Challenging the Diversity-Productivity Narrative: Evidence from U.S. Firms

Jeffrey L. Callen
Rotman School of Management
University of Toronto
callen@rotman.utoronto.ca

Dan Segal
Reichman University and Warwick University
dsegal@runi.ac.il

Zhongnan Xiang
Warwick Business School
Warwick University
Zhongnan.Xiang@wbs.ac.uk

Challenging the Diversity-Productivity Narrative: Evidence from U.S. Firms

Abstract

We utilize workforce gender and racial diversity data from mandated EEO-1 forms to determine if workforce diversity at the managerial and rank-and-file levels affect firm-level efficiency and productivity. Efficiency is measured by Data Envelopment Analysis (DEA). Productivity is measured both by a DEA-based Malmquist Index and by the (residual) dynamic production function approach of Ackerberg et al. (2015). Overall, the results are not consistent with the hypotheses that workplace diversity increases production efficiency and/or increases productivity, contrary to the popular view that workplace diversity is beneficial to firm production operations. Rather, the evidence suggests that, if anything, racial diversity *increases* inefficiency and *reduces* productivity. These results are consistent with the view that labor frictions from a diverse labor force offset benefits from diversity. Indeed, further analysis shows that racial diversity is associated with a more negative perception of their company by employees.

1. Introduction

The purpose of this study is to determine the impact of workforce diversity on U.S. firm-level efficiency and productivity at the rank-and-file and middle/lower management levels. By diversity we refer to (i) gender diversity, (ii) racial/ethnic diversity, and (iii) overall diversity as measured by the combination of the two dimensions. We posit that if workforce diversity has consequences for firm outcomes, it should manifest most strongly in areas where diversity is likely to have an immediate and direct impact—namely, firm production. But the direction of the impact is unclear ex ante. On the one hand, greater workforce diversity could result in the dissemination of new technical and human resource skills among workforce participants enabling them to learn from each other when implementing both established and new production practices. Workforce diversity could enhance talent utilization, team problem-solving quality, creativity, innovation, and leadership breadth. These potential positive aspects of workforce diversity should yield more efficient production and enhanced productivity. On the other hand, greater workforce diversity could result in lower productivity and efficiency, as frictions induced by gender and/or race differences reduce workplace cohesion, create misunderstandings, exacerbate conflicts, disrupt decision-making processes, and make consensus harder to achieve. Thus, the net impact of workforce diversity on firm-level efficiency and productivity remains an empirical issue.

Although linking workforce diversity to firm-level outcomes has long been a desideratum, the paucity of U.S. diversity data at the rank-and-file and lower management levels has prevented comprehensive analyses until recently. Indeed, this study is made possible only by the recent public release of a unique data set of Type 2 EEO-1 forms mandated by the Department of Labor for the years 2016 to 2020 inclusive. These forms contain detailed standardized demographic breakdowns of firms' workforces at both the managerial and rank-and-file worker levels. The newly released data are relatively free from endogeneity concerns, although not completely immune, even when excluding voluntary disclosers. On the positive side, because the data were released in 2023, three years after the relevant data period of 2016-2020, it is unlikely that these diversity data were managed to conform to public pressure regarding diversity. However, on the negative side, the data were released only for those firms that did not object to the release, leaving open the possibility that firms with "poor" diversity are not reflected in the released data.[1]

[1] We address some of the potential effects of endogeneity in Section 5.6.

We measure firm-level efficiency using Data Envelopment Analysis (DEA), a non-parametric frontier approach widely used in the productivity literature. We measure firm-level total factor productivity (TFP) in two ways. First, we calculate a DEA-based Malmquist productivity index, which measures shifts in firms' production frontiers over time and is grounded in the theory of distance functions. Second, we estimate firm-level total factor productivity (TFP) growth using the dynamic production function approach of Olley and Pakes (1996), as extended by Ackerberg et al. (2015). This approach explicitly addresses endogeneity concerns as they relate to input-output decisions and productivity.

Our empirical findings consistently suggest that workforce diversity, whether measured by race or gender, is not positively associated with firm efficiency or productivity. Across multiple specifications and diversity dimensions, we observe either insignificant or negative relationships, implying that the potential coordination and communication frictions introduced by greater diversity may, on balance, outweigh the hypothesized benefits in operational settings. Further decomposition analyses reveal that these patterns are predominantly driven by racial diversity, while gender diversity exhibits weaker and more heterogeneous effects. We further explore whether alignment in diversity across organizational layers matters for performance but find limited evidence that diversity congruence between executives and non-executives plays a significant role. To complement these results, we examine employee perceptions using Glassdoor data and find that racial diversity is either negatively or insignificantly related to perceptions of management quality, company outlook, and overall satisfaction. These findings suggest that employees' subjective experiences mirror the observed operational outcomes, reinforcing the interpretation that racial diversity introduces frictions into the workforce environment that reduce organizational effectiveness.

In what follows, Section 2 briefly reviews the extant literature on diversity focusing on studies that employ EEO-1 diversity data. Section 3 describes the EEO-1 data and provides descriptive statistics. Section 4 outlines the measures of technical efficiency and productivity used in this study, with more technical descriptions relegated to appendices. Section 5 presents the main analysis. Section 6 reports the sensitivity analyses. Section 7 concludes.

2. Brief Literature Review and Hypothesis

The literature on the effect of diversity on firm outcomes is quite large. Indeed, diversity has been conceptualized in many ways such as gender, race, ethnicity, culture, birthplace, occupation, work experience, religion, education, and demographic characteristics (Harrison and Klein 2007; Van Knippenberg and Schippers 2007). A growing body of research across economics, management, psychology and sociology emphasizes that diversity has a positive effect on firm performance through multiple channels. Diversity in demographics and cognitive backgrounds can enhance group problem-solving and decision-making by introducing varied perspectives and experiences (Page 2008; Hong and Page 2004). These studies further demonstrate that groups characterized by greater cognitive diversity may outperform more homogeneous, high-ability groups when addressing complex or novel problems. Moreover, diversity can stimulate creativity and innovation by introducing non-redundant knowledge (Østergaard et al. 2011), broaden firms' market understanding and customer reach (Cox and Blake 1991), improve adaptability in dynamic environments (Ely and Thomas 2001), and enhance decision-making quality by mitigating groupthink (Rock and Grant 2016).

Empirical studies provide supporting evidence that workforce diversity can promote firm innovation and productivity. For instance, Parrotta et al. (2014) show that ethnic diversity is positively associated with firm productivity in Denmark, although the effect is contingent on management quality. Nathan (2014) further documents that firms in regions with higher levels of skilled migrant diversity experience greater innovation outputs. In the context of organizational performance, Richard et al. (2007) find that racial diversity improves a firm's long-term performance especially when the firm operates in munificent rather than resource-scarce environments. In the corporate governance literature, Carter et al. (2003) provide early evidence that board diversity in terms of gender and race correlates with higher firm value. Collectively, these findings support the notion that diversity has the potential to enhance firm outcomes, although the realized benefits often depend on the organizational and environmental context and can be offset by the coordination and communication challenges that diverse groups introduce.

While diversity can enhance creativity and problem-solving, it may also introduce coordination challenges that negatively affect group functioning and firm performance. Scholars arguing for negative effects of diversity often draw on the similarity-attraction paradigm and social identity theory (Williams and O'Reilly 1998; Tajfel 1982). According to these theories, individuals prefer to affiliate with others who share similar social category memberships, and experience greater trust, communication ease, and collaboration within homogeneous groups. In contrast, diversity can increase interpersonal dissimilarities that trigger categorization processes, leading to the formation of in-groups and out-groups, heightening intergroup biases, and escalating relational conflict (Pelled 1996; Tsui et al. 1992). Such social divisions can impair cooperation, hinder information sharing, and ultimately reduce organizational cohesion and performance (Blau, 1977; Taylor, 1981). Empirical research supports these mechanisms, suggesting that, while diverse groups may possess broader informational resources, they also face greater barriers to integration and effective communication, particularly in settings requiring high levels of coordination (Ely and Thomas 2001; Smith et al. 1994). Thus, the organizational benefits of diversity are not automatic and may be offset by the social frictions that diversity introduces.

Prior studies in accounting and finance primarily focus on the diversity of top management teams or boards of directors, leaving workforce-level diversity relatively unexplored. Much of this literature investigates gender or racial diversity at the board level, linking it to firm performance, governance quality, and risk-taking behavior (e.g., Adams and Ferreira 2009; Bernile et al. 2018). Studies that expand beyond the boardroom, such as Richard et al. (2021) and Richard et al. (2007), rely on survey data, small samples, or voluntary disclosure, raising concerns about selection bias. Further, diversity studies based on non-US data may fail to generalize.

This lack of US workforce-level diversity data can be addressed to some extent by the recent release of EEO-1 reports, and several studies have begun to leverage this new resource. Bourveau et al. (2023) conduct a descriptive analysis of diversity patterns in a sample of approximately 800 firms, documenting significant underrepresentation of minority groups at the managerial level. They also find that racial diversity is positively associated with a firm's decision to disclose its EEO-1 report, suggesting potential selection biases in public diversity disclosures. Bratek et al. (2023) examine equity market reactions to EEO-1 disclosures and find that firms with greater workforce diversity, particularly racial diversity, experience more favorable stock returns and exhibit higher accounting-based performance measures such as ROA and Tobin's Q. However, their study does not directly investigate the operational mechanisms linking diversity to firm outcomes. Kim (2024) focuses on the concept of word-deed alignment in diversity initiatives, showing that firms whose workforce composition lags behind their public diversity commitments suffer stock price penalties around the disclosure event. While these studies highlight the informational value of EEO-1 reports, they primarily emphasize disclosure and investor reaction rather than a more direct relationship between diversity and firms' production efficiency or productivity.

In addition to these studies using mandated EEO-1 disclosures, a small number of papers examine workforce diversity based on voluntarily disclosed EEO-1 data, though voluntary disclosure raises more acute concerns about selection bias. Daniels et al. (2024) document positive stock price reactions for firms in the technology and financial sectors that voluntarily disclose relatively high gender diversity. Harit et al. (2025) extend this line of inquiry using a broader Bloomberg-collected sample, finding that workforce gender diversity positively impacts firm innovation, value, and workplace outcomes, particularly in firms with supportive organizational cultures. Richard et al. (2021), whose study is most closely related to ours, link racial diversity in upper and lower management to higher labor productivity among high-tech firms that voluntarily disclosed EEO-1 data. While their findings are important, their reliance on labor productivity (rather than total factor productivity), the focus solely on management rather than the broader workforce, and the voluntary nature of their sample limit the generalizability of their results.

We hypothesize in this paper that workforce diversity affects firms' production activities as measured by technical efficiency and productivity. The study by Richard et al. (2021), along with common wisdom, suggests that workforce diversity should positively affect firm efficiency and productivity. Nevertheless, since the impact of diversity on production is unclear ex ante as we noted above, we posit the following non-directional hypothesis:

Hypothesis: Workforce diversity affects firms' technical efficiency and productivity.

3. Diversity Data Sources, Variable Construction, and Sample Selection

3.1 EEO-1 Reports

Pursuant to the Civil Rights Act of 1964, comprehensive filings of workplace diversity data were initially mandated by the Equal Employment Opportunity Commission (EEOC) in standardized EEO-1 reports. All private sector employers with 100 or more employees and federal contractors with 50 or more employees (meeting certain criteria) are legally required to file an annual EEO-1 report with the EEOC. These reports are filed confidentially and kept confidential by the federal government, with only a minority of firms voluntarily disclosing these reports—or a summary of them—publicly in their 10-K filings or on their websites. While EEO-1 reports are not made publicly available, U.S. government contractors are required to share their reports with the U.S. Department of Labor's Office of Federal Contract Compliance Programs (OFCCP).

In June 2022, the confidentiality of these reports was challenged when a reporter from the Centre for Investigative Reporting submitted a Freedom of Information Act (FOIA) request to the OFCCP, requesting the release of all Type 2 EEO-1 reports filed by U.S. contractors from 2016 and 2020. After receiving the FOIA request, the OFCCP notified federal contractors of the disclosure demand through several methods, including publication in the Federal Register, postings on the OFCCP's website, individualized emails, and letters sent through the U.S. Mail. The OFCCP provided contractors with the opportunity to object to the disclosure of this information and informed them that if no objection was received, the requested EEO-1 data would be disclosed.

The OFCCP released the EEO-1 data in three stages. The first release was a partial release of consolidated Type 2 EEO-1 data for 2016-2020, including only entities that affirmatively consented to disclosure. The second release included contractors from whom the OFCCP received no objection, and additional entities that affirmatively consented to the release of their data. The third release consolidated all previous releases and included an additional 162 reports of entities that were determined to be federal contractors who had not respond to the OFCCP's notice confirming their status as a federal contractor. The OFCCP made several data adjustments to the data to ensure accuracy, including correcting inaccuracies in the 2017 submissions and removing reports from entities that were found not to have been federal contractors during the relevant period.

EEO-1 reports provide a standardized, detailed breakdown of the company's workforce by gender, race/ethnicity, and job category. Gender is reported as either male or female, with the option to include non-binary employees in a separate comments section. Race and ethnicity are divided into seven categories, including six specific groups (i.e., American Indian and Alaska Native, Asian, Black, Hispanic/Latino, Native Hawaiian and other Pacific Islander, and White) and an additional category for individuals identifying with two or more races. Employees self-identify their ethnicity, and employers place each employee into one of 10 job categories (e.g., senior-level officials and managers, mid-level officials and managers, professionals, technicians).

3.2 Diversity Sample Selection and Variable Construction

Table 1 presents our sample selection procedure. We obtain workplace demographics from Type 2 EEO-1 reports provided by the U.S. Department of Labor's (DOL) website.[2] Our initial dataset consists of 56,649 filings from 2016 to 2020 inclusive, covering over 23,000 public and private U.S. contractors. We match these reports with the Compustat-CRSP universe using contractor names through a fuzzy matching process.[3] This matching process yields 4,112 observations from 1,169 unique public firms. Next, we collected firm characteristics such as firm size, book-to-market ratio, leverage, profitability, and cash holdings from Compustat and remove observations with missing values. This process leaves us with 3,496 records from 1,008 unique firms.[4]

To measure workforce diversity, we calculate the proportions of 14 worker types, based on combinations of two gender categories and seven race categories (e.g., male American Indian, female Asian). In the spirit of the Herfindahl-Hirschman index and consistent with the literature, we calculate overall diversity (*DIVERS_GR*) as:

$$DIVERS\_GR = 1 - \sum_1^i PERC\_GR_i{}^2 \qquad (1)$$

where $PERC\_GR_i$ represents the proportion of each worker type i. For a maximally diversified firm with workers equally distributed across all 14 types, *DIVERS_GR* equals 0.93.

We also separately measure gender diversity (*DIVERS_G*) and racial diversity (*DIVERS_R*) as:

$$DIVERS\_G = 1 - \sum_1^j PERC\_G_j{}^2 \qquad (2)$$

$$DIVERS\_R = 1 - \sum_1^k PERC\_R_k{}^2 \qquad (3)$$

where $PERC\_G_j$ and $PERC\_R_k$ represent the proportions workers in gender category j and race category k, respectively. The maximum value of *DIVERS_G* is 0.5 (achieved with equal

[2] For access to these reports, see: https://www.dol.gov/agencies/ofccp/foia/library/Employment-Information-Reports.

[3] The fuzzy matching process involves the following steps: (1) Removing common words (e.g., "corp", "company", "inc", "co") from both the EEO reports and the Compustat-CRSP universe; (2) Standardizing nomenclature by replacing similar terms with consistent alternatives (e.g., "holdings" to "hldg", "technology" to "tech", "industry" to "ind", "international" to "intl"); (3) Matching the two lists of names using Jaro-Winkler distance and retaining the top five matches; (4) Manually verifying the matching results.

[4] Our sample is further reduced when we merge data on firm efficiency and productivity in the next section.

gender representation) and the maximum value of *DIVERS_R* is 0.86 (achieved with equal racial representation across all seven categories).

Since EEO-1 reports provide a breakdown of the workforce by job category, we further calculate overall diversity measures for both executive positions (senior-level officials and managers) and non-executive positions (all other categories). We denote these measures as *DIVERS_GR_E* (executive-level) and *DIVERS_GR_NE* (non-executive-level). To conduct a more detailed analysis, we disaggregate the metrics by gender and race, yielding four additional measures: executive-level gender diversity (*DIVERS_G_E*), non-executive gender diversity (*DIVERS_G_NE*), executive-level racial diversity (*DIVERS_R_E*), and non-executive racial diversity (*DIVERS_R_NE*). Appendix A provides detailed definitions of all variables.

3.3 Diversity Measure Summary Statistics

Table 2 presents a summary of the diversity measures. Panel A summarizes the diversity measures from 2016 to 2020, showing a noticeable increase in diversity across all measures during this period. The overall diversity index rose steadily from 0.64 in 2016 to 0.67 in 2020.[5] This upward trend obtains at both the executive level, which increased from 0.41 to 0.48, and the non-executive level, which increased from 0.64 to 0.67 over the same period. The change in diversity is driven primarily by racial composition, as gender diversity remains relatively stable among non-executives over the sample period.[6] At the executive level, however, we observe an increase in gender diversity. Race diversity increases monotonically among both executives and non-executives. These trends appear to reflect the gradual success of ongoing corporate initiatives to promote workforce diversity.

We also observe greater diversity among non-executives than executives. When examining gender and racial diversity separately, the disparity between executives and non-executives is more pronounced for racial diversity; whereas racial diversity is 0.46 in 2020 among non-executive, it is 0.23 among executives. Although race diversity improved over the period, the gap between executive and non-executive levels persists. These results suggest that

[5] For illustration, in a company with 1,400 employees, this represents a shift from: white male 630 (45%) and white female 490 (35%) to white male 560 (40%) and white female 420 (30%), while minority representation increased from black male 140 (10%), black female 70 (5%), and other groups 70 (5%) to black male 210 (15%), black female 112 (8%), and other groups 98 (7%). While a 0.03 change might seem small numerically, it represents a substantial shift in workforce composition.

[6] The increase in racial diversity is primarily driven by higher proportions of Black and Hispanic employees.

racial barriers to executive positions remain significant and are more substantial than those faced by women.

Panel B of Table 2 demonstrates significant variation in diversity measures across industries. The healthcare and utilities industries exhibit the highest and lowest levels of workforce diversity respectively. The healthcare industry leads in almost all aspects of diversity. Certain other industries show distinct patterns: the chemicals industry is more diversified at the executive level than the non-executive level, and the finance industry shows higher gender diversity than racial diversity. Regarding the gap between executive and non-executive levels, the utilities industry shows the smallest disparity, while the wholesale and retail industry shows the largest. These findings highlight the influence of industry-specific factors, such as workforce composition and prevailing industry norms, on diversity levels.

Panel C presents workforce diversity across states, illustrating that geographical location plays a significant role in workforce diversity. States with larger urban populations, such as California and New York, exhibit higher overall diversity scores of around 0.7. Conversely, states with smaller populations or less urbanization, such as North Dakota, show lower overall diversity scores of around 0.43. Some states display distinct diversity patterns: for instance, Alabama shows higher racial diversity than gender diversity, while Iowa and Maine show the opposite trend. These geographic variations underscore the influence of demographic and socioeconomic factors on workforce composition, highlighting the importance of regional characteristics in diversity analysis. Additionally, the disparity between executive and non-executive diversity levels varies substantially across states without following any clear geographic pattern.

Panel D explores the persistency of diversity measures over time within firms. The results indicate that there is little variation in diversity over time. The serial correlations among all diversity measures are over 0.8, with some of them close to 1, and are all highly significant, showing that firms maintain consistent diversity levels year over year. This stability suggests the sustained nature of diversity efforts within organizations and a long-term commitment to inclusion once these practices are established.

4. Firm Level Technical Efficiency and Productivity Measurement

4.1 Technical Efficiency

Technical efficiency measures the pure wastage of resources by the firm irrespective of input/output prices. In what follows, we measure technical efficiency (*TE*) using Data Envelopment Analysis (DEA) for each industry separately. Input and output usages of each firm in the industry are benchmarked relative to a convex combination of the inputs and outputs of all other firms in the industry. The distance of the firm's inputs and outputs from the latter benchmark (along a ray from the origin) constitutes the measure of technical efficiency.[7] DEA is described more fully in Appendix B. In this study, *TE* is measured based on an output distance function that allows for variable returns to scale. *TE* and the productivity measures that follow are calculated using annual data over the period of 2010 to 2020, inclusive.

4.2 Total Factor Productivity and Malmquist Indices

Productivity, also known as technical change, is the shift in the firm's production frontier over time. Under specific assumptions regarding the firms' objectives, the form of the industry production function and the aggregation index, productivity can be measured theoretically by the log change in Total Factor Productivity (TFP) where TFP is the ratio of the firm's aggregated weighted outputs to aggregated weighted inputs.

Under further assumptions about the production function and nature of technical change, the log change in TFP can be measured empirically by Malmquist Indices—see the development by Caves et al. (1982). Moreover, following Fare et al. (1992, 1994), we estimate the Malmquists indices using DEA, consistent with how we measured technical efficiency. See Appendix C for more detail.

For both technical efficiency and the Malmquist Index, output is measured in value-added terms as revenues less the cost of materials. In addition to the intermediate input of materials, other inputs include labor and capital. Materials are computed as total operating expenses excluding labor costs, R&D expenses, and depreciation. Labor is the number of firm employees. Capital is measured as the sum of Property Plant and Equipment (PPE) and intangible assets. PPE is computed on a net basis (less depreciation), plus capitalized leases.

[7] DEA was first developed by Charnes et al. (1981) on intuitive grounds and was subsequently extended by Banker et al. (1984) based on axiomatic foundations. Surveys of DEA include Callen (1998), Cooper et al. (2006), Liu et al. (2013), Kaffash et. al. (2020), among others.

Intangibles are measured by reported intangibles plus capitalized R&D expenses (amortized over 5 years). Industries are defined by 3-digit SIC codes.

4.3 The Ackerberg et al. (2015) TFP Measure

The Ackerberg et al. (2015) residual TFP productivity measure is based on a different conceptual framework from that of the DEA-based Malmquist index.[8] Conceptually, TFP here is the portion of output not explained by the quantity of inputs used in production—a residual-based approach. TFP increases as inputs are used more efficiently to produce outputs. The firm is assumed to operate under a log-linear dynamic Cobb-Douglas production function with output measured in value added terms (i.e., revenues minus material costs). Inputs are capital, labor, a productivity shock and a random mean-zero error term. The firm is assumed to choose its inputs prior to seeing (or forecasting) the productivity shock, which is visible only to the firm itself. Under the latter assumption, estimating the production function is challenging from an endogeneity perspective. Given that the researcher, unlike the firm, cannot directly observe or estimate the productivity shock, the productivity shock becomes a correlated omitted variable. Appendix D describes the assumptions underlying the model and the method by which the productivity shock can be identified empirically. In the empirical analysis, output and inputs are measured as above for the TE and Malmquist Index.

4.4 TFP Growth

As noted with regards to the Malmquist Index, productivity as a metric of technological change measures the shift of the production frontier over time. By contrast, the Ackerberg et al. (2015) TFP measure is a levels measure. One can convert the Ackerberg et al. (2015) TFP from a levels-type measure to a growth measure following Chun et al. (2011, 2016), who define TFP growth as:

$$\Delta\ln(TFP_{i,t}) = \Delta\ln(Y_{i,t}) - 1/2\,[S_{L,i,t} + S_{L,i,t-1}]\,\Delta\ln(L_{i,t}) - 1/2\,[S_{K,i,t} + S_{K,i,t-1}]\,\Delta\ln(K_{i,t}) \qquad (4)$$

where Δ is a first difference operator, Y denotes value added output, L the labor input, K the capital input, S_L share of firm's labor costs and S_K share of the firm's capital costs.[9] In the empirical analyses reported below, we use TFP growth rather than the level of TFP because the latter better conforms to the underlying theory than the latter.

---

[8] In addition to the economics literature, the Ackerberg et al. (2015) productivity measure has also been used in the finance literature (see Bennett et al., 2020).

[9] See Bournakis and Mallick (2018).

5. Research Design and Empirical Results

5.1 Research design

To examine the effect of the diversity on efficiency and productivity, we utilize the general "Within-Between Random Effects" (WBRE) regression model of Bell and Jones (2015) and Bell et al. (2019). This model is more general than standard fixed and random effects panel data methods. The WBRE model provides inter alia estimated coefficients (called Within coefficients) and standard errors *identical* to those of fixed effects models. In addition, the WBRE model provides cross-sectional (time invariant) fixed effects coefficient estimates (called Between coefficients) that would be netted out in a standard fixed effects regression. Often, the latter coefficients are at the heart of the hypothesis being tested. As noted by Bell et al. (2019), the WBRE model is closely aligned with, but more general than the well-known Mundlak (1978) regression formulation.

The WBRE regression model takes the form:

$$\boldsymbol{OUTCOMES_{j,t}} = \boldsymbol{\alpha_0} + \textstyle\sum_k \boldsymbol{\alpha_k}\,(\boldsymbol{X_{,j,t}} - \overline{\boldsymbol{X}}_{,j}\,) + \textstyle\sum_k \boldsymbol{\beta_k}\,\overline{\boldsymbol{X}}_{\boldsymbol{j}} + \boldsymbol{\beta_j Z_j} + \ \boldsymbol{\varepsilon_{j,t}}. \quad (1)$$

In this formulation, each of the *k* panel data regressors, including the diversity proxy, is decomposed into a "with-in effect" term $(\boldsymbol{X_{j,t}} - \overline{\boldsymbol{X}}_{\boldsymbol{j}})$ and a "between effect" term $\overline{\boldsymbol{X}}_{\boldsymbol{j}}$ where *k* is the number of covariates, *j* denotes industries, *t* time and the $\overline{\boldsymbol{X}}_{\boldsymbol{j}}$ are time-averaged means. Zj is the industry fixed effects dummy. The parameters α_k and β_k are estimated by panel data random effects.[10] Bell and Jones (2015) and Bell et al. (2019) emphasize that this random-effects panel-data regression formulation has many benefits. Most importantly for our purposes, unlike panel data fixed-effects estimation that essentially abstracts away from cross-sectional analyses, the between effects allow us to test in a more meaningful fashion the cross-sectional hypothesis that is at the heart of this study.

Specifically, the WBRE panel data regression format is especially useful when there is potential heterogeneity in the diversity measure across industries and time. This regression format indicates both (1) how differences in diversity *across* industries may lead to different economic

[10] We use industries (3-digits SIC), not firms, as the main time-invariant fixed effect for two reasons. First, efficiency and productivity are measured relative to an industry benchmark; hence, one cannot compare the efficiency and productivity scores of companies from different industries unless one controls for industry time-invariant fixed effects. Second, the time series spans over four years and changes in diversity over such a short period are quite small at the firm level. Another potentially important variable is state fixed effects. In addition, we also control for state fixed effects because states differ in terms of their racial diversity, which likely affects firm-level diversity.

consequences, *and* (2) how the dynamics of diversity over time may lead to different economic consequences within the industry. These clearly need not be the same. It may be that differences across industries are far more important in explaining the impact of the diversity on productivity than are the dynamics within the industry, or vice versa. We let the data decide.

The outcome variables include technical efficiency and the two productivity measures discussed above. The diversity measures are those defined in Equations (1)-(3). We further include a set of control variables known to influence firm productivity and efficiency: firm size (*SIZE*), book-to-market ratio (*BTM*), and financial leverage (*LEV*).

5.2 Sample and Summary Statistics

The sample size varies across our efficiency and productivity measures—see Table 1. The technical efficiency analysis is based on 2,816 firm-year observations from 862 unique firms. The Malmquist productivity analysis is based on a sample of 1,913 firm-year observations for 616 unique firms. The Ackerberg et al. (2015) productivity analysis is based on 2,494 (767) firm-year (firm) observations.

Table 3 presents descriptive statistics for our main variables. Panel A reports summary statistics for diversity measures, operational outcomes, and firm characteristics. The overall diversity index (*DIVERS_GR*) has a mean of 0.654, with values ranging from 0.184 to 0.873, indicating a relatively high level of diversity on average, but with significant variation across firms. Gender diversity (*DIVERS_G*) exhibits a mean of 0.397 and ranges from 0.051 to 0.500, suggesting that while some firms have achieved full gender parity, many still lag. Race diversity (*DIVERS_R*) shows greater dispersion, with a mean of 0.436 and values spanning from 0.000 to 0.764, highlighting varying levels of racial inclusion across firms.

At the executive level, the diversity index (*DIVERS_GR_E*) averages 0.442, with a minimum of 0.000 and a maximum of 0.814, reflecting substantial differences in executive team composition. Gender diversity at the executive level (*DIVERS_G_E*) is relatively lower (mean = 0.309), while race diversity at the executive level (*DIVERS_R_E*) has a mean of 0.203, indicating that racial diversity among top executives is more limited than in the broader workforce. In contrast, non-executive diversity measures are consistently higher, with an overall diversity (*DIVERS_GR_NE*) mean of 0.655, gender diversity (*DIVERS_G_NE*) mean of 0.396, and race diversity (*DIVERS_R_NE*) mean of 0.440, suggesting that diversity initiatives are more effective at lower organizational levels.

In terms of firm operational performance, technical efficiency (*TE*) demonstrates substantial heterogeneity, with a mean of 0.531 and a range from 0.060 to 1.000, indicating varying levels of operational efficiency. The Malmquist productivity index (*MALM*) exhibits an average of 1.026, reflecting moderate productivity growth, though the wide range suggests that some firms achieve markedly higher improvements. Total factor productivity (*TFP_OP*) displays considerable dispersion, ranging from 0.425 to 5.790, highlighting significant differences in firms' ability to convert inputs into outputs. Finally, productivity growth (*TFP_GR*) remains modest on average at 0.010, with notable variation across firms, including instances of both negative and positive growth.

Turning to firm characteristics, our sample firms are relatively large, with a mean market value of around $3 billion, book-to-market ratio of 0.46, and leverage of 0.26.

Panel B compares our sample firms to the broader Compustat universe. Our sample firms tend to be larger with lower leverage. In addition, our sample firms are more efficient.

5.3 Main Results

Table 4 reports our baseline regression results examining the relationship between *overall* workforce diversity and operational outcomes, using the Within-Between Random Effects (WBRE) framework.

First, technical efficiency (*TE*) is negatively associated with overall diversity, as indicated by a negative and statistically significant coefficient on the within-firm diversity measure (p-value < 0.1). This result suggests that when a firm experiences an increase in diversity over time, its production efficiency tends to decline. Such a finding aligns with the view that, while workforce diversity has the potential to promote creativity and innovation, it can also introduce short-run operational frictions. In particular, greater diversity may exacerbate communication barriers, complicate team coordination, and generate conflicts that impair the efficient use of inputs, especially in environments that lack strong mechanisms for managing a diverse workforce.

Second, the results for productivity, measured by the Malmquist Index (*MALM*) and the growth of Total Productivity Factor (*TFP_GR*), show a negative association with diversity at the between-firm level. Specifically, firms with higher average diversity over the sample period tend to exhibit lower productivity growth compared to firms with lower average diversity. The between-firm findings suggest that persistent differences in diversity across firms are linked to differences in long-term productivity trajectories. This outcome is consistent with the notion that, although diversity may offer latent advantages in knowledge breadth and adaptability, those advantages may not materialize automatically. Without deliberate efforts to foster inclusion and mitigate potential labor frictions, greater diversity at the organizational level may instead be associated with less efficient use of resources and lower technological advancement.

Moreover, the distinction between the within- and between-firm effects is critical for interpreting these results. The within-firm effect on efficiency suggests that even marginal increases in diversity can pose coordination challenges at the operational level. Meanwhile, the between-firm effects on productivity indicate that broader organizational factors—such as cultural alignment, managerial practices, and historical workforce composition—may mediate the long-term impacts of diversity on firm productivity trajectories.

The results for control variables are largely consistent with expectations from prior literature. A higher book-to-market ratio (*BTM*) is associated with lower efficiency and productivity, consistent with the notion that firms facing more adverse growth prospects or structural disadvantages perform less well operationally. Financial leverage (*LEV*) also tends to be negatively associated with firm outcomes, suggesting that firms under greater financial pressure may be less able to invest in processes and practices that enhance technical efficiency or productivity.

Overall, the evidence presented in Table 4 does not support the hypothesis that workforce diversity, in its aggregate form, improves firm production efficiency or productivity. Rather, the results suggest that the potential advantages of diversity may be offset by costs associated with labor market frictions and coordination difficulties, at least in the absence of effective management practices.

5.4 Decomposition analysis

Following the main analysis, we decompose aggregate diversity into components to investigate whether the effects of workforce diversity differ across various dimensions, such as gender, race, and organizational hierarchy. This additional analysis is motivated by the possibility that aggregate measures of diversity may mask important nuances in how diversity influences firm outcomes. By breaking down diversity into more specific categories, we aim to explore whether its impact is more pronounced in certain contexts or organizational levels.

Table 5 presents the results of decomposing overall workforce diversity into its gender and racial components. The findings indicate notable differences between these two aspects. Gender diversity does not exhibit a statistically significant relationship with either technical efficiency or productivity outcomes. Whether considering changes in gender diversity within firms over time or differences across firms, the estimated coefficients are small in magnitude and lack statistical significance. This suggests that, in the context of our sample, shifts in the gender composition of the workforce are not systematically associated with variations in production efficiency or productivity growth.

In contrast, racial diversity shows a stronger and more consistent association with firm outcomes. Increases in racial diversity within firms are negatively and significantly associated with technical efficiency, as reflected by a significant within-firm coefficient (p-value < 0.05). Furthermore, cross-sectional differences in racial diversity across firms are negatively associated with both productivity measures, as shown by significant between-firm coefficients (p-values < 0.01). These results suggest that racial heterogeneity, while potentially enriching in terms of ideas and perspectives, may also introduce operational frictions that hinder firms' ability to manage production processes and sustain productivity improvements over time. The decomposition underscores that the adverse effects observed for overall diversity are primarily attributable to the racial, rather than gender, composition of the workforce.

Table 6 separately decomposes workforce diversity into executive and non-executive segments, offering a different perspective on where within the organizational hierarchy diversity matters most. The results indicate a differentiated pattern. Diversity among non-executive workers is significantly negatively associated with technical efficiency within firms, as shown by a strong and statistically significant within-firm coefficient (p-value < 0.01). This suggests that day-to-day operational activities, which involve non-executive workers more directly, are particularly sensitive to the coordination and cohesion challenges that greater diversity may pose. In contrast, diversity among executive-level employees shows a more pronounced association with productivity outcomes at the between-firm level. Specifically, firms with higher average executive diversity exhibit lower long-term productivity growth, as indicated by a negative and significant between-firm coefficient (p-value < 0.05) for the Malmquist index. This pattern implies that diversity at the leadership level may influence the strategic direction, innovation management, and overall productivity potential of firms, but with effects that manifest over longer horizons rather than immediately through operational efficiency.

Table 7 offers a full decomposition, analysing both racial and gender diversity separately within executive and non-executive ranks. This more granular breakdown reveals a nuanced set of findings. Racial diversity continues to play a central role in explaining the negative relationship between diversity and firm outcomes. At the executive level, racial diversity is negatively associated with technical efficiency at the between-firm level (p-value < 0.01) and productivity (p-value<0.1), suggesting that greater heterogeneity in top management teams may complicate strategic alignment and hinder firms' ability to achieve high levels of operational performance. At the non-executive level, racial diversity is negatively related to both technical efficiency (within-firm), and productivity and productivity growth (between-firm), indicating that racial heterogeneity among the broader workforce affects not only short-term operational execution but also long-term productivity trajectories.

The results for gender diversity in Table 7 are more heterogeneous. Executive gender diversity is negatively associated with productivity (between-firm) but positively associated with productivity growth (within firm). The results concerning non-executives are also mixed – with negative effect on efficiency (within firm) and positive effect on productivity (between firm). However, the significance of these positive effects disappears in the 2SLS analysis further below.

The overall findings of these tables suggest that efficiency and productivity are either unrelated or negatively to racial diversity irrespective of the organizational level. The results are more nuanced as far as gender diversity is concerned. Whereas in most cases the gender diversity results are either insignificant or negative there are two exceptions where gender diversity has a positive impact on productivity (but not efficiency)—but see below when accounting for average gender endogeneity. The results also suggest the technical efficiency is negatively related to some forms of diversity. These findings may appear counterintuitive given the widespread belief that workforce diversity can enhance organizational performance through improved decision-making, greater innovation, and enhanced adaptability. However, the almost uniform absence of significant coefficients, and the negative impact of some diversity components on technical efficiency, suggest that diversity's potential impact might be more complex or context dependent. It is possible that the effects of diversity are subtle, in that positive aspects of diversity are offset by labor frictions, or contingent on other unobserved factors.

5.5 Additional analysis – Congruence of diversity

Building on our previous findings of distinct diversity effects across hierarchical levels, we explore whether the alignment—or congruence—between executive and non-executive diversity influences operational outcomes. To explore this question, we construct a variable representing the difference between non-executive and executive diversity levels (DIFF_DIVERS). This difference measures the degree of alignment, where a smaller absolute difference indicates greater congruence.

Table 8, Panel A presents the regression results. Columns (1), (3), and (5) show the relation between efficiency/productivity and the overall difference in diversity between the non-executive and executive ranks (diversity congruency). The other columns show congruency results when we separate overall diversity into gender and race diversity. The overall relation between diversity and performance remains negative and significant (between firms). However, diversity congruence does not play a major role in explaining firm efficiency or productivity. Most of the coefficients on the difference measures—whether considering overall diversity, racial diversity, or gender diversity—are statistically insignificant. This finding indicates that the simple gap in diversity between executive and non-executive employees, by itself, is not a strong predictor of firms' operational outcomes. In other words, it is not necessarily the case that firms perform better when diversity levels are aligned across organizational layers, nor that performance worsens when there is a mismatch, contrary to the findings of Richard et al. (2021).

In the few cases where the congruence measures are statistically significant, the direction of the effect is somewhat counterintuitive. Specifically, greater incongruence—that is, a larger gap in diversity levels between executives and non-executives—is associated with better productivity outcomes at the between-firm level. For instance, the difference in racial diversity between executive and non-executive ranks shows a positive and significant between-firm association with technical efficiency (p-value < 0.1), and differences in overall and gender diversity are positively related to the Malmquist productivity index (p-values < 0.1). These positive coefficients suggest that firms where executives and non-executives differ more in diversity composition may, in some contexts, achieve higher productivity growth.

One possible interpretation of these findings is that when firms maintain relatively less diverse executive teams compared to their more diverse non-executive workforces, they may preserve certain elements of hierarchical control, decision-making speed, or organizational cohesion at the top management level, while simultaneously benefiting from the broader talent pool and perspectives present in the wider workforce. However, this explanation is speculative, and the predominantly insignificant results caution against overinterpreting isolated significant coefficients. Overall, the evidence does not strongly support the view that diversity congruence across organizational levels is a critical determinant of firm efficiency or productivity. Instead, it appears that absolute diversity levels, particularly in racial composition and at specific organizational layers, matter more for explaining firm performance outcomes.

5.6 Additional Analysis- Endogeneity and Average Gender Diversity

Work by Adams (2024) and others indicate that gender diversity studies often suffer from selection biases especially at the management level. Women who "make it" to management and technical positions are often ambitious and quite different in ability and risk aversion by comparison to the general female population. Therefore, we might expect that on average women, and especially women managers, gravitate to industries over time which are more efficient and productive, resulting in simultaneity. To address this endogeneity issue, we analyse the impact of gender diversity on efficiency and productivity using a 2-stage least squares analysis. More specifically, following the approach of Steele et al. (2007), we estimate a multilevel random effects model based on equation (1) together with an equation relating average gender diversity to variables that might explain average gender diversity such as industry, state, efficiency, and productivity. Unlike standard two-stage least squares, endogeneity here also arises because of correlation between unobservables at the industry level rather than at the individual women level. Following, Harit et al. (2024), we instrument for average gender diversity using (1) the percentage of females on the under-40 Fortune list by industry and year and (2) growth in childcare and childcare development fund expenditures reported by state. The coefficient estimates (untabulated) show that only the percentage of females on the under-40 Fortune loads significantly in the first stage but that this instrument has no significant impact on efficiency or productivity in the second stage.[11]

5.7 Additional Analysis- Glassdoor Perceptions

While our primary analyses focus on the relationship between workforce diversity and firm-level efficiency and productivity, these operational outcomes do not directly capture how diversity is experienced or perceived within organizations. Employee perceptions are a critical

[11] Regression results are available from the authors.

yet often overlooked dimension of organizational effectiveness, particularly in relation to diversity management. To this end, we complement our main findings by examining employee sentiment data from Glassdoor. This analysis serves two purposes: first, to assess whether perceptions of diversity within firms are aligned with actual demographic composition; and second, to explore whether these perceptions are consistent with the productivity and efficiency implications observed in our main results. By incorporating employee-level sentiment, we aim to provide a more comprehensive understanding of how diversity shapes both the operational and social fabric of firms.

To operationalize this analysis, we utilize Glassdoor data that captures employee perceptions about their company across four key dimensions: company diversity, the overall company satisfaction, company outlook, and management effectiveness.[12] Higher rating scores indicate greater employee satisfaction. Table 9 shows the relationship between each employee perception metric and diversity. More specifically, we regress each of the four employee perceptions (diversity, overall, outlook, and management) on the several diversity measures we constructed previously: (a) overall workforce diversity, (b) separate gender and race diversity measures, and (c) disaggregated gender and race diversity at the non-executive level—except in the case of management perception, where the gender and race diversity are measured at the executive level.

The results show positive and significant relationship between diversity perception and overall diversity (at the 10% level), gender diversity (at the 1% level), and non-executive gender diversity (at the 1% level).[13] These results indicate that perceptions of diversity are, unsurprisingly, positively related to actual diversity. More notably, consistent with our findings on efficiency and productivity, race diversity is either insignificant or significantly negatively associated with overall satisfaction, company outlook, and management perception (at the 1% levels). These results suggest that employee perceptions align with actual efficiency/productivity outcomes, in that racial diversity does not appear to be a positive factor in firm operations.

[12] There are also data on culture, work-life balance, and compensation, but these are less relevant to our study.
[13] We include ROA in addition to the other covariates in this analysis because employee perceptions of the firm are likely affected by firm profitability.

6. Conclusion

Although many have argued that workforce diversity should have a positive effect on firm productivity, evidence is sparse. Richard et al. (2021) show that managerial workplace racial diversity has a positive effect on *labor* productivity for a sample of high-tech firms that *voluntarily* released EEO-1 data prior to 2023. They find that racial diversity congruence between upper and lower management positively impacts firm productivity and that organizations with high levels of racial diversity in both upper and lower management realized superior labor productivity compared to organizations with low levels of racial diversity in both upper and lower management. While their results are interesting, their sample sizes are small, they are focused solely on managerial diversity and labor productivity, and their results are based on voluntary EEO-1 diversity disclosures. In contrast, this study is far more comprehensive, based as it is on both managerial and rank-and-file workforce productivity, total factor productivity, and mandated EEO-1 diversity disclosure. Our sample size is relatively large. We find that overall managerial diversity and rank-and-file diversity either have no significant discernable impact on firm level efficiency/productivity or the effect is negative. These results are consistent with labor frictions induced by having a diverse labor force offsetting positive benefits if any from workforce diversity.

APPENDIX A: Variable Definition

Variable	*Definition*
Variables for diversity	
DIVERS_GR	Overall workforce diversity, calculated as 1 minus the sum of the squared proportions of 14 worker types, defined by combinations of gender and race, as shown in Equation (1).
DIVERS_G	Gender diversity, calculated as 1 minus the sum of the squared proportions of worker types, defined by two gender categories, as shown in Equation (2).
DIVERS_R	Racial diversity, calculated as 1 minus the sum of the squared proportions of worker types, defined by seven race categories, as shown in Equation (3).
DIVERS_GR_E	Overall workforce diversity among executive-level workers.
DIVERS_G_E	Gender diversity among executive-level workers.
DIVERS_R_E	Ratio diversity among executive-level workers.
DIVERS_GR_NE	Overall workforce diversity among non-executive workers.
DIVERS_G_NE	Gender diversity among non-executive workers.
DIVERS_R_NE	Ratio diversity among non-executive workers.
DIFF_DIVERS_GR	Absolute difference in overall workforce diversity between non-executive (*DIVERS_GR_NE*) and executive workers (*DIVERS_GR_E*).
DIFF_DIVERS_G	Absolute difference in overall workforce gender diversity between non-executive (*DIVERS_G_NE*) and executive workers (*DIVERS_G_E*).
DIFF_DIVERS_R	Absolute difference in overall workforce ratio diversity between non-executive (*DIVERS_R_NE*) and executive workers (*DIVERS_R_E*).
Variables for output (i.e., productivity and efficiency)	
TE	Technical efficiency measured using an output-oriented Data Envelopment Analysis (DEA) model under variable returns to scale. See Appendix B for details.
MALM	Productivity change measured by the Malmquist Productivity Index, which captures changes in a firm's productivity across two periods using output distance functions estimated via DEA. See Appendix C for details.
TFP_GR	Total factor productivity growth estimated using the Ackerberg et al. (2015) dynamic production function approach, which captures firm-level productivity shocks inferred from intermediate input demand. See Appendix D for details.
Variables for firm characteristics	
SIZE	Natural logarithm of one plus the firm's market value.
BTM	Book-to-market equity ratio, calculated as book value of equity divided by market value of equity.

LEV	Financial leverage, measured as total debt divided by total assets.
ROA	Return on assets, measured as extraordinary items divided by total assets.
Variables for Glassdoor employee perception	
GD_DIVERS	Employee's overall rating of diversity on a five-point scale, with five (one) being most favorable (unfavorable).
GD_OVERALL	Employee's overall rating of employer ranked on a five-point scale, with five (one) being most favorable (unfavorable).
GD_OUTLOOK	Employee's opinion of his or her opportunities for career prospects at the company ranked on a five-point scale, with five (one) being most favorable (unfavorable).
GD_MNGT	Employee's opinion of employer's senior management ranked on a five-point scale, with five (one) being most favorable (unfavorable).

Appendix B: Technical Efficiency and DEA

Technical efficiency was first defined by Farrel (1957) as the distance between the firm's inputs/outputs and the industry production frontier along a ray from the origin.[14] Distance can be defined either in terms of an output distance function or an input distance function and further allowing for constant returns to scale or variable returns to scale. Both the output distance function and input distance function consistently indicate which firms are efficient and which are inefficient, although the efficiency numbers will generally differ from each other unless the production function exhibits global constant returns to scale. In this study we measure efficiency based on an output distance function and allow for variable returns to scale.

More specifically, technical efficiency can be defined by the time t output distance function:

$$D^t(x^t, y^t) = \text{infimum } \{\theta: (x^t, y^t/\theta): (x^t, y^t) \in S^t\}$$

where S^t denotes the time t production technology. The distance function measures the infimum (or minimum) amount θ by which the vector of outputs y^t needs to be reduced radially so that is producible by the vector of inputs x^t given the production technology S^t.

Measuring technical efficiency for firms with multiple outputs and inputs is challenging and that is where DEA comes in. DEA involves the use of linear programming methods to construct a non-parametric piecewise linear production frontier based on the input-output data of all firms in the industry. Convex combinations of the efficient firms in the industry comprise the (empirical) production frontier whereas technically inefficient firms deviate from the frontier. DEA was first proposed by Charnes, Cooper, and Rhodes (1978) (hereafter, CCR) on intuitive grounds, and later axiomatized by Banker, Charnes and Cooper (1984). Based on these axioms and the assumption of piecewise linearity, technical efficiency can be measured by reference to an output distance function as in the following linear program:

$$TE = D^t(x^t, y^t) = \ minimize\ \theta \ \text{ wrt the } \lambda_i's$$

subject to:

$$\sum_{i=1}^{N} \lambda_i Y_{ri} \geq \theta * Y_{r0} \qquad r = 1, \ldots, s$$

[14] Measuring distance along a ray from the origin results in efficiency metrics that are independent of the units by which the inputs/outputs are measured, for example pounds versus kilograms.

$$\sum_{i=1}^{N} \lambda_i X_{ki} \leq X_{k0} \qquad k = 1, \ldots, m$$

$$\sum_{i=1}^{N} \lambda_i = 1 \qquad with\ \lambda_i \geq 0 \quad i = 1, \ldots., N$$

There are N firms in the industry denoted by i=1,…,N. There are s outputs Y_{ri} for each firm denoted by r=1,…,s. There are m inputs X_{ki} for each firm denoted by k=1,…,m. The λ_i are weights. The program chooses a set of weights for each firm (including the firm being evaluated denoted by the 0 subscript) to minimize the technical inefficiency of the firm being evaluated subject to the constraints that the firm in question cannot use less inputs than the frontier, nor produce more outputs than the frontier after adjusting for output inefficiency. Variable returns to scale obtain by requiring the weights to sum to one. This program is run for each firm in the industry thereby generating a measure of technical (in)efficiency θ for each firm. θ equals one for efficient firms and is less than one for inefficient firms.[15]

[15] This is not quite correct if there is pure slack/surplus and the weight is zero on the slack input/output. See Cooper et al. (2006)

Appendix C: Productivity and the Malmquist Index

The (output) Malmquist Index M^t is defined as:

$$M^t = D^t (x^{t+1}, y^{t+1}) / D^t (x^t, y^t)$$

where the output distance function $D^t (x^t, y^t)$ is defined in Appendix B. The Malmquist Index is the ratio of the technical efficiency of the year t+1 input-output combinations to the time t input-output combinations assuming the same production technology S^t in both years. In essence, the Malmquist index measures how much more productive the firm is in time t+1 in generating output relative to time t, had the production technology not changed over the two time periods.

Recognizing that firms may be both inefficient yet productive at the same time, based on the fundamental theoretical work by Caves et al. (1982), Fare et al. (1989) suggest measuring productivity by the Malmquist Productivity Index which is the geometric mean of the time t and time t+1 Malmquist Indices and defined as:

$$MPI = [D^t (x^{t+1}, y^{t+1}) / D^t (x^t, y^t) \cdot D^{t+1} (x^{t+1}, y^{t+1}) / D^{t+1} (x^t, y^t)]^{1/2}$$

The benefit of this metric is that the firm's productivity is measured after adjusting inputs and outputs for technical inefficiencies both in periods t and t+1. One can further decompose MPI into a pure Efficiency Change Index (ECI) and a (pure) Productivity Change Index (PCI) as follows:

$$MPI = ECI \times PCI$$

where

$$ECI = D^t (x^{t+1}, y^{t+1}) / D^t (x^t, y^t)$$

$$PCI = [D^t (x^{t+1}, y^{t+1}) / D^{t+1} (x^{t+1}, y^{t+1}) \cdot D^t (x^t, y) / D^{t+1} (x^t, y^t)]^{1/2}$$

The Malmquist Productivity Index (and its decomposition) can be measured by four DEA programs for each firm to obtain each of $D^t (x^{t+1}, y^{t+1})$, $D^t (x^t, y^t)$, $D^{t+1} (x^{t+1}, y^{t+1})$, and $D^{t+1} (x^t, y^t)$. As previously, $D^t (x^t, y^t)$ and $D^{t+1} (x^{t+1}, y^{t+1})$ can be obtained by running the program above for each of period t and period t+1 inputs and outputs, respectively. Furthermore, $D^t (x^{t+1}, y^{t+1})$ can be obtained by running the program:

$$minimize\ \theta \text{ wrt the } \lambda_i' s$$

subject to:

$$\sum_{i=1}^{N} \lambda_i Y_{ri}^{t} \geq \theta * Y_{r0}^{t+1} \qquad r = 1, \ldots, s$$

$$\sum_{i=1}^{N} \lambda_i X_{ri}^{t} \leq X_{r0}^{t+1} \qquad k = 1, \ldots, m$$

$$\sum_{i=1}^{N} \lambda_i = 1 \qquad with\ \lambda_i \geq 0 \quad i = 1, \ldots., N$$

This same program can be run to obtain $D^{t+1}(x^t, y^t)$ by reversing t for t+1.

APPENDIX D: The Ackerberg et al. (2015) Dynamic Production Function and Productivity Shocks

Dynamic production functions raise significant endogeneity issues. Although the firm may be able to observe or forecast productivity shocks before making input decisions, the same cannot be said for the researcher for whom future productivity is normally unobservable. This identification issue was addressed in a substantive fashion by Olley and Pakes (1996), further extended by Levinsohn and Petrin (2003), and more recently extended further by Ackerberg et al. (2015).

We adopt the semi-parametric identification approach by Ackerberg et al. (2015) in this study. They assume a time dependent log linear Cobb-Douglas value-added production function, which is a function of capital, labor, an intermediate input such as materials, a productivity shock and an error term. They further assume that: (1) the firm's information set includes current and past productivity shocks (but not future shocks) and that conditional on the information set, transitory shocks are mean zero; (2) Future productivity shocks are Markovian and dependent only on the current period productivity shock; (3) Firms accumulate capital dynamically this period based on past period capital and investment and labor is dynamic and chosen either in the current or past periods; (4) Firm's demand for the intermediate input—such as materials (or investment) is a function of current capital, labor and productivity; and where (5) the latter demand function is monotonic in productivity. These assumptions allow one to invert the intermediate input demand function to infer the current (otherwise unobservable to the researcher) productivity shock as a function of capital, labor and intermediate demand. Under these assumptions, the value-added production function can be estimated in a two-stage approach using a generalized method of moments.

For a relatively uncomplicated technical description of the semi-parametric identification approaches of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) approaches, see Section 2.3 of Bournakis and Mallick (2018) and Appendix C of Bennet et al. (2020).

References

Ackerberg, D. A., K. Caves, and G. Frazer. 2015. Identification properties of recent production function estimators. *Econometrica* 83 (6): 2411-2451.

Adams, R. B., and D. Ferreira. 2009. Women in the boardroom and their impact on governance and performance, *Journal of Financial Economics* 94 (2): 291-309.

Adams, R. B. 2024. Women (and men) in finance are not typical, *Revue D'économie Financière*. Forthcoming.

Balakrishnan, M., J. Nam, and R. Buell. 2022. Differentiating on diversity: How disclosing workforce diversity improves brand attitudes. Working Paper. Harvard University.

Banker, R. D., A. Charnes, and W. W Cooper. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 30 (9): 1078-1092.

Bell, A., M. Fairbrother, and K. Jones. 2019. Fixed and random effects models: Making an informed choice. *Quality & Quantity* 53: 1051-1074.

Bell, A., and K. Jones. 2015. Explaining fixed effects: Random effects modelling of time-series cross-sectional and panel data. *Political Science Research Methods* 3 (1): 133–153.

Bennett, B., R. Stulz, and Z. Wang, 2020. Does the stock market make firms more productive?. *Journal of Financial Economics* 136 (2): 281-306.

Bernile, G., V. Bhagwat, and S. Yonker. 2018. Board diversity, firm risk, and corporate policies. *Journal of Financial Economics* 127 (3): 588-612.

Blau, P. M. 1977. *Inequality and heterogeneity: A primitive theory of social structure*. New York: Free Press.

Bournakis, I, and S. Mallick. 2018. TFP estimation at firm level: The fiscal aspect of productivity convergence in the UK. *Economic Modelling* 70: 579-590.

Bourveau, T., R. W. Flam, and A. Le. 2023. Behind the EEO curtain. Working paper. Columbia University, and London Business School.

Bratek, F., A. Klein, and C. Shi. 2023. Do investors value workplace diversity?. Working paper. New York University, and HEC Paris

Callen, J. L. 1991. Data envelopment analysis: Partial survey and applications for management accounting. *Journal of Management Accounting Research* 3 (1): 35-56.

Carter, D. A., B. J. Simkins, and W. G. Simpson. 2003. Corporate governance, board diversity, and firm value. *Financial Review* 38 (1): 33-53.

Caves, D. W., L. R. Christensen, and W. E. Diewert. 1982. The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica* 50 (6): 1393-1414.

Charnes, A., W. W. Cooper, and E. Rhodes. 1981. Evaluating program and managerial efficiency: An application of data envelopment analysis to program follow-through. *Management Science* 27 (6):668-697.

Choi, J. H., M. McNichols, and M. Muhn. 2024. Decoding social disclosure decisions: A field experiment with workforce diversity data. Working paper. Stanford University, and University of Chicago.

Chun, H., J. W. Kim, and R. Morck. 2011. Varying heterogeneity among us firms: Facts and implications. *Review of Economics & Statistics* 93 (3): 1034–1052.

Chun, H., J. W. Kim, and R. Morck. 2016. Productivity growth and stock returns: Firm- and aggregate-level analyses. *Applied Economics* 48 (38): 3644–3664.

Cooper, W. W., L. M. Seiford, and K. Tone. 2006. *Introduction to data envelopment analysis and its uses: with DEA-solver software and references*. Springer Science & Business Media.

Cox, T. H., and S. Blake. 1991. Managing cultural diversity: Implications for organizational competitiveness. *Academy of Management Perspectives* 5 (3): 45-46.

Daniels, D. P., J. E. Dannals, T. Z, Lys, and M. A. Neale. 2025. Do investors value workforce gender diversity?. *Organization Science* 36 (1): 313-339.

Ely, R. J., and D. A. Thomas. 2001. Cultural diversity at work: The effects of diversity perspectives on work group processes and outcomes. *Administrative Science Quarterly* 46 (2): 229-273.

Färe, R., S. Grosskopf, C. A. K. Lovell, and C. Pasurka. 1989. Multiple productivity comparisons when some outputs are undesirable: A nonparametric approach. *Review of Economics and Statistics* 71 (1): 90-98.

Färe, R., S. Grosskopf, B. Lindgren, and P. Roos. 1992. Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis* 3 (1): 85-101.

Färe, R., S. Grosskopf, M. Norris, and Z. Zhang. 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review* 84 (1): 66-83.

Harit, T., V. Nanda, S. Parupati, and K. Sinha. 2025. Workforce gender diversity and firm outcomes: Evidence from voluntary disclosures. Working paper. University of Texas-Dallas

Harrison, D. A., and K. J. Klein. 2007. What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review* 32 (4): 1199-1228.

Hong, Lu, and S. E. Page. 2004. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences* 101 (46): 16385-16389.

Kaffash, S., R. Azizi, Y. Juang, and J. Zhu. 2020. A survey of data envelopment analysis applications in the insurance industry 1993–2018. *European Journal of Operational Research* 284 (3): 801-813.

Kim, S. 2025. Word-deed misalignment and firm value: Evidence from firms' diversity efforts. Working paper. Washington University in St. Louis.

Levinsohn, J., and A. Petrin. 2003. Estimating production functions using inputs to control for unobservables. *Review of Economic Studies* 70 (2): 317-341.

Liu, J. S., L. Y. Y. Lu, W. Lu, and B. J. Y. Lin. 2013. A survey of DEA applications. *Omega* 41 (5): 893-902.

Mundlak, Y. 1978. On the pooling of time series and cross section data. *Econometrica* 46 (1): 69-85.

Nathan, M. 2014. The wider economic impacts of high-skilled migrants: a survey of the literature for receiving countries. *IZA Journal of Migration* 3 (1): 1-20.

Olley, G. S., and A. Pakes. 1996. The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64 (6): 1263-1297.

Østergaard, C. R., B. Timmermans, and K. Kristinsson. 2011. Does a different view create something new? The effect of employee diversity on innovation. *Research Policy* 40 (3): 500-509.

Page, S. E. 2008. *The difference: How the power of diversity creates better groups, firms, schools, and societies*. Princeton University Press.

Parrotta, P., D. Pozzoli, and M. Pytlikova. 2014. Labor diversity and firm productivity. *European Economic Review* 66: 144-19.

Pelled, L. H. 1996. Demographic diversity, conflict, and work group outcomes: An intervening process theory. *Organization Science* 7 (6): 615-631.

Richard, O. C., B. S. Murthi, and K. Ismail. 2007. The impact of racial diversity on intermediate and long-term performance: The moderating role of environmental context. *Strategic Management Journal* 28 (12): 1213-1233.

Richard, O. C., M. D. C. Triana, and M. Li. 2021. The effects of racial diversity congruence between upper management and lower management on firm productivity. *Academy of Management Journal* 64 (5): 1355–1382.

Rock, D., and H. Grant. 2016. Why diverse teams are smarter. *Harvard Business Review* 4 (4): 2-5.

Steele, F., A. Vignoles, and A. Jenkins. 2007. The effect of school resources on pupil attainment: A multilevel simultaneous equation modelling approach. *Journal of the Royal Statistical Society Series A* 170 (3): 801-824.

TABLE 1

Sample Description

	# firm-years	# firms
EEO-1 Reports from 2016 to 2020 with a link to Compustat	4112	1169
# Obs after merging with non -missing Compustat data	3496	1008
# Obs for productivity analysis using Malmquist Indices	2816	862
# Obs for productivity analysis using Ackerberg et al. measure	2816	862
# Obs for productivity analysis using productivity growth	1913	616
# Obs for efficiency analysis	2673	822

Table 1 summarizes the sample selection procedure used in the study.

TABLE 2

Descriptives for Diversity Measures

Panel A: Summary of diversity measures across years

	DIVERS_GR	DIVERS_G	DIVERS_R	DIVERS_GR_E	DIVERS_GR_NE	DIVERS_G_E	DIVERS_G_NE	DIVERS_R_E	DIVERS_R_NE
2016 (obs = 579)	0.635	0.392	0.411	0.413	0.636	0.290	0.391	0.180	0.415
2017 (obs = 572)	0.645	0.391	0.428	0.427	0.647	0.301	0.390	0.190	0.432
2018 (obs = 578)	0.656	0.394	0.443	0.437	0.658	0.306	0.393	0.200	0.447
2019 (obs = 547)	0.664	0.404	0.447	0.459	0.666	0.320	0.402	0.216	0.451
2020 (obs = 540)	0.668	0.405	0.451	0.478	0.669	0.330	0.404	0.232	0.455

Panel B: Summary of diversity measures across industries

	DIVERS_GR	DIVERS_G	DIVERS_R	DIVERS_GR_E	DIVERS_GR_NE	DIVERS_G_E	DIVERS_G_NE	DIVERS_R_E	DIVERS_R_NE
Consumer Nondurables	0.706	0.434	0.488	0.438	0.707	0.331	0.434	0.180	0.489
Consumer Durables	0.679	0.410	0.463	0.408	0.683	0.280	0.412	0.194	0.469
Manufacturing	0.599	0.337	0.401	0.397	0.601	0.275	0.337	0.175	0.404
Energy	0.636	0.388	0.420	0.384	0.641	0.247	0.391	0.189	0.424
Chemicals	0.600	0.351	0.395	0.452	0.602	0.322	0.352	0.211	0.397
Business Equipment	0.695	0.408	0.496	0.487	0.700	0.294	0.411	0.278	0.501
Telecommunication	0.689	0.439	0.460	0.506	0.694	0.354	0.441	0.251	0.466
Utilities	0.581	0.359	0.368	0.470	0.582	0.341	0.359	0.218	0.369
Wholesale and Retail	0.694	0.407	0.501	0.406	0.696	0.293	0.408	0.173	0.505
Healthcare	0.723	0.473	0.481	0.517	0.725	0.360	0.473	0.250	0.485
Finance	0.619	0.426	0.345	0.431	0.613	0.355	0.413	0.134	0.351
Other	0.644	0.358	0.450	0.385	0.647	0.276	0.358	0.163	0.455

Panel C: Summary of diversity measures across states

	DIVERS_GR	DIVERS_G	DIVERS_R	DIVERS_GR_E	DIVERS_GR_NE	DIVERS_G_E	DIVERS_G_NE	DIVERS_R_E	DIVERS_R_NE
AK	0.637	0.456	0.349	0.622	0.633	0.455	0.455	0.417	0.345
AL	0.592	0.235	0.457	0.194	0.587	0.158	0.217	0.057	0.469
AR	0.571	0.327	0.356	0.301	0.572	0.244	0.322	0.093	0.365
AZ	0.712	0.395	0.531	0.409	0.715	0.264	0.397	0.207	0.535
CA	0.733	0.413	0.556	0.551	0.735	0.308	0.415	0.359	0.559
CO	0.634	0.372	0.424	0.396	0.637	0.306	0.372	0.155	0.428
CT	0.635	0.362	0.436	0.436	0.639	0.307	0.362	0.197	0.442
DC	0.698	0.478	0.435	0.416	0.715	0.272	0.486	0.219	0.454
DE	0.689	0.454	0.446	0.455	0.690	0.318	0.455	0.237	0.448
FL	0.667	0.390	0.467	0.432	0.670	0.292	0.390	0.200	0.472
GA	0.659	0.390	0.457	0.426	0.660	0.298	0.388	0.196	0.463
HI	0.754	0.446	0.559	0.741	0.751	0.450	0.441	0.557	0.558
IA	0.606	0.442	0.300	0.364	0.596	0.283	0.429	0.110	0.303
ID	0.614	0.378	0.392	0.399	0.616	0.278	0.378	0.173	0.396
IL	0.661	0.388	0.460	0.454	0.663	0.322	0.386	0.210	0.464
IN	0.546	0.382	0.265	0.434	0.540	0.355	0.375	0.120	0.267
KS	0.678	0.362	0.523	0.615	0.678	0.403	0.362	0.382	0.524
KY	0.569	0.376	0.314	0.368	0.567	0.297	0.371	0.109	0.317
LA	0.589	0.355	0.373	0.369	0.586	0.313	0.346	0.075	0.380
MA	0.669	0.428	0.428	0.454	0.672	0.333	0.427	0.186	0.435
MD	0.642	0.429	0.395	0.458	0.644	0.365	0.425	0.153	0.403
ME	0.598	0.456	0.276	0.457	0.596	0.393	0.451	0.107	0.281

MI	0.642	0.406	0.404	0.468	0.643	0.322	0.406	0.236	0.407
MN	0.616	0.403	0.361	0.412	0.618	0.336	0.404	0.120	0.365
MO	0.650	0.417	0.403	0.442	0.650	0.348	0.414	0.155	0.406
MS	0.672	0.426	0.412	0.343	0.672	0.250	0.424	0.158	0.413
MT	0.580	0.407	0.286	0.472	0.578	0.472	0.392	0.000	0.306
NC	0.643	0.372	0.437	0.437	0.640	0.338	0.363	0.164	0.443
ND	0.425	0.257	0.217	0.268	0.424	0.229	0.255	0.061	0.218
NE	0.596	0.325	0.383	0.363	0.598	0.284	0.325	0.112	0.386
NH	0.678	0.411	0.438	0.358	0.686	0.242	0.417	0.140	0.447
NJ	0.687	0.421	0.475	0.432	0.689	0.312	0.420	0.191	0.480
NM	0.698	0.358	0.552	0.600	0.697	0.376	0.354	0.357	0.554
NV	0.686	0.327	0.537	0.417	0.690	0.264	0.323	0.209	0.545
NY	0.672	0.425	0.449	0.450	0.675	0.308	0.425	0.221	0.454
OH	0.589	0.371	0.346	0.362	0.588	0.282	0.368	0.115	0.350
OK	0.580	0.351	0.364	0.358	0.580	0.282	0.346	0.114	0.369
OR	0.658	0.409	0.425	0.482	0.664	0.325	0.414	0.218	0.432
PA	0.600	0.385	0.357	0.436	0.599	0.311	0.383	0.187	0.360
RI	0.666	0.475	0.370	0.410	0.675	0.322	0.479	0.138	0.382
SC	0.592	0.385	0.345	0.359	0.587	0.282	0.374	0.112	0.350
SD	0.526	0.412	0.193	0.381	0.524	0.362	0.408	0.030	0.196
TN	0.555	0.398	0.273	0.391	0.552	0.306	0.391	0.124	0.277
TX	0.681	0.370	0.504	0.416	0.684	0.268	0.370	0.212	0.507
UT	0.628	0.450	0.333	0.391	0.629	0.304	0.449	0.143	0.338
VA	0.663	0.424	0.424	0.423	0.661	0.323	0.417	0.173	0.430
WA	0.658	0.388	0.463	0.472	0.658	0.318	0.386	0.240	0.467

WI	0.605	0.397	0.351	0.412	0.605	0.314	0.395	0.142	0.354
WV	0.567	0.406	0.279	0.351	0.555	0.310	0.390	0.069	0.283

Panel D: Stickiness of diversity measures

Diversity measure	Correlation coefficient between each measure and its lagged term
DIVERS_GR	0.976
DIVERS_G	0.983
DIVERS_R	0.977
DIVERS_GR_E	0.844
DIVERS_GR_NE	0.976
DIVERS_G_E	0.807
DIVERS_G_NE	0.982
DIVERS_R_E	0.864
DIVERS_R_NE	0.976

Table 2 presents descriptive statistics for the diversity measures used in the analysis. Panel A presents workforce diversity over year. Panel B reports diversity by industry. Panel C summarizes diversity across U.S. states. Panel D reports serial correlations of diversity measures.

TABLE 3

Summary Statistics

Panel A: Descriptives of regression variables

	N	Mean	SD	Min	P25	P50	P75	Max
Diversity measures								
DIVERS_GR	2816	0.654	0.112	0.184	0.588	0.669	0.738	0.873
DIVERS_G	2816	0.397	0.087	0.051	0.348	0.412	0.471	0.500
DIVERS_R	2816	0.436	0.153	0.000	0.343	0.450	0.552	0.764
DIVERS_GR_E	2816	0.442	0.156	0.000	0.343	0.461	0.559	0.814
DIVERS_GR_NE	2816	0.655	0.116	0.165	0.587	0.672	0.740	0.874
DIVERS_G_E	2816	0.309	0.122	0.000	0.236	0.322	0.402	0.500
DIVERS_G_NE	2816	0.396	0.088	0.045	0.344	0.409	0.470	0.500
DIVERS_R_E	2816	0.203	0.154	0.000	0.080	0.191	0.307	0.653
DIVERS_R_NE	2816	0.440	0.154	0.000	0.348	0.454	0.558	0.765
Output measures								
TE	2816	0.531	0.275	0.060	0.290	0.495	0.760	1.000
MALM	1913	1.026	0.217	0.425	0.932	1.018	1.094	1.954
TFP_GR	2494	0.010	0.190	-0.769	-0.061	0.017	0.087	0.644
Firm characteristics								
SIZE	2816	8.037	1.828	3.387	6.786	7.797	9.189	15.035
BTM	2816	0.458	0.388	-0.701	0.191	0.394	0.665	1.749
LEV	2816	0.257	0.194	0.000	0.089	0.244	0.379	0.862

Panel B: Comparison between our sample and the rest of the Compustat universe

	Current sample		Other firms from Compustat		
	(1) N	(2) Mean	(3) N	(4) Mean	*t*-stat for col(4) == col(2)?
TE	2816	0.531	10845	0.506	-4.1758
MALM	1913	1.026	6923	1.113	1.2622
TFP_GR	2494	0.010	9344	0.007	-0.4775
SIZE	2816	8.037	10845	7.832	-5.1827
BTM	2816	0.445	10845	0.576	1.2241
LEV	2816	0.259	10845	0.288	5.7029

Table 3 provides summary statistics for the main variables used in the regression analyses. Panel A reports descriptive statistics for diversity measures, firm-level operational outcomes (i.e., technical efficiency and productivity), and control variables. Panel B compares sample firms to the broader Compustat universe.

TABLE 4

The Impact of Overall Diversity on Productivity/Efficiency

VARIABLES	(1) TE	(2) MALM	(3) TFP_GR
Constant	0.752***	1.182***	0.169**
	(0.194)	(0.122)	(0.071)
DIVERS_GR_W	-0.123*	-0.076	-0.052
	(0.067)	(0.058)	(0.036)
DIVERS_GR_B	-0.173	-0.198*	-0.105*
	(0.185)	(0.110)	(0.061)
SIZE_W	0.041***	0.001	-0.001
	(0.010)	(0.002)	(0.002)
SIZE_B	-0.004	0.004	-0.002
	(0.013)	(0.009)	(0.005)
BTM_W	-0.016	-0.057***	-0.063***
	(0.021)	(0.018)	(0.016)
BTM_B	-0.200***	0.004	-0.045*
	(0.069)	(0.044)	(0.025)
LEV_W	-0.016	-0.008	-0.029
	(0.043)	(0.045)	(0.034)
LEV _B	0.118	-0.106**	-0.106***
	(0.124)	(0.053)	(0.037)
Observations	2,816	1,913	2,494

Table 4 presents results for the panel-data regression of the efficiency and productivity variables on the overall diversity and control variables. The regressions in both panels take the form:

$$\boldsymbol{OUTCOMES_{j,t}} = \boldsymbol{\alpha_0} + \textstyle\sum_k \boldsymbol{\alpha_k}\,(\boldsymbol{X_{,j,t}} - \overline{\boldsymbol{X}}_{,j}\,) + \sum_k \boldsymbol{\beta_k}\,\overline{\boldsymbol{X}}_{\boldsymbol{j}} + \boldsymbol{\beta_j Z_j} + \ \boldsymbol{\varepsilon_{j,t}}.$$

where j denotes the firm, t time, k the number of covariates $\boldsymbol{X_{,j,t}}$. Each of the panel data covariates is decomposed into a within (Suffix W) effect term $(\boldsymbol{X_{j,t}} - \overline{\boldsymbol{X}}_{\boldsymbol{j}})$ and a between (Suffix B) time-averaged term $\overline{\boldsymbol{X}}_{\boldsymbol{j}}$. $\varepsilon_{j,t}$ is a zero-mean error term. Z_j is a time invariant fixed effects variable measured as the firm's industry. The parameters α_k , β_k, β_j are estimated by panel data random effects. It should be noted that the within estimated coefficients α_k are identical to the estimated coefficients from a fixed effects panel data OLS regression.

TABLE 5

The Impact of Gender and Race Diversity on Productivity/Efficiency

VARIABLES	(1) TE	(2) MALM	(3) TFP_GR
Constant	0.714***	1.118***	0.136
	(0.169)	(0.153)	(0.122)
DIVERS_R_W	-0.069**	-0.032	-0.043
	(0.032)	(0.047)	(0.038)
DIVERS_R_B	-0.154	-0.229***	-0.142***
	(0.146)	(0.081)	(0.050)
DIVERS_G_W	-0.089	-0.118	-0.016
	(0.063)	(0.094)	(0.074)
DIVERS_G_B	-0.026	0.044	0.036
	(0.190)	(0.101)	(0.061)
SIZE_W	0.041***	0.000	-0.001
	(0.002)	(0.003)	(0.003)
SIZE_B	-0.004	0.004	-0.002
	(0.011)	(0.007)	(0.004)
BTM_W	-0.016	-0.058***	-0.063***
	(0.012)	(0.018)	(0.014)
BTM_B	-0.199***	-0.003	-0.048**
	(0.055)	(0.031)	(0.020)
LEV_W	-0.016	-0.006	-0.029
	(0.023)	(0.035)	(0.027)
LEV_B	0.124	-0.074	-0.090**
	(0.107)	(0.056)	(0.038)
Observations	2,816	1,913	2,494

Table 5 presents results for the panel-data regression of the efficiency and productivity variables on race and gender diversity and control variables. The regressions in both panels take the form:

$$\boldsymbol{OUTCOMES_{j,t}} = \boldsymbol{\alpha_0} + \sum_k \boldsymbol{\alpha_k}\,(\boldsymbol{X_{,j,t}} - \boldsymbol{\bar{X}_{,j}}\,) + \sum_k \boldsymbol{\beta_k}\,\boldsymbol{\bar{X}_j} + \boldsymbol{\beta_j Z_j} + \ \boldsymbol{\varepsilon_{j,t}}$$

where j denotes the firm, t time, k the number of covariates $\boldsymbol{X_{,j,t}}$. Each of the panel data covariates is decomposed into a within (Suffix W) effect term $(\boldsymbol{X_{j,t}} - \boldsymbol{\bar{X}_j})$ and a between (Suffix B) time-averaged term $\boldsymbol{\bar{X}_j}$. $\varepsilon_{j,t}$ is a zero-mean error term. Z_j is a time invariant fixed effects variable measured as the firm's industry. The parameters α_k , β_k, β_j are estimated by panel data random effects. It should be noted that the within estimated coefficients α_k are identical to the estimated coefficients from a fixed effects panel data OLS regression.

TABLE 6

The Impact of Overall Diversity at the Executive and Non-Executive Level on Productivity/Efficiency

VARIABLES	(1) TE	(2) MALM	(3) TFP_GR
Constant	0.741***	1.217***	0.178
	(0.185)	(0.162)	(0.125)
DIVERS_GR_E_W	0.040	0.022	0.014
	(0.028)	(0.042)	(0.034)
DIVERS_GR_E_B	-0.160	-0.227**	-0.056
	(0.154)	(0.098)	(0.056)
DIVERS_GR_NE_W	-0.144***	-0.079	-0.056
	(0.043)	(0.064)	(0.052)
DIVERS_GR_NE_B	-0.097	-0.085	-0.080
	(0.190)	(0.111)	(0.065)
SIZE_W	0.040***	0.000	-0.001
	(0.002)	(0.003)	(0.003)
SIZE_B	-0.001	0.008	-0.001
	(0.012)	(0.007)	(0.004)
BTM_W	-0.016	-0.056***	-0.063***
	(0.012)	(0.018)	(0.014)
BTM_B	-0.198***	0.001	-0.046**
	(0.056)	(0.031)	(0.020)
LEV_W	-0.019	-0.008	-0.030
	(0.023)	(0.035)	(0.027)
LEV_B	0.131	-0.105**	-0.107***
	(0.108)	(0.054)	(0.037)
Observations	2,816	1,913	2,494

Table 6 presents results for the panel-data regression of the efficiency and productivity variables on diversity at the executive and non-executive levels and control variables. The regressions in both panels take the form:

$$\boldsymbol{OUTCOMES_{j,t} = \alpha_0 + \textstyle\sum_k \alpha_k \,(X_{,j,t} - \bar{X}_{,j}\,) + \sum_k \beta_k \bar{X}_j + \beta_j Z_j +\ \varepsilon_{j,t}}$$

where j denotes the firm, t time, k the number of covariates $\boldsymbol{X_{,j,t}}$. Each of the panel data covariates is decomposed into a within (Suffix W) effect term $(\boldsymbol{X_{j,t} - \bar{X}_j})$ and a between (Suffix B) time-averaged term $\boldsymbol{\bar{X}_j}$. $\varepsilon_{j,t}$ is a zero-mean error term. Z_j is a time invariant fixed effects variable measured as the firm's industry. The parameters α_k , β_k, β_j are estimated by panel data random effects. It should be noted that the within estimated coefficients α_k are identical to the estimated coefficients from a fixed effects panel data OLS regression.

TABLE 7

The Impact of Gender and Race Diversity at the Executive and Non-Executive Level on Productivity/Efficiency

VARIABLES	(1) TE	(2) MALM	(3) TFP_GR
Constant	0.595***	1.179***	0.146
	(0.171)	(0.155)	(0.123)
DIVERS_R_E_W	0.040	0.030	-0.017
	(0.031)	(0.045)	(0.036)
DIVERS_R_E _ B	-0.542***	-0.189*	-0.098
	(0.174)	(0.110)	(0.066)
DIVERS_R_NE _W	-0.081**	-0.043	-0.037
	(0.034)	(0.050)	(0.040)
DIVERS_ R_NE_B	-0.059	-0.248**	-0.120**
	(0.148)	(0.100)	(0.055)
DIVERS_G_E_W	0.045	0.040	0.065*
	(0.033)	(0.050)	(0.040)
DIVERS_G_E _ B	0.274	-0.333***	-0.054
	(0.194)	(0.121)	(0.070)
DIVERS_G_NE _W	-0.128**	-0.122	-0.036
	(0.062)	(0.093)	(0.074)
DIVERS_ G_NE_B	-0.033	0.300**	0.078
	(0.208)	(0.135)	(0.073)
SIZE_W	0.040***	-0.001	-0.001
	(0.002)	(0.003)	(0.003)
SIZE_B	0.005	0.007	0.001
	(0.012)	(0.007)	(0.004)
BTM_W	-0.016	-0.057***	-0.062***
	(0.012)	(0.018)	(0.014)
BTM_B	-0.184***	-0.007	-0.049**
	(0.055)	(0.031)	(0.020)
LEVERAGE_W	-0.020	-0.007	-0.031
	(0.023)	(0.035)	(0.027)
LEVERAGE _B	0.165	-0.043	-0.090**
	(0.108)	(0.057)	(0.038)
Observations	2,816	1,913	2,494

Table 7 presents results for the panel-data regression of the efficiency and productivity variables on race and gender diversity at the executive and non-executive levels and control variables. The regressions in both panels take the form:

$$\boldsymbol{OUTCOMES_{j,t} = \alpha_0 + \sum_k \alpha_k\,(X_{j,t} - \bar{X}_j\,) + \sum_k \beta_k\,\bar{X}_j + \beta_j Z_j + \ \varepsilon_{j,t}}$$

where j denotes the firm, t time, k the number of covariates $\boldsymbol{X}_{j,t}$. Each of the panel data covariates is decomposed into a within (Suffix W) effect term $(\boldsymbol{X}_{j,t} - \bar{\boldsymbol{X}}_j)$ and a between (Suffix B) time-averaged term $\bar{\boldsymbol{X}}_j$. $\varepsilon_{j,t}$ is a zero-mean error term. Z_j is a time invariant fixed effects variable measured as the firm's industry. The parameters α_k , β_k, β_j are estimated by panel data random effects. It should be noted that the within estimated coefficients α_k are identical to the estimated coefficients from a fixed effects panel data OLS regression.

TABLE 8

Congruence in Diversity and Productivity

	(1) TE	(2) TE	(3) MALM	(4) MALM	(5) TFP_GR	(6) TFP_GR
Constant	0.734***	0.748***	1.217***	1.269***	0.175	0.188
	(0.185)	(0.185)	(0.162)	(0.165)	(0.125)	(0.127)
DIVERS_W	-0.095**	-0.080	-0.064	-0.037	-0.044	-0.039
	(0.046)	(0.050)	(0.069)	(0.073)	(0.055)	(0.059)
DIVERS_B	-0.244	-0.366*	-0.311***	-0.377***	-0.132*	-0.149*
	(0.188)	(0.213)	(0.115)	(0.129)	(0.068)	(0.077)
DIFF_DIVERS_W	-0.044		-0.021		-0.014	
	(0.028)		(0.042)		(0.033)	
DIFF_DIVERS_B	0.153		0.219**		0.052	
	(0.153)		(0.097)		(0.056)	
DIFF_G_DIVERS_W		-0.053*		-0.051		-0.057
		(0.031)		(0.047)		(0.038)
DIFF_G_DIVERS_B		-0.083		0.315***		0.087
		(0.178)		(0.118)		(0.067)
DIFF_R_DIVERS_W		-0.039		-0.029		0.005
		(0.030)		(0.043)		(0.035)
DIFF_R_DIVERS_B		0.312**		0.061		0.011
		(0.148)		(0.099)		(0.056)
SIZE_W	0.040***	0.040***	0.000	-0.000	-0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
SIZE_B	-0.001	0.002	0.008	0.005	-0.001	-0.001
	(0.011)	(0.012)	(0.007)	(0.007)	(0.004)	(0.004)
BTM_W	-0.016	-0.016	-0.056***	-0.057***	-0.063***	-0.063***
	(0.012)	(0.012)	(0.018)	(0.018)	(0.014)	(0.014)
BTM_B	-0.198***	-0.197***	0.003	0.007	-0.045**	-0.044**
	(0.055)	(0.056)	(0.031)	(0.031)	(0.020)	(0.020)
LEV_W	-0.019	-0.020	-0.008	-0.011	-0.030	-0.033
	(0.023)	(0.023)	(0.035)	(0.035)	(0.027)	(0.027)
LEV_B	0.130	0.126	-0.109**	-0.080	-0.108***	-0.103***
	(0.107)	(0.108)	(0.054)	(0.056)	(0.037)	(0.038)
Observations	2,816	2,816	1,913	1,913	2,494	2,494

Table 8 presents results for the panel-data regression of firm efficiency and productivity on the difference in diversity between executive and non-executive levels (i.e., diversity congruence) and control variables. The regressions in both panels take the form:

$$\boldsymbol{OUTCOMES_{j,t}} = \boldsymbol{\alpha_0} + \textstyle\sum_k \boldsymbol{\alpha_k} \left(\boldsymbol{X_{,j,t}} - \boldsymbol{\bar{X}_{,j}}\right) + \sum_k \boldsymbol{\beta_k} \boldsymbol{\bar{X}_j} + \boldsymbol{\beta_j Z_j} + \boldsymbol{\varepsilon_{j,t}}$$

where j denotes the firm, t time, k the number of covariates $\boldsymbol{X_{,j,t}}$. Each of the panel data covariates is decomposed into a within (Suffix W) effect term $(\boldsymbol{X_{j,t}} - \boldsymbol{\bar{X}_j})$ and a between (Suffix B) time-averaged term $\boldsymbol{\bar{X}_j}$. $\varepsilon_{j,t}$ is a zero-mean error term. Z_j is a time invariant fixed effects variable measured as the firm's industry. The parameters α_k , β_k, β_j are estimated by panel data random effects. It should be noted that the within estimated coefficients α_k are identical to the estimated coefficients from a fixed effects panel data OLS regression.

TABLE 9

Glassdoor Perceptions and Diversity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES		GD_DIVERS			GD_OVERALL			GD_OUTLOOK			GD_MNGT	
Constant	2.140***	2.308***	1.803***	2.771***	2.733***	2.733***	0.001	-0.003	-0.002	2.333***	2.340***	2.225***
	(0.762)	(0.727)	(0.321)	(0.280)	(0.272)	(0.272)	(0.180)	(0.174)	(0.174)	(0.313)	(0.303)	(0.298)
DIVERS_GR	0.934*			-0.375**			-0.103			-0.164		
	(0.514)			(0.155)			(0.100)			(0.174)		
DIVERS_G		1.410***			0.028			0.131			0.252	
		(0.543)			(0.168)			(0.108)			(0.187)	
DIVERS_R		-0.114			-.454***			-.218***			-.409***	
		(0.422)			(0.124)			(0.080)			(0.139)	
DIVERS_G_NE			1.420***			0.038			0.130			
			(0.479)			(0.168)			(0.108)			
DIVERS_R_NE			0.163			-.452***			-.216***			
			(0.338)			(0.124)			(0.080)			
DIVERS_G_E												0.165
												(0.140)
DIVERS_R_E												-0.059
												(0.126)
SIZE	0.143***	0.146***	0.149***	0.115***	0.116***	0.116***	0.064***	0.064***	0.064***	0.098***	0.099***	0.096***
	(0.027)	(0.027)	(0.025)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.010)
BTM	-0.331**	-0.304**	-0.227*	-0.023	-0.018	-0.018	-0.085***	-0.082***	-0.082***	-0.084*	-0.078	-0.080
	(0.137)	(0.137)	(0.127)	(0.044)	(0.044)	(0.044)	(0.029)	(0.029)	(0.029)	(0.050)	(0.050)	(0.050)
LEV	-0.089	-0.087	-0.191	-0.002	-0.001	-0.001	-0.252***	-0.252***	-0.253***	-0.070	-0.072	-0.070
	(0.255)	(0.254)	(0.228)	(0.079)	(0.079)	(0.079)	(0.051)	(0.051)	(0.051)	(0.089)	(0.089)	(0.089)
ROA	-0.721	-0.657	-0.706	0.443**	0.443**	0.441**	0.707***	0.708***	0.708***	0.541***	0.543***	0.554***
	(0.501)	(0.498)	(0.475)	(0.181)	(0.181)	(0.181)	(0.116)	(0.116)	(0.116)	(0.202)	(0.202)	(0.203)

Observations	284	284	284	1,517	1,517	1,517	1,507	1,507	1,507	1,514	1,514	1,514
R-squared	0.289	0.300	0.191	0.219	0.223	0.223	0.248	0.252	0.252	0.178	0.183	0.178
# of years used in the regression	1	1	1	5	5	5	5	5	5	5	5	5

Table 9 presents results from ordinary least squares (OLS) regressions of employee perception outcomes on workforce diversity measures. The dependent variables include employee-rated diversity (*GD_DIVERS*), overall satisfaction (*GD_OVERALL*), company outlook (*GD_OUTLOOK*), and management quality (*GD_MNGT*), all sourced from Glassdoor. The independent variables include overall diversity, gender diversity, racial diversity, and their disaggregated components at either the executive or non-executive level, depending on the perception metric. Specifically, perceptions of management quality are regressed on executive-level diversity measures, while the remaining perceptions are regressed on non-executive-level diversity. Each regression controls for firm size, book-to-market ratio, leverage, and industry fixed effects. Standard errors are clustered at the firm level.