Does the Market Mis-Value Non-Executive Employee Diversity?*

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September 19, 2023

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Keywords: Non-executive diversity, corporate innovation, human capital productivity, mispricing, trading strategy.

JEL Codes: G14, G32.

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1. Introduction

Recent social events have increased public awareness about workplace diversity. In response to this increased awareness, firms have implemented initiatives to increase diversity among non-executive employees. In particular, many firms have made commitments to hire underrepresented minorities. To reflect this shift, the U.S. Securities and Exchange Commission (SEC) amended *Regulation S-K* in August 2020 to enhance corporate disclosures about human capital. SEC Chairman Jay Clayton expressed his strong support, stating, "I am *particularly supportive of the increased focus on human capital disclosures, which for various industries and companies can be an important driver of long-term value.*"

Zingales (2000) highlights the growing importance of human capital as an essential asset in the modern economic environment. Media and social groups also frequently champion workforce diversity, presenting it as an intrinsic component of robust human capital. While the push for diversity is widely supported, there is limited evidence on the economic impact of diversified non-executive workforce. It is also not immediately clear whether investors are able to assess the economic value of diversity.

In this paper, using a new measure of non-executive employee diversity, I study the relation between diversity and firm value. I focus on two interrelated research questions: First, using measures on both intangible human capital productivity and tangible financial performance, I examine whether diversity among non-executive employees is associated with improvement in short-term and long-term firm value. Second, I investigate whether the market fairly estimates the benefit of diversified non-executive workforce. To keep the empirical analysis manageable, I focus on a specific form of diversity based on employee race/ethnicity.

Ex-ante, it is unclear whether non-executive workforce diversity is beneficial to firms. One viewpoint suggests that diversity-enhancing policies do not increase firm value. For example, demographic heterogeneity may lead to high productivity costs due to communication friction, lack of trust, and various psychological and social biases (e.g., Lazear (1999), Giannetti and Yafeh (2011)). Consistent with agency theory, top executives who overlook these potential costs may prioritize social commitments for their interests, perhaps to gain favor with influential stakeholders like local politicians, non-governmental organizations, or labor unions. This strategy could come at the expense of shareholders, potentially diminishing firm value (Tirole (2001), Benabou and Tirole (2010), Cheng, Hong, and Shue (2023)).

An alternative perspective posits that corporate managers adopt diversity-enhancing policies to increase firm value. In particular, diversity can encourage knowledge spillovers among employees, leading to better decision-making and problem-solving abilities at the aggregate level (Hong and Page (2001, 2004)). Diversity initiatives can also stimulate the creation of new ideas and facilitate knowledge transfer (Kerr and Lincoln (2010), Gompers and Wang (2017)). Additionally, workforce diversity may provide firms with valuable information about product markets, reducing their costs and improving their competitiveness in global markets (Wright et al. (1995)). Under these views, firms engage in socially responsible activities because they are expected to improve firm value, in line with the concept of "doing well by doing good" (e.g., Dowell, Hart, and Yeung (2000), Edmans (2011), Dimson, Karakas, and Li (2015), Servaes and Tamayo (2013), Kang, Kim, and Oh (2022)).

One of the key empirical challenges in examining the economic implications of workforce diversity is the limited availability of comprehensive demographic data at the firm level. While some data can be sourced from the Equal Employment Opportunity (EEO) Commission, these are

usually confidential and have only been voluntarily disclosed by a select number of firms.[1] Moreover, EEO records do not provide information about individual employees.

In this study, I overcome this data limitation by using demographic information extracted from individual employee resumes. My sample comprises 114 million job-year observations, spanning 27 million roles held by 16 million employees across over 4,000 U.S. public firms during the 1990-2021 time-period. The dataset is broadly representative of the demographic distribution of non-executive workforce and mid-managers in the private sector, mitigating potential selection bias concerns. In my sample, minority employees make up 19.8% of the workforce. Importantly, diversity levels do not show significant variation across industries, indicating that the sample is not skewed toward any particular sector. Further, I find that firms located in U.S. states with a history of immigration and industrialization have higher diversity levels.

Examining the relation between workforce diversity and firm characteristics, I find that firms with more diverse boards have more diverse non-executive employees. In addition, larger firms with higher visibility have higher levels of diversity. These firms may face greater societal pressure to maintain a diverse workforce and may be better equipped to achieve this objective. Similarly, financially robust companies are more likely to have the ability to invest in a diverse workforce. Young and growing companies, often highly reliant on human capital, also tend to foster diversity. Lastly, firms with extensive international operations have a workforce that reflects those diverse markets.

In my main empirical tests, I examine the impact of workforce diversity on both human capital productivity and financial performance. On the human capital productivity front, I find a robust relation between workforce diversity and future innovation output. Specifically, a one

[1] In April 2023, EEO Commission made public the EEO-1 reports from 2016-2020 for all federal contractors. For more information, you can visit: https://www.dol.gov/agencies/ofccp/foia/library/Employment-Information-Reports.

standard deviation increase in workforce diversity is associated with a 7.03% increase in the number of patents, a $0.038 billion increase in the value per patent, and an 8.69% increase in the number of citations. However, these gains in innovation occur without a corresponding increase in R&D expenses. Further, workforce diversity shows a positive correlation with employee satisfaction, as captured by Glassdoor Ratings. Particularly, a one standard deviation increase in workforce diversity is associated with a 2.26% increase in overall rating, relative to the mean. This effect is more pronounced among sub-ratings that are intrinsically tied to human capital productivity, such as Career Opportunities, Culture and Values, and Senior Management.

Despite its positive relation with future corporate innovation and employee satisfaction, workforce diversity does not have a clear relation with short-term financial performance measures, such as return on assets (ROA). If the market efficiently processes diversity-related information, current firm valuation should accurately reflect the positive relation between workforce diversity and both corporate innovation and employee satisfaction. Yet, even with the positive relation with these human capital productivity measures, I observe a negative relation between workforce diversity and contemporaneous firm valuation, as measured by Tobin's q. This correlation weakens over time. In addition, diversity-valuation relation is stronger among human-capital-intensive firms. These findings suggest that the market does not fully recognize the value of workforce diversity, potentially because its emphasis on tangible, short-term financial performance overshadows the benefits of intangible firm attributes associated with human capital productivity.

To quantify the economic magnitude of this market mis-valuation, I develop a trading strategy that involves longing firms with high workforce diversity and shorting firms with low diversity. During the 1990-2021 sample period, the strategy generates a statistically and

economically significant risk-adjusted return of 7.54% per year. These findings remain robust across various alternative specifications, including alternative diversity measures, different sorting window lengths, different sample periods, and different return weighting schemes.

In the next set of tests, I examine whether the market is able to assess the relation between non-executive employee diversity and firm performance. I find that equity analysts and investors do not accurately assess the impact of workforce diversity on corporate earnings. Equity analysts consistently underestimate the earnings of firms with high workforce diversity, while overestimating those with low diversity, after controlling for various factors that account for earnings surprises and analyst biases. Additionally, workforce diversity is positively associated with short-term earnings announcement returns. These findings indicate that investors behave similarly to equity analysts, failing to fully incorporate non-executive employee diversity into their earnings expectations. I also demonstrate that these abnormal short-run stock returns reverse over longer time horizons.

This evidence of mispricing suggests that the market lacks comprehensive information on the value of diversity. Beyond equity analysts, Environmental, Social, and Governance (ESG) ratings could serve as another potential source of information for the market. However, my analysis reveals no significant correlation between workforce diversity and the Social scores from two different ESG rating agencies. This evidence suggests that the market is unable to assess the value of workforce diversity using ESG metrics.

I perform several additional tests to examine the robustness of these findings and entertain alternative explanations for my results. First, I demonstrate that the relation between workforce diversity and stock returns is particularly pronounced among mid-tier managers who play a central role in the firm's operations and are closely linked to human capital enhancements. Second, I

confirm that my findings regarding racial/ethnic workforce diversity are not driven by a broader set of Diversity, Equity, and Inclusion (DEI) policies at the firm-level. Specifically, I examine the link between gender diversity, another demographic variable that DEI initiatives often emphasize, and firm performance. Unlike racial/ethnic diversity, firm-level gender diversity measure is not associated with human capital productivity and market mispricing. Lastly, by analyzing the frequency of diversity-related words in job postings, I address the potential concern that my firm-level diversity measure does not merely reflect a focus on diversity in hiring practices.

Together, these findings contribute to the emerging literature on the importance of diversity, equity, and inclusion policies. In particular, Giannetti and Zhao (2016) demonstrate that firms with ancestrally diverse boards drive innovation, but this diversity can also lead to performance volatility, decision-making inefficiencies, and boardroom conflicts. Further, Bernile et al. (2018) show that multi-dimensional board diversity is associated with reduced risk and improved performance. More recently, Klick (2021) documents that the academic research on boardroom gender diversity and firm performance often yields mixed results or insignificant findings.[2] My paper highlights the importance of diversity beyond the boardroom, building upon prior studies that focus on diversity among top executives and board members.

Recent studies also advocate for mandatory disclosure to ensure complete DEI transparency. Bourveau, Flam, and Le (2023) analyze the release of EEO data from federal contractors and find that public companies with less diverse workforces tend to withhold EEO-1 reports. Similarly, Baker et al. (2023) highlight substantial gaps between corporate DEI commitment and actual hiring, while Cai et al. (2023) demonstrate that firms with both the willingness and capability to enhance diversity are more likely to disclose such targets.

[2] Knyazeva, Knyazeva, and Naveen (2021) provide a summary of board diversity studies across various dimensions, including different types of demographic diversity.

The primary motivation for advocating DEI policies stem from considerations of social responsibility rather than financial performance. However, financial incentives should also be considered, as they serve as crucial drivers for the adoption and sustained implementation of effective DEI policies. Edmans, Flammer, and Glossner (2023) use proprietary survey data on the subjective perspective on firm's DEI implications. They find that DEI correlates with enhanced financial performance and valuation ratios, as well as increased innovation, but exhibits no connection with future stock returns. My findings provide complementary evidence and suggest that there is a positive relation between the racial/ethnic workforce diversity and long-term corporate performance, which the market fails to recognize immediately.[3]

Last, my work is related to the literature on market valuation of human capital. This line of research finds that market participants do not fully recognize the significance of human capital related information, such as employee satisfaction (Edmans (2011), Green et al. (2019), Sheng (2022)) and labor flows (Agrawal, Hacamo, and Hu (2021)). Further, Fedyk and Hodson (2022) find that the market overestimates the value of technical human capital. My study provides evidence of market's inability to incorporate diversity information that affects human capital productivity. Specifically, I demonstrate that the market under-estimates the value of racial/ethnic diversity at the non-executive employee level.

2. Data and Variables

2.1 Workforce Data

My main data set contains detailed resume-level data from Revelio Labs. It contains online professional profiles mainly from LinkedIn. Revelio Labs provides an extensive range of variables

[3] Parrotta, Pozzoli, and Pytlikova (2014) conclude nationality and linguistic grouping diversity is negatively correlated with firm productivity in Denmark setting. However, they refer to the diversity based on nationality and linguistic grouping as "ethnic" diversity, which contrasts with my measurement of racial/ethnic diversity.

for each individual, including employment history, geographical location, educational background, and demographic identifiers such as gender and race/ethnicity[4]. By combining Revelio Labs data with Compustat and CRSP, I create a comprehensive panel dataset that matches employees to employers. The sample spans 1990 to 2021 period and contains 114 million job-year observations from 27 million positions held by 16 million employees across 4,152 firms.

I benchmark my sample against firm-reported employment numbers in the Compustat database to check the coverage ratio. My sample only contains data on US-based employees,[5] while US public firms report their overall (global) employment numbers. Specifically, the mean and median of my sample employment to Compustat (global) employment coverage ratio are 35.43% and 21.15%, respectively. My data coverage is similar to Fedyk and Hodson (2022), who also utilize resume-level data from different data providers.

The correlation between the coverage ratio (my sample relative to Compustat) and my workforce diversity measure (see Section 2.2) is only 0.029. This finding alleviates potential concerns regarding potential selection bias. For instance, if non-executive minority employees are less inclined to have online profiles, firms with low coverage ratios might exhibit artificially low diversity measures due to an underrepresentation of minority employees. However, such concerns are not applicable in the context of my study.

Revelio Labs compiles employee names and locations in conjunction with data from the Social Security Administration and the US Census to identify employee race/ethnicity and gender. Among all employees in my sample, 27.38% individuals are classified as belonging to racial/ethnic

[4] Revelio Labs uses predictive algorithms to generate these metrics by comparing names and locations with social security, census, and voter data. Similar algorithms have been used in studies, such as Liu (2016) and Bursztyn et al. (2021).

[5] The focus on diversity within the United States is twofold. First, the U.S. has been notably impacted by challenges related to diversity. Second, I want to prevent my measure of workforce diversity from being mechanically influenced by the demographics of a firm's international locations. For instance, a firm with a substantial presence in Asia would logically have a large proportion of Asian employees.

minority groups,[6] while 44.62% are identified as female. Additionally, Revelio Labs uses an ensemble model to create seniority metric with seven ordinal seniority levels.[7] I exclude C-suite level employees as my focus is on the non-executive workforce,[8] and classify the remaining employees into mid-level managers and rank-and-file positions.[9]

I also compare the distribution of demographic characteristics among employees in my sample with the job patterns for minorities and women in private industry, as reported in the EEO-1 data.[10] The EEO data spans from 1996 to 2021 and provides demographic information for ten job categories:[11] Executive/Senior Level Officials & Managers, First/Mid-Level Officials & Managers,[12] Professionals, Technicians, Sales Workers, Office & Clerical Workers, Craft Workers, Operatives, Laborers, and Service Workers. To focus on non-executive workforce and considering that white-collar positions are more likely to be represented in the Revelio Labs sample than blue-collar positions, I use the following EEO categories as a basis of comparison for my sample: First/Mid-Level Officials & Managers, Professionals, Technicians, Sales Workers, and Office & Clerical Workers, excluding manual worker categories. Additionally, I specifically employ the

[6] 9.66% Black, 8.45% Asian and Pacific Islander, and 9.27% Hispanic. I focus on White, African American, Asian and Pacific Islander, and Hispanic racial/ethnic categories, as Revelio Labs assign each individual into one of the 4-class race/ethnicity taxonomy.

[7] The seven ordinal seniority levels are: 1. Entry level/Intern (e.g., Accounting Intern, Software Engineer Trainee, Paralegal); 2. Junior Level (e.g., Account Receivable Bookkeeper, Junior Software QA Engineer, Legal Adviser); 3. Associate/Analyst Level (e.g., Senior Tax Accountant; Lead Electrical Engineer; Attorney); 4. Manager Level (e.g., Account Manager; Superintendent Engineer; Lead Lawyer); 5. Vice President Level (e.g., Chief of Accountants; VP Network Engineering; Head of Legal); 6. Director Level (e.g., Managing Director, Treasury; Director of Engineering, Backend Systems; Attorney, Partner); and 7. C-suite Level (e.g., CFO; COO; CEO).

[8] The Revelio Labs data on top executives is sparse. I define diversity measures of top executives using the BoardEx data and use them as control variables in my analysis.

[9] Using Revelio Labs seniority matric, I categorize mid-level managers as levels 4 to 6, and rank-and-file positions as levels 1 to 3. Based on this classification, I identify 26.85% mid-level managers and 73.15% rand-and-file positions.

[10] See https://www.eeoc.gov/statistics/employment/jobpatterns/eeo1/historical.

[11] The detailed definition of each category can be found at: https://www.eeoc.gov/eeo-1/job-patterns-minorities-and-women-private-industry-glossary.

[12] Prior to 2007, EEO does not differentiate between "Executive/Senior Level Officials & Managers" and "First/Mid-Level Officials & Managers." Instead, both were grouped together under the single category of "Officials & Managers." To justify the proportions of "First/Mid-Level Officials & Managers" before 2007, I utilize the average ratios of this subgroup relative to the total "Officials & Managers" from 2007 to 2021.

First/Mid-Level Officials & Managers category to benchmark the demographic characteristics of mid-tier managers in my analysis.

Figure 1 presents the comparison results. Specifically, for each year, I present the percentage of minorities as the number of minority employees divided by the number of total employees. In Panel A, the percentage of minorities among all non-executive employees is 16.29% in my sample and 20.18% in the EEO sample in 1996. Both samples show a similar increasing trend, reaching 29.98% in my sample and 36.72% in the EEO sample by 2021. In Panel B, the percentage of minorities among mid-tier managers in my sample closely aligns with the EEO sample, with an average difference of about 1.4% throughout the entire period. These comparable trends and magnitudes suggest that my sample broadly represents the distribution of minorities in the private sector and alleviates potential concerns of selection bias, such as overrepresentation of minority employees.

2.2 Workforce Diversity Measures

My workforce dataset allows me to aggregate individual employment durations across various firms and measure diversity based on race/ethnicity. Every month, I tally the headcount of employees belonging to White and minority racial/ethnic groups in the prior month. Then, I determine the monthly proportion of minority employees by dividing the number of minority employees by the total number of employees in the firm. Next, I calculate my workforce diversity measure, *Diversity*, as the rolling average of the proportion of minorities in the prior three or twelve months. In an analogous manner, I construct the percentage of minorities on board, *Board Diversity*, using BoardEx data.[13]

[13] I predict the race/ethnicity based on the name of directors provided by BoardEx. For more information, refer to https://pypi.org/project/ethnicolr/.

Table 1 Panel A presents the summary statistics for employee diversity measures. On average, 19.8% of employees in a firm are racial/ethnic minorities. Additionally, on average, 8.4% of board members belong to minority groups.[14] The board diversity measure exhibits moderate correlation (= 0.42) with non-executive employee diversity. This evidence suggests that non-executive diversity measures do not merely reflect the diversity levels of top executives and board members. Further, Figure A.1 shows the proportion of all minority racial/ethnic groups increases over time from 14.06% in 1990 to 29.98% in 2021.

Figure 2 displays the industry and geographic distributions of workforce diversity. In Panel A, Industries (Fama-French 12 industry categories) with relatively high percentages of minorities among non-executive employees and mid-managers include *BusEq* (Business Equipment), *Telcm* (Telephone and Television Transmission), and *Enrgy* (Oil, Gas, and Coal Extraction and Products). The difference between the industry with the highest percentage of minorities (*BusEq*) and the lowest (*Manuf*) is less than 10%, indicating that my sample is not biased towards any specific industry. In Panel B, firms headquartered in states such as Hawaii, California, New Mexico, Texas, and Florida exhibit higher diversity levels, potentially reflecting their history of immigration and industrialization.

2.3 Additional Datasets

I obtain stock returns and other financial statement information from the Center for Research in Security Prices (CRSP) and Compustat. The Social score from ESG rating is from Kinder, Lydenberg, and Domini (KLD) and Refinitiv (Asset4). In additional analyses, I employ three other

[14] According to the EEO's report, the average representation of minorities among Executive/Senior Level Officials and Managers in private industry from 2007 to 2021 is 8.62%. In addition, the "Missing Pieces Report (4th edition)" published by the Alliance for Board Diversity and Deloitte emphasizes that race/ethnic minorities hold 12.8% of board seats in 2010 among Fortune 500 companies, which should ideally have a higher representation of minorities on their boards compared to other firms.

datasets related to human capital productivity. First, innovation is likely to reflect human capital productivity. I assess innovation outcomes by examining patent data from Kogan et al. (2017), which offers a panel dataset at the patent level covering the years 1926 to 2022.[15] Each year, I aggregate the data to the firm level as the proxy of innovation outputs, calculating the total number of patents, the average value per patent in billions, and the annual citation count for the subsequent 12 months as of the fiscal year-end. The summary statistics are in Panel B of Table 1.

Next, employee satisfaction is another aspect of human capital productivity. Employees can manifest their attitudes toward the company through different channels: by providing ratings on social media platforms like Glassdoor, or by opting to either stay with or leave the firm as a form of "voting with their feet". I utilize data from Glassdoor ratings, a platform established in 2008 that allows users to anonymously rate their employers.[16] The ratings contain individuals' overall assessment of the company, complemented by sub-ratings in various categories including "Work Life Balance", "Senior Management", "Culture and Values", "Compensation and Benefits", and "Career Opportunities". Each of these metrics is scored on a five-point scale, where five represents the highest level of satisfaction. For each year, I compute the average score for both the overall rating and each of the sub-ratings. In Panel C of Table 1, both the mean and median Glassdoor ratings are around 3, displaying similar distributions. These findings are consistent with prior research, such as Green et al. (2019).

Employment decisions is another avenue for employees to express their job satisfaction. The total number of employees leaving the firm per year can be accessed through Revelio Labs,

[15] Available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
[16] I thank Da Xu for generously sharing the Glassdoor ratings, as in Carter et al. (2023).

which combines both voluntary departures and forced layoffs.[17] However, only voluntary exits serve as a reliable indicator of employee satisfaction. To address this issue, I utilize layoff data from the Job Cut Announcement Reports provided by Challenger, Gray & Christmas, Inc. This dataset aggregates publicly disclosed information on U.S. layoff announcements, drawing from multiple sources such as the Worker Adjustment and Retraining Notification (WARN) Act, media reports, and corporate financial disclosures. Each recorded layoff event includes details such as the company's name, the date of the layoff announcement, the reason for the layoff, its location, and the number of employees affected.

Through the combination of fuzzy match and manual cross-checking, I successfully match 20,119 layoff events to 3,524 companies, spanning the years 2001-2020. Every year, I tally the total number of employees subject to layoffs. The voluntary turnover ratio is then computed by taking the total number of employees who left the following year and subtracting the number of those laid off, all scaled by the current total workforce. In Panel C of Table 1, the average voluntary turnover ratio in my dataset is 0.4%, with the median considerably higher at 12.9%. These statistics imply a disparity in voluntary turnover rates across firms, potentially signaling low levels of employee satisfaction in certain firms.

To address potential selection bias in hiring activities, I rely on the job postings data from LinkUp, which provides reliable coverage for the content of job postings starting from 2014.[18] Campello, Kankanhalli, and Muthukrishnan (2023) confirm that LinkUp aligns with the U.S. corporate hiring patterns, as reported in the Bureau of Labor Statistics' Job Openings and Labor Turnover Survey (JOLTS). I employ textual analysis to pinpoint DEI and equal opportunity (EO)

[17] For example, during the Great Recession, mass layoffs reached particularly high levels. According to BLS data, in 2009 there were 7,192 mass layoff events that involved more than 1.2 million initial claimants for unemployment insurance (https://www.bls.gov/spotlight/2012/recession/pdf/recession_bls_spotlight.pdf).
[18] Data from LinkUp prior to 2014 offers limited insight into the content of job postings.

keywords within these postings due to their direct implications for workforce diversity. Then, I count the number of DEI (*JP_DEI*) and EO (*JP_EO*) words within a firm's job postings per year, scaling by either the number of job postings or the word count within the job postings content, excluding stop words.

2.4 Univariate Statistics

To obtain a preliminary assessment of the association between firm characteristics and workforce diversity, I sort firms in my sample into following terciles based on their level of workforce diversity (*Diversity*): low (L), medium (M), and high (H) groups. I expect that firms with diverse top managers and board members are more likely to foster diversity among their non-executive staff (e.g., Susan, Avery, and Zemsky (2000) and Morgan and Vardy (2009)). Further, the relation between firm size and workforce diversity is unclear. On one hand, larger, more visible firms may prioritize workforce diversity, driven both by increased societal pressure and resource availability. On the other hand, smaller firms, with fewer employees, might find it simpler to achieve greater diversity across the organization through their hiring practices.

Additionally, firms in stronger financial conditions would have the resources to invest more in human capital (e.g., Berk, Stanton, and Zechner (2010) and Ghaly, Dang, and Stathopoulos (2017)), thereby supporting a diverse workforce. Furthermore, younger and growing firms, which are highly dependent on human capital, may also be motivated to enhance workforce diversity. Lastly, companies with a high volume of international sales might find it beneficial to employ staff from varied demographic backgrounds. For instance, a company with a significant share of its sales in Latin America is more likely to employ a higher number of Hispanic individuals.

As shown in Table 2, the average workforce diversity for the L, M, and H groups is 8.8%, 18.2%, and 32.5%, respectively. The *Board Diversity* correlates positively and monotonically with

workforce diversity, suggesting a top-down influence on diversity within the firm. There is a consistent increase in workforce diversity alongside *Market Capitalization*, implying that larger firms are more likely to be associated with higher diversity.[19] The analysis on book-to-market ratio (*BM*) and *Age* aligns with the prediction that young, growing firms are more likely to exhibit high levels of workforce diversity. Moreover, the results on *Leverage*, *Cash*, *Loss*, zero dividends indicator (*DD*), and *ROA* indicate that firms in stronger financial positions and with better performance also have greater workforce diversity.

It is important to highlight that not all these associations are linear. For instance, the *Leverage* variable shows no statistically significant difference between the High (H) and Low (L) diversity groups. Finally, firms with a higher percentage of international sales (*Foreign Sales*) have a more diverse workforce.

3. Workforce Diversity, Human Capital, and Financial Performance

In this section, I present my main results. I start by assessing the correlation between workforce diversity and human capital, using innovation and employee satisfaction as proxies. Subsequently, I examine the influence of workforce diversity on financial performance.

3.1 Non-Employee Diversity and Corporate Innovation

Although advocates frequently champion workforce diversity as an intrinsic component of robust human capital, quantifying the direct impact of diversity on human capital is difficult due to the intangible nature of human capital. As a workaround, I use two productivity indicators tied to strong human capital: the promotion of innovation and the improvement in employee satisfaction.

To begin, I examine the association between workforce diversity and innovation, which is often cited as a key indicator of enhanced human capital productivity. Proponents contend that one

[19] My results exhibit a similar pattern when I use total assets as a proxy for firm size.

of the primary channels that a diverse workforce enhances human capital is by serving as a catalyst for innovative thinking. Such a varied talent pool contributes a wide array of information and specialized skills, enriching the organizational capacity for creativity and problem-solving. Specifically, I estimate the following regression:

$$Innovation_{i,t+1} = \beta Diversity_{i,t} + CX_{i,t} + \delta_i + \tau_t + \varepsilon_{it}\,, \quad (1)$$

where $Innovation_{i,t+1}$ is the firm *i*'s innovation input and output in year *t*+1. Innovation input is measured by R&D expenses, defined as research and development spending scaled by lagged assets, where missing R&D values are set to zero. Innovation output is measured by the number of patents, the average value per patent, and the number of citations from Kogan et al. (2017).

My main variable of interest is $Diversity_{i,t}$, the firm *i*'s annual workforce diversity in year *t*. I consider a vector of firm-specific controls (*X*) in year *t*, including market capitalization (ln(ME)), BM, Leverage, Cash, Foreign Sales, zero dividends indicator (DD), and firm age (ln(Age)). To address the potential concern that non-executive employee diversity is related to diversity within the board of directors, I incorporate controls for board of directors' diversity, *Board Diversity*. Finally, my regression specification includes firm and state-year fixed effects, which account for potential time-invariant heterogeneity at the firm level and state-year-specific shocks. Standard errors are clustered at the firm level.

Table 3 reports the innovation regression estimates. In Column (1), *Diversity* is not significantly associated with R&D expenses, as workforce diversity is not linked to increased investment in R&D.[20] However, in Columns (2) to (4), I find that workforce diversity is positively associated with innovation output in the following year, [21] as evidenced by the larger number of

[20] My findings remain consistent after excluding zero or missing R&D values or using the concurrent R&D expenses.
[21] My findings remain consistent when I consider innovation outputs during the next 3 years.

patents, higher average value per patent, and more citations. In economic terms, one standard deviation increase in *Diversity* is associated with a 7.03% ($= e^{0.5566\times0.122} - 1$) increase in the number of patents, a \$0.038 billion (= 0.3132 × 0.122) increase in the value per patent, and an 8.69% ($= e^{0.6829\times0.122} - 1$) increase in the number of citations. Overall, I find that the workforce diversity is associated with better innovation outcomes, without any significant increase in innovation expenses.

3.2 Non-Employee Diversity and Employee Satisfaction

Edmans (2011) shows high employee satisfaction causes higher firm value as predicted by human capital theories. However, it is *ex ante* unclear whether employees experience high satisfaction in a diverse working environment. On one hand, a diverse workplace can offer enhanced creativity and problem-solving, personal growth opportunities, and an inclusive atmosphere that makes all employees feel valued. On the other hand, such environments can also present challenges like communication barriers, resistance to change from those unaccustomed to diversity, and the potential for division if not managed effectively.

To measure employee satisfaction levels, I use both Glassdoor ratings and voluntary turnover ratio. My first measure of employee satisfaction is Glassdoor ratings. The ratings contain individuals' "Overall" assessment of the company, complemented by sub-ratings in various categories including "Work Life Balance", "Senior Management", "Culture and Values", "Compensation and Benefits", and "Career Opportunities". Each of these metrics is scored on a five-point scale, where five represents the highest level of satisfaction. As an alternative measure of employee satisfaction, I calculate the voluntary turnover ratio by subtracting the number of employees laid off from the number of employees who left in the following year, scaled by the current total number of employees. Using these measures, I estimate the following model:

$$Satisfaction_{i,t+1} = \beta Diversity_{i,t} + CX_{i,t} + \delta_i + \tau_t + \varepsilon_{it}\,, \quad (2)$$

where $Satisfaction_{i,t+1}$ is the firm *i*'s Glassdoor ratings or the voluntary turnover ratio in year *t*+1. My main variable of interest is $Diversity_{i,t}$, the firm *i*'s annual workforce diversity in year *t*. I consider a vector of firm-specific controls (*X*) in year *t*, including *Board Diversity*, ln(ME), BM, Leverage, Cash, Foreign Sales, DD, and ln(Age), as studied in Table 3. Finally, my regression specification includes firm and state-year fixed effects, which standard errors are clustered at the firm level.

Table 4 reports the employee satisfaction regression estimates. In Column (1), the workforce diversity is significantly positively correlated with employee overall assessment in the next year. In economic terms, a one standard deviation rise in *Diversity* results in an overall rating boost of 0.073 (= 0.5948 × 0.122) on a five-point scale, which is equivalent to 2.26% of the sample mean for the overall rating (= 3.223, as shown in Table 1).

It is possible that workforce diversity affects employees' views along certain dimensions more than others. For example, Susan, Avery, and Zemsky (2000) find that entry-level employees are more likely to receive mentoring and consequently gain human capital and promotion opportunities when more senior-level employees have the same type (gender or race/ethnicity). I anticipate that enhanced diversity would cultivate a more inclusive corporate culture and management approach, thereby mitigating the "glass ceiling" faced by minorities. This, in turn, is likely to boost employee satisfaction, particularly in the categories of "Culture and Values", "Senior Management", and "Career Opportunities".

In line with my predictions, estimates in Columns (2) to (4) show a significant positive relation between workforce diversity and next year's sub-ratings in "Career Opportunities", "Culture and Values", and "Senior Management", respectively. Specifically, a one standard

deviation boost in *Diversity* yields a 2.96% (= (0.7274 × 0.122)/3) increase in "Career Opportunities" rating relative to mean. Similarly, it results in a 3.34% (= (0.8790 × 0.122)/3.206) rise in "Culture and Values", and a 2.36% (= (0.6438 × 0.122)/3.333) uplift in "Senior Management". I do not find significant relation of workforce diversity on "Work Life Balance" and "Compensation and Benefits" (see Columns (5) and (6)).

Employees also have the option of "voting with their feet" to signal their satisfaction. If they find that a diverse work environment enhances their personal growth, they are inclined to stay; otherwise, they may opt to depart. However, the data in Column (7) does not show a significant association between workforce diversity and voluntary turnover rates. This evidence suggests that the benefits of workforce diversity may be accompanied with some drawbacks. Collectively, these results indicate that workforce diversity is related to enhanced employee satisfaction, particularly in categories that are likely most relevant for human capital productivity.

3.3 Non-Employee Diversity, Financial Performance, and Firm Value

Beyond its influence on human capital documented in previous sections, workforce diversity should also affect tangible outcomes, such as financial performance. If the market is able to promptly integrate information related to both human capital and financial performance, then firm valuation would accurately reflect the impact of workforce diversity. Otherwise, firm valuation could misrepresent the value of workforce diversity.

I examine the relation between workforce diversity and firm's financial performance using return on assets (ROA). Specifically, ROA is calculated as the net income for the year scaled by the previous year's assets. Subsequently, I turn my focus to firm valuation, employing Tobin's *q* as the dependent variable. Tobin's *q* is defined as the market value of the firm's equity and liabilities, scaled by their respective book values. My regression model closely aligns with the regression

specifications employed in Sections 3.1 and 3.2. When Tobin's *q* is the dependent variable, I omit the B/M ratio from the control set given its role as an alternate valuation proxy. However, this exclusion does not impact the overall findings.

The regression estimates are reported in Table 5. In Column (1), I observe that the relation between *Diversity* and ROA for the subsequent year is statistically insignificant. The results are similar when I consider alternate financial performance measures, including return on equity, return on sales, and earnings change. These findings collectively imply that workforce diversity does not have a clear impact on short-term financial performance.

In Column (2), I find a negative relation between *Diversity* and the firm's concurrent Tobin's *q*. Specifically, a one-standard-deviation increase in *Diversity* leads to a 0.0903 (= -0.7404 × 0.122) lower Tobin's *q* in the same year, which represents a 4.33% decrease relative to the mean Tobin's *q* of 2.085. However, in Column (3), this negative relation turns statistically insignificant when I examine the effect of diversity on Tobin's *q* for the subsequent year. These findings suggest that the market's focus on short-term financial performance may overshadow the benefits of workforce diversity on human capital, although the market appears to gradually assimilate this information over time.

To examine why the market fails to promptly recognize the positive impact of workforce diversity on human capital productivity, I carry out additional tests focusing on a subset of companies that are heavily reliant on human capital. I categorize firms in high-technology sectors as human-capital-intensive, given the strong reliance of these industries on human capital (e.g., Zucker, Darby, and Brewer (1998); Israelsen and Yonker (2017)). Following Barron et al. (2002), I categorize human-capital-intensive companies based on the following three-digit SIC codes: 283 for Pharmaceuticals; 284 for Specialty Chemicals; 357 for Computer and Office Equipment; 366

for Communications Equipment; 367 for Electronic Components; 371 for Motor Vehicles; 382 for Measurement and Control Devices; 384 for Medical Instruments; and 737 for Software.

In Column (4), the relation between *Diversity* and future ROA remains insignificant among firms that are highly reliant on human capital. In Columns (5) and (6), I observe a negative relation between diversity and Tobin's q for both the current and subsequent year. This evidence suggests that the market's delayed recognition of the benefits of diversity is more pronounced in sectors that are highly dependent on human capital.

Together, the relation between workforce diversity and financial performance is not as straightforward as its positive impact on human capital. The market's focus on tangible financial performance might eclipse the intangible advantages of workforce diversity on human capital productivity. Consequently, the market may not fully appreciate the value of workforce diversity in the immediate term. However, this undervaluation does not appear to be persistent, indicating that the market gradually adjusts to recognize the benefits generated by diversity.

4. Workforce Diversity and Stock Returns

4.1 Workforce Diversity Based Trading Strategies

If the market is unable to immediately recognize the value of diversity, but does so gradually, non-executive diversity could be related to future stock returns in a predictable manner. To quantify this relation. I construct a trading strategy that takes a Long position in firms with high workforce diversity and a Short position in firms with low diversity. To measure the risk-adjusted performance of the Long-Short portfolio, I use Fama-French five-factors (Fama and French (2015)) and the Carhart (1997) factor:

$$r_{p,t} = \alpha + \beta_{MP} MP_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \beta_{UMD} UMD_t + \varepsilon_t, \quad (3)$$

where t represents the calendar month, and $r_{p,t}$ is the monthly return of the value-weighted portfolio. MP is the market premium calculated as the value weighted market return on all NYSE-Amex-Nasdaq stocks minus the 1-month Treasury-bill rate. SMB (small minus big) is the average return of small firms minus the average return of big firms. HML (high minus low) is the average return of value (high BM) firms minus the average return of growth (low BM) firms. RMW (robust minus weak) is the average return of robust-profitability firms minus the average return of weak-profitability firms. CMA (conservative minus aggressive) is the average return of firms with low investment minus the average returns of firms with high investment. UMD (up minus down) is the average return of firms with high prior returns minus the average return of firms with low prior returns. To avoid potentially illiquid stocks driving my result, I exclude stocks with stock price below $1.

I sort firms over a given month into quintiles based on *Diversity,* which is the proportion of minority employees at a firm during the previous 3 months. The dependent variable captures the difference in returns between firms in the top and bottom *Diversity* quintiles. Alpha (α), the main coefficient of interest, is the intercept that captures the average abnormal monthly returns of the L-S portfolio relative to the benchmark model.

The trading strategy performance estimates are reported in Table 6. In Column (1), I find that the returns of *Diversity* sorted portfolios vary in a monotonic manner. A trading strategy based on *Diversity* generates a raw return of 1.22% per month for the Long portfolio and 0.765% per month for the Short portfolio. The L-S portfolio has a statistically significant alpha of 0.628% per month, which translates into an abnormal return of 7.54% per year.[22]

[22] In unablated results, the alpha is similar in magnitude when I measure portfolio returns using an equal-weighting scheme.

To examine the robustness of these estimates, I consider alternative specifications. First, I confirm the consistency of my results by limiting the analysis to post-2010 sample years, which is the time that follow the rise of LinkedIn in popularity among employees.[23] In Columns (2), the L-S portfolio has a statistically significant alpha of 0.382% per month, which translates into an abnormal return of 4.58% per year. This evidence suggests that my primary findings are not driven by the potential difficulty of accessing historical employee data from LinkedIn.

Second, I restrict my sample to S&P 1500 firms, which operate in a relatively transparent informational environment and is unlikely to vary with employee demographic composition. In Columns (4), the L-S portfolio yields a statistically significant abnormal return of 6.41% per year, suggesting that my findings are not concentrated among firms with weak information environment, thus reducing the concern on potential sample selection bias.

Third, as shown in Figure 2 Panel B, variation in the historical immigration and industrialization patterns among states influence the characteristics of the local labor demographics. I construct a state-adjusted diversity measure by subtracting the average diversity of all companies headquartered in the same state from my initial diversity measure. My findings remain consistent when I consider state-adjusted diversity measures in Column (5). This adjustment helps mitigate the influence of local labor market demographic conditions.

Fourth, in unreported results, I find comparable outcomes when I conduct identical tests utilizing the Herfindahl index for diversity and labor flow diversity.[24] Fifth, my results are similar

[23] "2010: LinkedIn shifts into hyper-growth mode, reaching 90 million members and nearly 1,000 employees in 10 offices around the world." See: https://press.linkedin.com/content/dam/press/docs/linkedin-company-fact-sheet-12-08-16.pdf.

[24] Agrawal, Hacamo, and Hu (2021) show that net labor flows reflect the collective expectations of non-executive employees, informed by the signals they perceive about the company's future. As a result, compared to the existing diversity level in a company, shifts in company outlook might be mirrored in the collective labor market choices of various racial/ethnic groups.

when I measure *Diversity* during the previous one month or 12 months, instead of the past three months.

Overall, the portfolio performance estimates show that workforce diversity can be used to predict stock returns, and this relation is robust to a variety of specification choices. The findings support the hypothesis that investors are unable to fully incorporate the value of diversity into stock prices.

4.2 Fama-MacBeth Regression Estimates

To provide further support for my key hypothesis, I estimate the following Fama and Macbeth (1973) regression:

$$r_{i,t} = b_0 + b_1 Diversity_{i,t-1} + cX_{i,t-1} + \epsilon_{i,t}, \quad (4)$$

where $r_{i,t}$ is firm *i*'s monthly return at month *t*. $Diversity_{i,t-1}$ is the proportion of minority employees in the previous 3-month rolling basis. $X_{i,t-1}$ is a vector of control variables for firm *i* in month *t-1*, including *Board Diversity,* ln(ME) in June, ln(BM), and various past return measures, such as the previous month return, $Ret_{-1,-1}$, previous year return,, $Ret_{-12,-2}$, and previous three year returns, $Ret_{-36,-13}$. The tests use Newey and West (1987) standard errors corrected for autocorrelation using 12 lags.

Table 7 reports the Fama-MacBeth regression results. Consistent with the univariate sorting results, Column (1) shows that higher *Diversity* is associated with higher returns. In Column (2), the results remain similar in magnitude and statistical significance when I consider various controls. In economic terms, a one standard deviation increase in *Diversity* is associated with an 8.62 basis points (= 0.7066 × 0.122) higher return in the following month. This magnitude is similar to the findings in Fedyk and Hodson (2022). Columns (3) and (4) show that the estimates with post-2010 and S&P1500 subsamples yield similar results. In addition, my result is robust by using state-

adjusted diversity in Column (5). Taken together, the Fama-MacBeth regression estimates illustrate that workforce diversity is related to stock returns.

4.3 Workforce Diversity and Analyst Forecasts

Next, I examine whether market's earnings expectations vary with workforce diversity. Similar to Agrawal, Hacamo, and Hu (2021), I use sell-side equity analysts' earnings expectations as a proxy for informed investors, given their motivation to generate precise earnings forecasts. Specifically, the standardized unexpected earnings (SUE) for firm *i* in month *t* is defined as:

$$SUE_{i,t} = \frac{EPS_{i,t}^{actual} - \mu_{i,t}}{\sigma_{i,t}}, \quad (5)$$

where $EPS_{i,t}^{actual}$ is the ex-post actual EPS in the firm's upcoming quarter. $\mu_{i,t}$ and $\sigma_{i,t}$ are the mean and standard deviation of analysts' EPS forecasts for the upcoming quarterly earnings announcement for a given firm *i* in month *t*, respectively.

Motivated by So (2013), earnings expectation regressions include various firm controls, including earnings per share when earnings are positive and zero otherwise (*E*+), negative earnings indicator (*NEGE*), negative and positive accruals per share (*ACC*−, *ACC*+), percent change in total assets (*AG*), zero dividends indicator (*DD*), dividends per share (*DIV*), share price (*PRC*), and book-to-market value (*BM*).[25] I also include board diversity to control for executive diversity. All variables are defined in Appendix Table A.1.

Table 8 presents earnings surprise regression estimates. The results reported in Column (1) indicate a positive correlation with future earnings surprises (coefficient = 1.2225, *t*-statistic = 6.25). This finding indicates that workforce diversity can predict analyst forecast errors, which suggests that analyst expectations do not fully account for non-executive diversity. In Columns (2)

[25] Refer to Hughes, Liu, and Su (2008) for additional insights on predictable components of earnings forecast errors and analyst biases.

and (3), the magnitude and statistical significance of these results hold for both the post-2010 and S&P 1500 subgroups. In addition, the estimates are similar when I consider state-adjusted diversity in Columns (4).

Overall, the earnings expectation results align with my core hypothesis, indicating that workforce diversity contributes to the analysts' earnings forecast errors. The presence of higher workforce diversity suggests improved earnings prospects; however, sell-side analysts do not seem to incorporate this information into their forecasts ahead of earnings announcements. This mis-valuation of workforce diversity holds across various empirical specifications, reinforcing the notion that workforce diversity carries valuable earnings-related information that can potentially be exploited to develop profitable trading strategies.

4.4 Market Reaction Following Earnings Announcements

Following the approach in La Porta et al. (1997), I use market reaction to earnings announcements as a tool to investigate the market's capacity for anticipating differences in workforce diversity across firms. If the earlier-noted excess returns arise because market participants do not adequately recognize the distinction between firms with strong workforce diversity and those with weak workforce diversity, then I expect that the market will react more positively to the earnings reports of companies with strong workforce diversity compared to those with weaker workforce diversity when new information is realized.

To conduct this analysis, I examine the market-adjusted returns (abnormal returns defined in excess of CRSP value-weighted market return) over a three-day window centered around quarterly earnings announcements dates. The earnings announcements dates are obtained from the quarterly Compustat data. Table 9 presents the estimates from Fama-MacBeth regressions of quarterly earnings announcement returns on the workforce diversity. Consistent with my prediction, the

workforce diversity is positively associated with earnings announcement returns (see Column (1)). In economic terms, a one standard deviation increase in *Diversity* is associated with a 5.75 basis points (= 0.4716 × 0.122) increase in 3-days earnings announcement returns.

As with my previous findings, these results remain similar in post-2010 (Column (2)) and S&P 1500 subsets (Column (3)). The findings are also similar when I consider state-adjusted diversity in Column (4). Together, these findings suggest that the market does not fully absorb the value of workforce diversity. It is surprised more positively by earnings announcements of firms with strong workforce diversity than by those with weaker workforce diversity.

4.5 Return Persistence or Long-Run Return Reversal?

In the next test, I examine whether the abnormal stock returns around earnings announcements persist or exhibit a reversal. If these returns reverse over longer horizons, workforce diversity may not be strongly related to stock prices. Instead, workforce diversity might be associated with a transitory phenomenon that temporarily influence prices in the short run. To investigate this hypothesis, I estimate Fama and Macbeth (1973) regressions to analyze the cumulative market-adjusted return for each stock on a monthly basis, spanning across the subsequent eight quarters. The first quarter (Q1) comprises the cumulative market-adjusted returns from month 1 to month 3, and the same pattern follows for the subsequent quarters.

Table 10 presents the regression estimates for long-term returns. The relation between *Diversity* and cumulative market-adjusted returns generally maintains a positive and statistically significant relation in the following five quarters (see Columns (1) to (5)). However, in the remaining Columns (6) to (8), the relation between *Diversity* and cumulative market-adjusted returns for subsequent quarters is no longer statistically distinguishable from zero.

These results align with my previous findings presented in Sections 4.3 and 4.4, suggesting that the market is unable to immediately recognize the value of workforce diversity due to mispricing in the short run. This may be because the enhancements to human capital productivity, facilitated by workforce diversity, are intangible and difficult to observe.

4.6 Divergence between Workforce Diversity and ESG Ratings

A possible source of information regarding the value of workforce diversity is ESG ratings. Third-party ESG rating agencies may offer insights of workforce diversity, given that diversity, equity, and inclusion (DEI) are essential aspects of the "Social" dimension in ESG assessments. Nevertheless, such agencies may not always be objective or focused on diversity. This is evidenced by phenomena such as "diversity washing", where firms that engage in more DEI discussions than actual diverse hiring practices receive inflated ESG scores (Baker et al. (2023)).

Due to data availability, I focus on two rating agencies: Kinder, Lydenberg, and Domini (KLD) and Refinitiv (Asset4).[26] My main variable of interest is the score on social aspects, as it most closely relates to workforce diversity. Following Dube and Zhu (2021), I calculate the corporate social responsibility (CSR) scores on employee relations and diversity based on the difference of employee-related strength and concern indicators from KLD. In addition, I obtain the social pillar score of ESG from Refinitiv.

Table 11 presents the results. Workforce diversity shows no significant relation with either the CSR employee relation or the diversity score from KLD (Column 1), or the social score from Refinitiv (Column 2) in the following year. This observation implies that ESG rating agencies are unable to effectively capture the value of workforce diversity, possibly due to its complex intrinsic

[26] Berg, Kolbel, and Rigobon (2022) document the divergence of ESG ratings based on data from six prominent ESG rating agencies.

valuation or because their assessments predominantly focus on broader social considerations. Consequently, it is difficult for the market to get information on the value of diversity even from ESG scores.

5. Robustness Checks and Alternative Explanations

5.1. Diversity of Mid-Managers and Rank-and-File Employees

Misvaluation of workforce diversity could be contingent on the hierarchical level at which the diversity is situated, given that the influence of diversity on human capital can differ based on the level of employment. For example, mid-tier managers serve as important intermediaries between top executives and rank-and-file employees in a firm, facilitating effective leadership and communication.[27] To further establish the relative importance of diversity of mid-level managers (MM) and rank-and-file employees (RF), I employ the seniority metric from Revelio Labs to categorize positions into MM and RF.

Table A.2 presents the results of these analyses. Panel A reveals that, on average, 16.8% of mid-tier managers and 21.6% of rank-and-file employees among non-executive employees are minorities. In Panel B, both mid-manager diversity (*MM Diversity*) and rank-and-file diversity (*RF Diversity*) exhibit a positive relation with innovation. However, only *MM Diversity* shows a significant positive association with employee satisfaction. In Panel C, *MM Diversity* stands out as being significantly and positively correlated with future returns and SUE, whereas *RF Diversity* does not display statistical significance.

[27] Mid-tier managers play a vital role in complex and geographically dispersed organizations, acting as mediators between different levels and units (Wooldridge, Schmid, and Floyd (2008)). Compared to top managers, middle-tier managers have a deeper understanding of daily operations and are adept at identifying operational issues. Firms often grant stock options to middle managers to enhance retention (Oyer and Schaefer (2005)). Diversity among middle managers has been found to have a significant impact on innovation outcomes (Schubert and Tavassoli (2020)). Social networks are instrumental in helping firms attract talented middle-tier personnel, as evidenced by research on career choices of recent MBA graduates (Hacamo and Kleiner (2021)).

Overall, these results suggest that the relation between workforce diversity and stock returns is stronger when there is greater diversity among employees who play a more important role in firm operations and are more responsible for enhancements in human capital.

5.2. Corporate DEI Policies: Does Gender Diversity Have Similar Effects?

One potential concern with my findings is that the observed valuation differences can be primarily attributed to DEI policies of firms and their broader implications, rather than to racial/ethnic diversity itself. This might occur because racial/ethnic diversity is just one of the outcomes stemming from broad DEI initiatives. Consistent with this conjecture, Li and Nagar (2012) present evidence that firms adopting same-sex domestic partnership benefits (SSDPB) outperform non-adopters and generate excess returns. Similarly, Edmans, Flammer, and Glossner (2023) utilize survey data to demonstrate that firms with a focus on DEI exhibit improved accounting performance and innovation, although they find no direct association with future returns.

To address the possibility that my results may be primarily driven by DEI policies and their implications, I investigate gender diversity, another key aspect of demographic diversity emphasized by DEI initiatives. The workforce gender diversity measure is defined in an analogous manner as workforce racial/ethnic diversity.

The correlation between gender diversity and racial/ethnic diversity is 0.143, signifying a relatively weak association between the two forms of diversity. In Panel A of Table A.3, I find that, on average, female employees comprise 41.9% of the non-executive workforce and 14.6% of board members. These percentages are higher than those for racial/ethnic minorities, who make up 19.8% of non-executive employees and 8.4% of board members. Moreover, when I focus on gender diversity as the variable of interest to replicate my main findings, the results diverge from those of racial/ethnic diversity. Specifically, *Gender Diversity* is not correlated with enhancements

in either innovation or employee satisfaction (see Panel B of Table A.3). Furthermore, in Panel C of Table A.3, portfolios sorted based on *Gender Diversity* do not produce statistically significant abnormal returns.

These results align with the findings of Edmans, Flammer, and Glossner (2023), who also document insignificant or negative relation between their DEI measure and racial/ethnic workforce diversity at the senior management, CEO, and boardroom levels. Overall, my evidence does not support the conjecture that firm mis-valuation is driven by broader DEI initiatives.

5.3. Are Results Influenced by Selection Bias in Hiring Practices?

One potential concern with my findings is that heterogeneity in hiring activities among firms might introduce a selection bias towards workforce diversity. On the labor supply front, workers from minority backgrounds might be more inclined to seek employment in firms that offer a diverse work environment. Choi et al. (2023) illustrate that job seekers take note of diversity-related information in job postings, with such attention varying across jobseeker demographics. From the labor demand perspective, certain companies may recruit employees from underrepresented minority groups. Pacelli, Shi, and Zou (2023) reveal that companies strategically design their job postings to convey information about their culture to attract job seekers.

To mitigate this potential concern, I estimate the following model:

$$Diversity_{i,t} = \beta Diversity\ Hiring_{i,t} + CX_{i,t} + \delta_i + \tau_t + \varepsilon_{it}\ , \quad (6)$$

where $Diversity_{i,t}$ is the firm *i*'s annual workforce diversity in year *t*. I consider a vector of firm-specific controls (*X*) in year *t*, including *Board Diversity*, ln(ME), BM, Leverage, Cash, Foreign Sales, DD, and ln(Age). δ_i is the firm fixed effect, and τ_t is the state-year fixed effect. My main variable of interest is $Diversity\ Hiring_{i,t}$, which represents the frequency of diversity-related keywords in job postings. Specifically, I rely on job postings data from LinkUp. I count the number

of DEI (*JP_DEI*) and EO (*JP_EO*) words within a firm's job postings per year, scaling by either the number of job postings or the word count within the job postings content, excluding stop words.

My results, presented in Table A.4, indicate that the coefficients for workforce diversity are not statistically significant in relation to diversity hiring activities in the same year, which suggests that there is no discernible association between workforce diversity and either *JP_DEI* or *JP_EO*. This finding helps alleviate concerns regarding selection bias, as it suggests that firms' existing diversity levels are not significantly influenced by their diversity-focused hiring practices.

6. Summary and Conclusions

This study examines whether non-executive employee diversity affects firm value and whether different types of market participants accurately assess the economic value of diversity. Utilizing a unique and large resume-level dataset, I introduce a new measure of non-executive employee diversity. Using this measure, I demonstrate that workforce diversity is associated with higher levels of corporate innovation and greater employee satisfaction, which are strong proxies for human capital productivity. Examining the relation between non-executive diversity and short-run financial performance, I find no significant relation.

However, the market does not fully appreciate the value of minority employees, possibly because it places greater emphasis on tangible and short-term financial performance over intangible human capital productivity and long-term firm performance. Even relatively more sophisticated market participants such as sell-side equity analysts do not incorporate information about non-executive employee diversity in their earnings expectations. During the 1990-2021 sample period, a trading strategy that exploits market mis-valuation earns an annualized risk-adjusted return of over 7%.

Future research can examine whether the market exhibits diversity in its assessment of the value of different forms of diversity. To keep the empirical analysis manageable, the focus of my research has been on racial/ethnic diversity. But other forms of diversity such as gender-based, age-based, cultural, and geographic diversity at non-executive employee level could potentially affect firm valuation. Although I show that non-executive employee gender-diversity is not related to firm performance, a comprehensive analysis of different forms of workforce diversity is beyond the scope of the current paper. The economic mechanisms linking diversity and aggregate firm outcomes are likely to differ across different forms of diversity. It may be useful to examine those differences in the future.

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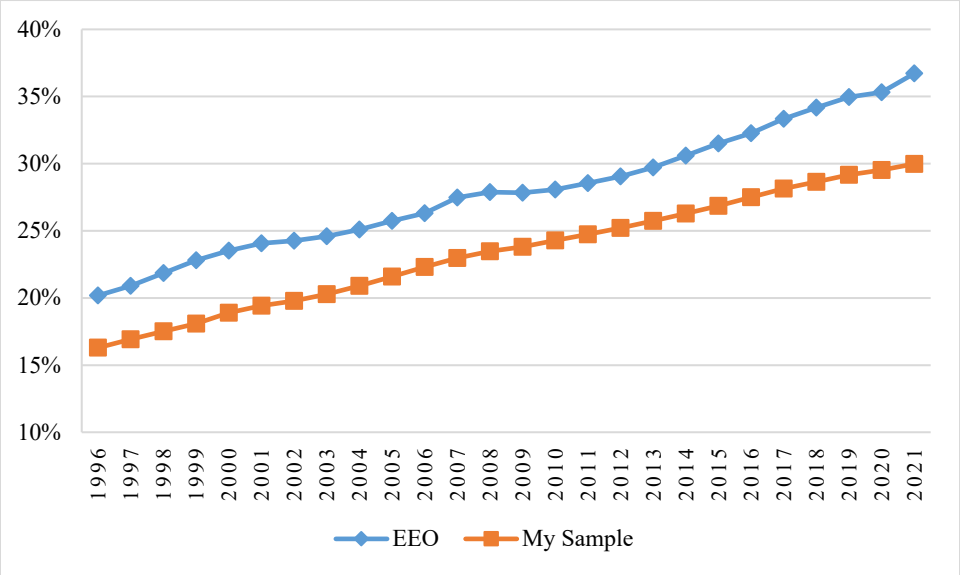
Panel A: Percentage of Minorities among Non-executive Employees



Panel B: Percentage of Minorities among Mid-tier Managers

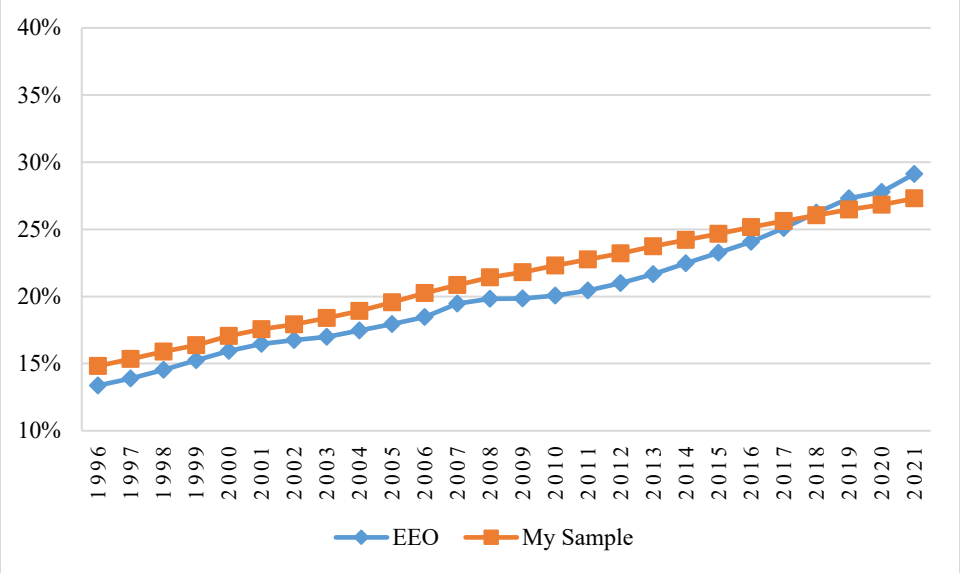
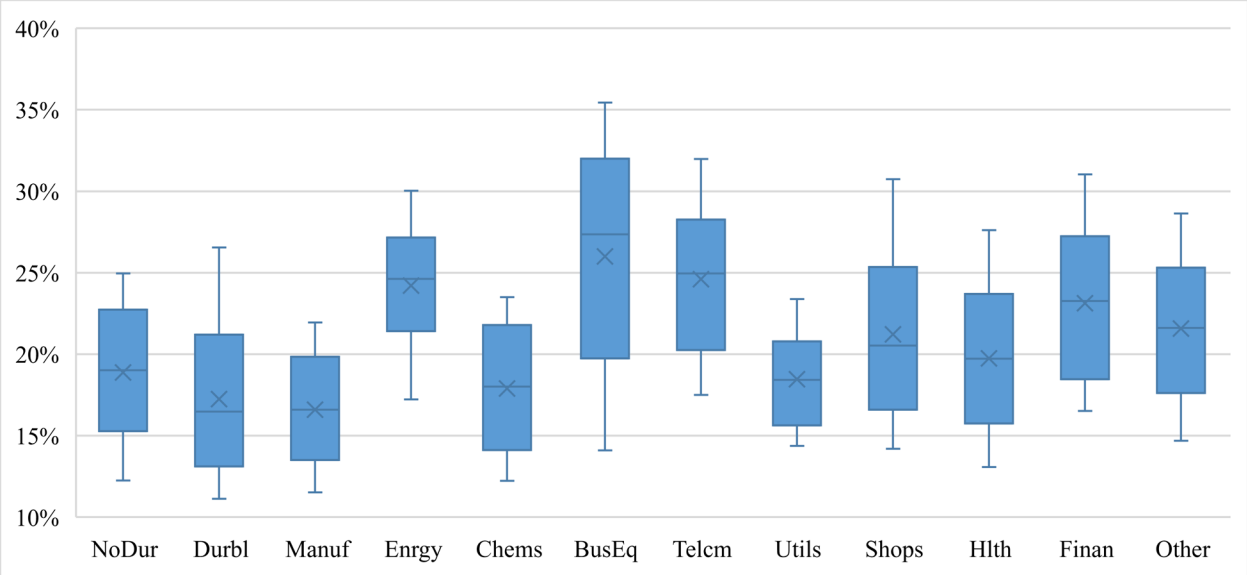


Figure 1: The figure illustrates the comparison of the representation of minorities in the EEO data (blue diamonds) and my sample (orange squares). Panel A displays the comparison among all non-executive employees, while Panel B focuses specifically on mid-tier managers.

Panel A: Industry Distribution



Panel B: Geographic Distribution

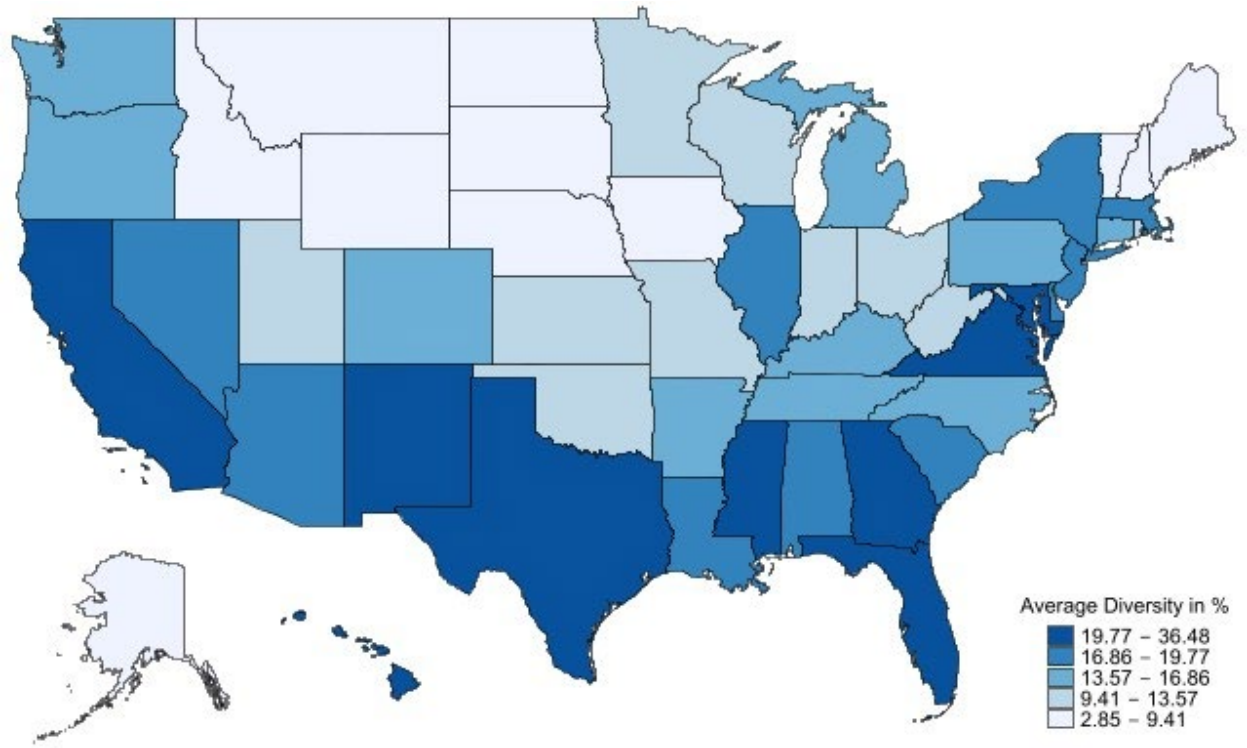


Figure 2: The figure illustrates the distribution of my diversity measure across the Fama-French 12 industry categories (Panel A) and the average diversity among firms headquartered in each state (Panel B).

Table 1: Summary Statistics

This table presents summary statistics for workforce diversity measures (Panel A), innovation measures (Panel B), employee satisfaction measures (Panel C), and other firm characteristics (Panel D). All variables are winsorized at 0.5th and 99.5th percentile levels. Appendix Table A.1 presents the definitions of all variables.

	Mean	SD	25th Pct.	Median	75th Pct.
Panel A: Diversity Measures					
Diversity	0.198	0.122	0.114	0.18	0.26
Board Diversity	0.084	0.098	0	0.067	0.125
Panel B: Innovation Measures					
R&D Expenses	0.061	0.153	0	0	0.062
ln(1+N Patents)	1.784	1.161	0	2.565	2.565
Value per Patent ($b)	0.117	0.496	0	0.002	0.021
ln(1+N Citations)	2.026	2.547	0	0	3.951
Panel C: Employee Satisfaction Measures					
Overall	3.223	0.694	2.84	3.244	3.667
Career	3	0.668	2.629	3	3.4
Culture	3.206	0.747	2.75	3.222	3.687
Senior Mgt	3.333	0.647	2.98	3.351	3.75
Compensation	3.296	0.685	2.92	3.313	3.729
WL Balance	2.883	0.735	2.462	2.883	3.3
Voluntary Turnover	0.004	0.811	0.062	0.129	0.183
Panel D: Other Firm Characteristics					
Tobin's q	2.085	1.812	1.083	1.474	2.33
ROA	-0.019	0.248	-0.023	0.032	0.083
ln(ME)	6.299	2.12	4.785	6.292	7.736
BM	0.587	0.669	0.25	0.473	0.79
Leverage	0.219	0.222	0.027	0.171	0.339
Cash	0.275	0.585	0.035	0.114	0.317
Loss	0.177	0.382	0	0	0
Foreign Sales	0.21	0.295	0	0.023	0.358
DD	0.54	0.498	0	1	1
ln(Age)	2.799	0.842	2.197	2.833	3.434
CSR Emp. Relation and Diversity Score	0.393	1.243	0	0	1
ESG Social Score	0.405	0.209	0.243	0.371	0.542

Table 2: Univariate Analysis

This table presents the univariate analysis of the relations between various firm characteristics and the workforce diversity. Firms in my sample are sorted into tercile based on workforce diversity, *Diversity*, as low (L), medium (M), and high (H) groups. For each group, the table reports the average of various firm characteristics, including Board Diversity, ME, BM, Leverage, Cash, Loss, Foreign Sales, zero dividends indicator (DD), Age and return on assets (ROA). Additionally, the table reports the mean differences and *t*-stat between high diversity and low diversity groups (H-L), and high diversity and medium diversity groups (H-M). Appendix Table A.1 presents the definitions of all variables.

Diversity Groups	L (Mean = 8.8%)	M (Mean = 18.2%)	H (Mean = 32.5%)	H-L	*t*-stat	H-M	*t*-stat
Board Diversity	0.057	0.076	0.120	0.063	64.95	0.044	44.55
Market Cap	1706.9	5238.5	7235.5	5528.7	31.55	1997.0	9.75
BM	0.657	0.571	0.534	-0.122	-19.2	-0.037	-5.9
Leverage	0.215	0.230	0.211	-0.004	-1.6	-0.019	-8.7
Cash	0.220	0.241	0.365	0.145	25	0.123	21.4
Loss	0.154	0.147	0.232	0.077	20.65	0.085	22.8
Foreign Sales	0.172	0.206	0.251	0.079	27.75	0.045	15.25
DD	0.470	0.526	0.623	0.153	32.55	0.098	20.7
Age	23.7	24.0	20.3	-3.4	-20.3	-3.7	-21.3
ROA	-0.023	-0.014	-0.052	-0.03	-9.25	-0.038	-12.5

Table 3: Innovation Regression Estimates

This table presents coefficient estimates of the firm innovation inputs and outputs on the workforce diversity. The dependent variables are the firm's innovation expenses and output in the next year. Innovation expenses are measured by R&D expenses scaled by the total assets in the previous year. Innovation output is measured as the number of patents, value per patent ($b), and the number of citations in the next year. *Diversity* is the average monthly percentage of minority employees over the previous twelve months. *Board Diversity*, ln(ME), BM, Leverage, Cash, Loss, Foreign Sales, zero dividends indicator (DD), and ln(Age) are included as control variables. Appendix Table A.1 presents the definitions of all variables. All regressions include firm and state-year fixed effects. Robust t-statistics are in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	R&D Expenses	ln(1+N Patents)	Value per Patent	ln(1+N Citations)
	(1)	(2)	(3)	(4)
Diversity	0.0189	0.5566	0.3132	0.6829
	[0.73]	[3.05]***	[4.03]***	[2.13]**
Board Diversity	-0.0141	0.3775	0.0364	-0.4302
	[-1.15]	[2.50]**	[0.55]	[-1.51]
ln(ME)	-0.0091	0.0968	0.0600	0.2513
	[-8.08]***	[8.63]***	[6.98]***	[10.88]***
BM	-0.0142	0.0538	0.0287	0.0978
	[-10.96]***	[3.31]***	[4.68]***	[3.28]***
Leverage	-0.0138	0.0403	0.0234	-0.1541
	[-1.78]*	[0.81]	[0.85]	[-1.57]
Cash	-0.0142	-0.0181	-0.0185	0.0228
	[-6.96]***	[-1.97]**	[-4.50]***	[1.19]
Loss	0.0253	0.0435	0.0175	0.1474
	[10.02]***	[1.99]**	[2.14]**	[3.43]***
Foreign Sales	-0.0044	-0.0220	0.0069	-0.0661
	[-1.13]	[-0.58]	[0.35]	[-0.86]
DD	-0.0041	0.0116	-0.0118	0.0705
	[-1.95]*	[0.47]	[-0.88]	[1.50]
ln(Age)	-0.0122	0.0162	-0.0656	0.4675
	[-4.76]***	[0.45]	[-2.30]**	[5.94]***
N	65,503	36,283	25,613	36,283
R^2	0.692	0.743	0.707	0.753
Firm FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Table 4: Employee Satisfaction Regression Estimates

This table presents coefficient estimates of employee satisfaction on the workforce diversity. The dependent variables are the Glassdoor rating in the next year. Employee satisfaction is first measured by the average rating on Glassdoor, ranging from one to five stars, for a given year. The evaluations encompass the following aspects: Overall, Career Opportunities (Career), Compensation & Benefits (Compensation), Work/Life Balance (WL Balance), Culture & Values (Culture), and Senior Management (Senior Mgt). The data on Glassdoor rating starts from 2008. As the alternative measure of employee satisfaction, the *Voluntary Turnover* ratio is calculated by subtracting the number of employees laid off from the number who left in the following year, scaled by the current total number of employees. The layoff data is from 2001 to 2020. *Diversity* is the average monthly percentage of minority employees over the previous twelve months. *Board Diversity*, ln(ME), BM, Leverage, Cash, Loss, Foreign Sales, zero dividends indicator (DD), and ln(Age) are included as control variables. Appendix Table A.1 presents the definitions of all variables. All regressions include firm and state-year fixed effects. Robust t-statistics are in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Glassdoor Ratings						Labor Flow
	Overall	Career	Culture	Senior Mgt	Compensation	WL Balance	Voluntary Turnover
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Diversity	0.5948	0.7274	0.8790	0.6438	-0.0073	0.2794	0.5398
	[1.82]*	[2.27]**	[2.01]**	[1.81]*	[-0.03]	[0.87]	[1.11]
Board Diversity	0.0973	0.1015	-0.1367	-0.0101	0.1364	-0.1110	0.2484
	[0.61]	[0.71]	[-0.77]	[-0.06]	[1.02]	[-0.69]	[0.91]
ln(ME)	0.0616	0.0853	0.0571	0.0714	0.0610	0.0036	0.0125
	[4.81]***	[7.29]***	[3.41]***	[5.14]***	[5.87]***	[0.28]	[0.82]
BM	-0.0293	-0.0145	-0.0409	-0.0414	-0.0017	-0.0266	-0.0394
	[-1.92]*	[-1.03]	[-1.66]*	[-2.61]***	[-0.13]	[-1.57]	[-2.40]**
Leverage	-0.0772	-0.0714	-0.0594	-0.0614	-0.0188	-0.0021	0.0873
	[-1.32]	[-1.31]	[-0.86]	[-1.00]	[-0.42]	[-0.04]	[0.90]
Cash	0.0996	0.1263	0.0993	0.1609	0.0219	0.0360	0.1395
	[3.26]***	[4.08]***	[2.94]***	[4.80]***	[0.90]	[1.20]	[1.85]*
Loss	-0.0039	-0.0223	0.0065	-0.0360	0.0332	0.0138	0.0463
	[-0.13]	[-0.70]	[0.17]	[-1.08]	[1.25]	[0.45]	[0.90]
Foreign Sales	0.0015	-0.0587	-0.0162	-0.0039	-0.0004	-0.0206	-0.0409
	[0.04]	[-1.48]	[-0.34]	[-0.09]	[-0.01]	[-0.55]	[-0.84]
DD	0.0002	0.0170	-0.0198	-0.0159	0.0234	-0.0077	0.0795
	[0.01]	[0.77]	[-0.67]	[-0.63]	[1.20]	[-0.32]	[1.67]*
ln(Age)	-0.0367	-0.0901	-0.0573	-0.0317	-0.0326	0.0843	-0.0009
	[-0.78]	[-2.01]**	[-0.91]	[-0.60]	[-0.85]	[1.91]*	[-0.01]
N	18,294	18,188	14,201	18,176	18,182	18,180	10,975
R^2	0.430	0.399	0.506	0.391	0.521	0.431	0.410
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Financial Performance and Valuation Regression Estimates

This table presents coefficient estimates of financial performance and valuation on workforce diversity. The dependent variables are the return on assets (ROA) in the next year and Tobin's *q* (Q) in the concurrent and the next years. ROA is measured as the net income scaled by assets in the previous year. Diversity is the average monthly percentage of minority employees over the previous twelve months. Q is measured as the ratio of the market value of a firm's equity and liabilities to the book value of equity and liabilities. *Board Diversity*, ln(ME), BM, Leverage, Cash, Loss, Foreign Sales, zero dividends indicator (DD), and ln(Age) are included as control variables. BM is omitted from the control set when Q is the dependent variable. In Columns (4) - (6), I rerun the tests on a high-tech industry sub-sample, based on the classification from Barron et al. (2002). Appendix Table A.1 presents the definitions of all variables. All regressions include firm and state-year fixed effects. Robust t-statistics are in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Full Sample			High-tech Industries		
	ROA_{t+1}	Q_t	Q_{t+1}	ROA_{t+1}	Q_t	Q_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)
Diversity	-0.0055	-0.7404	-0.4258	0.0135	-1.5280	-1.2796
	[-0.20]	[-2.61]***	[-1.50]	[0.26]	[-2.69]***	[-2.21]**
Board Diversity	0.0068	-0.1260	-0.1220	-0.0518	-0.2144	0.1511
	[0.32]	[-0.57]	[-0.59]	[-1.20]	[-0.48]	[0.34]
ln(ME)	0.0182	0.7084	0.2487	0.0262	1.0649	0.3053
	[8.81]***	[35.48]***	[15.23]***	[6.52]***	[27.90]***	[8.80]***
BM	-0.0172			-0.0016		
	[-7.19]***			[-0.23]		
Leverage	-0.0641	0.4633	0.3162	-0.0662	0.5671	0.3631
	[-4.95]***	[4.32]***	[3.13]***	[-2.59]***	[2.88]***	[1.95]*
Cash	0.0011	0.3788	0.0077	0.0053	0.2763	-0.0617
	[0.17]	[6.19]***	[0.32]	[0.62]	[3.67]***	[-2.18]**
Loss	-0.1333	0.2955	0.2230	-0.1631	0.4633	0.2892
	[-25.70]***	[7.29]***	[6.03]***	[-20.69]***	[6.59]***	[4.22]***
Foreign Sales	-0.0227	-0.4322	-0.3406	-0.0258	-0.5404	-0.3740
	[-2.92]***	[-6.24]***	[-5.19]***	[-1.85]*	[-4.35]***	[-3.00]***
DD	0.0100	-0.0102	-0.0915	0.0229	-0.0341	-0.1283
	[2.73]***	[-0.28]	[-2.56]**	[2.66]***	[-0.40]	[-1.45]
ln(Age)	0.0099	-0.4914	-0.4301	0.0450	-0.6335	-0.5965
	[2.39]**	[-10.84]***	[-10.13]***	[4.03]***	[-5.32]***	[-5.46]***
N	65,503	65,503	65,475	21,243	21,243	21,239
R^2	0.635	0.609	0.563	0.655	0.586	0.515
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Performance of Diversity-Based Trading Strategies

This table presents coefficient estimates from the calendar-time portfolio return analysis. Each month, firms are sorted into quintiles based on workforce diversity, which is the average monthly percentage of minority employees over the previous three months. The long (short) portfolio consists of firms with the highest (lowest) *Diversity*. The long-short portfolios are rebalanced monthly, and returns are computed using value-weighted specifications. Abnormal returns are assessed using the Fama and French (2015) five-factor and the Carhart (1997) model. Appendix Table A.1 presents the definitions of all variables. Monthly returns and alphas are reported in percentages for the long-short portfolio and each individual quintiles, and *t*-statistics are in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Full Sample	Post-2010	S&P1500	State adj. Diversity
	(1)	(2)	(3)	(4)
α (%)	0.628	0.382	0.534	0.527
	[3.59]***	[2.03]**	[3.67]***	[3.58]***
MP	0.217	0.238	0.19	0.232
	[4.22]***	[5.27]***	[4.36]***	[5.48]***
SMB	-0.516	-0.515	-0.418	-0.45
	[-11.47]***	[-6.30]***	[-8.41]***	[-8.54]***
HML	-0.227	-0.274	-0.258	-0.144
	[-2.08]**	[-1.69]*	[-2.79]***	[-1.15]
RMW	-0.459	-0.202	-0.448	-0.546
	[-6.52]***	[-2.43]**	[-5.73]***	[-6.86]***
CMA	-0.321	-0.409	-0.135	-0.213
	[-2.17]**	[-1.47]	[-1.07]	[-1.32]
UMD	-0.021	0.02	-0.01	-0.049
	[-0.46]	[0.24]	[-0.21]	[-1.42]
R^2	0.49	0.459	0.446	0.454
Raw long return (%)	1.22	1.6	1.234	1.216
Raw short return (%)	0.765	0.915	0.839	0.858
H = 5 (α%)	0.336	0.173	0.35	0.296
	[3.39]***	[1.44]	[3.87]***	[2.86]***
4 (α%)	0.05	-0.057	0.07	0.066
	[0.88]	[-1.02]	[1.04]	[1.24]
3 (α%)	-0.142	-0.022	-0.101	0.008
	[-2.08]**	[-0.28]	[-1.44]	[0.13]
2 (α%)	-0.109	-0.067	-0.084	-0.101
	[-1.49]	[-0.92]	[-1.08]	[-1.34]
L = 1 (α%)	-0.292	-0.209	-0.184	-0.231
	[-2.76]***	[-2.03]**	[-2.16]**	[-2.77]***
Starting Year	1990	2010	1990	1990

Table 7: Fama-MacBeth Cross-sectional Regression Estimates

This table presents coefficient estimates of Fama and MacBeth (1973) cross-sectional regressions of monthly returns on the workforce diversity. *Diversity* is the average monthly percentage of minority employees over the previous three months. *Board Diversity*, *ME* (firm size), *BM* (book-to-market), and $Ret_{-x,-y}$ (cumulative stock return from month *t-x* to month *t-y*, inclusive) are included as control variables. Appendix Table A.1 presents the definitions of all variables. *t*-statistics are in parentheses and are based on Newey and West (1987) standard errors corrected for autocorrelation using 12 lags. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Full Sample		Post-2010	S&P1500	State adj. Diversity
	(1)	(2)	(3)	(4)	(5)
Diversity	0.7095	0.7066	0.5505	1.4303	0.7132
	[1.82]*	[2.29]**	[2.07]**	[3.16]***	[2.53]**
Board Diversity	0.1377	0.1743	0.0777	0.1862	0.2278
	[0.38]	[0.55]	[0.18]	[0.62]	[0.66]
ln(ME)		-0.0169	0.0781	-0.2183	-0.0171
		[-0.36]	[1.16]	[-4.75]***	[-0.37]
ln(BM)		0.1385	0.1275	-0.0626	0.1360
		[1.45]	[1.20]	[-0.76]	[1.42]
Ret_{t-1}		-0.0299	-0.0189	-0.0243	-0.0301
		[-6.59]***	[-3.67]***	[-4.66]***	[-6.61]***
$Ret_{t-12, t-2}$		0.0015	0.0016	0.0014	0.0015
		[0.55]	[0.85]	[0.42]	[0.56]
$Ret_{t-36, t-13}$		-0.0018	0.0002	-0.0020	-0.0018
		[-2.07]**	[0.19]	[-2.35]**	[-2.06]**
N	735,796	712,919	326,727	348,882	712,203
R^2	0.004	0.047	0.039	0.072	0.046
Starting Year	1990	1990	2010	1990	1990

Table 8: Earnings Surprises Regression Estimates

This table presents coefficient estimates of Fama and MacBeth (1973) cross-sectional regressions of quarterly earnings surprises on the workforce diversity. Standardized unexpected earnings ($SUE_{i,t}$) is the actual earnings per share minus the consensus of analyst' forecasts scaled by the standard deviation. *Diversity* is the average monthly percentage of minority employees over the previous three months. Following So (2013), *E+, NEGE, ACC−, ACC+, AG, DD, DIV, PRC, and BM* are included as controls. *Board Diversity* is included as an additional control. Appendix Table A.1 presents the definitions of all variables. *t*-statistics are in parentheses and are based on Newey and West (1987) standard errors corrected for autocorrelation using 12 lags. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Full Sample	Post-2010	S&P1500	State Adj. Diversity
	(1)	(2)	(3)	(4)
Diversity	1.2225	1.3293	1.4491	0.9180
	[6.25]***	[5.14]***	[4.78]***	[3.21]***
Board Diversity	0.6071	2.3104	0.7120	0.8368
	[1.72]*	[8.02]***	[1.99]**	[2.25]**
E+	-0.0644	0.0025	-0.0430	-0.0676
	[-3.42]***	[0.12]	[-2.14]**	[-3.55]***
NEGE	-0.3316	-0.7731	-0.2282	-0.3256
	[-3.08]***	[-6.91]***	[-2.24]**	[-3.05]***
ACC+	-0.0005	0.0000	-0.0004	-0.0005
	[-1.24]	[0.10]	[-1.10]	[-1.17]
ACC-	-0.0002	-0.0002	-0.0002	-0.0002
	[-0.71]	[-2.13]**	[-0.68]	[-0.82]
AG	-0.1192	-0.1351	-0.1210	-0.1157
	[-2.70]***	[-3.22]***	[-2.30]**	[-2.61]***
DD	0.1741	0.2946	0.2100	0.1943
	[3.15]***	[6.07]***	[3.37]***	[3.49]***
DIV	0.0898	-0.0687	0.0722	0.0874
	[1.53]	[-1.51]	[1.02]	[1.49]
PRC	0.0029	0.0026	-0.0027	0.0031
	[1.61]	[2.14]**	[-1.49]	[1.72]*
BM	-0.2989	-0.3391	-0.2545	-0.3044
	[-3.28]***	[-5.12]***	[-3.10]***	[-3.31]***
N	287,406	153,729	188,726	287,200
R^2	0.036	0.033	0.042	0.035
Starting Year	1990	2010	1990	1990

Table 9: Earnings Announcements Returns Regression Estimates

This table presents coefficient estimates of Fama and MacBeth (1973) cross-sectional regressions of quarterly earnings announcement returns on the workforce diversity. Earnings announcement returns are the market-adjusted returns (abnormal returns defined in excess of CRSP value-weighted market return) over a three-day window centered around quarterly earnings announcements dates. *Diversity* is the average monthly percentage of minority employees over the previous three months. *Board Diversity*, *ME* (firm size) and *BM* (book-to-market) are included as controls. Appendix Table A.1 presents the definitions of all variables. *t*-statistics are in parentheses and are based on Newey and West (1987) standard errors corrected for autocorrelation using 12 lags. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Full Sample	Post-2010	S&P1500	State Adj. Diversity
	(1)	(2)	(3)	(4)
Diversity	0.4716	0.4399	1.1923	0.6786
	[1.80]*	[3.16]***	[4.35]***	[2.56]**
Board Diversity	0.4098	0.3016	0.2049	0.3814
	[1.76]*	[1.37]	[0.85]	[1.54]
ln(ME)	-0.0002	0.0516	-0.1763	-0.0015
	[-0.01]	[2.00]*	[-8.10]***	[-0.06]
ln(BM)	0.1898	0.1519	-0.0012	0.1886
	[7.90]***	[5.35]***	[-0.03]	[7.84]***
N	230,812	107,440	114,122	230,582
R^2	0.006	0.004	0.010	0.006
Starting Year	1990	2010	1990	1990

Table 10: Return Persistence Regression Estimates

This table presents coefficient estimates of Fama and MacBeth (1973) cross-sectional regressions of cumulative market-adjusted returns on the workforce diversity spanning across the subsequent 8 quarters. Each column corresponds to the cumulative market-adjusted returns in each subsequent quarter. *Diversity* is the average monthly percentage of minority employees over the previous three months. *Board Diversity*, *ME* (firm size), *BM* (book-to-market), and $Ret_{-x,-y}$ (cumulative stock return from month *t-x* to month *t-y*, inclusive) are included as control variables. Appendix Table A.1 presents the definitions of all variables. *t*-statistics are in parentheses and are based on Newey and West (1987) standard errors corrected for autocorrelation using 12 lags. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Diversity	2.2391	2.385	2.4999	2.5713	2.2857	1.8741	1.7516	1.472
	[2.39]**	[2.43]**	[2.35]**	[2.22]**	[1.82]*	[1.53]	[1.52]	[1.42]
Board Diversity	0.9617	1.0875	1.1948	1.4474	1.3476	1.2063	1.0543	0.7855
	[0.94]	[1.04]	[1.26]	[1.56]	[1.44]	[1.25]	[1.16]	[0.86]
ln(ME)	-0.143	-0.1975	-0.2112	-0.2104	-0.1803	-0.1665	-0.1367	-0.1039
	[-0.99]	[-1.34]	[-1.43]	[-1.36]	[-1.21]	[-1.13]	[-0.94]	[-0.74]
ln(BM)	0.3456	0.3283	0.2609	0.1859	0.2607	0.2718	0.2815	0.2975
	[1.14]	[1.13]	[0.84]	[0.54]	[0.77]	[0.83]	[0.89]	[1.00]
Ret_{t-1}	-0.0187	0.0071	0.0158	0.0037	-0.0219	-0.0251	-0.0091	0.0065
	[-2.09]**	[0.77]	[1.82]*	[0.41]	[-2.79]***	[-2.68]***	[-1.36]	[1.06]
$Ret_{t-12, t-2}$	0.0009	-0.0048	-0.0099	-0.0125	-0.0112	-0.0099	-0.0101	-0.0111
	[0.12]	[-0.69]	[-1.90]*	[-2.94]***	[-2.39]**	[-2.68]***	[-2.96]***	[-3.24]***
$Ret_{t-36, t-13}$	-0.0058	-0.004	-0.0022	-0.0018	-0.0004	0.0017	0.0011	-0.0002
	[-2.15]**	[-1.66]*	[-0.96]	[-0.79]	[-0.17]	[0.86]	[0.63]	[-0.16]
N	720,529	720,067	718,712	716,131	712,335	700,898	689,111	677,568
R^2	0.051	0.047	0.045	0.043	0.041	0.039	0.038	0.037

Table 11: ESG Rating Regression Estimates

This table presents coefficient estimates of the workplaces or social scores from different ESG rating agencies on the workforce diversity. In Column (1), the dependent variable is the CSR scores on employee relations and diversity in the next year from KLD. In Column (2), the dependent variable is the ESG social score from Refinitiv in the next year. *Diversity* is the average monthly percentage of minority employees over the previous twelve months. *Board Diversity*, ln(ME), BM, Leverage, Cash, Loss, Foreign Sales, zero dividends indicator (DD), and ln(Age) are included as control variables. Appendix Table A.1 presents the definitions of all variables. All regressions include firm and state-year fixed effects. Robust t-statistics are in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	KLD Employee Relations and Diversity	Refinitiv Social Score
	(1)	(2)
Diversity	0.2838	0.1241
	[0.52]	[1.44]
Board Diversity	0.1291	0.0684
	[0.40]	[1.42]
ln(ME)	0.0837	0.0149
	[2.96]***	[4.29]***
BM	0.0402	0.0057
	[1.52]	[1.77]*
Leverage	0.0467	0.0330
	[0.39]	[2.41]**
Cash	-0.1211	-0.0058
	[-2.16]**	[-1.20]
Loss	0.0020	0.0129
	[0.04]	[2.03]**
Foreign Sales	0.2417	-0.0152
	[2.97]***	[-1.22]
DD	-0.0092	-0.0201
	[-0.17]	[-2.94]***
ln(Age)	0.4262	0.0034
	[3.40]***	[0.20]
N	17,386	17,452
R^2	0.626	0.806
Firm FE	Yes	Yes
State×Year FE	Yes	Yes

Appendix A

Table A.1: Variable Definitions

Variable	Definitions	Source
Panel A: Diversity Measures		
Diversity	The average monthly percentage of minority non-executive employees over the previous three or twelve months.	Revelio Labs
Diversity Board	The percentage of minority board members in the fiscal year.	BoardEx
Panel B: Other Variables		
R&D Expenses	R&D expenses scaled by the total assets in the previous year.	Compustat
ln(1+N Patents)	The natural logarithm of one plus the number of patents.	Kogan et al. (2017)
Value per Patent	The total value of all patents scaled by the number of patents ($b).	Kogan et al. (2017)
ln(1+N Citations)	The natural logarithm of one plus the number of citations.	Kogan et al. (2017)
Overall	The average overall employer rating on Glassdoor, ranging from one to five stars, for a given year. Similarly, I formulate ratings for specific subcategories: Career Opportunities (Career), Compensation & Benefits (Compensation), Work/Life Balance (WL Balance), Culture & Values (Culture), Senior Management (Senior Mgt) and Diversity & Inclusion.	Glassdoor Rating, Job Cut Ann. Reports
Voluntary Turnover	The voluntary turnover ratio is calculated by subtracting the number of employees laid off from the number who left in the following year, scaled by the current total number of employees. The layoff data is from 2001 to 2020.	Revelio Labs,
Tobin's *q*	The market value of the firm's equity and liabilities scaled by the book value of the firm's equity and liabilities.	Compustat
ROA	The net income scaled by total assets in the previous year.	Compustat
Profit Growth	Profitability growth is measured as the percentage change of gross profitability ratio, where gross profitability is measured as the difference between revenues and cost of goods sold, scaled by total assets in the previous year.	Compustat
ln(ME)	The natural logarithm of market value of equity.	Compustat
BM	The book to market ratio as the book value of equity divided by the market value of equity. The book value of equity depends on availability in the following order: the shareholders' equity, or	Compustat, CRSP

	commons/ordinary equity. If both items are missing, the shareholders' equity is total assets minus total liabilities and minority interests.	
Leverage	The sum of short-term debt and long-term debt, divided by total assets.	Compustat
Cash	The cash and short-term investment scaled by total assets in the previous year.	Compustat
Loss	A dummy takes a value of one when operating income after depreciation (OIADPQ) is negative, and zero otherwise.	Compustat
Foreign Sales	The foreign sales scaled by the total sales.	Compustat Segments
DD	A dummy takes a value of one when the past 12-month dividends is zero, and zero otherwise.	CRSP
ln(Age)	The natural logarithm of the firm age, where the age is determined as the number of years since its IPO date, the first date in Compustat, or the first date in CRSP, whichever occurred earlier.	Compustat, CRSP
E+	Earnings per share when earnings are positive and zero otherwise.	Compustat
NEGE	A dummy takes a value of one when earning is negative, and zero otherwise.	Compustat
ACC+, ACC-	Negative and positive accruals per share, where accruals equal the change in current assets plus the change in debt in current liabilities minus the change in cash and short-term investments and minus the change in current liabilities.	Compustat
AG	The percent change in total assets.	Compustat
DIV	Dividends per share.	Compustat, CRSP
PRC	The share price at the end of the fiscal year.	Compustat
CSR Emp. Relation and Diversity Score	The difference of employee-related strength and concern indicators from KLD. Strength indicators include: Diversity Promotion, Work-life Balance, Women and Minority Contracting, Employment of the Disabled, Gay and Lesbian Policies, Diversity Other Strength, Union Relations, Cash Profit Sharing, Employee Involvement, Retirement Benefits Strength, Health and Safety Strength, and Employee Other Strengths. Concern indicators include: Diversity Controversies, Diversity Other Concerns, Union Relation Concerns, Health and Safety Concern, Workforce Reductions, Retirement Benefits Concern, and Employment Relations Other Concerns.	KLD
ESG Social Score	Social pillar score of ESG.	Refinitiv
JP_DEI, JP_EO	The number of words associated with diversity, equity, and inclusion (DEI) or with equal opportunity (EO), scaled by the number of job postings or the number of words.	LinkUP

Table A.2: Mid-Managers or Rank-and-File Employees

This table presents coefficient estimates when the main analyses are rerun, substituting the original diversity measure with separate diversity metrics for mid-level managers (MM) and rank-and-file (RF) employees. Panel A shows the summary statistics of the diversity measures on MM and RF. In Panel B, I revisit the outcomes related to firm innovation and employee satisfaction, as originally presented in Tables 3 and 4, but now in relation to gender diversity within the workforce. In Panel C, I apply the Fama and MacBeth (1973) cross-sectional regressions of monthly returns in Table 7 and SUE in Table 9 to the diversity measures on MM and RF. Appendix Table A.1 presents the definitions of all variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Panel A: Diversity Measures

	Mean	SD	25th Pct.	Median	75th Pct.
MM Diversity	0.168	0.124	0.087	0.149	0.224
RF Diversity	0.216	0.144	0.119	0.194	0.285

Panel B: Innovation and Employee Satisfaction Estimates

	Innovation			Employee Satisfaction	
	ln(1+N Patents)	Value per Patent	ln(1+N Citations)	Career	Culture
	(1)	(2)	(3)	(4)	(5)
MM Diversity	0.4349	0.1568	0.2142	0.6369	0.7146
	[2.94]***	[2.81]***	[0.90]	[2.28]**	[1.89]*
RF Diversity	0.2348	0.1383	0.3415	0.1575	0.3027
	[1.93]*	[3.54]***	[1.71]*	[0.63]	[0.92]
Board Diversity	0.3622	0.0363	-0.4228	0.0937	-0.1487
	[2.39]**	[0.55]	[-1.48]	[0.65]	[-0.84]
N	36,283	25,613	36,283	18,188	14,201
R^2	0.744	0.707	0.753	0.399	0.506
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes

Panel C: Return and SUE Estimates

	Return		SUE	
	(1)	(2)	(3)	(4)
Diversity	0.7066		1.2225	
	[2.29]**		[6.25]***	
MM Diversity		0.6863		1.4767
		[2.72]***		[5.50]***
RF Diversity		0.0966		-0.0176
		[0.43]		[-0.07]
Board Diversity	0.1743	0.1740	0.6071	0.5538
	[0.55]	[0.56]	[1.72]*	[1.59]
N	712,919	704,065	287,406	286,955
R^2	0.047	0.048	0.036	0.037
Controls	Yes	Yes	Yes	Yes

Table A.3: Replication of Main Findings on Gender Diversity

This table presents coefficient estimates when the main findings are mirrored using gender diversity. The workforce gender diversity measure is defined in an analogous manner as workforce racial/ethnic diversity. Panel A shows the summary statistics of gender diversity. In Panel B, I revisit the outcomes related to firm innovation and employee satisfaction, as originally presented in Tables 3 and 4, but now in relation to gender diversity within the workforce. In Panel C, I apply the trading strategy detailed in Table 6 to the context of workforce gender diversity. Appendix Table A.1 presents the definitions of all variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Panel A: Gender Diversity Measures

	Mean	SD	25th Pct.	Median	75th Pct.
Gender Diversity	0.419	0.154	0.308	0.399	0.518
Board Gender Diversity	0.146	0.114	0.063	0.136	0.217

Panel B: Innovation and Employee Satisfaction Estimates

	Innovation			Employee Satisfaction	
	ln(1+N Patents)	Value per Patent	ln(1+N Citations)	Career	Culture
	(1)	(2)	(3)	(4)	(5)
Diversity	-0.1189	-0.0895	-0.7034	-0.0652	-0.0229
	[-0.68]	[-1.16]	[-2.47]**	[-0.22]	[-0.05]
Board Diversity	0.0937	0.0268	-0.0419	-0.0079	-0.1574
	[0.67]	[0.44]	[-0.16]	[-0.07]	[-1.12]
N	36,283	25,613	36,283	18,188	14,201
R^2	0.743	0.706	0.753	0.398	0.505
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes

Panel C: Trading Strategy on Gender Diversity

	Full	From 2010	S&P1500	State Adj.
	(1)	(2)	(3)	(4)
α (%)	0.038	0.218	-0.019	0.085
	[0.22]	[0.97]	[-0.11]	[0.57]
MP	-0.137	-0.221	-0.077	-0.129
	[-2.01]**	[-4.57]***	[-1.33]	[-1.95]*
SMB	-0.31	-0.183	-0.387	-0.033
	[-3.08]***	[-1.75]*	[-3.83]***	[-0.32]
HML	0.339	0.028	0.273	0.231
	[2.58]***	[0.26]	[1.60]	[1.88]*
RMW	0.499	0.032	0.355	0.31
	[3.23]***	[0.29]	[2.42]**	[2.37]**
CMA	-0.092	-0.024	-0.072	-0.319
	[-0.63]	[-0.11]	[-0.46]	[-2.18]**
UMD	0.018	0.079	0.006	0.017
	[0.25]	[0.74]	[0.08]	[0.29]
R^2	0.326	0.149	0.268	0.128
Starting Year	1990	2010	1990	1990

Table A.4: Hiring Activities

This table presents coefficient estimates of the workforce diversity on the hiring activities. The dependent variable is the concurrent workforce diversity, *Diversity*, which is the average monthly percentage of minority employees over the previous twelve months. *JP_DEI* (*JP_EO*) is measured as the number of words associated with diversity, equity, and inclusion (equal opportunity), scaled by the number of job postings or the number of words. *Board Diversity*, ln(ME), BM, Cash, Loss, zero dividends indicator (DD), D/P Ratio and ln(Age) are included as control variables. Appendix Table A.1 presents the definitions of all variables. All regressions include firm and state-year fixed effects. Robust t-statistics are in parentheses and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Scaled by No. of Job Postings			Scaled by No. of Words		
	(1)	(2)	(3)	(4)	(5)	(6)
JP_DEI	0.0006			0.0495		
	[1.61]			[0.64]		
JP_EO		0.0002			0.0026	
		[0.80]			[0.11]	
JP_DEI & EO			0.0002			0.0061
			[1.26]			[0.31]
Board Diversity	0.0335	0.0335	0.0334	0.0335	0.0335	0.0335
	[3.75]***	[3.75]***	[3.74]***	[3.75]***	[3.75]***	[3.75]***
ln(ME)	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008
	[1.05]	[1.07]	[1.06]	[1.07]	[1.07]	[1.07]
BM	0.0003	0.0003	0.0003	0.0004	0.0004	0.0004
	[0.45]	[0.46]	[0.45]	[0.47]	[0.47]	[0.47]
Leverage	-0.0020	-0.0020	-0.0020	-0.0019	-0.0019	-0.0019
	[-0.55]	[-0.55]	[-0.55]	[-0.53]	[-0.53]	[-0.53]
Cash	-0.0025	-0.0026	-0.0025	-0.0026	-0.0026	-0.0026
	[-1.72]*	[-1.72]*	[-1.71]*	[-1.73]*	[-1.73]*	[-1.73]*
Loss	0.0016	0.0017	0.0016	0.0016	0.0017	0.0017
	[1.09]	[1.11]	[1.10]	[1.10]	[1.10]	[1.10]
Foreign Sales	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	[-0.01]	[-0.03]	[-0.02]	[-0.04]	[-0.04]	[-0.04]
DD	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
	[0.27]	[0.28]	[0.27]	[0.28]	[0.29]	[0.29]
ln(Age)	0.0038	0.0039	0.0038	0.0040	0.0040	0.0040
	[0.92]	[0.94]	[0.92]	[0.96]	[0.97]	[0.97]
Observations	10,570	10,570	10,570	10,570	10,570	10,570
R^2	0.981	0.981	0.981	0.981	0.981	0.981
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes

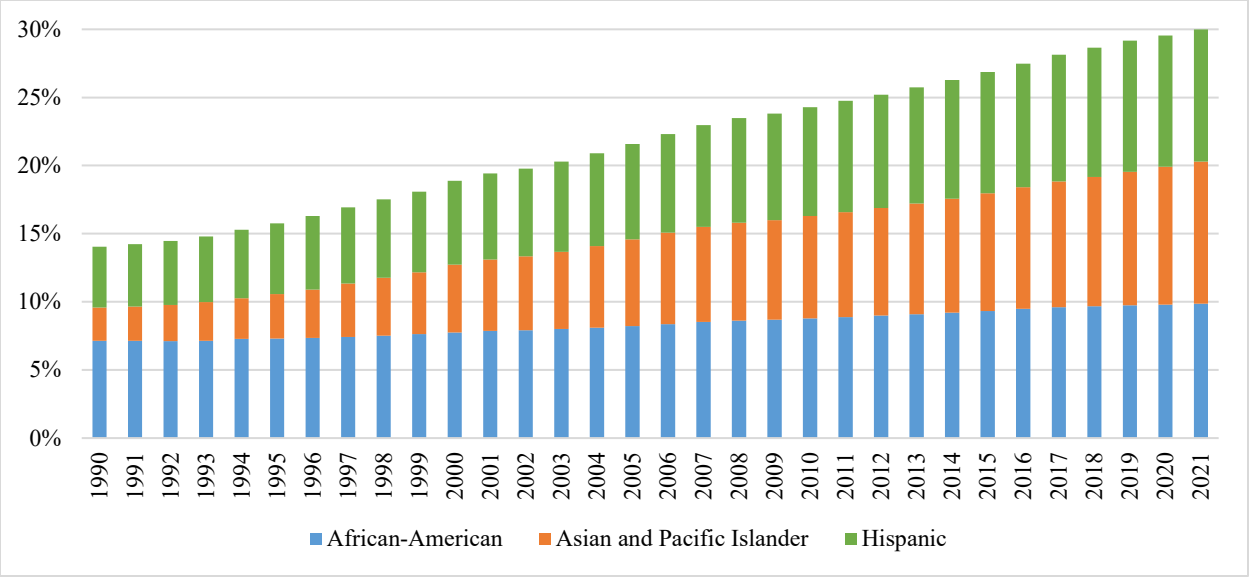


Figure A.1: The figure illustrates the time-series trend of each minority race/ethnic groups during my sample period.