a DEI officer also increase their overall gender diversity: In Panel A, the difference between the coefficients in column 1 and column 2 is 0.4 percentage points (t=2.08). In contrast, we continue to observe negligible changes in ethnic/racial diversity (columns 3 and 4 in both panels).

When we explore the long-term effects of Regulation S-K, we continue to find significant effects for gender diversity (particularly in senior positions), but not for ethnic/racial diversity, consistent with the results in Tables 10 and 11 (see Online Appendix Section V, Figure OA 4). However, measuring long-term effects and connecting them to a single event is inherently challenging, so these results should be interpreted with caution.

6 Conclusions

In this paper, we study the real effects of the 2020 Regulation S-K. The regulation mandates human capital disclosure in 10K filings, reflecting a broader trend by the SEC toward expanding disclosure requirements beyond traditional financial metrics. By examining the labor market consequences of this regulation, we shed light on the interconnections between securities regulations and organizational practices, expanding the understanding of the impact of securities regulation beyond capital markets. Our findings suggest that while Regulation S-K prompts firms to increase the extent and length of DEI disclosure in job postings, consistent with inelastic labor supply in the short-term, the impact of the regulation on workforce diversity remains limited. This suggests that addressing diversity issues in the labor market entails substantial challenges.

Our study also highlights the need for further research to explore additional mechanisms through which Regulation S-K influences labor market dynamics and HR management. We focus on DEI because it is the most common topic resulting from Regulation S-K, and because it directly relates to labor market outcomes (i.e., workforce diversity) that we can precisely measure. However, Arif et al. (2024) show that Safety & Health and Employee Development are other value-relevant HCD topics discussed in 10Ks following the regulation. Future studies could investigate whether Regulation S-K also leads to further changes in HR management, like employee turnover or workplace safety. Our study and future studies on this topic can inform the SEC in its current examination of a more prescriptive, rule-based human capital disclosure mandate.[21]

[21] https://www.warner.senate.gov/public/index.cfm/2022/6/warner-brown-urge-sec-to-implement-improvements-to-their-human-capital-disclosure-rules.

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Appendix A: Variable Definitions and Data Sources

Variable	Definition	Source
d(DEI)	The monthly proportion of job postings with DEI information for each firm–job-type. For example, if firm *i* in month *t* has 3 job postings for job type *j*, one with 6 DEI entities, one with 3 DEI entities, and one with 0, *d(DEI)* is equal to 0.67 (2/3).	RavenPack, LinkUp
IHS(DEI Length)	The monthly average of the inverse hyperbolic sine (IHS) of the number of DEI entities used in job postings for each firm–job-type. For example, if firm *i* in month *t* has 3 job postings for job type *j*, one with 6 DEI entities, one with 3 DEI entities, and one with 0, *IHS(DEI Length)* is equal to 1.44 (IHS(6)+IHS(3)+IHS(0)/3).	RavenPack, LinkUp
Treatment	An indicator variable equal to 1 for public firms, and equal to zero for private firms. To ensure comparability between public and private firms, we keep only private firms with more than 100 million USD in sales and employ entropy balancing to reweight firms on sales throughout our analyses.	COMPUSTAT, Factiva
Post	An indicator variable equal to 1 for the months from August 2020 to January 2021, and equal to zero for the months from March 2020 to July 2020.	COMPUSTAT
Gender Diversity	The monthly proportion of women employees in a firm.	Revelio Labs
Ethnic/Racial Diversity	The monthly proportion of non-white employees in a firm.	Revelio Labs
Asian Pacific Islander	The monthly proportion of employees who are Asian or Pacific Islander in a firm.	Revelio Labs
Hispanic	The monthly proportion of employees who are Hispanic in a firm.	Revelio Labs

Black	The monthly proportion of employees who are Black in a firm.	Revelio Labs
Poaching	For public (private) firms, poaching is measured as the number of employees hired from another public (private) firm each month, scaled by the total number of new hires in that month.	Revelio Labs
IHS(N Filling Days)	The firm's monthly average of the inverse hyperbolic sine of the number of filling days for each job type.	LinkUp
Filled 90 Days	The firm's monthly proportion of job positions filled within 90 days for each job type.	LinkUp
IHS(N Interviews)	The firm's monthly total of the inverse hyperbolic sine of the number of interviews conducted for each job type.	GlassDoor

Figure 1
Hiring Process

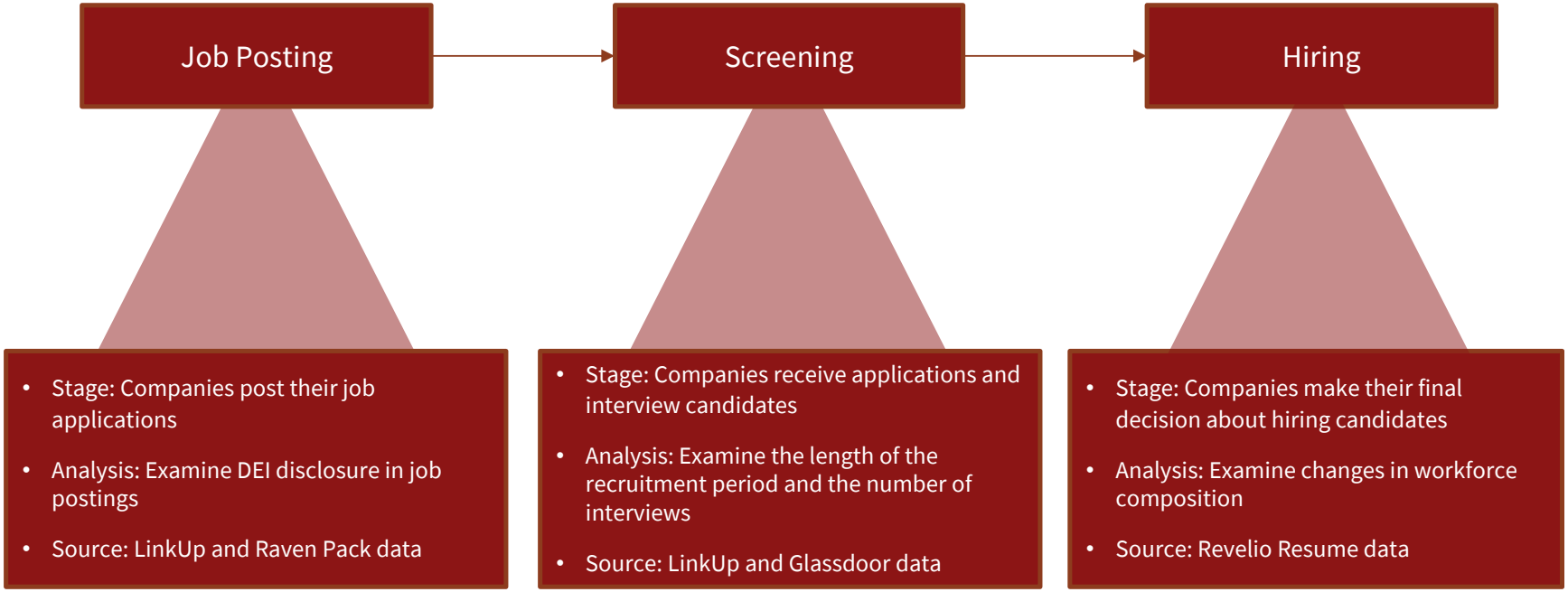


Figure 2
Word Cloud of DEI Disclosure

Panel A: Word Cloud of Job-Postings DEI Disclosure



Panel B: Word Cloud of 10Ks DEI Disclosure



Figure 3
Effect of Regulation S-K on Firms' Job-Postings DEI Disclosure

The figure reports results from Eq. (1) in event time with 95% confidence interval. The orange dotted vertical line indicates the amendment of Regulation S-K in August 2020, while the red dotted vertical line indicates the deadline when the regulation took effect in November 2020. On the x-axis, we report the months relative to August 2020. On the y-axis, we report *IHS(DEI Length)*.

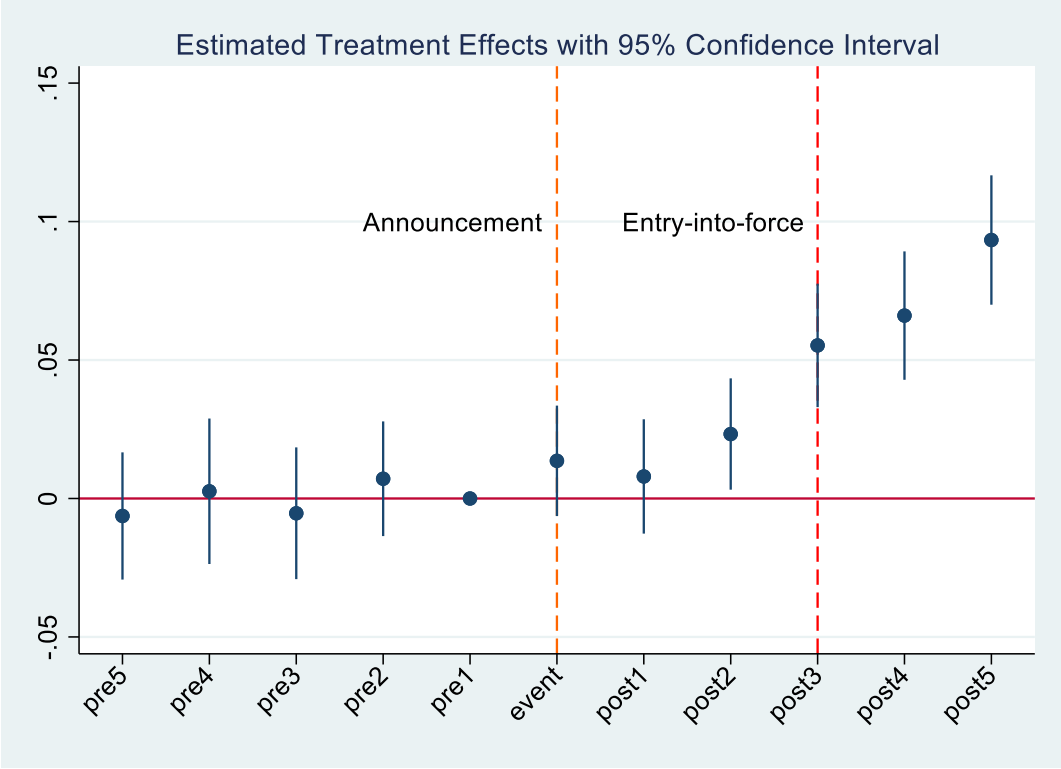


Table 1
Sample Composition

Panel A: Sample selection procedure for firm–job-type–month level analyses

	Number of Observations
Job postings that can be matched to public firms and large private firms	5,169,408
Aggregate to firm–job-type-month level	391,224
Excluding firm–job-type–months with missing sales information	(8,981)
Excluding firm–job-type–months with only pre- or post- observations	(38,148)
Final Sample	344,095

Panel B: Sample selection procedure for firm–month level analyses

	Number of Observations
Firm-months with workforce diversity measure from Revelio Labs matched to job posting sample	25,938
Excluding firm-months with fewer than 100 employees on LinkedIn profiles	(4,567)
Excluding firm-months with only pre- or post- observations	(196)
Final Sample	21,175

Table 2
Descriptive Statistics

This table reports summary statistics for our outcome variables. We report the number of observations, the mean, the standard deviation, and the 10^{th}, 50^{th}, and 90^{th} deciles of the distribution. Appendix A provides variable definitions and data sources.

	N	Mean	SD	p10	Median	p90
	(1)	(2)	(3)	(4)	(5)	(6)
Job-postings disclosure measures:						
d(DEI)	344,095	0.62	0.47	0.00	1.00	1.00
IHS(DEI Length)	344,095	1.04	0.92	0.00	0.96	2.16
Workforce diversity measures:						
Gender Diversity (%)	21,175	40.98	14.13	24.44	39.63	60.32
Gender Diversity (Senior) (%)	21,175	34.37	13.20	18.91	32.93	51.85
Ethnic/Racial Diversity (%)	21,175	24.97	12.54	10.46	23.85	40.91
Ethnic/Racial Diversity (Senior) (%)	21,175	21.24	11.94	7.81	19.67	36.05
Asian Pacific Islander (%)	21,175	8.24	9.24	0.95	5.05	20.35
Hispanic (%)	21,175	8.72	7.56	2.40	7.07	16.04
Black (%)	21,175	8.01	5.05	2.59	7.20	14.47
Hiring measures:						
Poaching Gender	18,766	0.04	0.10	0.00	0.00	0.11
Poaching Gender (Senior)	15,728	0.04	0.13	0.00	0.00	0.10
Poaching Ethnic/Racial	18,843	0.03	0.08	0.00	0.00	0.08
Poaching Ethnic/Racial (Senior)	15,893	0.03	0.10	0.00	0.00	0.07
Recruitment period measures:						
IHS(N Filling Days)	343,573	4.09	1.01	2.78	4.13	5.33
Filled in 90 Days	343,573	0.82	0.32	0.17	1.00	1.00
IHS(N Interviews)	12,396	1.07	0.43	0.88	0.88	1.44

Table 3
Regulation S-K and DEI Disclosure in Job Postings

This table reports the results from estimating the difference-in-differences model in Eq. (1). In columns 1 and 3, the dependent variable is *IHS(DEI Length)*, the monthly average of the inverse hyperbolic sine (IHS) of the number of DEI words used in job postings for a specific job type. In columns 2 and 4, the dependent variable is *d(DEI)*, the monthly proportion of job postings with DEI information for each job type. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–job-type–year-month level. Job type is defined by a 6-digit O*NET code. All regressions include year-month and firm-by-job-type fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm-job-type level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Dependent variable:	*IHS(DEI Length)*	*d(DEI)*	*IHS(DEI Length)*	*d(DEI)*
	(1)	(2)	(3)	(4)
Treatment × Post	0.044***	0.014***		
	(6.668)	(3.989)		
Pre 5			-0.005	0.005
			(-0.426)	(0.831)
Pre 4			0.003	0.009
			(0.244)	(1.327)
Pre 3			-0.008	-0.009
			(-0.649)	(-1.473)
Pre 2			0.004	0.002
			(0.424)	(0.309)
Event			0.014	0.005
			(1.437)	(0.901)
Post 1			0.009	0.003
			(0.906)	(0.484)
Post 2			0.023**	0.009*
			(2.227)	(1.761)
Post 3			0.055***	0.017***
			(4.921)	(2.938)
Post 4			0.065***	0.025***
			(5.571)	(4.222)
Post 5			0.092***	0.033***
			(7.798)	(5.513)
Observations	344,095	344,095	344,095	344,095
R-squared	0.869	0.887	0.869	0.887
Month FE	Yes	Yes	Yes	Yes
Firm*Job Type FE	Yes	Yes	Yes	Yes

Table 4
Falsification Test: the #MeToo Movement

This table reports the results from estimating the changes in job-postings DEI disclosure during the surge of the #MeToo movement. The regression model follows a difference-in-differences approach consistent with Equation (1), but centers the pre- and post- periods around October 2017, spanning 5 months before and after this date. In column 1, the dependent variable is *IHS(DEI Length)*, the monthly average of the inverse hyperbolic sine (IHS) of the number of DEI words used in job postings for a specific job type. In column 2, the dependent variable is *d(DEI)*, the monthly proportion of job postings with DEI information for each job type. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–job-type–year-month level. Job type is defined by a 6-digit O*NET code. All regressions include year-month and firm-by-job-type fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm-job-type level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Dependent variable:	*IHS(DEI Length)*	*d(DEI)*
	(1)	(2)
Treatment × *Post*	0.007	-0.001
	(1.113)	(-0.268)
Observations	294,997	294,997
R-squared	0.918	0.916
Month FE	Yes	Yes
Firm*Job Type FE	Yes	Yes

Table 5
Regulation S-K and DEI Disclosure in Job Postings – Cross-sectional Analyses

This table reports the results from various cross-sectional analyses of the difference-in-differences model in Eq. (1). In Panel A, we partition the sample based on pre-regulation levels of gender (columns 1 and 2) and ethnic/racial diversity (columns 3 and 4). In Panel B, we partition the sample based on pre-regulation levels of ownership by ESG funds (columns 1 and 2) and pre-regulation pressure from analysts on DEI issues during conference calls. In Panel C, we partition the sample based on levels of geographical dispersion of employees (columns 1 and 2), geographical dispersion of HR personnel (columns 3 and 4), and the use of intranet technology (columns 5 and 6). Across all panels and specifications, the dependent variable is *d(DEI)*, the monthly proportion of job postings with DEI information for each job type. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–job-type–year-month level. Job type is defined by a 6-digit O*NET code. All regressions include year-month and firm-by-job-type fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm–job-type level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Panel A: Pre-period diversity levels

Dependent variable:	*d(DEI)*		*d(DEI)*	
Sample:	Low Gender Diversity	High Gender Diversity	Low Ethnic/Racial Diversity	High Ethnic/Racial Diversity
	(1)	(2)	(3)	(4)
Treatment × Post	0.025***	0.007	0.018***	0.012**
	(4.437)	(1.554)	(3.673)	(2.354)
Observations	157,149	163,935	144,584	178,097
R-squared	0.883	0.893	0.900	0.877
Month FE	Yes	Yes	Yes	Yes
Firm*Job Type FE	Yes	Yes	Yes	Yes
F-test	t = 2.47		t = 0.81	

Panel B: Pre-period pressure from investors and analysts

Dependent variable:	*d(DEI)*		*d(DEI)*	
Sample:	High ESG Fund	Low ESG Fund	Analysts Pressure	No Analysts Pressure
	(1)	(2)	(3)	(4)
Treatment × Post	0.031***	0.010**	0.066***	0.013***
	(6.017)	(2.335)	(4.695)	(3.596)
Observations	205,534	170,604	41,055	335,083
R-squared	0.883	0.887	0.906	0.888
Month FE	Yes	Yes	Yes	Yes
Firm*Job Type FE	Yes	Yes	Yes	Yes
F-test	t = 3.81		t = 3.82	

Table 5 (cont'd)

Panel C: Organizational complexity and coordination needs

Dependent variable:	*d(DEI)*		*d(DEI)*		*d(DEI)*	
Sample:	Geographical Dispersion of Employees		Geographical Dispersion of HR		Intranet Technology	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × *Post*	0.005	0.030***	0.014***	0.026***	0.030***	0.002
	(1.052)	(4.350)	(3.198)	(3.793)	(6.220)	(0.383)
Observations	246,486	84,489	245,276	85,699	177,912	164,515
R-squared	0.883	0.876	0.881	0.881	0.892	0.884
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Job Type FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test	t = -3.13		t = -1.44		t = 4.00	

Table 6
Regulation S-K and Changes in Workforce Diversity

This table reports the results from estimating the difference-in-differences model in Eq. (2). In Panel A, we examine the overall workforce diversity, whereas in Panel B, we examine workforce diversity only for senior positions. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–year-month level. All regressions include year-month and firm fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Panel A: Overall workforce

Dependent variable:	*Gender Diversity*	*Ethnic/Racial Diversity*	*Asian/Pacific Islander*	*Hispanic*	*Black*
	(1)	(2)	(3)	(4)	(5)
Treatment × Post	-0.082	0.011	0.002	0.025	-0.016
	(-1.240)	(0.193)	(0.049)	(0.689)	(-0.480)
Observations	21,175	21,175	21,175	21,175	21,175
R-squared	0.998	0.998	0.998	0.998	0.996
Month FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Panel B: Senior positions

Dependent variable:	*Gender Diversity (Senior)*	*Ethnic/Racial Diversity (Senior)*	*Asian/Pacific Islander (Senior)*	*Hispanic (Senior)*	*Black (Senior)*
	(1)	(2)	(3)	(4)	(5)
Treatment × Post	-0.081	-0.084	-0.071	-0.027	0.014
	(-0.730)	(-0.991)	(-1.349)	(-0.515)	(0.255)
Observations	21,175	21,175	21,175	21,175	21,175
R-squared	0.994	0.995	0.996	0.995	0.989
Month FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 7
Regulation S-K and Poaching

This table reports the results from estimating the difference-in-differences model in Eq. (2). The dependent variable is *Poaching*. For public (private) firms, *Poaching* measures the number of minority employees hired from another public (private) firm scaled by the total number of employees hired in that month. In column 1, minorities are defined in terms of gender. In column 2, minorities are defined in terms of gender in senior positions. In column 3, minorities are defined in terms of race and ethnicity. In column 4, minorities are defined in terms of race and ethnicity in senior positions. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–year-month level. All regressions include year-month and firm fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Dependent variable:	*Poaching*			
Sample:	Gender	Gender Senior	Ethnic/Racial	Ethnic/Racial Senior
	(1)	(2)	(3)	(4)
Treatment × *Post*	0.010*	0.018*	0.008*	0.016*
	(1.726)	(1.683)	(1.754)	(1.955)
Observations	18,700	15,633	18,777	15,801
R-squared	0.318	0.260	0.239	0.191
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 8
Regulation S-K and Labor Supply

This table reports the results from estimating the difference-in-differences model in Eq. (2). To capture diversity in labor supply, we partition the sample based on whether a firm's operations are located in U.S. states and industries with high or low gender diversity (columns 1 and 2, respectively) and high or low ethnic/racial diversity (columns 3 and 4, respectively). The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–year-month level. All regressions include year-month and firm fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Dependent variable:	*Gender Diversity*		*Ethnic/Racial Diversity*	
Sample:	Firm operates in high Gender Diversity states and industries	Firm operates in low Gender Diversity states and industries	Firm operates in high Ethnic/Racial Diversity states and industries	Firm operates in low Ethnic/Racial Diversity states and industries
	(1)	(2)	(3)	(4)
Treatment × *Post*	0.052	-0.142	0.079	-0.053
	(0.553)	(-1.292)	(0.960)	(-0.635)
Observations	7,755	6,215	7,381	6,402
R-squared	0.998	0.998	0.998	0.998
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F - test	t = 1.64		t = 1.33	

Table 9
Regulation S-K and the Recruitment Period

This table reports the results from estimating the difference-in-differences model in Eq. (1). In Panel A, we examine the time to fill a position. In column 1, the dependent variable is *IHS(N Filling Days)*, which measures the monthly average of the inverse hyperbolic sine of the number of filling days for each job type. In column 2, the dependent variable is *Filled in 90 Days*, which measures the proportion of job postings filled in 90 days for each job type. In Panel B, we examine the number of interviews. In columns 1 and 2, the dependent variable is *IHS(N Interviews)*, the firm's monthly total of the inverse hyperbolic sine of the number of interviews conducted for each job type. In column 2, we control for the inverse hyperbolic sine of the number of job postings. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–job-type–year-month level. In Panel A, job type is defined by a 6-digit O*NET code. In Panel B, job type is defined by a 2-digit O*NET code due to the small sample size. All regressions include year-month and firm-by-job-type fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm–job-type level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Panel A: Time to fill a position

Dependent variable:	*IHS(N Filling Days)*	*Filled in 90 Days*
	(1)	(2)
Treatment × *Post*	0.033**	-0.021***
	(2.362)	(-4.232)
Observations	343,453	343,453
R-squared	0.474	0.418
Month FE	Yes	Yes
Firm*Job Type FE	Yes	Yes

Panel B: Number of interviews

Dependent variable:	*IHS(N Interviews)*	*IHS(N Interviews)*
	(1)	(2)
Treatment × *Post*	0.037**	0.036***
	(2.213)	(2.184)
Observations	12,396	12,396
R-squared	0.642	0.642
Control	No	Yes
Month FE	Yes	Yes
Firm*Job Type FE	Yes	Yes

Table 10
Regulation S-K and Workforce Diversity – Change in Job-Postings DEI Disclosure

This table reports the results from estimating the difference-in-differences model in Eq. (2). In columns 1 and 3 (columns 2 and 4), the treatment sample is composed of public firms that record an above-median (below-median) change in DEI disclosure in job postings following the regulation, whereas the control group is composed of private firms. In Panel A, we examine the overall workforce diversity, whereas in Panel B, we examine workforce diversity only for senior positions. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–year-month level. All regressions include year-month and firm fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Panel A: Overall workforce

Dependent variable:	*Gender Diversity*		*Ethnic/Racial Diversity*	
Sample:	High change in DEI disclosure in job postings	Low change in DEI disclosure in job postings	High change in DEI disclosure in job postings	Low change in DEI disclosure in job postings
	(1)	(2)	(3)	(4)
Treatment × Post	0.105	-0.143*	0.056	-0.000
	(1.201)	(-1.890)	(0.679)	(-0.001)
Observations	9,031	12,133	9,031	12,133
R-squared	0.998	0.998	0.998	0.998
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F-test	t = 3.06		t = 0.66	

Panel B: Senior positions

Dependent variable:	*Gender Diversity (Senior)*		*Ethnic/Racial Diversity (Senior)*	
Sample:	High change in DEI disclosure in job postings	Low change in DEI disclosure in job postings	High change in DEI disclosure in job postings	Low change in DEI disclosure in job postings
	(1)	(2)	(3)	(4)
Treatment × Post	0.244	-0.077	0.064	-0.112
	(1.380)	(-0.622)	(0.483)	(-1.164)
Observations	9,031	12,133	9,031	12,133
R-squared	0.994	0.994	0.995	0.995
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F-test	t = 1.93		t = 1.42	

Table 11
Regulation S-K and Workforce Diversity – DEI Officer

This table reports the results from estimating the difference-in-differences model in Eq. (2). We partition the sample based on whether a firm has a DEI officer (columns 1-3) or not (columns 2-4). In Panel A, we examine the overall workforce diversity, whereas in Panel B, we examine workforce diversity only for senior positions. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–year-month level. All regressions include year-month and firm fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Panel A: Overall workforce

Dependent variable:	*Gender Diversity*		*Ethnic/Racial Diversity*	
DEI Officer:	Yes	No	Yes	No
	(1)	(2)	(3)	(4)
Treatment × *Post*	0.291	-0.103	0.077	0.014
	(1.500)	(-1.456)	(0.771)	(0.242)
Observations	6,182	15,246	6,182	15,246
R-squared	0.998	0.998	0.999	0.998
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F-test	t = 2.08		t = 0.63	

Panel B: Senior positions

Dependent variable:	*Gender Diversity (Senior)*		*Ethnic/Racial Diversity (Senior)*	
DEI Officer:	Yes	No	Yes	No
	(1)	(2)	(3)	(4)
Treatment × *Post*	0.719***	-0.064	0.209	-0.070
	(2.798)	(-0.535)	(1.386)	(-0.758)
Observations	6,182	15,246	6,182	15,246
R-squared	0.994	0.994	0.996	0.995
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F-test	t = 3.16		t = 1.98	

ONLINE APPENDIX

"Human Capital Disclosure and Labor Market Outcomes: Evidence from Regulation S-K"

By Jung Ho Choi, Dan Li, and Daniele Macciocchi

This appendix provides additional information to supplement the analyses presented in the paper:

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Section I: OpenAI's Generative Large Language Model for Job Posting Evaluation

1. Introduction

Generative Large Language Models (GLLM) were publicly introduced in 2022 and quickly gained popularity for their capabilities of understanding textual information. ChatGPT Batch API (Application Programming Interface) allows users to send requests to the API, which responds with generated texts, pictures, or code. We use OpenAI's ChatGPT Batch API to conduct a parsimonious content analysis of job postings and examine if our DEI measure used in the paper captures a credible commitment.

There are three advantages of using GLLMs to validate our DEI measurement. First, given the large sample size of our job postings data (5.2 million job postings), traditional validation method—such as using human coder to hand score each job posting—would not be feasible. In contrast, GLLMs are efficient in terms of time and resources, allowing us to examine our full sample in an effective way.

Second, research shows that GLLMs not only automate standard textual analysis but also generate nuanced interpretations that previously required human judgment (de Kok, 2024). When extracting information from text, it's critical not only to identify specific words or phrases, such as the typical bag-of-words approach, but also to consider their context. GLLMs can understand complex relations within text, integrate broader contexts in which relevant topics or words are mentioned, and draw inferences (Kim et al., 2024). This allows us to incorporate nuances and context into the evaluation of DEI information in job postings.

Third, the GLLMs process is systematic and free from human bias, which often affects the interpretation of context and nuances. For example, in our validation process, we employed two human reviewers to evaluate a random sample of 100 job postings. Despite extensive prior discussions with the reviewers, our follow-up conversations revealed that each reviewer had different perspectives on several aspects of the evaluation. Subtle differences in approaches of different individuals can ultimately lead to different conclusions. Specifically, in our context, each reviewer had an idiosyncratic interpretation of what constituted an exclusive or discriminatory factor in the job postings, likely influenced by their cultural or personal backgrounds. Interestingly, ChatGPT's reasoning during the evaluation consistently captured elements from both reviewers' perspectives, reducing the risk of systematic biases affecting the analysis of job postings.

2. Methodology

2.1. GLLM Analysis: Evaluation Criteria

We start our process by designing four evaluation criteria to assess job postings along four dimensions of DEI. The evaluation criteria are the following:

1) DEI Commitment

2) Non-discriminatory job requirements

3) Corporate culture

4) Benefits

These criteria provide the conceptual framework to comprehensively assess job postings for their inclusivity and support for DEI. They ensure a holistic evaluation by examining explicit DEI mentions, the inclusiveness of job requirements, the promotion of an inclusive corporate culture,

and the provision of benefits that support minority groups. The table below illustrates the criteria in greater detail.

Evaluation Criteria

Criterium	Score	Description
DEI Commitment	**0**	No mention of diversity, equity, or inclusion in the job posting.
	0.5	Brief mention of DEI initiatives or a general statement about valuing diversity.
	1	Detailed description of DEI programs; specific policies or actions taken to promote DEI.
Non-discriminatory Job Requirement	**0**	Explicitly state exclusion of certain groups.
	0.5	Include elements that may exclude or disadvantage certain groups.
	1	Specific about required skills related to the job itself, not emphasizing factors beyond job-related skills such as education level.
Corporate Culture	**0**	No mention of inclusive culture.
	0.5	General or vague statements about inclusive culture.
	1	A detailed description of the company's inclusive culture, highlighting how it supports employees and fosters a sense of inclusion.
Benefit	**0**	No mention of benefits in the job posting.
	0.5	General mention of benefits without specific benefits related to DEI.
	1	A list of benefits that could support minorities, such as women, including flexible hours, parental leave, and childcare.

2.2. AI Model

Among the different AI models offered by OpenAI, we use the ChatGPT 4o-mini Batch API service. ChatGPT 4o-mini is derived from the latest version of ChatGPT available to date, the 4o model, and features approximately 1.8 trillion parameters and can handle up to 128,000 tokens. We conducted a pilot comparative analysis on a subsample of job postings and observed that ChatGPT 4o-mini exhibits similar capabilities to ChatGPT 4o in our setting, but at a significant lower cost. Hence, we opted for ChatGPT 4o-mini to score each job posting on our four DEI-related criteria.

2.3. Analysis Procedures

In our analysis, we employ both quantitative (scoring) and qualitative (reasoning) methods for the evaluation of job postings. Specifically, we fed our sample of 5.2 million job postings to ChatGPT and asked it to score each job posting on the four DEI-related criteria presented in Section 2.1. After receiving the scores, we requested ChatGPT to provide the rationale (reasoning) behind them. Our objectives were to:

1) Assess whether ChatGPT applied the provided criteria reasonably and insightfully;
2) Get a sequential breakdown of how ChatGPT arrived at its answers, allowing for a clear understanding and validation of the thought process;
3) Make the model's thought process more transparent;
4) Improve problem-solving skills.

We carefully designed the prompt, indicating the specific role and task. The table below shows the prompt selected for our analysis.

Role/Task	Prompt content
Role	*The following are actual job postings that have been posted on the website for the purpose of recruiting new employees. You are a jobseeker who is considered to belong to a minority group in certain areas.*
Task	*Evaluate the job postings if they are fostering DEI based on the following criteria and give 0 (less likely), 0.5, or 1 (most likely) for each criterion. As a job seeker, evaluate each job posting based on whether you don't feel exclusive based on factors unrelated to the job itself. However, don't limit your evaluation to the written criteria - use your own judgment as well.*

To minimize the inconsistency on the output, we set the temperature hyper-parameter to zero, which encourages the GLLM to produce deterministic and consistent results (Fu et al., 2023; de Kok, 2024).

3. Validation

Establishing construct validity is a fundamental step in content analysis. In our examination of job postings, we followed three steps for validation:

A. Small sample human review,

B. Comparison with benchmark job posting classifications,

C. Comparison with human ratings.

A. Small Sample Human Review: In our initial step to validate ChatGPT's work, we randomly selected 20 job postings and manually entered them into the ChatGPT interactive window. We then asked ChatGPT to assign scores, provide the reasoning behind the score on each of our four DEI criteria, and provide the parts of the text used in the scoring process. Upon receiving the results, we reviewed them, focusing on three key aspects:

a. Whether the scores were assigned reasonably;

b. Whether the evaluation was based solely on the presence of relevant terms or demonstrated a nuanced understanding of context;

c. Whether the reasoning was fair and supported by specific parts of the job posting.

This process served as a preliminary assessment to ensure the validity of the AI's responses before implementing API-based evaluations on the whole sample of 5.2 million job postings. Below, we report two examples of the human review process: Case A—a job posting with high scores, and Case B—a job posting with low scores.

Case A: Job Posting with High Score

Job Description	*GoDaddy is empowering everyday entrepreneurs around the world by providing all of the help and tools to succeed online. With 20 million customers worldwide, GoDaddy is the place people come to name their idea, build a professional website, attract customers and manage their work. Our mission is to give our customers the tools, insights and the people to transform their ideas and*

personal initiative into success. To learn more about the company visit www.GoDaddy.com.

Location:

You'll work in our Kirkland, WA or Tempe/Scottsdale, AZ

What you'll get to do...

** Build next generation e-commerce services and APIs using JAVA*

** Design and drive the implementation of the technical architecture working across multiple micro-services*

** Work on cloud platform technologies on AWS using Kubernetes (EKS)*

** Working in an agile environment within a technical team while providing long range planning, milestone deliverables mentoring and coaching*

** Performing code reviews and participate in suggesting and supporting coding best practices.*

** Working closely with service engineering, operations, and data analytics teams to engineer cutting-edge observable and scalable solutions.*

Your experience should include...

** Java Services development (Spring, Vert.x)*

** Understanding of Linux and shell scripting.*

** Familiar with designing and using REST APIs and HTTP.*

** Experience working with databases and CRUD operations in MySQL and Cassandra/Dynamo.*

** Familiar with Github and Jenkins CI/CD*

** Familiar with Java module such as Micrometer, Spring security, Spring data, etc*

** Writing Unit tests*

You might also have...

** Experience developing in C++, C#, NodeJS, and ReactJs*

** Experience with Microsoft MSSQL*

** Experience with Elastic Search (ELK)*

** Experience developing core Commerce systems*

** Integration and Performance testing*

We've got your back...

Enjoy our many benefits (My Wallet), including paid time off, 401k, equity grants and parental leave. Join one of our employee resource groups (Culture). Continue to have a side hustle, if you have one (we love entrepreneurs, remember?). Most importantly, come as you are and make your own way.

	GoDaddy is proud to be an equal opportunity employer. We will not discriminate against any applicant or employee on the basis of age, race, color, ethnicity, national origin, citizenship, religion, creed, sex, sexual orientation, gender, gender identity or expression (including against any individual that is transitioning, has transitioned, or is perceived to be transitioning), marital status or civil partnership/union status, physical or mental disability, medical condition, pregnancy, childbirth, genetic information, military and veteran status, or any other basis prohibited by applicable federal, state or local law. GoDaddy will consider for employment qualified applicants with criminal histories in a manner consistent with local and federal requirements. *If you need help completing an application for a position with GoDaddy, please reach out to our Recruiting Team at myrecruiter@godaddy.com.* *GoDaddy doesn't accept unsolicited resumes from recruiters or employment agencies.*
Company Name	GoDaddy
Created Date	November 25, 2020
Public/Private	Public firm
d(DEI)	1

ChatGPT's Analysis Result

DEI Commitment	1
Reasoning	The job posting includes a detailed DEI commitment statement, explicitly stating that GoDaddy is an equal opportunity employer and outlining the basis on which discrimination will not occur.
Snippets	*GoDaddy is proud to be an equal opportunity employer. We will not discriminate against any applicant or employee on the basis of age, race, color, ethnicity, national origin, citizenship, religion, creed, sex, sexual orientation, gender, gender identity or expression (including against any individual that is transitioning, has transitioned, or is perceived to be transitioning), marital status or civil partnership/union status, physical or mental disability, medical condition, pregnancy, childbirth, genetic information, military and veteran status, or any other basis prohibited by applicable federal, state or local law. GoDaddy will consider for employment qualified applicants with criminal histories in a manner consistent with local and federal requirements.*
Non- discriminatory Job Requirement	1
Reasoning	The job requirements focus solely on the necessary skills and experiences relevant to the position, without any exclusionary language or criteria that could disadvantage certain groups.

Snippets	*Your experience should include...* ** Java Services development (Spring, Vert.x)* ** Understanding of Linux and shell scripting.* ** Familiar with designing and using REST APIs and HTTP.* ** Experience working with databases and CRUD operations in MySQL and Cassandra/Dynamo.* ** Familiar with Github and Jenkins CI/CD* ** Familiar with Java module such as Micrometer, Spring security, Spring data, etc* ** Writing Unit tests* *You might also have...* ** Experience developing in C++, C#, NodeJS, and ReactJs* ** Experience with Microsoft MSSQL* ** Experience with Elastic Search (ELK)* ** Experience developing core Commerce systems* ** Integration and Performance testing*
Corporate Culture	1
Reasoning	The posting describes an inclusive culture, encouraging applicants to come as they are and highlighting the support for employee resource groups, which fosters a sense of belonging.
Snippets	*Join one of our employee resource groups (Culture). Continue to have a side hustle, if you have one (we love entrepreneurs, remember?). Most importantly, come as you are and make your own way.*
Benefit	1
Reasoning	The benefits section lists various supportive measures such as paid time off, parental leave, and equity grants, which are beneficial for diverse groups, including women and parents.

Snippets	*Enjoy our many benefits (My Wallet), including paid time off, 401k, equity grants and parental leave.*

Human Evaluation

DEI Commitment	1
Non-discriminatory Job Requirement	1
Corporate Culture	1
Benefit	1

Case B: Job Posting with Low Score

Job Description	*WHO ARE WE? HOM Furniture is a growing company that ranks as one of the nation's largest furniture retailers serving customers in the upper Midwestern states. Since its founding in 1974, HOM Furniture has continued to evolve and grow while cultivating an excellent working environment and great opportunities for all of HOM Furniture's employees. With 17 stores and counting, HOM Furniture serves as the primary furniture destination for thousands of customers. WHY WE WANT YOU HOM Furniture is seeking an individual who is self-motivated, enjoys physical work and helping customers. Our Delivery Drivers have one of the most important responsibilities, they ensure our customer's product gets to their home safely, in a timely manner and with a smile. At times they also assist in the warehouse with various projects as needed. We'd love to have you join our hardworking HOM Furniture team. read more read less Qualifications Must be 21 years of age or older Must pass a D.O.T. Medical Physical Must have a clean driving record Employees in this position must maintain a well-groomed professional appearance, including no visible tattoos, no more than one stud piercing per ear, and a natural color hair. Must be able to physically lift and/or move product weighing up to 150 lbs., and frequently lift and/or move up to 300 lbs. with other employees. Reasonable accommodations may be made to enable individuals with disabilities to perform the essential functions. Essential Duties and Responsibilities Trains and assists Delivery Assistant in company procedures so they can be a successful driver. Responsible for delivering furniture in a timely and efficient manner Drive a straight truck to timely and efficiently deliver furniture to the customer's home or place of business, and then successfully install and place furniture or provide instruction as necessary. Responsible for listening and resolving any customer complaints as they should arise, in a time-oriented and efficient manner. Obtain the customer's signature on receipt for pickup or delivery and record transactions on customer receipt. Ensure outstanding customer service and maintain positive customer relations. Record delivery information on daily or delivery record. Assistant's will also work in the warehouse to load the truck if required, assuming responsibility for inventory on the truck. Inspects product and does any needed touch up. Clean inside of the truck. During downtimes, may be required to work in the warehouse assisting customers with pick-ups, doing inventories and various other tasks assigned by the Warehouse Management team. Adheres to safe lifting techniques, follows proper training for learned job hazards and ergonomic risk factors, participates in departmental stretching program, and overall maintains a safe working environment. Creates a positive company image by wearing a uniform appropriately while grooming regularly. Other duties may be assigned by Service Coordinator or Delivery*

	*Manager. Education and/or Experience Must be working towards a High School Diploma or General Education Degree (GED) 1-3 years related experience and/or training Language Skills Requires skills to read and interpret documents such as safety rules, operating and maintenance instructions, and procedure manuals. Ability to write routine reports and correspondence. Competently speak before groups of customers or employees of organization. Demonstrate the ability to communicate in English, both verbally and in written format. Mathematical Skills Mathematical aptitude to add, subtract, multiply, and divide in all units of measure, using whole numbers, common fractions, and decimals. Ability to compute rate, ratio, percent, and to draw and interpret bar graphs. Physical Demands The physical demands described here are representative of those that must be met by an employee to successfully perform the essential functions of this job. Reasonable accommodations may be made to enable individuals with disabilities to perform the essential functions. While performing the duties of this job, the employee is regularly required to stand for sustained periods of time, move about on foot to accomplish tasks, use spoken word to communicate, and perceive the nature of sounds at normal speaking levels with or without correction. The employee is occasionally required to sit or remain in a stationary position for extended periods of time; use hands to handle or feel objects with either the entire hand or fingers, including typing. Reach with hands and arms in any direction, ascend and descend ladders and stairs using feet and legs and/or hands and arms. Stooping by bending downward and forward by bending at the waist, kneeling or bending at the knees to come to a rest on knee or knees, crouching by bending the body downward and forward, or crawling by moving about on hands or hands and feet. The employee must occasionally lift and/or move up to 100 pounds. Specific vision abilities required by this job include close visual acuity to perform activities such as: preparing and analyzing data or figures, transcribing, viewing a computer terminal, extensive reading, visual inspection involving small defects, and using measurement devices. Reasoning Ability Must be able to apply commonsense understanding to carry out instructions furnished in written, oral, or diagram form. Skills needed to deal with problems involving several concrete variables in standardized situations. Work Environment The work environment characteristics described here are representative of those an employee encounters while performing the essential functions of this job. Reasonable accommodations may be made to enable individuals with disabilities to perform the essential functions. While performing the duties of this job, the employee regularly works in outside weather conditions and is regularly exposed to fumes or airborne particles. The employee is frequently exposed to wet and/or humid conditions and vibration. The employee occasionally works in high, precarious places and is occasionally exposed to toxic or caustic chemicals. The noise level in the work environment is usually moderate. Other CERTIFICATES, LICENSES, REGISTRATIONS - DOT certification required. Must have a current driver's license. * Maintain a well-groomed personal appearance, including no visible tattoos, no more than one stud piercing per ear, and natural color hair.*
Company Name	HOM Furniture
Created Date	March 4, 2020
Public/Private	Private firm
d(DEI)	0

ChatGPT's Analysis Result

DEI commitment	0

Reasoning	The job posting does not mention any commitment to diversity, equity, or inclusion, which indicates a lack of focus on DEI initiatives.
Snippets	*N/A*
Non-discriminatory Job Requirement	0.5
Reasoning	While the job requirements focus on skills and experience, the emphasis on grooming standards and appearance may disadvantage certain groups.
Snippets	*Employees in this position must maintain a well-groomed professional appearance, including no visible tattoos, no more than one stud piercing per ear, and a natural color hair. Creates a positive company image by wearing a uniform appropriately while grooming regularly.*
Corporate Culture	0.5
Reasoning	There is a vague mention of a positive working environment, but no detailed description of how the company fosters an inclusive culture.
Snippets	*Since its founding in 1974, HOM Furniture has continued to evolve and grow while cultivating an excellent working environment and great opportunities for all of HOM Furniture's employees.*
Benefit	0
Reasoning	The job posting does not mention any benefits that could support minorities or promote inclusivity.
Snippets	*N/A*

Human Evaluation

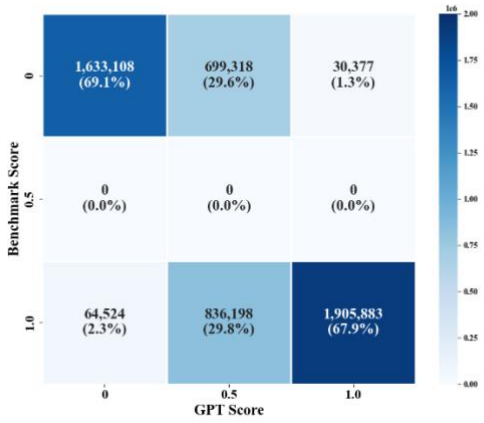
DEI Commitment	0
Non-discriminatory Job Requirement	0.5
Corporate Culture	0.5
Benefit	0

B. Comparison with benchmark job posting classification: In the second step of our validation process, we assessed the consistency and reliability of the AI model's classifications by comparing its output to a benchmark classification. We employed a confusion matrix to

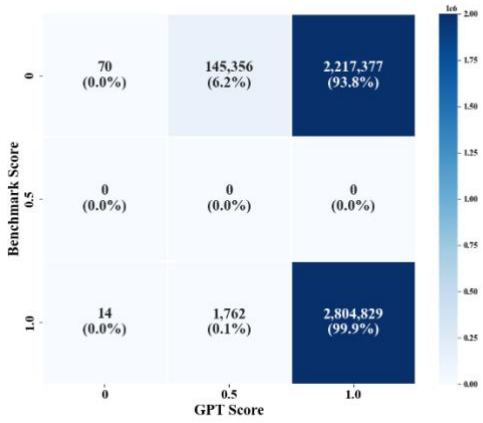
evaluate the performance of the AI model by quantifying the agreement between its classifications and RavenPack's benchmark classifications of DEI disclosure that we use in the manuscript. This approach allowed us to validate the AI's ability to accurately evaluate job postings based on the given criteria. Results are reported in Figure OA 1. The high precision scores indicate that DEI disclosures in job postings measured by RavenPack are classified as job postings committing to DEI factors by ChatGPT.

Figure OA 1
Confusion matrix for each evaluation criteria

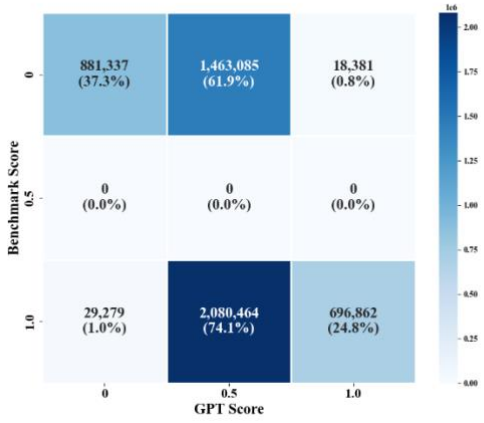
DEI Commitment



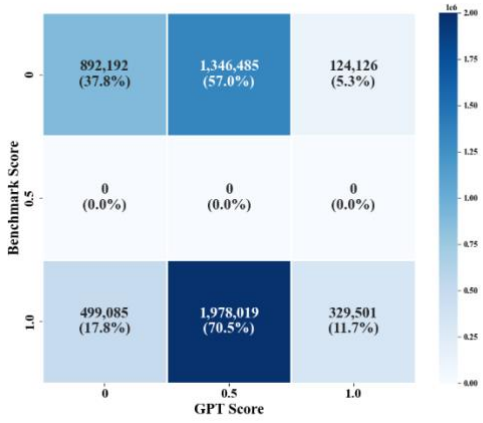
Non-discriminatory Job Requirements



Corporate Culture



Benefits

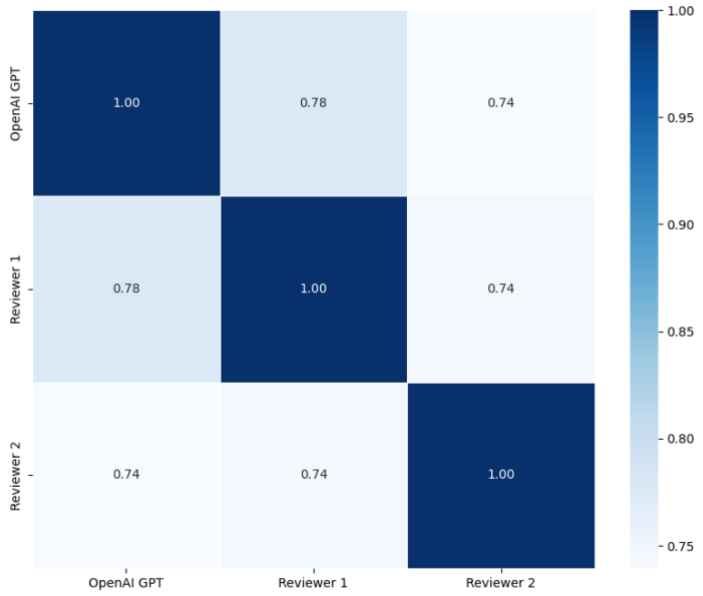


Error indicators calculated from the Confusion matrix

	DEI Commitment	Job Requirements	Corporate Culture	Benefits
Precision	0.8685	0.6750	0.7964	0.6247
Recall	0.8464	0.5429	0.7078	0.6190
F1 Score	0.8419	0.3821	0.6730	0.5978

C. Comparison with Human Evaluation: Human raters are commonly used to evaluate samples, with sample sizes ranging from a few hundred to several thousand (de Kok, 2024). We asked two reviewers to provide human scores for a random sample of 100 job postings. The reviewers assigned scores on the same four criteria. We then averaged these human scores across all four criteria and compared them to the ChatGPT-generated scores. The results are reported in Figure OA2. The strong correlation between ChatGPT's scores and the human scores (ranging from 74% to 78%) indicates that ChatGPT's evaluations closely match those of human evaluators, which we consider a clear indication of the high quality of the ChatGPT assessment.

Figure OA 2
Correlation matrix of average scores between ChatGPT and two reviewers



5. Results

Finally, we examine whether the DEI measure we use in the manuscript—*d(DEI)*—captures a credible commitment. We regress ChatGPT's job posting scores for each of the four criteria on *d(DEI)*. The results for the four OLS models are presented in Table OA 1 along with descriptive statistics. Across the board, we find a positive and statistically significant relationship between *d(DEI)* and ChatGPT DEI scores, underscoring that job postings including DEI information demonstrate credible commitments.

Table OA 1
ChatGPT DEI Scores and Job Postings DEI disclosure

Panel A reports the mean values of the ChatGPT DEI scores on each of our four DEI criteria. Panel B reports the results from estimating formal regressions (OLS) between the ChatGPT DEI scores and our measure for DEI disclosure in job postings, *d(DEI)*. The analysis is conducted at the job posting level. T-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ChatGPT DEI scores by *d(DEI)*

ChatGPT DEI Scores:	*Score-DEI Commitment*	*Score-Job Requirements*	*Score-Corporate Culture*	*Score-Benefits*
	(1)	(2)	(3)	(4)
d(DEI) = 0	0.161	0.969	0.317	0.337
d(DEI) = 1	0.828	1.000	0.619	0.470

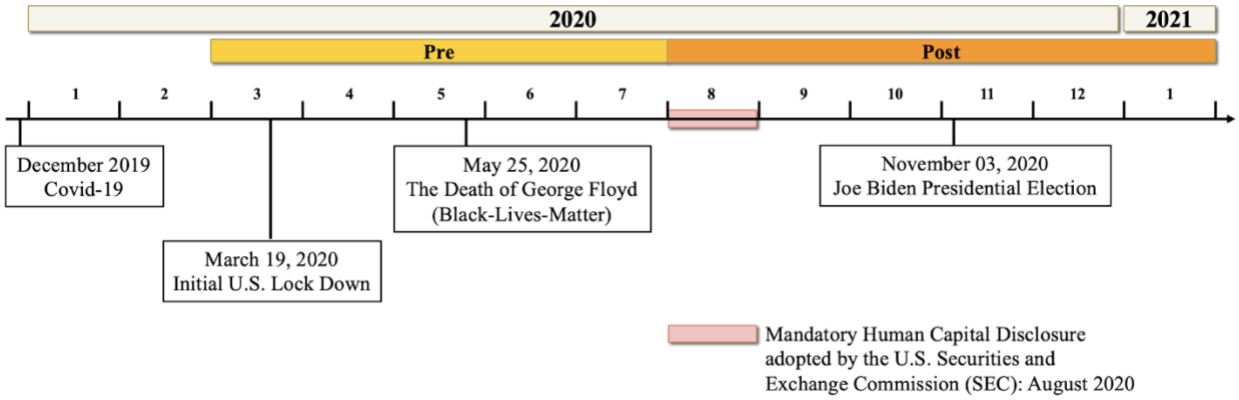
Panel B: OLS Regressions

Dependent variable:	*Score-DEI Commitment*	*Score-Job Requirements*	*Score-Corporate Culture*	*Score-Benefits*
	(1)	(2)	(3)	(4)
d(DEI)	0.667***	0.031***	0.302***	0.132***
	(15.46)	(2.42)	(14.25)	(4.71)
Observations	5,169,408	5,169,408	5,169,408	5,169,408
R-squared	0.631	0.033	0.288	0.054

Section II: Timeline

Figure OA 3
Timeline

This figure summarizes the main events around the amendment of Regulation S-K.



1. Covid-19 (December 2019)

- The first known case of Covid was detected in Wuhan, China in December 2019 and then the virus spread worldwide, leading to a global pandemic. It caused widespread illness, significant mortality, and major disruptions to daily life and the labor market.

2. Initial U.S. Lock Down (March 2020)

- The first statewide lockdown was issued in California on March 19, 2020. Other states quickly followed with similar stay-at-home orders to mitigate the spread of COVID-19. It led to significant economic disruptions, including business closures and job losses. Even after the shutdown ended, many people continued to work fully remotely or in a hybrid environment, which has become a lasting change in work culture. In addition, this transition highlighted the importance of flexibility, work-life balance, and the potential for increased productivity and job satisfaction in remote work arrangements.

3. The Death of George Floyd (May 2020)

- In Minneapolis, a man named George Floyd died during an arrest on May 25, 2020. His death sparked widespread protests advocating for racial justice and police reform, bringing racial issues to the surface worldwide. The incident led to a global outcry and significant

discussions about systemic racism, resulting in policy changes and increased awareness of racial and ethnicity inequality.

4. Mandatory Human Capital Disclosure adopted

- Adopted on August 26, 2020, mandatory Human Capital disclosure (HCD) is Item 101(c) of Regulation S-K by the SEC. This regulation requires a description of the firm's human capital resources, including disclosure of the number of employees and any human capital measures or objectives that the firm focuses on in managing its business, such as those that address the attraction, development, and retention of employees.

5. Joe Biden Presidential Election

- The presidential election on November 3, 2020, saw Joe Biden defeat incumbent President Donald Trump. Biden was inaugurated as the 46th President on January 20, 2021. The election was highly unpredictable, with close national polls and unprecedented changes in voting methods due to the Covid-19 pandemic, making predictions difficult.

Section III: Examples of Job Postings

GoDaddy Inc

GoDaddy is empowering everyday entrepreneurs around the world by providing all of the help and tools to succeed online. With 20 million customers worldwide, GoDaddy is the place people come to name their idea, build a professional website, attract customers and manage their work. Our mission is to give our customers the tools, insights and the people to transform their ideas and personal initiative into success. To learn more about the company visit www.GoDaddy.com.

Location: You'll work in our Kirkland, WA or Tempe/Scottsdale, AZ

What you'll get to do:
* Build next generation e-commerce services and APIs using JAVA
* Design and drive the implementation of the technical architecture working across multiple micro-services
* Work on cloud platform technologies on AWS using Kubernetes (EKS)
* Working in an agile environment within a technical team while providing long range planning, milestone deliverables mentoring and coaching
* Performing code reviews and participate in suggesting and supporting coding best practices.
* Working closely with service engineering, operations, and data analytics teams to engineer cutting-edge observable and scalable solutions.

Your experience should include...
* Java Services development (Spring, Vert.x)
* Understanding of Linux and shell scripting.
* Familiar with designing and using REST APIs and HTTP.
* Experience working with databases and CRUD operations in MySQL and Cassandra/Dynamo.
* Familiar with Github and Jenkins CI/CD
* Familiar with Java module such as Micrometer, Spring security, Spring data, etc
* Writing Unit tests

You might also have:
* Experience developing in C++, C#, NodeJS, and ReactJs
* Experience with Microsoft MSSQL
* Experience with Elastic Search (ELK)
* Experience developing core Commerce systems
* Integration and Performance testing

We've got your back:
Enjoy our many benefits (My Wallet), including paid time off, 401k, equity grants and parental leave. Join one of our employee resource groups (Culture). Continue to have a side hustle, if you have one (we love entrepreneurs, remember?). Most importantly, come as you are and make your own way.

GoDaddy is proud to be an equal opportunity employer. We will not discriminate against any applicant or employee on the basis of age, race, color, ethnicity, national origin, citizenship, religion, creed, sex, sexual orientation, gender, gender identity or expression (including against any individual that is transitioning, has transitioned, or is perceived to be transitioning), marital status or civil partnership/union status, physical or mental disability, medical condition, pregnancy, childbirth, genetic information, military and veteran status, or any other basis prohibited by applicable federal, state or local law. GoDaddy will consider for employment qualified applicants with criminal histories in a manner consistent with local and federal requirements.

If you need help completing an application for a position with GoDaddy, please reach out to our Recruiting Team at myrecruiter@godaddy.com.

GoDaddy doesn't accept unsolicited resumes from recruiters or employment agencies.

Lyft Inc.

Job Description	At Lyft, our mission is to improve people's lives with the world's best transportation. To do this, we start with our own community by creating an open, inclusive, and diverse organization. Here at Lyft, Data is the only way we make decisions. It is the core of our business, helping us create a transportation experience for our customers and providing insights into the effectiveness of our product launch & features. As a Data Engineer at Lyft, you will be a part of an early stage team that builds the data transport, collection, and storage, and exposes services that make data a first-class citizen at Lyft. We are looking for a Data Engineer to build a scalable data platform. You'll have ownership of our core data pipeline that powers Lyft's top line metrics; You will also use data expertise to help evolve data models in several components of the data stack; You will help architect, building, and launching scalable data pipelines to support Lyft's growing data processing and analytics needs. Your efforts will allow access to business and user behavior insights, using huge amounts of Lyft data to fuel several teams such as Analytics, Data Science, Marketplace and many others. You will report to a Data Engineering Manager. Responsibilities: Owner of the core company data pipeline, responsible for scaling up data processing flow to meet the rapid data growth at Lyft Evolve data model and data schema based on business and engineering needs Implement systems tracking data quality and consistency Develop tools supporting self-service data pipeline management (ETL) SQL and MapReduce job tuning to improve data processing performance Experience: Experience with Hadoop (or similar) Ecosystem (MapReduce, Yarn, HDFS, Hive, Spark, Presto, Pig, HBase, Parquet) Proficient in at least one of the SQL languages (MySQL, PostgreSQL, SqlServer, Oracle) Good understanding of SQL Engine and able to conduct advanced performance tuning Strong skills in scripting language (Python, Ruby, Bash) 1+ years of experience with workflow management tools (Airflow, Oozie, Azkaban, UC4) Comfortable working directly with data analytics to bridge Lyft's business goals with data engineering Benefits: Great medical , dental, and vision insurance options. In addition to 11 observed holidays , salaried team members have unlimited paid time off, hourly team members have 15 days paid time off. 401(k) plan to help save for your future 18 weeks of paid parental leave. Biological, adoptive, and foster parents are all eligible Monthly commuter subsidy to cover your transit to work & 20% of all Lyft rides. Lyft is an Equal Employment Opportunity employer that proudly pursues and hires a diverse workforce. Lyft does not make hiring or employment decisions on the basis of race, color, religion or religious belief, ethnic or national origin, nationality, sex, gender, gender identity, sexual orientation, disability, age, military or veteran status, or any other basis protected by applicable local, state, or federal laws or prohibited by Company policy. Lyft also strives for a healthy and safe workplace and strictly prohibits harassment of any kind. Pursuant to the San Francisco Fair Chance Ordinance and other similar state laws and local ordinances, and its internal policy, Lyft will also consider for employment qualified applicants with arrest and conviction records.

Section IV: Examples of DEI disclosure in 10Ks

2020 Annual Report of Citi

Workforce Size and Distribution

As of December 31, 2020, Citi employed 210,153 colleagues in nearly 100 countries. The following table shows the geographic distribution of those colleagues by segment, region and gender:

Business segment	North America	EMEA	Latin America	Asia	Total[1]	Female	Male
Global Consumer Banking	32,936	4,087	30,276	31,849	99,148	58 %	42 %
Institutional Clients Group	16,905	16,457	7,166	22,349	62,877	44	56
Corporate/Other	17,130	9,510	7,000	14,488	48,128	42	58
Total	66,971	30,054	44,442	68,686	210,153	51 %	49 %

(1) Part-time colleagues represented less than 1.5% of Citi's global workforce.

Diversity

In 2020, Citi also:

• expanded the standard for a diverse slate to include at least one woman globally and one woman and/or U.S. minority for U.S. hires at the assistant vice president, vice president and senior vice president levels, in addition to managing director and director level hires;

• included a diverse slate of candidates, with at least one woman and/or U.S. minority, for 86% of roles that were posted globally with a qualified slate;

• increased representation of underrepresented minorities in its full-time U.S. campus recruitment program from 18% in 2019 to 26% in 2020;

• increased female representation in its full-time U.S. campus recruitment program from 45% in 2019 to 46% in 2020; and

• increased female representation in its summer internship program from 47% in 2019 to 52% in 2020 in the U.S. and from 48% in 2019 to 50% in 2020 globally, while Black and Hispanic/Latino representation in its summer class increased from 26% to 27% over the same timeframe. This was Citi's most diverse intern class to date.

2021 Annual Report of P&G

Human Capital.

As a consumer products company, we believe that it is important for our workforce to reflect the diversity of our consumers. We also seek to foster an inclusive work environment where each individual can bring their whole self, which helps drive innovation and enables us to better serve our consumers. We aspire to achieve equal gender representation globally and at key management and leadership levels. As of June 30, 2021, 40% of our global employees are women. In the U.S. workforce, we are progressing towards our aspiration of 40% multicultural representation overall as well as at management and leadership levels. As of June 30, 2021, 26% of our U.S. employees identify as multicultural.

Section V: Supplementary Analyses

In this section, we report two supplementary analyses that are referenced in the paper.

Table OA 2
Regulation S-K and Workforce Hiring

This table reports the results from estimating the difference-in-differences model in Eq. (2) in the manuscript. Different from the manuscript, we examine the hiring of diverse candidates. Hiring is defined as the monthly number of diverse candidates based on gender or ethnic/racial diversity, scaled by the total monthly number of new hires. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–year-month level. All regressions include year-month and firm fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A in the manuscript provides variable definitions and data sources.

Dependent variable:	*Hiring*			
	Gender Diversity	Gender (Senior)	Ethnic/Racial Diversity	Ethnic/Racial (Senior)
	(1)	(2)	(3)	(4)
Treatment × *Post*	-0.015	-0.005	0.012	0.004
	(-1.239)	(-0.809)	(1.167)	(0.746)
Observations	21,131	21,131	21,131	21,131
R-squared	0.316	0.233	0.383	0.227
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table OA 3
Regulation S-K and Inelastic Labor Supply – Senior Positions

This table reports the results from estimating the difference-in-differences model in Eq. (2) in the manuscript. To capture diversity in labor supply, we partition the sample based on whether a firm's operations are located in the U.S. states and industries with high ethnic/racial diversity (columns 1 and 2) and gender diversity (columns 3 and 4). We examine workforce diversity only for senior positions. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales. The data are aggregated at the firm–year-month level. All regressions include year-month and firm fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Dependent variable:	*Gender Diversity*		*Ethnic/Racial Diversity*	
Sample:	Firm operates in high Gender Diversity states and industries	Firm operates in low Gender Diversity states and industries	Firm operates in high Ethnic/Racial Diversity states and industries	Firm operates in low Ethnic/Racial Diversity states and industries
	(1)	(2)	(3)	(4)
Treatment × *Post*	0.069	-0.011	-0.042	-0.092
	(0.432)	(-0.076)	(-0.363)	(-0.767)
Observations	7,755	6,215	7,381	6,402
R-squared	0.994	0.994	0.995	0.995
Month FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F - test	t = 0.47		t = 0.38	

Table OA 4
Regulation S-K and Job Posting DEI Disclosure – Industry match

This table reports the results from estimating the difference-in-differences model in Eq. (1). In column 1, the dependent variable is *IHS(DEI Length)*, the monthly average of the inverse hyperbolic sine (IHS) of the number of DEI words used in job postings for a specific job type. In column 2, the dependent variable is *d(DEI)*, the monthly proportion of job postings with DEI information for each job type. The treatment group is composed of public firms, whereas the control group is composed of private firms. We use entropy balancing to reweight public and private firms on their total sales and industry. The data are aggregated at the firm–job-type–year-month level. All regressions include year-month and firm-by-job-type fixed effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm-job-type level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Appendix A provides variable definitions and data sources.

Dependent variable:	*IHS(DEI Length)*	*d(DEI)*
	(1)	(2)
Treatment × *Post*	0.043***	0.020***
	(7.503)	(6.307)
Observations	341,017	341,017
R-squared	0.852	0.873
Month FE	Yes	Yes
Firm*Job Type FE	Yes	Yes

Figure OA 4.
Long-term Effect of Regulation S-K on Workforce Diversity



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