Diversity, Equity and Inclusion is not bad for business: Evidence from employee review data for companies listed in the UK and the US*

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Abstract

Diversity, equity and inclusion (DEI) is a growing strategic focus area. However, measuring DEI remains a challenge, partly due to self-reporting biases and limitations of cross-sectional survey data. This paper proposes a novel measure of DEI using a data set of online employee reviews that encompasses more than 3.2 million reviews posted between 2015 and 2022 on the career intelligence website Glassdoor. We investigate the relationship between this measure of DEI and firm performance for 945 US and UK-listed firms. We find that DEI is associated with higher long-term market performance, with positive impacts larger for growth compared to steady state firms, but not short-term market performance. We find evidence of a mixed relationship between DEI and accounting performance, and a consistent positive relationship with higher innovation. Finally, we examine the interaction between firm DEI and senior management diversity, with results indicating that the positive effects of DEI on long-term market performance and innovation are amplified in firms with higher levels of ethnic diversity in senior management. Overall, we conclude that DEI has either a positive or neutral association with firm performance.

Keywords: DEI, diversity, inclusion, firm performance, ESG, employee reviews

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In recent years, Environmental, Social, and Governance (ESG) performance has become a primary area of strategic focus for organisations given its growing importance for investors, regulators, consumers and other stakeholders. Investors are incorporating ESG into investment analysis and decision-making processes, with more than 5,000 investors managing assets worth an estimated $121.3 trillion having signed the "Principles of Responsible Investment" by March 2022 (PRI 2022). Regulators are demanding greater levels of transparency and representation on corporate boards. The European Parliament introduced regulation in 2022 establishing a target of at least 40% of non-executive director posts to be occupied by the under-represented sex by 2026 (Parliament 2022), and the Financial Conduct Authority in the UK requires at least one board member from an ethnic minority background and a woman in a senior board position (FCA 2022). Moreover, the public's increased awareness of social movements such as Black Lives Matter and global campaigns for LGBT rights has led to heightened attention to and importance of Diversity, Equity, and Inclusion (DEI) in the workplace (World Economic Forum 2023). As a result, investors, business leaders, and regulators are demanding greater transparency in DEI progress and its impact on firm performance.

A significant body of literature has examined the relationship between diversity and firm performance, establishing that diversity can enhance performance through better information elaboration (i.e., broader access and integration of pertinent knowledge) while also potentially creating interpersonal tensions and being detrimental to group processes and performance (Milliken and Martins 1996, van Knippenberg, De Dreu and Homan 2004, van Knippenberg and van Ginkel 2022). In response, inclusion has emerged as a crucial area of focus in both academic and practical contexts, aimed at mitigating the negative effects of diversity and harnessing the benefits of diverse knowledge (De Dreu 2006, Shore et al. 2011). Specifically, inclusion refers to the extent to which employees feel that their contributions are appreciated, and their participation is actively encouraged within the organisation and is widely regarded as a necessary characteristic of an organisation for enhancing organisational performance (Nishii 2013, Roberson 2006). Conversely, exclusion represents a significant problem for today's workforce, characterised by the individual experience or perception of not being an integral part of the organisation (Mor Barak 2015, p.85). Research on social exclusion shows that people are less likely to cooperate after being rejected, ignored or ostracised (Baumeister et al. 2005), and shift to more negative emotional and psychological states (Blackhart et al. 2009).

In the context of organisations, inclusion/exclusion is a continuum of the degree to which employees feel a part of significant organisational processes by being included in workgroups, accessing information and resources, and influencing decision-making (Mor-Barak and Cherin 1998). Empirical research on organisational inclusive climate has focused on how it enhances individuals' ability to relate to one other at work, resulting in beneficial outcomes such as higher psychological safety, job satisfaction, commitment, tenure, and retention (Brimhall and Mor Barak 2018, Mor Barak et al. 2016, Nguyen et al. 2024). Furthermore, when an organisation fails to foster inclusion, studies have shown employees experience negative outcomes, like increased disengagement and conflict, leading to detrimental outcomes such as emotional exhaustion, heightened stress, increased intention to leave and losses in productivity and performance (Brimhall and Mor Barak 2018, Nishii 2013, Sabharwal et al. 2019).

Despite the academic interest in inclusion, there is a paucity of empirical evidence on the relationship between workplace inclusion/exclusion and organisational performance (Sabharwal 2014, Mor Barak 2015, Shore, Cleveland and Sanchez 2018). One empirical limitation in inferring the dynamics between employee inclusion and organisational performance is that the existing studies typically measure the variables of interest using self-reported measures, often limited to cross-sectional observations. This work typically proceeds by linking measures of employees' perceptions of inclusion, using the Inclusion-Exclusion scale (Mor-Barak 2022) or the climate for inclusion scale (Nishii 2013), with self-reported measures of innovation or organisational performance. For example, Li et al. (2022*b*) collected data in three waves from 102 organisations in China and showed that inclusive climate was positively associated with innovation (reported by team leaders), and that age and regional diversity strengthened this relationship. Further, Sabharwal (2014) collected data from a sample of 198 employees in Texas governmental agencies and found that inclusion was positively associated with performance (reported by managers). These studies limit the understanding of how employees experience inclusion to the predefined constructs used (Symitsi et al. 2021), and to a static perception of inclusion inferred from a sub-section of employees who respond to the survey.

Moreover, practitioners increasingly see measuring diversity, equity and inclusion (DEI) as a top priority, with a focus that extends beyond demographic diversity and hiring to also encompass equity and inclusion. Despite this growing focus, current company DEI metrics often focus primarily on demographic diversity, while the aspects of inclusion and equity remain more elusive to quantify and discern. A review of the progress of DEI conducted by the UK Financial Conduct Authority highlights that companies continue to rely on unclear diversity and inclusion (D&I) goals, and while DEI is gaining prominence in the business agenda, most UK businesses have yet to implement formal inclusion programmes. Additionally, they conclude there is a lack of consistency when collecting diversity data across industries and countries, and little evidence of systematic inclusion data collection (FCA 2022). This disparity makes it particularly challenging for stakeholders to distinguish between genuine commitments and superficial "lip service," as well as to understand the value generated by an inclusive culture (Dobbin and Kalev 2022, Romansky et al. 2021, Wang et al. 2023).

In this paper, we develop a novel measure of DEI, using a data set of online employee reviews that encompasses more than 3.2 million reviews posted between 2015 to 2022 on the career intelligence website Glassdoor for 945 US and UK-listed firms. Recent advances in data science and the availability of public data mean employee reviews are a rich source of naturally occurring data that offer a promising avenue to uncover valuable and largely unexplored firm information without requiring the cooperation of the firm or employees (Hill, White and Wallace 2014). Anonymous reviews submitted by employees are unrestricted to a specific subject and offer an unfiltered opinion on employers (Sainju, Hartwell and Edwards 2021, Symitsi et al. 2021).

We explore the information content of these reviews to extract perceptions of DEI from the free-form text of the reviews. Specifically, we match reviews to a manually constructed and validated dictionary of DEI keywords present in the "Pros" and "Cons" fields of employee reviews. We then use a lasso regression to weigh how much these terms matter to reviewers when rating their companies. We finally construct a company-quarter measure that we call *DEI Signal*, which captures aspects of diversity, equity and inclusion that are salient to employees' when rating their workplace. This measure differs from traditional DEI indicators, as it does not encompass the full range of company policies and formal practices, which may be neutral or irrelevant to employees' individual experiences. Instead, the *DEI Signal* reflects the positive and negative elements of DEI that employees perceive as meaningful to their overall experience of an organisation, serving as an indicator of DEI as it is experienced and valued by employees. We consider this measure to be a credible proxy for DEI, as it captures experiences of inclusion and exclusion, aspects of equity that reflect equality of opportunities and the presence of discrimination, and specific diversity factors related to gender and ethnicity such as gender and racial bias.

We then investigate the relationship between the *DEI Signal* and firm performance. We are particularly interested in examining the value of DEI as an intangible asset in creating long-term value, growth potential and innovation. As a result, we examine market-based measures of performance (Tobin's Q and stock returns) which reflect the market's expectation of the firm's potential growth, with Tobin's Q providing a forward-looking measure of intangible capabilities while stock returns measure more short-term market expectations of firm's future success. Following prior research, we further examine patent applications as a proxy for a firm's innovation. We finally also examine accounting-based measures (return on equity, return on assets) to provide a comprehensive view of the relationship between DEI and performance, which are more backwards-looking, reflecting how a firm performs based on financial statements data. Our sample includes 945 US and UK firms from Q2 of 2015 to Q1 of 2022.

To quantify the relationship between the signal measures and firm performance, we employ panel data models. In addition, we look at heterogeneity between sectors and firm's growth stages. We expect that DEI will have a more meaningful impact in the financial and innovation performance of firms that are actively growing, given the importance of human capital. To test the robustness of our findings, we construct a shift-share instrument and apply an instrumental variable design to establish the causal effect of *DEI Signal* on performance, addressing some of the limitations that are prevalent in the literature, particularly endogeneity.

There are several key takeaways from this analysis. Firstly, our results reveal positive, significant relationships between DEI and Tobin's Q. By analysing different lags, we observe that this positive DEI relationship persists over time. We also find that this effect is larger for firms in growth compared to those in a steady-state growth stage. This suggests that a company's DEI signal is predictive of firm future firm value and growth potential. In contrast, we consistently find that DEI is unrelated to short-term market performance, measured by stock returns. This difference could be due to the fact that short-term market returns are to a larger extent, driven by what investors perceive and believe as an immediate reaction to information and investors do not assume that DEI can create value (Brinkhuis and Scholtens 2018, Jeong and Harrison 2017).

Regarding innovation, we find a small positive effect of DEI on the number of patents filed, with consistent results across sectors that are known to patent their innovations. However, this effect does not persist after the one-year lag, or when looking at different growth stages, where we find that DEI is unrelated to innovation performance. We also find that DEI is not consistently related to accounting-based performance, with firms that are in growth stages showing a positive relationship between DEI and ROE, while no evidence of a relationship in firms that are in a steady growth stage. Moreover, results disaggregated by industry indicate heterogeneity between sectors, with positive, non-significant and negative relationships observed.

Together, our results reveal that DEI has either a consistent positive or non-significant association with firm performance, meaning that, at a minimum, DEI is not detrimental to firm performance. Moreover, the results suggest that DEI could serve as a strategic intangible asset that investors associate with long-term value creation and innovation potential.

To better understand the relationship between diversity, equity and inclusion and performance, we extend the analysis to include the demographic diversity of senior management teams. While our *DEI Signal* captures employees' experiences, it does not reflect the actual levels of diversity within the firms. To address this, we construct measures of senior team ethnic and gender diversity using a workforce dataset aggregated by Revelio Labs. We then examined the interaction of DEI and senior team diversity on performance. The results indicate that ethnic diversity within senior management is positively associated with firm performance and innovation in four out of our five measures of performance, while gender diversity is unrelated to market-based performance and negatively associated with accounting-based performance and innovation. We also identify a positive interaction effect between *DEI Signal* and ethnic diversity for Tobin's Q and the number of patents filed, suggesting that the benefits of DEI are amplified in environments where senior management teams are more ethnically diverse.

This study extends the existing literature on organisational inclusion in several directions. First, while several studies investigate perceived organisational inclusion, we extend these findings by harnessing a unique and unobtrusive indicator of DEI from review text data. Moreover, while recent studies have used textual data to understand diversity and inclusion in the workplace (Hofhuis et al. 2023, Wang et al. 2023), this study is the first to extract information on DEI from employee reviews. In doing so, we also differ from other studies that use employee ratings from Glassdoor, which primarily focus on job satisfaction or use numerical rating data to derive diversity and inclusion measures (Green et al. 2019, Kim, Jeon and Kim 2022, Landers, Brusso and Auer 2019). We also contribute to the literature that explores the degree to which firms can benefit from inclusion and diversity by considering models that go beyond individual and team-level performance to investigate the longitudinal relationship between DEI, demographic diversity and firm-level indicators of innovation and performance.

Finally, this study also has significant business implications by examining the relevance of big data that is not subject to access constraints, rich in information, and is not self-reported by the firm as a source of information for investors and other stakeholders to track and benchmark DEI progress, and to understand if firms react to information regarding diversity and inclusion in employee reviews. For firms, such data can also be effectively used to evaluate the impact of diversity and inclusion actions by providing insight regarding issues that employees might be hesitant to disclose directly due to managerial pressures.

I. Measuring DEI Using Employee Reviews

A. Data Description and Sample Selection

The measure of DEI (*DEI Signal*) was developed from the textual analysis of employee reviews posted on the career intelligence website Glassdoor between April 2015 and June 2022. Glassdoor currently holds over 90 million reviews and insights on companies, salaries, and interviews, making it one of the largest repositories of employee feedback in the world (Glassdoor 2023). Current and former employees submit anonymous views of their employer, as well as information regarding the company, location, job, and position. Each employee review contains a numerical overall rating of the employer and optional ratings of several job elements such as career opportunities, compensation and benefits, culture and senior management. Additionally, employees can provide open-ended textual entries detailing the positive (Pros) and negative (Cons) aspects of working for their employer, and advice to Management.[1]

Reviews are voluntarily and anonymously submitted on the website, offering an environment where employees can disclose experiences without fear of reprisal or managerial pressures. However, a common concern when using online reviews is self-selection and polarization bias arising from the voluntary nature of contributions (Chevalier and Mayzlin 2006, Hu, Pavlou and Zhang 2017, Li and Hitt 2008). Employees are more likely to seek out such websites if they have extremely positive or negative views (e.g., very frustrated, or very eager to make the company look good), while the true underlying distribution of the full employee population is less likely to be so highly polarized (Marinescu et al. 2021). Moreover, companies may manipulate ratings by encouraging employees to write positive reviews or by offering incentives to improve their ratings (Winkler and Fuller 2019). To reduce these potential biases in employer reviews, Glassdoor uses self-oriented incentives in the form of a give-to-get policy, whereby users have to contribute a review to the platform to gain access to it is knowledge (Marinescu et al. 2021). Further, as the emerging literature on social media behaviour suggests, voluntary reviews and online word-of-mouth communications provide value-relevant information beyond other private sources (Chen et al. 2014). Particularly, prior studies demonstrate that Glassdoor employee ratings are a valid source of employee perceptions that contain meaningful assessments of gender-related issues (Sharkey, Pontikes and Hsu 2022); employee views and evaluations which firms take into account to then update corporate policies (Dube and Zhu 2021, Green et al. 2019); value-relevant information that predicts stock returns (Luo, Zhou and Shon 2016); and risk-relevant information that can predict corporate financial distress (Dunham et al. 2023) and corporate misconduct risk (Campbell and Shang 2022). Following this stream of recent studies, we focus our analysis on textual data in open-ended questions in the "Pros" and "Cons" fields to derive a measure of employee perceptions of DEI. Overall, we expect that the reviews will offer a proxy for the aspects of DEI culture that matter within the organisation.

While Glassdoor includes reviews for thousands of firms, we restrict our analysis to a sample matched to: (1) Companies in the U.K. S&P BMI as of August 2022 and (2) U.S. companies that belonged to the MSCI USA index at any point between 2015 and 2022, including reviews

[1]See A.A1 for more details on the sections of employee reviews.

for subsidiaries which are aggregated at the parent-firm level. These firms are large enough to reasonably expect sufficient reviews to capture the proxy. As several companies were not reviewed immediately at the launch of Glassdoor in 2008 and the numbers of reviews ramp-up over time, we restrict our analysis to the seven years spanning 2015 to 2022. The resulting sample is comprised of more than 3.2 million reviews for 945 firms (673 in the U.S. sample and 273 in the UK sample).[2]

B. DEI Measure Construction

We derived and validated a measure of diversity, equity and inclusion (*DEI Signal*) using the text from the "Pros" and "Cons" section of Glassdoor employee reviews. We use a dictionary method for text analysis in order to capture domain-specific experiences of inclusion and exclusion, diversity related to gender and ethnicity, and instances of equity and discrimination. We draw on Mor-Barak and Cherin's (1998) conceptualisation of inclusion, which considers the extent to which individuals feel a part of organisational processes, including their connectedness with colleagues, access to information and involvement in decision-making. Reflecting this and related literature, we include for instance terms associated with inclusion, belonging, respect, and openness (Randel et al. 2016, Shore et al. 2011). Recognizing that experiences of inclusion and exclusion in organizations are often linked to differences in attributes and status (Kalev, Dobbin and Kelly 2006, van Knippenberg, De Dreu and Homan 2004), our measure captures both overall experiences of inclusion/exclusion, and overtly inequitable behaviours towards minority groups across demographic characteristics, which should not be considered in isolation (van Knippenberg and van Ginkel 2022). Additionally, we capture aspects of equity/inequity that relate to equality of opportunities and the presence of systematic barriers such as discrimination, as experienced and perceived by individuals, rather than equality of outcomes within firms. This approach aligns with Tang's (2024) definition of equity, which refers to ensuring equal access to opportunities and resources for all employees, regardless of background or circumstance. Regarding diversity, we capture specific aspects of DEI related to gender and ethnicity, including racial and gender bias.

Each review was pre-processed, and textual analysis was performed on the free text written in the "Pro" and "Cons" sections to classify it regarding DEI. We use keywords along two dimen-

[2]Our sample includes 77.51% of the UK S&P BMI constituent firms and 85.31% of the MSCI USA constituent firms, for an overall coverage rate of 82.81%.

sions: (1) employee's experiences of inclusion, exclusion, equity and discrimination, regardless of diversity characteristics, with example terms such as "equality", "microaggression", "respect", and (2) gender and race-ethnicity specific terms, such as "sexist", "female", "misogyny" and "racial".

To develop the manually validated lexicon, five researchers with subject expertise in Diversity and Inclusion independently compiled a long list of words anticipated to appear in employee reviews related to diversity and inclusion. This preliminary list was used to conduct a comprehensive search of Glassdoor reviews across a random sample of 100 firms. The initial retrieval enabled a co-occurrence analysis, which allowed for the lexicon to be expanded by identifying additional relevant terms. A further search for the expanded lexical field was then carried out on the random sample of 100 firms. The resulting dataset was then manually validated by three data scientists independent of the original researchers who identified false positives and false negatives. Their findings were passed on to the Principal Investigator on the project, who refined the lexical field based on the validation results. To ensure robustness, the retrieved reviews were sent back to the first five researchers to independently assess the false positives and false negatives, leading to further refinement and reduction of the lexicon. The refined lexicon was then applied to classify a new review sample of 100 firms, and the five researchers once again manually identified false positives and negatives. Finally, the identified words were systematically grouped into the final lexicon, organised according to semantic and thematic similarity (fully detailed in A.A1).

The final lexicon is comprehensive and reflects the nuanced language used in employee reviews regarding DEI. However, it does not take into account the relative importance of these words to the reviewer. To achieve this, we use a lasso (least absolute shrinkage and selection operator) model to identify which groups of keywords predict employee satisfaction ratings significantly, along with the strength of their association. The lasso approach is advantageous in text analysis due to its ability to reduce the dimensionality of the variables under consideration (Gentzkow, Kelly and Taddy 2019). It allows us to identify groups of keywords with the strongest predictive power while avoiding over-fitting by shrinking some coefficients to exactly zero and thereby excluding those variables from the set of explanatory variables (Tibshirani 1996). Using a lasso method allows us to capture the most important words in employee reviews that relate to inclusion, while at the same time excluding the groups of keywords that, while related to DEI, are not meaningful for employees when assessing their companies, as they do not explain variation in employee satisfaction ratings.

Our lasso approach closely follows the methodology outlined by Freo and Luati (2024). For each review, we designate the overall rating of the employer (on a scale of 1 to 5) as the response variable. The predictor variables are derived from the DEI lexicon. Each subset of words in the DEI lexicon is prefixed by "p" if they appear in the positive ("pro") field and "c" if they appear in the negative ("con") field, allowing us to capture the contextual valence of the words.[3] As our level of observation is firm-quarter, we construct the variables by weighting the count of occurrences of each group of keywords by the number of reviews for each company in each year-quarter. The response variable is the mean rating for each company-year quarter. Constructing variables at the company-quarter level allow us to reduce the prevalence of zero entries, which is a common issue in sparse datasets, thereby improving model stability.[4] Specifically, we estimate the following regression model:

$$y_{it} = \beta_0 + \sum_{j=1}^{p} \beta_j \; x_{ijt} + \; \epsilon_{it} \tag{1}$$

Where y_{it} denotes the mean rating for company i in quarter t, x_{ijt} represents the frequency of DEI-related keyword j for company i in quarter t ; β_j are the coefficients associated with each keyword j; ϵ_{it} is the error term. The lasso regression is estimated as follows:

$$\min_{\beta} \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} \left| \beta_j x \right| \right\} \tag{2}$$

Where $\lambda > 0$ is a tuning parameter that controls the degree of shrinkage applied to the coefficients. As λ increases, more coefficients are shrunk to zero, effectively selecting a model with fewer variables.

As there is no universal way of selecting the tuning parameter, λ we follow the commonly used data-driven approach of cross-validation (Wu and Wang 2020) and consider several variants of lasso.

[3]To verify that a certain word being included in the "Pro" vs the "Con" section is an accurate proxy of its positive and negative valence, we also applied sentiment models to the comments and found a strong association between the positive and negative sentiment scores and if they were in the "Pro" and "Con" sections, detailed in Table A2 in A.A1.

[4]Table A3 in A.A1 presents descriptive statistics on ratings and the constructed predictor variables.

We randomly split the data into a training and a testing set for validation. We then run several variants of the lasso on the training set and evaluate their performance based on the calculated R-squared and the minimum cross-validated mean squared error (MSE) in the test set. This random search process is considered efficient in the machine-learning literature for hyper-parameter optimisation (Akyapi, Bellon and Massetti 2022, Bergstra and Bengio 2012).[5] Table 1 shows the results of the lasso regression, documenting the 74 non-zeros coefficients that were selected through the shrinkage process, from the initial 136 variables included in the model. The main variable DEI Signal is then constructed at quarter firm-level by weighing the variables selected by the lasso model by their post-selection coefficients.

Table 1— Lasso Regression Output

Dependent variable: Mean employee ratings at company-quarter observation							
"Pro" Section				"Con" Section			
meritocracy	1.95	family	0.34	authoritarian	-3.01	male	-0.73
openness	1.84	ethic	0.32	ethic	-1.61	trust	-0.72
culture	1.35	collegiate	0.29	dysfunction	-1.60	hatred	-0.70
inclusive	1.17	friendly	0.25	disengage	-1.57	unappreciated	-0.65
advocate	1.07	respect	0.21	compassion	-1.52	collaborate	-0.56
equality	0.98	people	0.12	groupthink	-1.43	culture	-0.50
aggressive	0.88	bigot	-0.39	nepotism	-1.39	transparent	-0.45
unappreciated	0.78	hierarchic	-1.00	backstab	-1.34	toxic	-0.45
collaborate	0.77	toxic	-1.32	corrupt	-1.20	gossip	-0.44
divers	0.62	corrupt	-1.83	respect	-1.18	politic	-0.44
transparent	0.61	dysfunction	-2.21	abuse	-1.16	clicky	-0.41
opportunities	0.60	hatred	-3.12	belittle	-1.14	team	-0.38
politic	0.54	exploit	-4.43	minority	-1.12	race	-0.34
work	0.52	degrading	-6.82	micromanage	-1.05	unprofessional	-0.30
silo	0.52	feminine	-7.36	crying	-0.97	sexist	-0.23
team	0.47			people	-0.81	opportunities	-0.23
atmosphere	0.37			atmosphere	-0.81	gender	-0.21
accessible	0.36			family	-0.76	exclusion	-0.11
				bigot	-0.75	accessible	0.84
Constant	3.49			sexual	-0.74	dignity	2.72
Out-of-Sample R-squared	0.35					feminine	2.78

Note: Table displays the output from the lasso regression in equation X, separating the non-zero coefficients into the "Pro" and "Con" sections. Each coefficient indicates a group of keywords which relate to the title of the group.

[5]Full details of the models tested, and their goodness-of-fit results are in Table A4 in A.A1

Panel A of Table 2 reports review-level data for the 2015-2022 period. In total, 1,747,845 reviews were matched to the DEI lexical field, meaning 53.3% of reviews contained a DEI-related word in the "Pros" or "Cons" text fields. We then tabulate reviews by sector, using the GICS 11-sector classification. The sectors with the highest proportion of DEI reviews are Information Technology (60.25%), Utilities (59.8%) and Financials (59%). Of those, Utilities has the highest proportion of DEI negative reviews (28.6%), while Information Technology has the highest proportion of positive DEI reviews (48.48%) The sectors with the lowest proportion of DEI reviews are Consumer Staples (44.8%), Consumer Discretionary (46.5%) and Materials (48.32%). Companies in the Consumer Discretionary sector account for the largest fraction of reviews (24.8%) and 14.2% of sample firms.

Table 2— Descriptive Statistics

Panel A: Employee Reviews				
	Total DEI Reviews	Total Reviews	% DEI	No of Firms
Total	1,747,845	3,277,760	53.32%	945
Communication Services	149,972	268,320	55.89%	52
Consumer Discretionary	377,781	813,266	46.45%	134
Consumer Staples	121,616	271,216	44.84%	53
Energy	32,412	60,291	53.76%	44
Financials	247,867	420,311	58.97%	135
Health Care	138,003	248,599	55.51%	96
Industrials	195,649	381,784	51.25%	142
Information Technology	427,147	708,976	60.25%	132
Materials	20,132	41,668	48.32%	52
Real Estate	24,251	41,545	58.37%	62
Utilities	13,015	21,784	59.75%	36

Panel B: Firm-Quarter Signal Statistics						
	Mean	Median	SD	Min	Max	Observations
Average No Reviews	1,338	510		1	14,106	26,460
Average No DEI reviews	623	259		0	5,883	26,460
Signal						
DEI Signal	0.060	0.048	0.293	-1.064	0.993	26,460

Note: The table shows summary statistics for the sample of employee reviews from Glassdoor. Panel A reports the review-level statistics and count of company observations (excluding those missing industry). Panel B reports the summary statistics for reviews and Signal measure at the firm-quarter level, winsorised at the 99% and 1% levels. Sample includes data from 2015-2022 for 945 companies. Source: Review data from Glassdoor.com collected by Citi.

Summary statistics for the *DEI Signal* measure are reported in Table 2 Panel B. Figure A2 in Appendix A.A1 illustrates the *DEI Signal* over time, measured quarterly. Across our time period of interest, there is an overall upward trend in DEI, gradually increasing from 2015. From 2019 to Q1 2020 there is a decline, followed by significant growth from 2020 onwards, peaking in early 2021, which could mean that the COVID-19 pandemic, the murder of George Floyd and social movements such as Black Lives Matter taking place in the summer of 2020 influenced employees' perceptions and attention of DEI issues as well as firms' DEI actions (as Glassdoor's analysis of the weeks of May 25 to June 2021 shows a spike in U.S based reviews discussing D&I (Stansell 2020)).

II. DEI and Firm-Level Performance

To quantify the relationship between the *DEI Signal* and firm performance, we employ panel data models at the firm level. Specifically, we gather quarterly financial data for each firm in the sample of employee reviews to measure organisational performance and retrieve patent information data derived from IFI claims[6] as an indicator of firm innovation. We examine changes in the main measure *DEI Signal* in predicting firm performance and innovation. We further explore heterogeneity by considering sector variations and growth-stage variation models to assess differences in the relationship between DEI and firm performance across steady-state and growth-state conditions.

A. Firm Performance and Innovation Measures

We obtain performance data from S&P Global Capital IQ for the sample of 945 US and UK listed firms and match it to our review dataset by firm identifier and year-quarter from 2015 Q2 to 2022 Q1. Following the literature, we examine organisational performance via measures that capture multiple dimensions of performance, specifically, market measures, accounting performance and innovation (Combs, Russell Crook and Shook 2005, Post and Byron 2015).

Tobin's Q and stock returns are measures of market performance and return on equity (ROE) and return on assets (ROA) are measures of accounting-based performance previously used in several diversity studies (Corritore, Goldberg and Srivastava 2020, Foster et al. 2021, Post and Byron 2015). Both types of measures provide information on firm performance, with accounting-

[6]Patent data is provided by a Patent and IP analytics company (Quant IP) which aggregates raw patent data provided by IFI Claims from over 80 patent offices globally using S&P for company-level processing.

based measures being relatively more backwards-looking (assessing how the company has performed recently). Conversely, market-based measures (Tobin's Q, stock returns) are more forward-looking as they also reflect the firm's potential success, and are influenced by the perceptions and behaviours of investors and market reactions (Haslam et al. 2010, Lee and James 2007). Finally, we measure innovation using the number of patents filed.

Dependent Variables

We examine firm performance in each year-quarter using market-based and accounting-based measures as our dependent variables. Tobin's Q is a measure of the investors' expectation and confidence in the firm's potential growth and is associated with innovation and R&D intensity (Hall, Jaffe and Trajtenberg 2005). A high ratio reflects confidence in the firm's future growth potential relative to the value of its assets, whereas a low ratio suggests the company is undervalued by the market, or investors are concerned about its growth prospects.[7] Stock returns are also a market-based measure and a proxy of investment performance, capturing more short-term changes such as news announcements or company information that is not yet reflected in accountancy-based performance. Return on equity (ROE) and return on assets (ROA) are accounting-based measures of company profitability.

While the above measures serve as proxies for organisational performance, and particularly Tobin's Q is used to capture a firm's growth and innovation potential, we also measure firm innovation more directly. Beyond financial performance, one of the main predicted benefits of DEI is its positive influence on innovation (Makkonen 2022, Qi et al. 2019), with studies indicating the positive impact of diversity-generating interpersonal dynamics that foster novel solutions (Díaz-García, González-Moreno and Jose Sáez-Martínez 2013) and the role of inclusion in fostering innovation (Li et al. 2022*b*). Following prior research, we use patents as an indicator of innovation (Bloom and Van Reenen 2002, Hagedoorn and Cloodt 2003, Owen-Smith and Powell 2004). Specifically,

[7] We calculate the ratio as market capitalisation (current market price per share multiplied by the total number of outstanding shares) divided by total assets given the data availability in Capital IQ. We also create an alternative proxy for Tobin's Q, following Chung and Pruitt (1994), to validate this calculation, which has a 98% correlation with the current measure, but we lose observations given missing data.

we use the number of patent families[8] (using the DOCDB simple patent family[9]) for each firm in each time period. A patent family is a set of interrelated patent applications filed in one or more countries to protect the same or a similar invention by a common inventor and linked by a common priority. We exclude data for any company that has a median of less than one patent family to reduce the impact of companies which are not engaged in patenting activity. Table 3 provides the descriptions and descriptive statistics for the outcome measures used at the company-quarter level for the sample period of 2015 to 2022.

Independent Variables

The primary independent variable is the firm's *DEI Signal* lagged by one year, to allow for the impact of company culture change on subsequent innovation and performance. The use of lags is common in studies in economics, accounting and finance examining the culture-performance relationship (Boyce et al. 2015, Chatman et al. 2014, Green et al. 2019) and innovation studies (e.g., innovation activity impact on firm performance, (Artz et al. 2010)). Based on past studies, we chose a one-year lag as our primary specification to reduce endogeneity, as culture and diversity changes need some time to impact firm performance and it is a commonly used lag when considering the impact of culture or diversity representation on firm performance (Jeong and Harrison 2017). For instance, Symitsi et al. (2021) examine the effect of one-year lagged employee satisfaction on ROA, finding that UK firms rated highly by their current employees in terms of satisfaction, achieve higher ROA compared to those rated poorly; Kyaw, Treepongkaruna and Jiraporn (2022) and Usman et al. (2018) use a one-year lag of gender board diversity measures to assess its association with performance.

However, organisational theorists have remained largely undecided on the temporality of the culture-performance relationship (Boyce et al. 2015) and management theorists and practitioners have called for a better understanding of how organisational change occurs and transforms over

[8]Beyond patent applications, the quality of the patents warrants consideration, as not all patents filed will be granted, nor will they represent innovation, with prior research showing there are a small number of highly valuable patents and a high volume of patents with little value (Nagaoka, Motohashi and Goto 2010). However, due to international patent lag, there is a 2-year average lag between patent application, and it being granted, creating a natural lag in measuring innovation. Further, as highlighted by Bloom and Van Reenen (2002), the full value of a patent cannot be calculated until it is at the end of its lifecycle. Given the recency of our data, we use the count of patent family which represents the collection of all documents (applications, granted patents, international filing, etc) for a single invention.

[9]https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patent-families/docdb.html

Table 3— Performance and Innovation Measures

Panel A: Measure Descriptions

Type of Performance	Variable	Description
Market-based performance	Tobin's Q	Measure of the investors' expectation and confidence in the firm's potential growth. Market value divided by total assets.
	Stock Returns (log)	Measure of the investors' expectation and confidence in the firm's potential growth, reflecting the firm's market valuation changes. Quarterly company stock returns.
Accounting-based performance	ROE	Measure of the firm's ability to generate profits from shareholder's equity. Percent of net income to shareholder equity.
	ROA	Measure of how efficiently a firm uses its assets to generate earnings. Percent of returns to total assets of the company.
Innovation	Patent Families	Quarterly count of annual number of patent families.

Panel B: Descriptive Statistics

Variables	All sample			US sample			UK sample		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Tobin's Q	1.885	2.138	23,686	2.075	2.242	17,188	1.384	1.739	6,498
Stock Returns (log)	0.044	0.208	24,501	0.048	0.194	17,623	0.033	0.240	6,878
ROE (%)	13.233	43.255	24,621	13.874	44.811	17,889	11.529	38.771	6,732
ROA (%)	5.186	6.745	24,494	5.238	6.732	17,830	5.049	6.778	6,664
Patent families	34.570	249.634	26,460	47.601	294.509	18,844	2.330	21.062	7,616

Note: Sample includes 945 companies. Observations are company-quarter. Tobin's Q is winsorized at the 98% level and ROE winsorized at the 2% and 98% level to reduce the impact of outliers.

time (Granqvist and Gustafsson 2016, Langley et al. 2013). To better understand the longitudinal relationship between DEI and firm performance, we further analyse different time-frames by examining the relationship with *DEI Signal* at the same time period as firm performance, as well as two-year and three-year lags of *DEI Signal*.

Control Variables

Based on the financial and organisational culture literature (Ahern and Dittmar 2012, Arora 2022, Li et al. 2022*a*), we control for the firm's total assets, number of employees, firm leverage (total liabilities scaled by total assets) and listed country. We log-transform total assets and total number of employees and standardise all control variables. A.A2 provides descriptions and summary statistics for each variable.

In addition, we include an interactive fixed effect sector×quarter-year, commonly used in finance panel studies (using the FactSet 19-sector classification[10]), which offers greater flexibility compared to including separate industry and period fixed effects, as it controls for industry-specific shocks over time (Verbeek 2021).

B. Models

We start by estimating the effect of the *DEI Signal* on firm performance using fixed effects panel regressions. Specifically, we estimate the following model:

$$y_{ijt} = \delta DEI_{ijt-1} + \beta' X_{ijt} + f_{jt} + \epsilon_{ijt} \tag{3}$$

where i denotes the individual firm and t denotes time (in quarter-years); y_{ijt} is the measure of performance/innovation of firm i in sector j and quarter t (Tobin's Q, return on equity, stock returns, or Patent Counts, standardized to allow comparisons); DEI denotes the *DEI Signal*; X is a vector of the control variables (firm size, number of employees, leverage and headquarters country) and f_{jt} is the interactive fixed effect for industry j and time period t (456 categories) which accounts for unobserved time and industry specific-shocks such as changes in the regulatory environment (Verbeek 2021). We report heteroscedasticity-robust standard errors.

We could add other time-varying controls to equation 3 such as R&D expenditure, which may affect the performance and innovation variables, particularly Tobin's Q and patents. However, following Ahern and Dittmar (2012) we chose not to include them as the endogenous nature of corporate choices means these could be "bad controls" in that a change in a company's DEI strategy could also change R&D expenditure decisions. To increase the robustness of our results we examine alternative timings for the relationship between the *DEI Signal* change and the outcome variables. Specifically, we estimate additional models based on equation 3, where *DEI Signal* is either not lagged, or with two and three year lags.

To better understand the relationship between DEI and firm performance, we then disaggregate equation 3 by sector and by firms' growth stage. As firms' capabilities are affected by sector vari-

[10]The 19-sector FactSet classification is more detailed than the 11-sector GICS classification, allowing for a more robust control.

ations concerning profitability, performance and innovation such as technological regimes (Hansen and Wernerfelt 1989, Malerba 2002) as well as DEI characteristics such as demographic diversity composition (Ozgen 2021), estimating equation 3 separately by sector allows us to capture these variations.

Moreover, capturing organisational growth stages is important given the differing dynamics, resource allocation and strategic decisions firms make. Steady-state firms are more likely to focus on incremental innovation and optimising existing processes (Tidd, Bessant and Pavitt 2005) while growth-state firms are characterised by rapid expansion, innovation and evolving organisational structures which might amplify the impact of DEI initiatives on innovation and performance (Colombelli, Krafft and Quatraro 2014, Mazzucato and Parris 2015). We therefore estimate equation 3 separately for growth and steady-state firms. To classify firms, we calculated the average 5-year dividend yield data from the Security and Exchange Commission (SEC)'s website for a subset of 256 firms in our data. We can distinguish between firms in steady-state growth if their average yield over the past 5 years is above 2%, and 2% or below as growth-state. We also investigate resource intensity by categorising firms into labour-intensive and capital-intensive based on their employee-to-capital-expenditure ratio tertiles, with the results reported in Table A7 (A.A3).

Equation 3 controls for sector and time shocks, however, to address potential endogeneity arising from the use of panel fixed effects models, we complement this with an instrumental variable (IV) design, detailed in A.A4. Doing so addresses potential causes of endogeneity identified in studies primarily interested in uncovering the relationship between DEI (particularly demographic diversity) and firm performance (Sieweke, Bostandzic and Smolinski 2023), namely omitted variable bias, omitted selection and selection.

C. Results

Market Performance

Figure 1 illustrates the coefficients of the *DEI Signal* from separate regressions following equation 3 for the market performance variables across different time lags (no lag, one-year, two-year, three-year, and four-year lags). For Tobin's Q, a consistent positive and significant relationship with *DEI Signal* over these periods indicates a long-term impact that gradually diminishes. This could

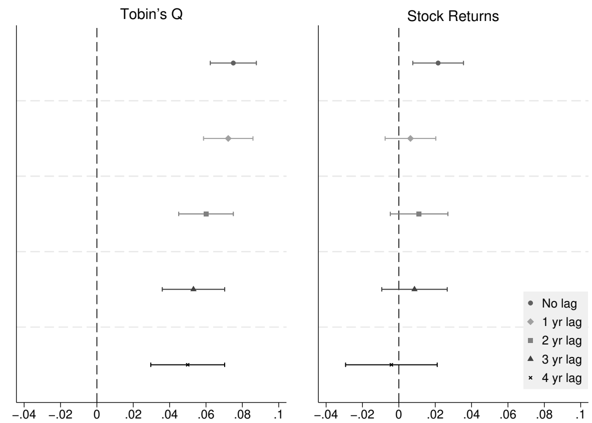

Figure 1. DEI Signal Effect on Market Performance at Different Time Lags

Note: Figure plots the coefficients for separate fixed effects models with different lags of DEI Signal. Confidence intervals plotted at the 95% level.

suggest that enhancements in DEI contribute to firm performance, with the effect stabilising and waning as such practices become customary or embedded within the organisational culture. Stock returns exhibit a positive relationship with *DEI Signal* at lag 0, albeit with a smaller magnitude than that of Tobin's Q. However, this effect is not maintained in the longer term, as evidenced by non-significant coefficients at subsequent lags.

Table 4, Panel A presents the estimated results of equation 3 for the entire sample, and separately for steady-state firms and growth-state firms, where DEI is lagged by one year. This and subsequent tables display the standardised effects on company performance. We find a significant positive relationship between the *DEI Signal* and Tobin's Q, with a 1 standard deviation increase in DEI associated with a 0.072 standard deviation increase in Tobin's Q. Moreover, the coefficients in columns (3) and (5) indicate that the association between *DEI Signal* and Tobin's Q is more pronounced for growth-state firms compared to steady-state firms.[11] Specifically, a one standard deviation increase in *DEI Signal* is associated with an uplift in Tobin's Q of 0.085 standard deviations for growth-state firms and 0.041 standard deviations for steady-state firms.

Conversely, in line with Figure 1, Table 4, Panel A shows that the relationship between DEI

[11] We also conducted an alternative specification for growth-state firms that includes firms that did not report dividend yields, or with yields equal to zero, with results remaining consistent. Reported in Table A8 of A.A3.

Table 4— Effect of DEI Signal on Firm Market Performance

Panel A: Overall Effects and Differences by Growth Stages						
	Overall Sample		Steady-state firms		Growth-state firms	
	(1)	(2)	(3)	(4)	(5)	(6)
	Tobin's Q	Stock Returns	Tobin's Q	Stock Returns	Tobin's Q	Stock Returns
DEI Signal	0.072***	0.006	0.041***	0.012	0.085***	0.000
(1yr lag)	(0.007)	(0.007)	(0.009)	(0.016)	(0.016)	(0.015)
Total Employees	0.147***	-0.013	0.272***	-0.014	0.488***	0.015
(log)	(0.012)	(0.012)	(0.024)	(0.026)	(0.033)	(0.028)
Total Assets	-0.562***	-0.053***	-0.499***	0.019	-0.791***	0.002
(log)	(0.013)	(0.011)	(0.025)	(0.028)	(0.029)	(0.027)
Leverage	-0.012	-0.010	0.131***	-0.020	-0.326***	-0.022
	(0.012)	(0.007)	(0.016)	(0.019)	(0.020)	(0.023)
Country	-0.596***	-0.131***	0.008	-0.130**		
	(0.015)	(0.016)	(0.035)	(0.061)		
Obs	18,837	18,837	2,844	2,844	2,458	2,458
Adjusted R^2	0.442	0.368	0.347	0.513	0.535	0.534

Panel B: Sector Differences							
	(1)	(2)			(3)	(4)	
	Tobin's Q	Stock Returns	Obs		Tobin's Q	Stock Returns	Obs
Communication	0.189***	-0.036	890	Health Care	0.027	-0.003	1,925
Services	(0.057)	(0.039)			(0.024)	(0.027)	
Consumer	0.112***	-0.001	2,759	Industrials	-0.035***	-0.021	3,019
Discretionary	(0.021)	(0.025)			(0.011)	(0.014)	
Consumer	0.129***	-0.016	1,148	Information	0.291***	0.027	2,601
Staples	(0.026)	(0.020)		Technology	(0.025)	(0.022)	
Financials	0.078***	0.013	2,586				
	(0.017)	(0.013)					

Note: All variables have been standardized. Values in Panel A are coefficients for regressions with time dummies (quarter from 2015 to 2022) interacted with sector fixed effects. Models by growth stage are estimates for a subset of 131 firms which have been classified as: dividend yield bigger than 2%, steady growth state; below 2% growth state. Values in Panel B are DEI Signal coefficients for separate regressions with full sets of controls and time fixed effects for separate models by sector. Sectors are classified according to GICS classification. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and stock returns, our alternative measure for market performance, is not significant and centred around zero for both the entire sample and when examining firms by growth stages. Tobin's Q is a measure of long-term performance (Foster et al. 2021), while stock returns are relatively short-term, which suggests that DEI impacts are not related to immediate market reactions, but more long-term, structural or strategic benefits.

Given the influence of sector variations on firm capabilities regarding profitability, performance and innovation such as technological regimes (Hansen and Wernerfelt 1989, Malerba 2002) as well as DEI characteristics such as demographic diversity composition (Ozgen 2021), we next examine variations by sector. We exclude Energy, Materials, Real Estate and Utilities because of the small number of firms and reviews (see Table 2). Table 4, Panel B presents the coefficients of *DEI Signal,* as obtained from equation 3 when estimated separately by sector.[12] The coefficients for *DEI Signal* are both positive and significant for the Tobin's Q models in sectors that are service-oriented or rely heavily on critical thinking and creativity (Communication Services, Consumer Discretionary and Staples, Financials and Information Technology), with the largest effect observed in Information Technology firms (0.377 standard-deviations). In sectors primarily reliant on high capital expenditure and physical infrastructure, namely Industrials and Healthcare, we find no association between DEI and Tobin's Q in Healthcare firms and a negative, small association in Industrials firms. In line with the results in Panel A, *DEI Signal* is not associated with stock returns across sectors.

These results suggest that an increase in DEI is positively related to better long-term market performance, measured by Tobin's Q, consistent with prior results findings that firms with higher diversity and inclusion exhibit higher Tobin's Q (Foster et al. 2021). At the same time, the non-significant relationship with stock returns indicates that DEI is not reflected in short-term market valuation. This discrepancy may arise because stock returns are somewhat noisy. For instance, Pástor, Stambaugh and Taylor (2022) investigate ESG investing, specifically "green" stocks, and show that both a taste premium and a risk premium can drive investors' decisions towards ESG investing, which cannot be fully accounted for in a fixed effects model. Moreover, higher DEI might not impact stock returns because investors might not believe that DEI is value-relevant, consistent with previous findings on diversity studies that found that the gender of top executive appointments is unrelated to stock market responses (Brinkhuis and Scholtens 2018). However, this result contrasts with Shan, Fu and Zheng (2017), who examine the market performance of US publicly listed firms between 2002 and 2006 and show that firms with a higher degree of corporate sexual equality also exhibit higher market performance, both in terms of Tobin's Q and higher stock returns.

[12]Equation 3 is modified, by replacing the time and sector interaction fixed effects with only time fixed effects. Sectors are classified using GICS 11-sector classification due to sample size restrictions compared to the more detailed FactSet-19 classification.

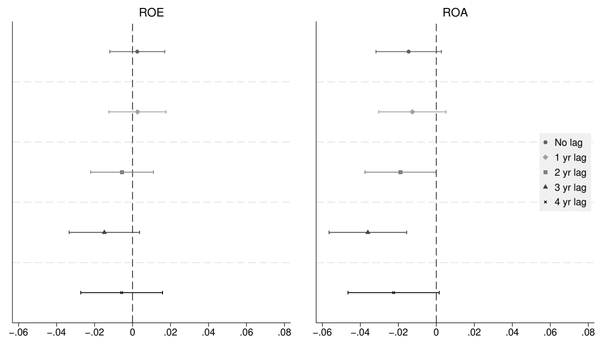

Figure 2. DEI Signal Effect on Accounting Performance at Different Time Lags

Note: Figure plots the coefficients for separate fixed effects models with different lags of DEI Signal. Confidence intervals plotted at the 95% level.

Accounting Performance

In Figure 2 and Table 5, we examine Return on Assets (ROA) and Return on Equity (ROE) to understand the extent to which DEI impacts accounting performance. We find no consistent evidence of a relationship between DEI and either measure across the time lags shown in Figure 2.

Table 5, Panel A presents the estimated results of equation 3 again for the full sample and separately for steady-state and growth-state firms. We find that DEI is insignificantly related to ROA in all models (columns 2, 4, and 6), and unrelated to ROE for the full sample and when examining steady-state firms. However, there is a significant and substantive relationship between the *DEI Signal* and ROE for growth firms, where a 1 standard deviation increase in DEI is associated with a 0.047 standard deviation increase in ROE. This could suggest that DEI may play a more important role in terms of profitability in periods of dynamic change. This could be because growth-stage firms are more likely to use and integrate the different perspectives and unique information from team members, found to enhance team performance to innovate more rapidly (Mesmer-Magnus and DeChurch 2009).

Table 5 Panel B illustrates the effects of DEI on firm accounting performance, disaggregated by sector. We find evidence of sector heterogeneity in the relationship between DEI and accountancy-based firm performance, with effects consistent across ROE and ROA. In Consumer Staples and Financials, DEI is positively associated with ROE and ROA, while in Communication Services

Table 5— Effect of DEI Signal on Firm Accounting Performance

Panel A: Overall Effects and Differences by Growth Stages

	Overall Sample		Steady-state firms		Growth-state firms	
	(1)	(2)	(3)	(4)	(5)	(6)
	ROE	ROA	ROE	ROA	ROE	ROA
DEI Signal	0.003	-0.013	0.026	0.019	0.047**	0.021
(1yr lag)	(0.008)	(0.009)	(0.021)	(0.015)	(0.022)	(0.020)
Total Employees	0.145***	0.361***	0.199***	0.229***	0.250***	0.495***
(log)	(0.015)	(0.016)	(0.077)	(0.045)	(0.041)	(0.033)
Total Assets	-0.077***	-0.412***	-0.205***	-0.411***	-0.102***	-0.691***
(log)	(0.014)	(0.016)	(0.076)	(0.050)	(0.038)	(0.034)
Leverage	-0.051***	0.045***	0.168***	0.087***	-0.155***	-0.163***
	(0.009)	(0.011)	(0.037)	(0.025)	(0.049)	(0.026)
Country	-0.071***	-0.159***	0.106	0.129**		
	(0.017)	(0.017)	(0.089)	(0.061)		
Obs	18837	18837	2844	2844	2458	2458
Adjusted R^2	0.047	0.140	0.130	0.312	0.093	0.380

Panel B: Sector Differences

	(1)	(2)			(3)	(4)	
	ROE	ROA	Obs		ROE	ROA	Obs
Communication	-0.049	0.149***	890	Health Care	0.052*	-0.012	1,925
Services	(0.056)	(0.057)			(0.030)	(0.032)	
Consumer	-0.023	-0.119***	2,759	Industrials	-0.005	-0.036**	3,019
Discretionary	(0.027)	(0.034)			(0.019)	(0.018)	
Consumer	0.179***	0.113***	1,148	Information	-0.043**	-0.105***	2,601
Staples	(0.044)	(0.024)		Technology	(0.022)	(0.026)	
Financials	0.040***	0.039**	2,586				
	(0.011)	(0.016)					

Note: All variables have been standardized. Values in Panel A are coefficients for regressions with time dummies (quarter from 2015 to 2022) interacted with sector fixed effects. Models by growth stage are estimates for a subset of 131 firms which have been classified as: dividend yield bigger than 2%, steady growth state; below 2% growth state. Values in Panel B are DEI Signal coefficients for separate regressions with full sets of controls and time fixed effects for separate models by sector. Sectors are classified according to GICS classification. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

also shows a positive association with ROA, though the relationship with ROE is non-significant. Specifically, Consumer Staples exhibits the strongest positive impact, with a 1 standard deviation increase in *DEI Signal* associated with increases of 0.179 standard deviations in ROE and 0.113 standard deviations in ROA. Conversely, in Consumer Discretionary, Industrials, and Information Technology, DEI is negatively associated with performance, particularly when measured by ROA. This variation across sectors may help explain why, in Panel A, there is no overall significant relationship between DEI and accounting measures. It suggests that the impact of DEI on financial performance is not uniform across industries and highlights the importance of sector-specific factors when examining DEI and company culture.

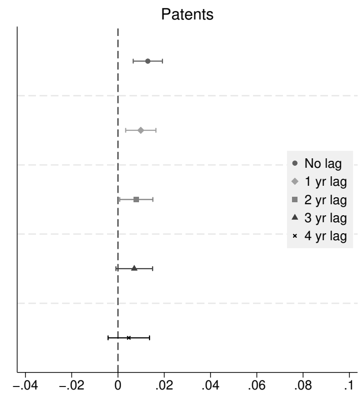

Figure 3. DEI Signal Effect on Accounting Performance at Different Time Lags

Note: Figure plots the coefficients for separate fixed effects models with different lags of DEI Signal. Confidence intervals plotted at the 95% level.

Innovation

Our final set of analyses focuses on innovation, as measured by the number of patent families. Figure 3 illustrates the relationship between patents and *DEI Signal* at different time lags. The *DEI Signal* shows a positive and significant effect for lag 0 and the 1-year lag, which becomes non-significant in subsequent lags. The coefficient for 1-year lag, shown in Table 6, Panel A which provides the results of equation 3, shows that a 1 standard deviation increase in *DEI Signal* is associated with a 0.01 standard deviation increase in patents, a smaller effect than the one found for Tobin's Q. It follows also, given the lifecycle of patents from conception to acceptance that the relationship between DEI and patents, also represents a long-run benefit. In terms of growth stages, we find that DEI is non-significantly related to patents in steady-state (column 2) and growth-state firms (column 3).

In Table 6 Panel B, we disaggregate the sample by industry. We find there is a consistent positive relationship with *DEI Signal* across most sectors, except for Financials, where we observe a negative small significant relationship, consistent with the financial sector's typical lack of reliance on patenting.[13]

[13]While the number of patented innovations in finance has consistently increased since the 2000s, Lerner et al. (2021) show that patenting activity in the US is driven by information technology and payments firms which hold the majority of patents, whereas banks represent a small percentage of patenting activity in financial innovation.

Table 6— Effect of DEI Signal on Firm Innovation

Panel A: Overall Effects and Differences by Growth Stages

	Overall Sample	Steady-state firms	Growth-state firms
	(1)	(2)	(3)
	Patent Count	Patent Count	Patent Count
DEI Signal (1yr lag)	0.010***	-0.023	-0.019
	(0.003)	(0.035)	(0.017)
Total Employees (log)	0.163***	0.682***	0.349***
	(0.022)	(0.170)	(0.046)
Total Assets (log)	0.132***	0.326***	0.314***
	(0.011)	(0.119)	(0.050)
Leverage	0.024***	0.883***	-0.059**
	(0.005)	(0.117)	(0.023)
Country	0.080***	-0.215**	
	(0.012)	(0.094)	
Obs	18,837	2,844	2,458
Adjusted R^2	0.068	0.237	0.201

Panel B: Sector Differences

	(1) Patent Count	Obs		(2) Patent Count	Obs
Communication Services	0.073***	890	Health Care	0.013***	1,925
	(0.016)			(0.002)	
Consumer Discretionary	0.038***	2,759	Industrials	0.062***	3,019
	(0.005)			(0.011)	
Consumer Staples	0.072***	1,148	Information Technology	0.076***	2,601
	(0.011)			(0.024)	
Financials	-0.003***	2,586			
	(0.001)				

Note: All variables have been standardized. Values in Panel A are coefficients for regressions with time dummies (quarter from 2015 to 2022) interacted with sector fixed effects. Models by growth stage are estimates for a subset of 131 firms which have been classified as: dividend yield bigger than 2%, steady growth state; below 2% growth state. Values in Panel B are DEI Signal coefficients for separate regressions with full sets of controls and time fixed effects for separate models by sector. Sectors are classified according to GICS classification. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Robustness Tests

We test the sensitivity of our findings and address endogeneity concerns by conducting additional analyses. The detailed results are presented in A.A3 and A.A4, and we summarise the results here.

Firstly, we estimate equation 3 separately for firms headquartered in the UK and the US. The results for market-based performance and innovation are similar to the main specification, with a larger magnitude observed for US compared to UK-listed firms. The results in Appendix Table A6 also show that the *DEI Signal* in the ROA models is statistically significant for both countries, with a small positive effect found in UK firms and a small negative effect in US firms, suggesting that DEI's impact on accounting performance may vary depending on the national context.

We then check the robustness of our main specification by replacing the sector $\times$ time fixed effects with i) firm and fixed effects, and ii) firm fixed effects and estimating these models with and without controls. The results in Table A9 show that for most outcomes, the *DEI Signal* coefficient becomes non-significant, apart from Tobin's Q where the *DEI Signal* remains significant and positive in the firm fixed effects model.

To address endogeneity problems, we also propose an instrumental variable model using a shift-share instrument fully detailed in A.A4. The results of the instrumental variable estimates are in line with our main result for Tobin's Q, however, the magnitude of the estimate is larger than the main estimates.

Importantly, our DEI measure captures perceptions of exclusion and inclusion for employees and specific diversity-related issues such as gender or racial barriers, but it does not capture the actual levels of diversity within the firms, which we address in the following section.

III. DEI, Senior Team Diversity and Firm-Level Performance

We also wish to better understand the relationship between DEI, as perceived by employees, and the demographic diversity of senior management, and how these factors together impact firm performance. In this section, we extend existing research by examining how these elements interact at the senior management level, focusing on gender and ethnic diversity, to influence a firm's financial and innovation outcomes.

The composition, attitudes and actions of senior management teams are likely crucial in shaping an organization's culture and overall DEI climate, yet only a few studies have directly investigated this relationship to date (Homan et al. 2020, Martins 2020, Shore and Chung 2022). Research on the effects of diverse leadership teams on financial performance has predominantly focused on board-level diversity, often limited to a single aspect of diversity, typically gender, partly reflecting national policies such as quotas for female representation (Terjesen, Aguilera and Lorenz 2015, Triana, Richard and Su 2019). Although some studies have started looking at senior management beyond the upper echelons (Sieweke, Bostandzic and Smolinski 2023, Triana, Richard and Su 2019), other aspects of diversity such as ethnicity warrant further scholarly attention. The findings of the literature are not consistent: with evidence pointing towards a positive relationship between board gender diversity and accountancy-based performance and long-term market performance such as Tobin's Q, and near-zero or negatively related to short-term market measures such as stock returns (Jeong and Harrison 2017, Post and Byron 2015). These mixed findings are attributed to correlational designs, differences in measurement use and methodologies, and omitted variable biases (Adams et al. 2015). Beyond financial performance, research has also examined other outcomes, suggesting that senior management diversity particularly on boards, is positively related to changing dynamics of the group, board diversity policies, and firms' social performance (Bernstein et al. 2020, Buse, Bernstein and Bilimoria 2016, Byron and Post 2016). Yet, there is a clear need to investigate how diversity within the entire senior management team interacts with DEI to impact firm performance.

An increase in demographic diversity is also proposed to increase cognitive diversity, due to the increased range of information, skills, and perspectives that diverse attributes and backgrounds bring to cognitive processes (Bell et al. 2011, Williams and O'Reilly 1998). Given the focus on workforce composition data, we do not directly measure cognitive diversity and therefore are limited in our ability to draw conclusions regarding the benefit of cognitive differences for organisational outcomes (Miller et al. 2022). We expect that diversity in senior management can amplify the effects of workforce DEI as diverse members shape policies, practices and behaviours that promote inclusion (Bernstein et al. 2020). At the same time, improvements in DEI should lead to greater diversity within senior management. However, we hypothesize that improvements in diversity shares alone, without corresponding levels of inclusion, are unlikely to impact financial and innovation outcomes as the gains from diversity (i.e., cognitive diversity and variety of experiences) are not being fully realised by the firm.

To explore these dynamics, we use a novel dataset from Revelio Labs, which provides detailed demographic data on workforce composition. From this dataset we construct quarterly measures of senior management diversity for 2015-2022, spanning the 945 firms. These measures are then analysed in conjunction with the *DEI Signal* measure to assess how the interaction between senior management ethnic and gender diversity and DEI influences firm performance.

A. Measures of Diversity

To develop measures of senior management diversity, we use data from Revelio Labs. Revelio Labs is a data provider that aggregates workforce data from multiple sources, including online professional profiles (e.g., LinkedIn), job postings, company websites, government records and census data. Data are aggregated by firm and time and weighted to correct for underrepresentation in online professional profiles, such as lower-skilled or lower-paid roles, as well as to address issues such as mapping discrepancies and the presence of fake or duplicate profiles. For each firm, Revelio provides global and local headcounts and demographic characteristics of employees including gender and ethnicity, based on probabilistic estimations.

From this data, we focus on the gender and ethnicity diversity of employees located in the US or the U.K., serving as a proxy for headquarters location, since the firms in our sample are listed on the MSCI US and S&P U.K. indices. Our analysis is concentrated on senior management positions, defined as executive and senior executive roles (e.g., Managing Director, Partner, CEO, CFO). This selection is informed by a sensitivity analysis of the thresholds gender and ethnicity classification, detailed in A.A5, aimed at maximizing classification and minimizing the number of "unassigned" individuals.[14] We restrict the sample to senior management in the headquartered country as there is a growing literature indicating that executive and senior management characteristics impact management practices and firm performance (Flabbi et al. 2019). Additionally, these roles are less likely to be underrepresented in the Revelio dataset.

Diversity is operationalised as 'variety' using Blau's index (1977), the most commonly used measure for capturing differences in group composition on a categorical variable.[15] The Blau index is defined as:

$$H = 1 - \sum_{i=1}^{k} p_i^2 \tag{4}$$

[14] An individual's gender and ethnicity are predicted by estimating the probability of their gender and ethnicity based on their name and location for ethnicity. Ethnicity is only assigned when the probability of belonging to the ethnic group is above 45%, and gender if the probability is above a threshold of 60%.

[15] For a detailed discussion on the different operationalisations of diversity, see Budescu and Budescu (2012) and Harrison and Klein (2007).

Where p is the proportion of individuals belonging to the ith category, and k denotes the number of categories for an attribute of interest. Statistically, the Blau index represents the probability that two randomly selected individuals from a population belong to different categories, with higher values reflecting greater diversity (Budescu and Budescu 2012).

We construct Blau indices for gender and ethnicity based on the categories available in the Revelio dataset. Gender is classified into two categories (male and female) and ethnicity into six categories derived from the US Census classification (White, Black, Asian and Pacific Islander, Hispanic, Multiple ethnicities, and Native) categories. The resulting Blau indices are normalised by dividing each index by its theoretical maximum, yielding the Index of Qualitative Variation (IQV; Agresti and Agresti (1978)) so that they range between 0 and 1, allowing for comparability between them. Given that ethnicity is derived based on an individual's name and location, it can be interpreted as a proxy for cultural assimilation with local conditions, rather than fixed ethnic categories.[16]

Table 7 provides descriptive statistics for senior management diversity. In our sample, on average about 27% of senior management are women, and 82% are White. Figure A3 in A.A5 illustrates their trend over time. From 2015 onwards, there was a steady increase in the share of women in top seniority positions at headquarters locations, rising from approximately 24% in early 2015 to around 31% by the first quarter of 2022. Similarly, there was a rise in the share of non-white individuals in executive positions, growing from roughly 17% in early 2015 to about 20% by the first quarter of 2022. Figure A4 further illustrates the differences between UK and US firms, with US firms having a higher average share of non-white employees in senior management and also experiencing a greater gain in share for the 2015 to 2022 time period. Table 7 also illustrates the correlations between our measures of senior management diversity and *DEI Signal*. The correlation with *Blau Gender* is only 0.054 and with *Blau Ethnicity* 0.138, suggesting that *DEI Signal* is capturing information above and beyond diversity.

[16] For a more in-depth view of names and assimilation Carneiro, Lee and Reis (2020) provide a historic view of immigrants in the US adopting American names and examine the economic and social incentives that drive this assimilation process. Goldstein and Stecklov (2016) analyse the naming choices of the children of immigrants and the relevance of assimilation for economic success.

Table 7— Descriptive Statistics - Senior Management Diversity

	Mean	SD	Correlations		
Descriptive Variables					
Share of Senior Management Women	0.273	0.131			
Share of Senior Management Non-White	0.183	0.121			
Main Variables			(1)	(2)	(3)
(1) Blau Gender Senior Management	0.736	0.248	1.000		
(2) Blau Ethnicity Senior Management	0.327	0.185	0.305	1.000	
(3) DEI Signal			0.054	0.138	1.000

B. Model

To estimate the impact of DEI and senior management diversity on firm performance, we extend the fixed effects model presented in equation 3 to include diversity. We test two specifications:

$$y_{ijt} = \delta DEI_{ijt-1} + \gamma MD_{ijt-1} + \beta' X_{ijt} + f_{jt} + \epsilon_{ijt} \tag{5a}$$

$$y_{ijt} = \delta DEI_{ijt-1} + \gamma MD_{ijt-1} + \theta(DEI_{ijt-1} * MD_{ijt-1}) + \beta' X_{ijt} + f_{jt} + \epsilon_{ijt} \tag{5b}$$

where MD denotes the lagged senior management diversity measure for firm i at quarter-year t (either Blau Gender or Blau Ethnicity), and all other variables remain the same as equation 3, apart from X_{it} the vector of controls, which also now includes the number of employees in the headquarters country and the share of employees in top senior positions in the headquarters country.

C. Results

Table 8 presents the estimation results for equations 5a and 5b. Panel A presents the coefficients for the models with Blau Ethnicity, while Panel B presents the results for the models with Blau Gender. An additional specification, with results presented in Table A12 in A.A5, includes only the diversity measure and relevant controls.

Turning to Panel A, we observe that the ethnic diversity of senior management is positively related to most performance and innovation measures, except ROE, where the relationship is negative and marginally significant ($p < 0.1$) across both models 5a and 5b. Columns (1), (3), (5), (7) and (9) report the estimates following equation 5a, showing a positive and significant DEI coefficient for Tobin's Q, consistent with the DEI-only models of Section II, and non-significant coefficients for the remaining outcomes. Turning to the results following equation 5b that account for the interaction term *Blau Ethnicity* × *DEI Signal*, we find the interaction terms are also positive and significant for Tobin's Q and Patents, as shown in columns (2) and (10), with a larger effect size in the Tobin's Q specification. However, when the interaction term is included, the *DEI Signal* coefficient becomes insignificant in the Tobin's Q model and negative in the Patents model. This suggests that the interaction between Blau Ethnicity and *DEI Signal* captures the combined effect more accurately than the *DEI Signal* alone, and the presence of the negative coefficient for patents might indicate that the positive effects of *DEI Signal* on Patents are conditional upon a certain level of ethnic diversity, which we further explore in Figure 4.

In Panel B, the results for gender diversity reveal no significant relationship with market-based performance measures such as Tobin's Q and Stock Returns, and a negative association with accounting-based performance (ROE and ROA) and patents. These findings are also consistent when we exclude the *DEI Signal* (as reported in Appendix Table A12) and suggest that while increased ethnic diversity in senior management is positively associated with performance across four of the five measures, increased gender diversity alone either shows no relationship or a negative relationship with performance outcomes. These results align with the "glass cliff" hypothesis, which proposes that female candidates are more likely to be appointed into top management positions in times of crisis and during downturns in company performance (Reinwald, Zaia and Kunze 2023, Ryan and Haslam 2007). The *DEI Signal* coefficients following equation 5a align with the DEI-only models from Section II, where the *DEI Signal* coefficient is positive and significant for Tobin's Q, and Patents, with similar effect sizes. When incorporating the *Blau Gender* × *DEI Signal* interaction following equation 5b, the interaction term is positive and significant for Tobin's Q and Stock Returns (columns 2 and 4), although the effect sizes are smaller than those observed for ethnic diversity. The inclusion of the interaction term renders the *DEI Signal* coefficient insignificant in the Tobin's Q model and negative in the Stock Returns model.

To better understand the interaction between senior team ethnic diversity and DEI, Figure 4

Table 8— Effect of DEI and Senior Management on Firm Performance

Panel A: Ethnicity										
	Tobin's Q		Returns		ROE		ROA		Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Blau Ethnicity	0.693***	0.704***	0.150***	0.152***	-0.111*	-0.111*	0.138**	0.138**	0.248***	0.253***
Senior Mng	(0.049)	(0.049)	(0.047)	(0.047)	(0.059)	(0.060)	(0.057)	(0.057)	(0.057)	(0.057)
DEI Signal	0.067***	0.000	0.003	-0.008	0.004	0.008	-0.010	-0.008	0.005	-0.026***
	(0.007)	(0.012)	(0.007)	(0.011)	(0.008)	(0.013)	(0.009)	(0.015)	(0.003)	(0.005)
Blau Ethnicity		0.250***		0.044		-0.015		-0.007		0.118***
× DEI Signal		(0.038)		(0.042)		(0.041)		(0.048)		(0.019)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18,753	18,753	18,753	18,753	18,753	18,753	18,753	18,753	18,753	18,753
R-Squared	0.464	0.466	0.385	0.385	0.073	0.073	0.165	0.165	0.096	0.097
Panel B: Gender										
	Tobin's Q		Returns		ROE		ROA		Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Blau Gender	-0.025	-0.014	-0.056*	-0.047	-0.114***	-0.112***	-0.159***	-0.164***	-0.145***	-0.147***
Senior Mng	(0.031)	(0.031)	(0.033)	(0.034)	(0.039)	(0.039)	(0.041)	(0.042)	(0.030)	(0.030)
DEI Signal	0.074***	0.017	0.005	-0.046**	0.003	-0.007	-0.008	0.015	0.009**	0.015**
	(0.007)	(0.018)	(0.007)	(0.019)	(0.008)	(0.019)	(0.009)	(0.025)	(0.003)	(0.008)
Blau Ethnicity		0.083***		0.074***		0.015		-0.033		-0.009
× DEI Signal		(0.025)		(0.027)		(0.028)		(0.035)		(0.010)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18,753	18,753	18,753	18,753	18,753	18,753	18,753	18,753	18,753	18,753
R-Squared	0.456	0.457	0.385	0.385	0.073	0.073	0.166	0.166	0.096	0.096

Note: Values are coefficients of separate models where the independent variables are DEI Signal and senior management diversity lagged by one year, controls and sector interacted with time fixed effects. Controls are total employees, total employees in headquarters country, total assets, leverage, country and lagged share of senior management in headquarters country. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

illustrates the predictions of performance based on combinations of *DEI Signal* and Blau Ethnicity following equation 5b, presented in contour plots. The x-axis represents the Ethnicity Blau Index, ranging from 0 to 0.7 (covering 2 standard deviations from the mean), while the y-axis represents the *DEI Signal*, ranging from -2 to 2 (also spanning 2 standard deviations from the mean, as it is a standardized variable). The grey-scale gradient indicates the predicted values of performance outcomes (Tobin's Q, Stock Returns, Patents, ROA). The plots reveal that the highest levels of performance are observed in the top-right-hand quadrant, where both *DEI Signal* and Blau Ethnicity are at the upper ranges for Tobin's Q, Stock Returns and Patents. However, the plot for ROA shows higher performance occurring in the bottom-right quadrant, where ethnic diversity is high, but the *DEI Signal* is not as strongly differentiated. It is important to note that in this model, *DEI Signal* was non-significant and should be interpreted with caution.

Overall, these findings suggest that the benefits of DEI on firm performance are not linear but rather conditional upon reaching a certain threshold level of ethnic diversity within senior management. Further, the interaction between DEI and ethnic diversity implies that without sufficient diversity, the positive impacts of DEI on performance might not be fully realised, in line with findings of a "critical mass" needed in terms of diversity in senior management for its effects to enhance performance meaningfully (Cook and Glass 2015, Konrad, Kramer and Erkut 2008, Schwartz-Ziv 2017). The results from the gender analysis are either non-significant or point towards a negative relationship with senior gender diversity, supporting previous meta-analytical findings of a mixed effect of female representation in CEO and top senior positions and financial performance (Jeong and Harrison 2017). However, in contrast with their results, our findings point to a non-significant relationship with long-term financial performance (as measured by Tobin's Q) instead of a weak positive relationship.

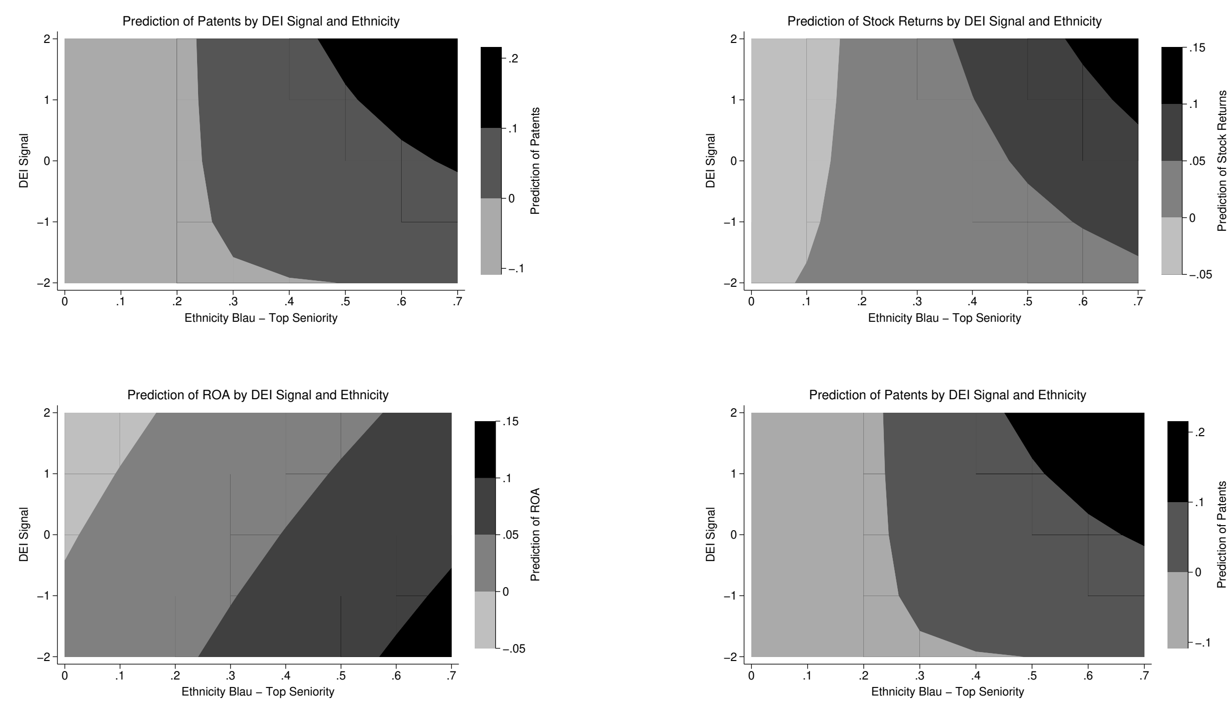

Figure 4. Interaction Plots DEI and Senior Management Diversity

IV. Conclusion

This paper investigates whether employee experiences, as expressed in Glassdoor reviews, can provide a meaningful assessment of DEI. We demonstrate that by analysing the naturally occurring data available in these reviews, we can capture valuable insights into individuals' DEI experiences. This approach offers a unique perspective on organisational practices, values, and experiences that extends beyond traditional metrics (Campbell and Shang 2022, Reader and Gillespie 2023). Moreover, it has important implications for the development of DEI metrics that go beyond demographic diversity, are not reliant on self-reports and can be constructed for a large set of firms.

We contribute to the growing literature on DEI and firm performance and the "business case" for DEI. We find that DEI is positively associated with long-term market valuation, as our results show a consistent positive association between DEI and Tobin's Q across different specifications. However, DEI appears unrelated to short-term financial market performance. We also find that DEI is positively linked to higher levels of innovation, measured by patents, yet shows a mixed relationship with accounting-based performance. Together, these results suggest that DEI may function as a strategic intangible asset, predictive of firm's future innovation and performance, which is also not at odds with firm profitability.

Our analysis of firm's growth stages may also illuminate the mixed findings of prior research on DEI and firm performance. Specifically, we find that the *DEI Signal* coefficient is larger for firms in a growth-state compared to steady-state firms. Additionally, there is evidence of a positive association between DEI and ROE for growth-state firms, while this association is non-significant for steady-state firms. This suggest that DEI may be a more significant predictor of performance in contexts where adaptability and high-quality human capital drive grow.

Our analysis also reveals that the interaction between employee DEI experiences and senior management diversity plays an important role in understanding the relationship between DEI and performance. Specifically, we find that the positive effects of DEI on long-term market performance and innovation are amplified in firms with higher levels of ethnic diversity in senior management. However, this is not the case when examining the gender diversity of senior management, mirroring previous findings of a mixed effect of gender diversity on performance (Jeong and Harrison

2017). This may indicate that in addition to DEI, other cultural, organisational, and environmental dynamics influence the relationship between gender diversity and firm performance.

While these results are correlational and should be interpreted with caution, they are useful in understanding the predictive relationship between DEI and firm performance. Our findings reveal that, in several key areas, higher DEI, as perceived by a firm's employees, can be an important predictor of future firm success, indicating that firms may benefit from investing in and prioritising DEI initiatives aligned with employee experiences. At the same time, the impact of DEI varies by context, growth-stage and industry. This suggests that both firms and investors could consider DEI as a potential intangible asset that contributes to long-term value in specific areas. Future research could expand on these findings through experimental work to better understand the causal pathways through which DEI affects performance. Moreover, as more public data sources become available for researchers to analyse firms' internal cultures, future analyses could capture additional aspects of DEI, such as employees' psychological safety or team diversity and revisit the present analyses to focus on these individual and team level constructs of DEI and their relationship with firm outcomes.

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Supplemental Appendix for "Diversity, Equity and Inclusion is not bad for business: Evidence from employee review data for companies listed in the UK and the US"

Teresa Almeida, Yehuda Dayan, Helen Krause, Grace Lordan, Andreas Theodoulou

A1. Glassdoor Reviews and DEI Signal Measure Construction

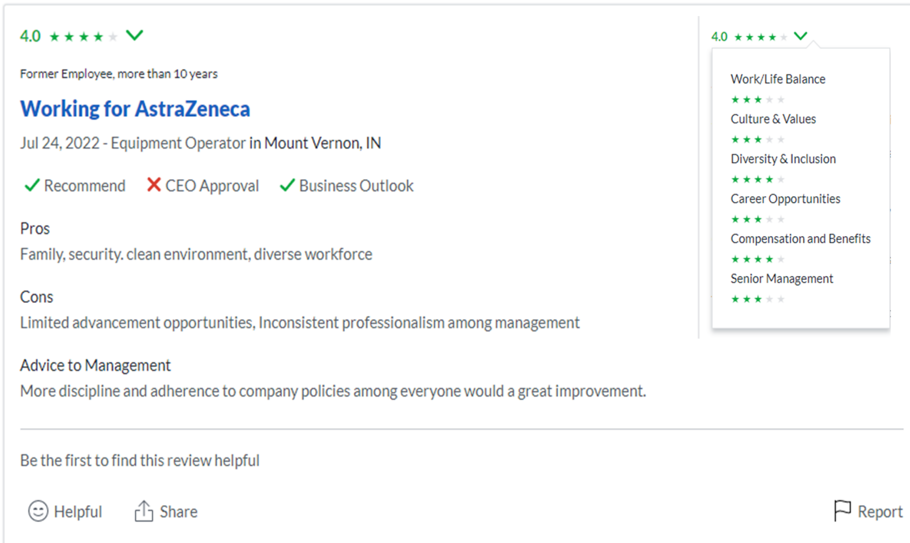


Figure A1. Example of employee review on Glassdoor.com

Figure A1 provides an example of a review on the Glassdoor platform. Each review includes an overall numerical rating (top left corner) and a drop-down menu with sub-ratings (visualised in the top right corner). The review can also include whether they recommend the company to others, state whether they approve of the company CEO and provide a personal outlook of the business. Reviewers then submit open-ended written answers expanding upon the benefits and disadvantages of working for the employer ("Pros" and "Cons" text fields) and can leave personal advice to management.

Table A1— Lexical Field for each Category of DEI

Keywords		
abuse, abusive	equality	nepot*, cronyism,
accessib*	ethic*, integrity, moral	openness
advocate, mentor, nurtur	ethnic, multicultural,	opportunities
aggressive	exclus*, excluded, alienat*,	politic*, power,
authoritarian, autocratic,	ignore*	punish, punitive,
backstab*, behind your back,	exploit*	race, racial, racist
bulli*, bully	family	religion
bame, bipoc, people of color,	femini*	respect*, dignit*,
people of colour	friendly, welcoming,	sexis*
belittle, condescending, devalue,	gender, women, woman, female	sexual, harass*,
looked down on,	gossip	silo*
bias, stereotype,	groupthink	snobby, jugdmental,
bigot, discriminat*, xenophob*	hatred, hostil*, unfriendly	transparen*
prejudic*	hierarchical	trust
clicky, clique*, ingroup,	inclusiv*	unappreciate*,
who you know	inequality, ineq*	underappreciate*,
degrading, offensive	masculine	undervalue*, value*,
collaborat*	misog, macho, patriarc	unprofessional
collegia*, camaraderie, comradery	male	toxic
compassion, empath*	marginalise*, marginalize*	work life balance,
corrupt, unethical*, dishonest,	meritocrac*	work from home
manipulative	micromanage*	paternalistic
crying	minorit*	team
culture	misconduct	atmosphere
dignit*		people
disengage		
divers*		
dysfunctional, unprofessional		
empower, autonomy		

Note: Keywords are the stemmed terms of the words, with * indicating any ending e.g., divers* includes for example diverse, diversity.

Table A1 describes the lexicon used to parse employee reviews, developed as described in the main text, aggregated based on lexical and thematic similarity.

Table A2— Relationship Between Review Section And Sentiment Signal

	Sentiment	
	Positive	Negative
Review Section		
Pro	1,014,516	11,977
	97.31%	2.49%
Con	28,095	469,794
	2.69%	97.51%
Total	481,771	1,042,611
χ^2 (1, N=1,524,382) = 1,300,000, p < 0.001		
V=0.94		

Table A2 shows the association between review sections matched to the DEI lexicon in the "Pro" and "Con" columns with having positive and negative sentiment scores constructed using the RoBERTa sentiment model (Liu et al. 2019).

A chi-square test of independence was conducted to examine the relationship between review section (Pro vs. Con) and sentiment signal (Positive vs. Negative). The results revealed a significant association between Section and Sentiment χ^2 (1, N=1,524,382) = 1,300,000, $p < 0.001$. The strength of this association, as measured by Cramér's V, was very large (V=0.94).

Table A3— Summary Statistics for Variables in Lasso Model

	Mean	Median	SD	Min	Max	N
Mean Review Rating	3.548	3.571	0.583	1	5.000	25,734
Number of Reviews	130.760	36.000	393.930	1	14106	25,734
Sample from Dataset of Keywords						
p_abuse	0.000	0.000	0.004	0	0.333	25,734
p_accessib	0.002	0.000	0.018	0	1	25,734
p_advocate	0.006	0.000	0.026	0	1	25,734
p_aggressive	0.001	0.000	0.011	0	1	25,734
c_unappreciate	0.016	0.000	0.041	0	1	25,734
c_unprofessional	0.005	0.000	0.026	0	1	25,734
c_toxic	0.009	0.000	0.036	0	1	25,734

Note: Variables constructed at the company, year-quarter level. A "p" prefix indicates the keyword is in the "Pro" category and a "c" in the "Con" category of the employee review.

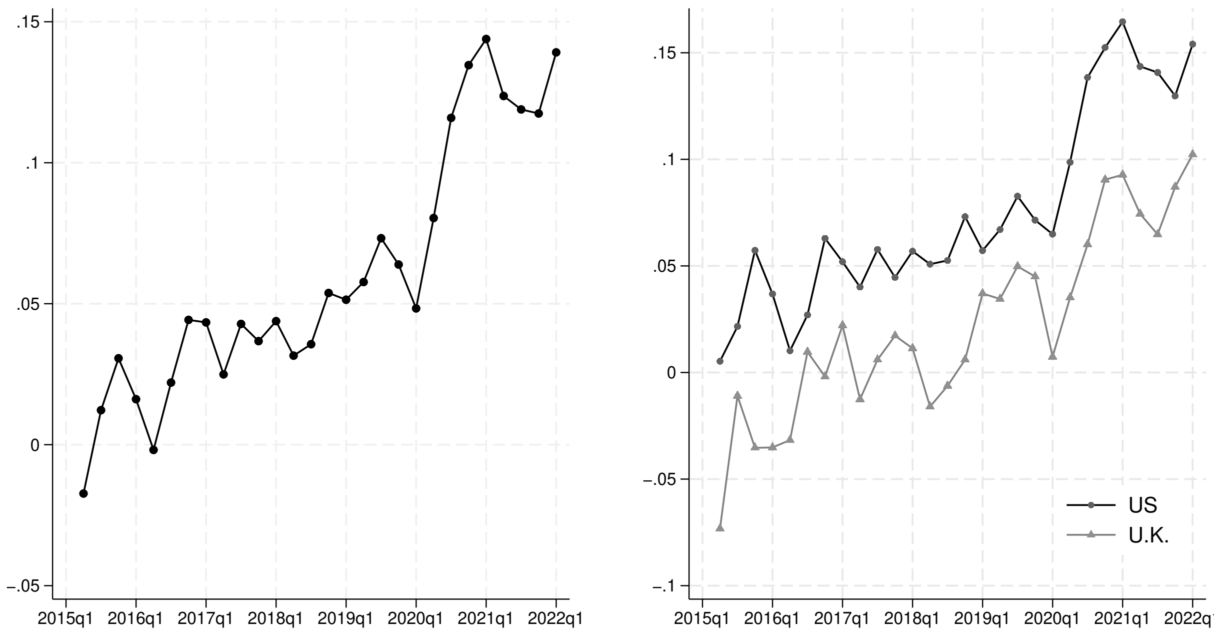
Table A3 shows the descriptive statistics for the variables used in the lasso model, specifically the mean review rating at the company-quarter level and a subset of the 136 predictor variables for the keywords, where the p or c prefix indicate their presence in the Pro or Con section of the employee reviews.

Table A4— Lasso Results

Model	Selection criterion	No of selected variables	Predictive R-Squared	MSE
A	CV min.	74	0.353	0.216
B	BIC min.	69	0.352	0.217
C	Plugin	33	0.342	0.220
D	Adaptive CV min.	56	0.351	0.217

Note: Total number of observations = 25,734, with 19,301 in the training set and 6,433 in the test set. Variables constructed at the company, year-quarter level.

Table A4 presents the results for the separate variants of lasso models tested using the Stata lasso command, and their goodness of fit. The models considered varied in terms of how they tune the lasso's penalty parameter (λ). Model A minimises the cross-validation error (CV), Model B minimizes the Bayes Information Criterion (BIC), Model C uses the plugin method to estimate and normalize the penalty parameter, and Model D is a variation of a CV model and applies an adaptive lasso approach with cross-validation to optimize variable selection resulting in fewer variables selected compared to the CV model (StataCorp. 2023). The model selected was Model A.



(a) DEI Over Time

(b) DEI Over Time by Country

Figure A2. DEI Signal Time Trends

Note: Figure plots the DEI signal for the 2015 to 2022 time period, with the right-hand side panel illustrating the trend separately for UK and US listed companies.

A2. Control Variables

Table A5— Control Variables Definitions and Summary Statistics

Variable	Description	Mean	SD	Min	Max	N
Total Assets	Log of total assets	16.060	1.825	7.265	22.098	25,011
Number of Employees	Total number of employees per quarter from Revelio Labs demographic data (log transformed)	8.943	1.678	0.033	13.755	25,822
Firm leverage	Total debt divided by total assets	0.301	0.228	0	3.945	24,997
Country	Dummy indicator if a firm is listed in the UK S&P BMI or US MSCI USA	1.288	0.453	1	2	26,460
Number of employees in HQ	Total number of employees per quarter from Revelio Labs demographic data (log transformed) in country (UK or US)	8.232	1.817	0.033	12.992	25,822
Share of senior management	Number of employees in senior management occupations divided by total number of employees in HQ country from Revelio Labs	0.032	0.036	0.000	1	25,435

Table A5 documents the control variables used in the *DEI Signal* models and additional controls used in the senior management diversity models.

A3. DEI Signal Additional Results

Table A6— Effect of DEI signal on Firm performance: Country Differences

	Tobin's Q	Stock Returns	ROE	ROA	Patents
UK Firms					
DEI Signal (1yr lag)	0.058***	-0.017	0.020*	0.040***	0.002**
	(0.011)	(0.011)	(0.012)	(0.013)	(0.001)
Observations	4,419	4,419	4,419	4,419	4,419
R-squared	0.427	0.478	0.187	0.326	0.137
US Firms					
DEI Signal (1yr lag)	0.077***	0.003	0.000	-0.040***	0.016***
	(0.009)	(0.009)	(0.010)	(0.011)	(0.005)
Observations	14,068	14,068	14,068	14,068	14,068
R-squared	0.479	0.394	0.082	0.181	0.111

Note: Values are *DEI Signal* coefficients for separate regressions by country with full sets of controls and time dummies (quarter from 2015 to 2022) interacted with sector fixed effects.. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6 documents the results for the effect of *DEI Signal* on firm performance where the sample is separated by UK and US listed firms. In line with the main results, DEI is positively and significantly associated with Tobin's Q in both regions, indicating that higher DEI is associated with greater long-term value. For stock returns, *DEI Signal* does not show a significant relationship with firms in either country, reinforcing that DEI's influence on short-term financial performance is limited. In terms of profitability, *DEI Signal* is positively related to both ROE and ROA in the UK. In contrast, in the US, *DEI Signal* shows a non-significant association with ROE and a negative relationship with ROA, which may imply different market dynamics or varying influence of DEI practices in profitability. DEI's impact on innovation, measured by the number of patents, is positive and significant in both countries, with the effect being larger in the US estimation.

Table A7— Effect of DEI Signal on Firm Performance: Labour and Capital Intensive Firms

	Tobin's Q	Stock Returns	ROE	ROA	Patents
	(1)	(2)	(3)	(4)	(5)
Employee to Capex Ratio: Top Tertile					
DEI Signal (1yr lag)	0.101***	0.001	-0.028**	-0.024	0.009
	(0.013)	(0.010)	(0.013)	(0.016)	(0.006)
Observations	5920	5920	5920	5920	5920
R-squared	0.501	0.416	0.033	0.185	0.008
Employee to Capex Ratio: Bottom Tertile					
DEI Signal (1yr lag)	0.031***	-0.004	0.003	-0.030*	0.028***
	(0.010)	(0.013)	(0.015)	(0.017)	(0.009)
Observations	5768	5768	5768	5768	5768
R-squared	0.548	0.365	0.085	0.158	0.247

Note: Values are *DEI Signal* coefficients for separate regressions by tertiles of employee to capex ratio with full sets of controls and time dummies (quarter from 2015 to 2022) interacted with sector fixed effects. Robust standard errors are in parentheses. Employee to Capex ratio is constructed as total employees divided by capital expenditure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A8— Effect of DEI signal on Firm Performance: Growth State Including Zeros

	Tobin's Q	Stock Returns	ROE	ROA	Patents
	(1)	(2)	(3)	(4)	(5)
DEI Signal (1yr lag)	0.080***	-0.004	0.038*	0.015	0.001
	(0.018)	(0.015)	(0.021)	(0.020)	(0.013)
Total Employees (log)	0.492***	0.029	0.223***	0.398***	0.277***
	(0.033)	(0.028)	(0.036)	(0.032)	(0.034)
Total Assets (log)	-0.847***	-0.025	-0.111***	-0.550***	0.272***
	(0.029)	(0.028)	(0.033)	(0.032)	(0.045)
Leverage	-0.354***	-0.021	-0.118***	-0.186***	-0.076***
	(0.022)	(0.021)	(0.039)	(0.024)	(0.018)
Country	-1.370***	0.216	0.100	-1.286***	0.455***
	(0.100)	(0.317)	(0.269)	(0.424)	(0.092)
Obs	3,007	3,007	2,986	2,987	3,007
Adjusted R-squared	0.511	0.474	0.079	0.281	0.173

Note: Values are coefficients for separate regressions for each of the outcomes considered in the column title, for a subsect of firms that are classified as in a growth state so that they have a yield below 2%, have not reported dividend yields, or with yields equal to zero. Models include full sets of controls and time dummies (quarter from 2015 to 2022) interacted with sector fixed effects. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A9— Effect of DEI Signal on Firm Performance: Company and Time Fixed Effects

	Tobin's Q				Stock Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DEI Signal (1yr lag)	0.005	0.012***	0.005	0.007*	-0.004	0.000	-0.003	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.010)	(0.009)	(0.010)
Company FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✗	✓	✗	✓	✗	✓	✗
Controls	✗	✗	✓	✓	✗	✗	✓	✓
Obs	18,948	18,948	18,828	18,828	18,948	18,948	18,828	18,828
Adjusted R-squared	0.889	0.883	0.897	0.892	0.305	0.004	0.310	0.007

	ROE				ROA			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
DEI Signal (1yr lag)	0.008	0.010*	0.007	0.008	0.006	0.005	0.004	0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Company FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✗	✓	✗	✓	✗	✓	✗
Controls	✗	✗	✓	✓	✗	✗	✓	✓
Obs	18,948	18,948	18,828	18,828	18,948	18,948	18,828	18,828
Adjusted R-squared	0.319	0.316	0.329	0.326	0.688	0.679	0.705	0.697

	Patents			
	(17)	(18)	(19)	(20)
DEI Signal (1yr lag)	0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Company FE	✓	✓	✓	✓
Time FE	✓	✗	✓	✗
Controls	✗	✗	✓	✓
Obs	18,948	18,948	18,828	18,828
Adjusted R-squared	0.956	0.956	0.957	0.957

Note: Values are are DEI Signal coefficients for separate regressions for each of the outcomes considered in the column title. Models include company fixed effects, time fixed effects and full sets of controls as depicted in the rows as ticks and crosses below the results. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A4. Shift-Share Instrument Analysis

Model Description

A large number of papers use Bartik or "shift-share" instruments across economics and finance to address endogeneity problems. These instruments involve using an aggregate shock such as changes that affect all units in a panel, with unit-specific weights to measure exposure to these shocks (Borusyak, Hull and Jaravel 2022). In labour market dynamics studies, following the work of Bartik (1991) and Blanchard and Katz (1992), the instrument is defined as the local employment growth rate predicted by interacting local industry employment shares with national industry employment growth rates (shift part of the instrument), which allows for an estimation of a causal effect by exploiting the exogenous part of the variation in the treatment variable (Goldsmith-Pinkham, Sorkin and Swift 2020).

In the context of diversity and firm performance studies, Sieweke, Bostandzic and Smolinski (2023) use a shift-share instrument to analyse the effect of gender diversity of senior management on firm performance by interacting an industry's growth rate in senior gender composition with a firm's pre-determined shares in gender composition. We follow their approach in constructing our instrument but deviate from it by i) using DEI as opposed to gender composition and ii) focusing on national growth rates, in addition to industry rates. Formally, we start by decomposing a firm's (i) DEI in period t as the product of the firm's growth rate in DEI in period t and the firm i's shares in DEI in a base year, as follows:

$$DEI_{it} = \sum g_{it} \times s_i \tag{A.1a}$$

where g_{it} is the firm's growth rate at year-quarter t and s_i is the share of DEI for firm i. We can decompose the firm's growth rate as:

$$g_{it} = g_i + g_c \tag{A.1b}$$

Where g_i is the firm's growth rate and g_c is the national growth rate, common to all firms within a country or the sector growth rate, common to all firms in that sector. The shift-share instrument

z for firm i at time-period t is then the product of the firm's DEI shares at the base period and the national or sector component of the growth rate in DEI, formally:

$$z_{it} = s_i \times g_c \tag{A.1c}$$

To construct the share component of equation A.1c, we calculate the average *DEI Signal* score for firm i over the first three quarters of 2015. Following Sieweke, Bostandzic and Smolinski (2023) we use a moving average approach to mitigate the impact of short-term fluctuations and to handle potential missing data at the firm level.

For the shift component (g_c), we calculate this in two ways, to allows us to explore both national and sector growth trends. For the national model, we calculate the national *DEI Signal* score (for the UK or the US), excluding the focal firm i at time-period t and divide it by the national *DEI Signal* score, again excluding the focal firm, based on the moving average of the first three quarters of 2015. We take a similar approach to constructing the shift component at the sector level, where instead of a national *DEI Signal* score, we compute the industry score, excluding the focal firm. We then multiply the shift and the share parts to obtain the instrument z_{it}. To ensure the exogeneity of the shares in the base year, we restrict our analysis to starting from 2016. Removing the focal firm, as per Flabbi et al. (2019) and Sieweke, Bostandzic and Smolinski (2023) further ensures the exogeneity of the shift component. Moreover, constructing the shift part of the instrument at the national level, and separately at the industry level, helps to maintain the exclusion restriction. Given the shift-share instrument, we employ a two-stage least squares (2SLS) IV design to estimate the causal impact of DEI on firm performance. In the first stage, we regress the endogenous variable (*DEI Signal*) on the shift-share instrument and covariates:

$$DEI_{ijt-1} = \alpha_0 + \alpha_1 z_{ijt-1} + \beta' X_{ijt} + f_{jt} + \eta_{ijt} \tag{A.2a}$$

where α_1 is the coefficient of interest showing the impact of the shift-share (z_{itj-1}) instrument on DEI_{ijt-1}; X_{ijt} is the vector of controls and f_{jt} is the industry $\times$ time fixed effects and η_{ijt} is the first-stage error term. In line with the main analysis, both the *DEI Signal* and the instrument are lagged by one year. In the second stage, we use the predicted values of *DEI Signal* to estimate the impact on firm performance. The second-stage equation is specified as follows:

$$y_{ijt} = \delta \hat{DEI}_{ijt-1} + \boldsymbol{\beta}' X_{ijt} + f_{jt} + \epsilon_{ijt} \tag{A.2b}$$

where y_{ijt} represents the firm performance outcome variable (Tobin's Q, return on equity, stock returns, or patent counts); the term $\hat{DEI}$ represents the predicted values of DEI from the first stage, and ϵ_{ijt} is the error term in the second stage. As in the fixed-effects model, we use robust standard errors.

Instrumental Variable Estimates

Table A10— Shift-Share Instrument Results

	First Stage	Second Stage				
	(1)	(2)	(3)	(4)	(5)	(6)
	DEI Signal	Tobin's Q	Returns	ROE	ROA	Patents
Panel A: National Shift Component						
Shift-Share instrument	0.283***					
	(0.016)					
DEI Signal		0.528***	0.124***	-0.072	-0.260***	-0.047
		(0.056)	(0.047)	(0.057)	(0.063)	(0.032)
Total Employees	0.082***	0.092***	-0.027**	0.148***	0.375***	0.170***
	(0.017)	(0.015)	(0.013)	(0.016)	(0.017)	(0.024)
Total Assets	-0.004	-0.438***	-0.026**	-0.061***	-0.375***	0.115***
	(0.015)	(0.015)	(0.011)	(0.013)	(0.016)	(0.010)
Leverage	-0.034***	0.055***	0.005	-0.048***	0.048***	0.015***
	(0.007)	(0.012)	(0.007)	(0.010)	(0.012)	(0.004)
C-test		73.257	6.529	1.872	17.262	3.364
C-test p-value		0.000	0.011	0.171	0.000	0.067
Observations	18,837	18,837	18,837	18,837	18,837	18,837
Panel B: Industry Shift Component						
Shift-Share instrument	-0.009***					
	(0.002)					
DEI Signal		-0.180	-0.136	-0.384	0.089	0.224*
		(0.281)	(0.182)	(0.259)	(0.207)	(0.120)
Total Employees	0.080***	0.164***	-0.004	0.179***	0.358***	0.146***
	(0.017)	(0.025)	(0.019)	(0.028)	(0.022)	(0.021)
Total Assets	-0.013	-0.561***	-0.053***	-0.083***	-0.415***	0.134***
	(0.015)	(0.014)	(0.012)	(0.016)	(0.016)	(0.011)
Leverage	-0.048***	-0.024	-0.014	-0.078***	0.038**	0.034***
	(0.007)	(0.019)	(0.011)	(0.017)	(0.016)	(0.009)
Country	-0.105***	-0.624***	-0.144***	-0.114***	-0.152***	0.103***
	(0.020)	(0.034)	(0.026)	(0.033)	(0.028)	(0.020)
C-test		0.844	0.642	2.668	0.233	3.455
C-test p-value		0.358	0.423	0.102	0.629	0.063
Observations	18,837	18,837	18,837	18,837	18,837	18,837

Note: The results from the first stage IV estimation are reported in collum 1. Coefficients for second-stage results are depicted in the remaining columns with the outcome considered in the title. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A10 provides the results of the IV estimates, together with the results of the first-stage regression. Panel A shows the estimates when the instrument is constructed with the national shift component. The coefficient for the shift-share instrument in column (1) indicates that the instrument predicts the *DEI Signal* sufficiently well that we have a strong instrument. Columns (2) to (5) provide the estimates of the second-stage estimations. Consistent with the fixed-effects estimates, we find evidence of a positive relationship between the *DEI Signal* and Tobin's Q. The effect size is larger than in the fixed-effects estimates. Moreover, we find that the relationship between *DEI Signal* and Stock Returns is also positive and significant, albeit with a smaller effect than Tobin's Q, and no evidence for a relationship between *DEI Signal* and ROE and Patents measures. In contrast to the fixed-effects estimates, the *DEI Signal* coefficient is negative for the ROA model. However, for all coefficients of *DEI Signal,* the magnitude is greater than the fixed effects estimate.

In Panel B, we present the results of the instrument constructed with the industry growth rate (shift component). The results of the first-stage regression show that the instrument once more predicts *DEI Signal*, however the coefficient is negative. This result is in line with Flabbi et al. (2019) and Sieweke, Bostandzic and Smolinski (2023), which detail that while counter-intuitive, the negative signal could indicate the vast majority of firms within an industry have modest or even negative growth rates, while a small number have large growth rates. In our sample, we do find that most firms have a growth rate centred around zero. In the second-stage results, shown in columns (2) to (5), we do not find a statistically significant result for any of the outcomes considered, which suggest the results in Panel A are not robust to the sector-level construction of the instrument.

A5. Senior Management Diversity Over Time

Table A11— Proportion of Unclassified Individuals by Gender and Ethnicity

	Region			
	Total	UK	US	All other countries
Gender				
Women	35.810%	36.496%	40.921%	30.039%
Unassigned	6.796%	4.207%	3.887%	10.490%
Ethnicity				
White	59.371%	85.862%	69.709%	43.040%
Unassigned	2.413%	0.915%	3.015%	2.026%

Note: Proportion of overall workforce data. Gender is tagged as unclassified if the probability of belonging to either gender group is below 60%; ethnicity is classified as unassigned if the probability of belonging to any ethnic group is below 45%.

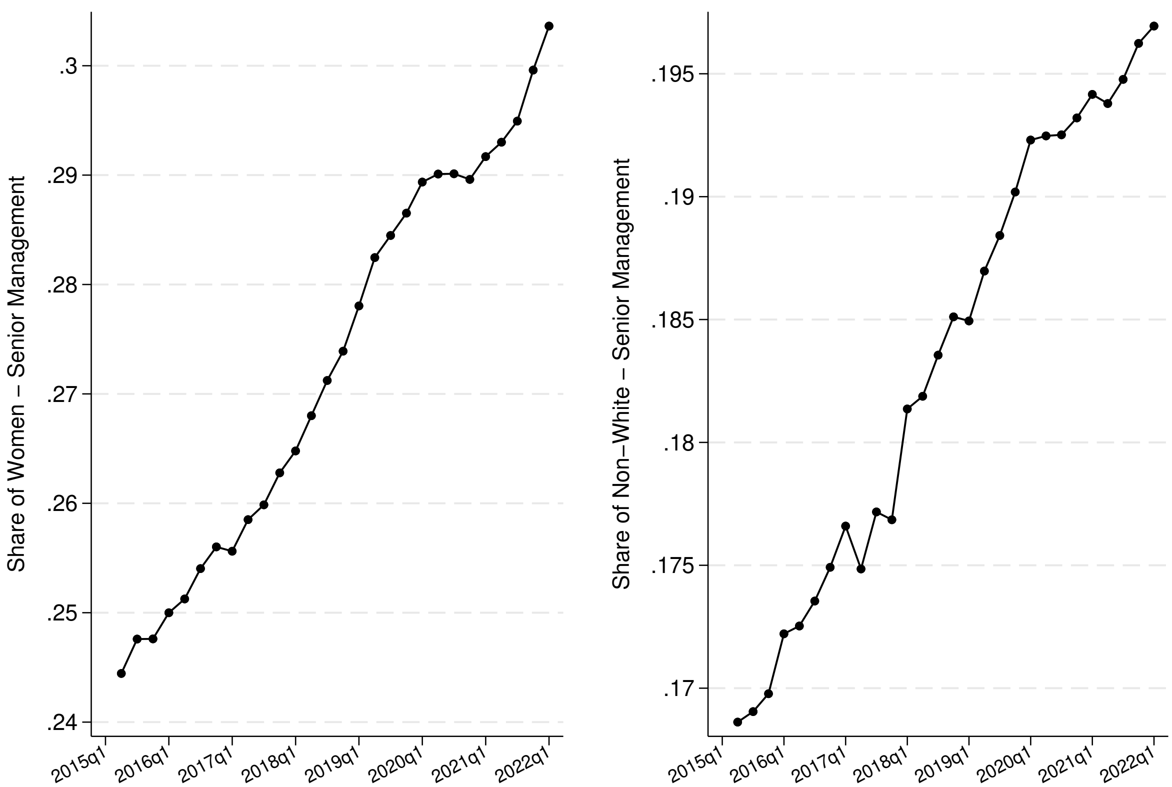


Figure A3. Diversity in Senior Management over Time

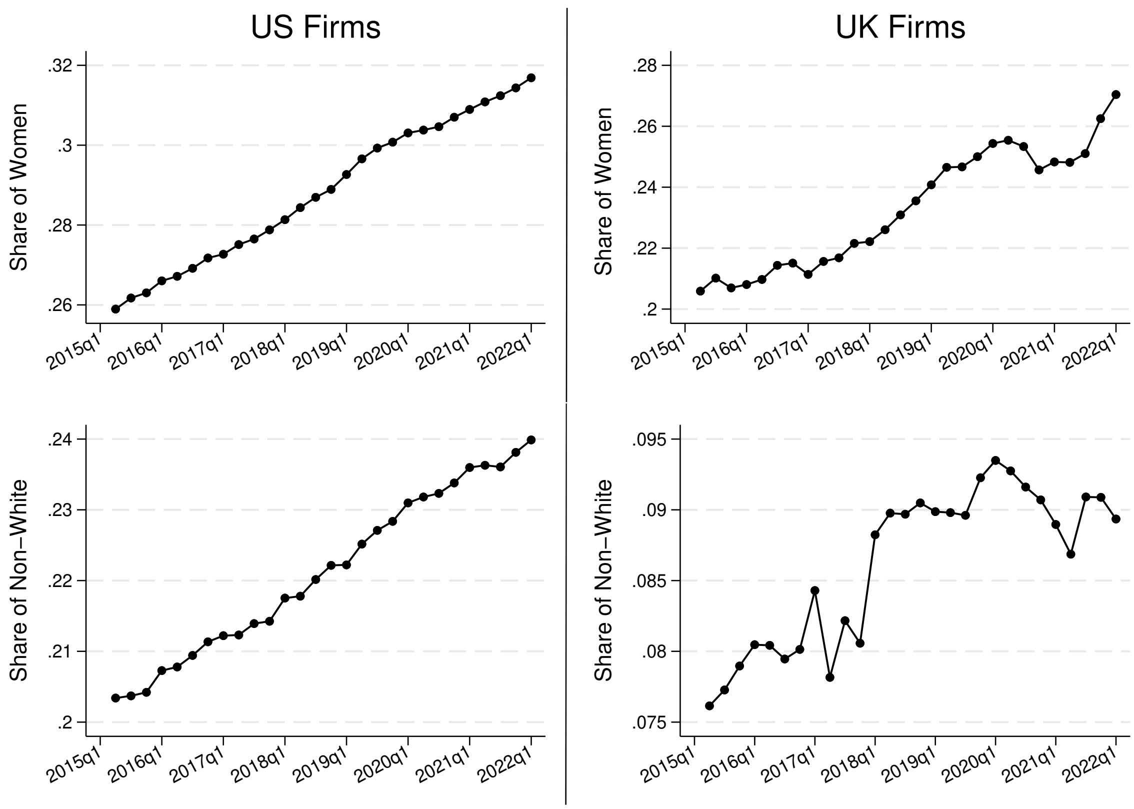


Figure A4. Diversity in Senior Management over Time by Country

Table A12— Senior Management Diversity Results

Panel A:Ethnicity					
	Tobin's Q	Stock Returns	ROE	ROA	Patents
	(1)	(2)	(3)	(4)	(5)
Blau Ethnicity Senior Management	0.726***	0.152***	-0.109*	0.133**	0.251***
	(0.049)	(0.047)	(0.059)	(0.057)	(0.057)
Total Employees (log)	0.082***	0.008	0.088***	0.330***	0.049
	(0.023)	(0.020)	(0.023)	(0.024)	(0.031)
Total Emps HQ (log)	0.039	-0.039*	0.082***	0.006	0.169***
	(0.026)	(0.021)	(0.023)	(0.024)	(0.016)
Total Assets (log) STD	-0.575***	-0.053***	-0.077***	-0.398***	0.099***
	(0.013)	(0.011)	(0.014)	(0.016)	(0.010)
Leverage STD	-0.013	-0.010	-0.052***	0.041***	0.033***
	(0.013)	(0.007)	(0.009)	(0.012)	(0.006)
Country	-0.463***	-0.117***	-0.069***	-0.143***	0.189***
	(0.021)	(0.019)	(0.022)	(0.022)	(0.017)
Lag Share of Senior Management HQ	-0.294	0.156	-1.337***	-3.015***	3.248***
	(0.346)	(0.299)	(0.370)	(0.525)	(0.388)
Observations	18,753	18,753	18,753	18,753	18,753
R-squared	0.460	0.385	0.073	0.165	0.096

Panel B: Gender					
	Tobin's Q	Stock Returns	ROE	ROA	Patents
	(1)	(2)	(3)	(4)	(5)
Blau Gender Senior Management	-0.014	-0.055*	-0.114***	-0.161***	-0.144***
	(0.031)	(0.033)	(0.039)	(0.041)	(0.030)
Total Employees (log)	0.131***	0.015	0.074***	0.330***	0.058**
	(0.021)	(0.019)	(0.022)	(0.024)	(0.027)
Total Emps HQ (log)	0.030	-0.034*	0.097***	0.023	0.183***
	(0.024)	(0.021)	(0.023)	(0.024)	(0.016)
Total Assets (log) STD	-0.566***	-0.050***	-0.075***	-0.391***	0.106***
	(0.013)	(0.011)	(0.014)	(0.016)	(0.010)
Leverage STD	-0.013	-0.010	-0.052***	0.041***	0.033***
	(0.013)	(0.007)	(0.009)	(0.012)	(0.006)
Country	-0.588***	-0.146***	-0.055***	-0.172***	0.140***
	(0.019)	(0.017)	(0.020)	(0.020)	(0.013)
Lag Share of Senior Management HQ	0.781**	0.438	-1.372***	-2.647***	3.771***
	(0.340)	(0.290)	(0.357)	(0.508)	(0.403)
Observations	18,753	18,753	18,753	18,753	18,753
R-squared	0.452	0.385	0.073	0.166	0.096

Note: Values are coefficients of separate models where the independent variable is senior management diversity lagged by one year. Robust standard errors are in parenthesis *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$