Does Diversity Promise Higher Firm Productivity? The Role of Corporate Leadership

Econometric B project

2012483
5617026
5662119

Table of Contents

1. Overview

Although women employees and workers from diverse cultural background have increased their participation in the job market, they are facing new threat from strongly divided public opinions on cultural and gender diversity agenda. As in the recent 2024 US presidential election, public worries diversity initiatives are supported solely on ethical and social grounds, while making little economic contribution. In this paper, we evaluate the impact of culture and gender diversity in top management on firm's productivity. Our research brings new insights into the research in diversity and economics impact, focusing on board members and executives as they have huge influence on the company's policy and decision making.

In this paper, we leverage the Arellano-Bond model to test the causal relationship between diversity and productivity for the dynamic panel data. Our results indicate that an inclusive workplace can enhance firm productivity performance in the selected industry. While diversity drive Total Factor Productivity (TFP) in Industrial & Services sector, board cultural diversity may negatively moderate this effect. In Technology & Consumer Goods sector, employees' training hours and the interaction of diversity with executive cultural diversity are highlighted with positively influence on productivity.

2. Literature Review

Most of the research focus on macro or regional level impact of diversity (Ottaviano & Peri, 2006; Berliant & Fujita, 2012). Puzzlingly, the results often contradict. For example, Leonard and Levine (2006) found that there are no consistent results to support diversity in workplaces would increase turnover. Meanwhile, Fassio et al. (2019) shows only highly educated migrants brings positive effect in productivity in service sector. The paper suggests that the impact in diversity is based on the level of skills in labour and the influence are vary across industry. The above research indicate that the result of cultural diversity on productivity is likely to be influenced by spatial scales and mechanisms (Ozgen, 2021). The reasons behind this phenomenon might be demand of labour's type vary across industry and the skills level of workforce are different across countries. As much research focus on European countries, we want to add value on the existing literature in micro perspective by using new data from 2017-2024 among the US public list companies.

The other aspects we notice in existing literature is that very few models breakdown the diversity composition in the company hierarchy. Parrotta et al. (2014) addresses how diversity of workers would affect TFP from a micro-perspective. In their findings, ethical diversity has small negative impact to TFP while demographic diversity is statistically insignificant. Although the authors include the gender diversity in the index of demographic diversity, similar to other micro approach paper (Fassio et al., 2019; Trax et al., 2015;) the diversity variables usually reflect the composition among all employees instead of focusing on top management. The influence of diversity in senior managers on TFP is still unclear.

We found papers that describe similar topics. Carter et al. (2010) suggest that the ethnic minority and cultural diversity of the board are endogenous variable on firm financial performance, but they also mention that the effect of diversity may different across companies and timeframe. Meliá-Martí et al. (2024) provide insights into the impact of board gender diversity on employee's productivity. They found that there is a nonlinear relationship between board gender diversity and productivity. However, the results of a female CEO on productivity are inconclusive. This paper only focuses on agriculture-food sector and social economy firms, but we want to know whether other sectors and profit-maximizing firms would make a difference.

3. Empirical Design

3.1. Data

3.1.1 Data Description

We analyzed panel data from 268 publicly listed firms in US market, covering 8 years from 2017 to 2024. The data were collected from LSEG's Refinitiv Eikon. Industrial & Services and Technology & Consumer Goods companies were specifically chosen due to their significant reliance on their substantial workforce in delivering products or services directly to customers. We used total capital and number of employees as proxies for capital and labour input in Cobb-Douglas production function for the estimation of total factor of productivity (TFP). Our primary variables are diversity score and inclusion score powered by Refinitiv ESG data. The components of diversity and inclusion scores are in Appendix table 1. We should also note that cultural diversity is looking at percentage of members from a different cultural background from the location of firm headquarter.

We also explored secondary variables to discuss how individual components affect TFP and their interaction with other variables. They include executive gender diversity, executive cultural diversity, board gender diversity, board cultural diversity, and employee training hours. Additionally, we replaced missing data in each variable with the mean value of their reported years for consistency of measurement.

3.1.2 Descriptive Statistics

Table 3.2 provides descriptive statistics of variables in the full dataset of 268 companies. We split the dataset into two sub-datasets Industrial & Services sector and Technology & Consumer Goods. Their descriptive statistics are in Table 3.3 and Table 3.4 respectively. Companies in Industrial & Services sector rely less on R&D input and sell products or services directly to customers. While Companies in Technology & Consumer Goods sector rely more on R&D and sell products mainly through retail. Appendix table 2 shows that the panel data is well balanced.

Table 3.2 Full Dataset Descriptive Statistics

Variable	Definition	Full Dataset		
		Obs	Mean	Sd
year	Financial year	2144	2020.5	2.292
ebitda	EBITDA	2144	4.04e+09	7.93e+09
totalcapital	Total capital	2144	2.32e+10	4.88e+10
Labour	Total labour	2144	58760.3	99426.01
DI	Diversity core	2144	42.798	13.596
IN	Inclusion core	2144	30.766	23.617
BCDI	Board cultural diversity	2144	37.441	26.955
BGDI	Board gender diversity	2144	55.356	26.430
EGDI	Executive gender diversity	2144	52.102	25.388
ECDI	Executive cultural diversity	2144	49.620	27.220
TRtotal	Training hours	2144	1641618	5013804

Table 3.3 Industrial & Services Descriptive Statistics

Variable	Definition	Industrial & Services		
		Obs	Mean	Sd
year	Financial year	1488	2020.5	2.292
ebita	EBITA	1488	4.12e+09	8.48e+09
totalcapital	Total capital	1488	2.49e+10	5.51e+10
Labour	Total labour	1488	60138.26	104326.8
DI	Diversity core	1488	42.079	13.103
IN	Inclusion core	1488	29.010	22.682
BCDI	Board cultural diversity	1488	35.713	26.689
BGDI	Board gender diversity	1488	54.368	26.447
EGDI	Executive gender diversity	1488	51.646	24.501
ECDI	Executive cultural diversity	1488	46.522	26.229
TRtotal	Training hours	1488	1699043	5476985

Table 3.4 Technology & Consumer Goods Descriptive Statistics

Variable	Definition	Technology & Consumer Goods		
		Obs	Mean	Sd
year	Financial year	608	2020.5	2.293
ebita	EBITA	608	3.78e+09	6.34e+09
totalcapital	Total capital	608	1.84e+10	2.72e+10
Labour	Total labour	608	57786.84	89844.69
DI	Diversity core	608	45.007	14.420
IN	Inclusion core	608	35.635	25.618
BCDI	Board cultural diversity	608	40.687	26.962
BGDI	Board gender diversity	608	58.295	26.063
EGDI	Executive gender diversity	608	54.889	26.647
ECDI	Executive cultural diversity	608	57.021	27.623
TRtotal	Training hours	608	1565611	3889095

3.2. Methodology

3.2.1 Model Specification

As the research question is to measure the impact of diversity in hierarchy to a company's production performance, we follow the classic **Cobb-Douglas production function** (Griliches, 1979) and interpretation of the variables to define our dependent variables, TFP (Total Factor Productivity).

$$Y_{it} = A_{it}\, K_{it}^{\alpha}\, L_{it}^{\beta} \qquad (1)$$

where *Y* stands for the firm real value output (we use EBITDA, Earnings before Interest, Taxes, Depreciation, and Amortization), *K* and *L* stand for the capital and labour inputs respectively. The indices *i* and *t* refer to individual firm *i* at year *t. A* is the TFP at interest, which we derived by rearranging the model with log transformation:

$$\ln TFP_{it} = \ln Y_{it} - \alpha \ln K_{it} - \beta \ln L_{it} \qquad (2)$$

By regressing *Y* on *K* and *L* while treating TFP as the residual, we obtained the coefficients, and compute *TFP* for the model specification. To test out the hypothesis, if gender and cultural diversity in the company composition have an effect on the level of Total Factor Productivity, the specification includes the diversity and inclusion score, secondary board and executive measurements in gender and cultural diversity, and some other factors that affect TFP in general:

$$TFP_{it} = \beta_1 DI_{it} + \beta_2 IN_{it} + \beta_3 (BCDI_{it} \times DI_{it}) + \beta_4 (BGDI_{it} \times DI_{it}) + \beta_5 (ECDI_{it} \times DI_{it}) + \beta_6 (EGDI_{it} \times DI_{it}) + \beta_7 TTH_{it} + d_i + f_i + u_{it} \quad (3)$$

where *DI* indicates the diversity score that measures the company's effort in maintaining a gender and culturally diverse workforce. While IN is the inclusion score in terms of maintaining a work-life balance and disability-friendly working environment, which account for broader dimensions of diversity other than gender and culture. In order to check if the diversity of the management influences the effect of workforce diversity on TFP, we also introduce four interaction terms with *DI*, including *BCDI, BGDI, ECDI* and *EGDI*. The first two terms indicate the percentage of board members with a cultural background different from the location of the corporate headquarters and the percentage of female board members, while the remaining two assess the exact same aspects among the executive members. We also suspect that total training hours, *TTH*, have a positive effect on *TFP* as it enhances labour quality and skillsets. To account for the time trend effect, we add d_i as the time fixed effect, which is a dummy variable. We also consider the firm heterogeneity characteristics, and proxy it with the firm specific fixed effect, f_i. Lastly, u_i refers to the idiosyncratic fluctuations of *TFP*.

3.2.2 Endogeneity

1. Reverse Causality

As many literatures have suggested, casual inference in regression often suffers from the curse of reverse causality. Within our research context, higher *TFP* might lead firms to allocate more resources to diversity initiatives e.g., investing more in a diverse recruitment scheme. While *TFP* affects *diversity*, u_{it} is necessarily correlated with the independent variables which induce biases in examining the effect of diversity on *TFP* if a vanilla Fixed-Effect model is used. In other words, the assumption of strict exogeneity, $E(\varepsilon_{is}|x_{it}, \alpha_i) = 0 \text{ for all } t = 1, \dots, T$, is violated.

Leszczensky & Wolbring (2019) discovered that dynamic panel models (Arellano and Bond, 1991) can address reverse causality by leveraging the lagged-dependent variable

(LDV) as instruments. Since the LDV from the first lag is correlated with the error term, these GMM-based dynamic estimators remove time-invariant unobserved heterogeneity as well. We regress each independent variable on first lag of *ln_TFP*, and identify the statistically significant variables as those suffer from reverse causality. These variables are estimated dynamically by including the lagged value in formula (3). Incorporating the structure of the dynamic model, we rewrite the model specification as follows:

$$\begin{aligned}\Delta \ln TFP_{it} = {} & \beta_1 \Delta \ln DI_{it} + \beta_2 \Delta \ln IN_{it} + \beta_3 \Delta \ln(BCDI_{it} \times DI_{it}) + \beta_4 \Delta \ln(BGDI_{it} \times DI_{it}) \\ & + \beta_5 \Delta \ln(ECDI_{it} \times DI_{it}) + \beta_6 \Delta \ln(EGDI_{it} \times DI_{it}) + \beta_7 \Delta \ln TTH_{it} + u_{it} \qquad (4)\end{aligned}$$

This model also addresses the problem of autocorrelation since the Wooldridge test rejects the null hypothesis for both sectors, indicating that *TFP* is persistent over time[1]. This is expected as firm productivity is typically influenced by prior-year productivity due to stable structures, policies, and resources.

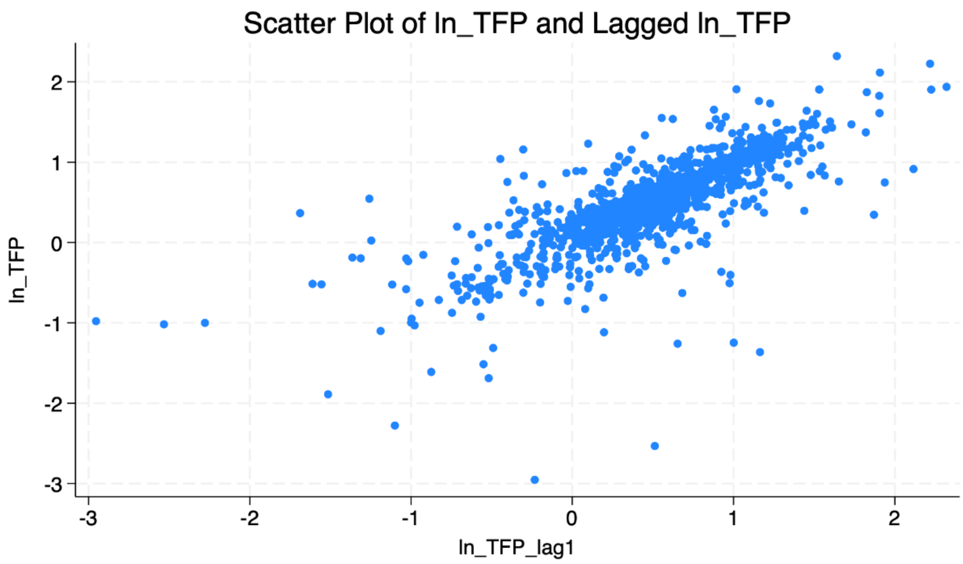

Figure 1: Industrial & Services

[1] Autocorrelation coefficient is 0.78 for the Industrial and Service Sector; 0.87 for the Technology and Consumer Goods Sector.

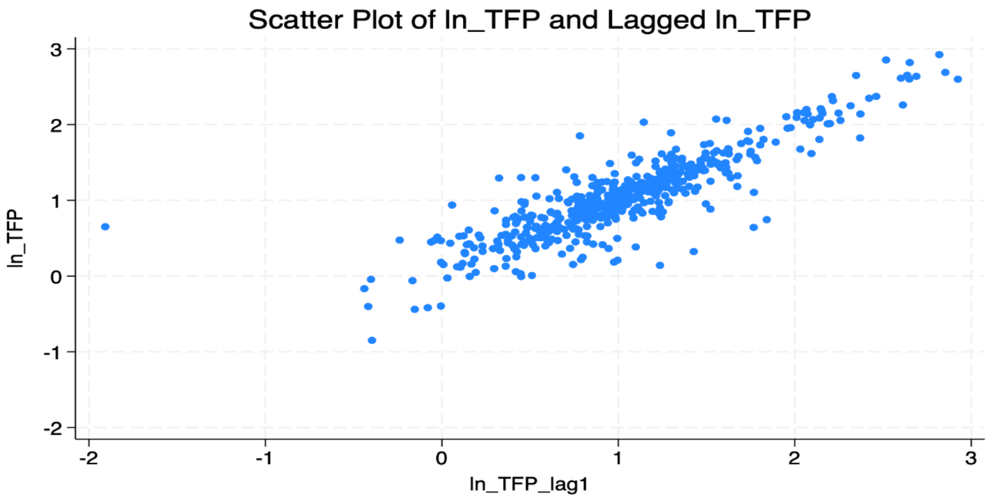

Figure 2: Technology & Consumer Goods

2. Unobserved heterogeneity

The AB model uses first differences to remove firm-specific, time-invariant unobserved heterogeneity that lies within the observations across different regions and sectors, limiting the focus on the within-firm diversity impact over time. Heterogeneous characteristics such as communication effectiveness between workers and workplace culture, can be unobserved determinants of *TFP*, hence distorting the results. The AB model can resolve it by instrumenting the first-differenced lagged TFP with its second-order lags, reducing bias from correlation with the error term.

4. Empirical Result

4.1 Fixed-Effect Model

In table 4.1, the estimation of reduced form Cobb-Douglas production functions is highly significant across datasets at all levels, allowing us to proceed with further analysis of TFP. Even though capital has consistently large coefficients, it doesn't indicate a larger impact of capital on firm production output. The result is due to the scale and measurement of capital inputs rather than their economic impact.

Table 4.1 Results of Cobb-Douglas Production Function

Variable	Variable Description	All Sectors	Industrial & Services	Technology & Consumer Goods
ln_totalcapital	Total capital input	0.806***	0.816***	0.810***
		(0.010)	(0.011)	(0.023)
ln_Labour	Total labour input	0.190***	0.190***	0.162***
		(0.010)	(0.010)	(0.025)

p < 10%*, p < 5%**, p < 1%***

In Table 4.2, The fixed-effects model results indicate that the first lag term of TFP has a positive and significant effect on the current TFP. This parallels the practice of treating technology as a first-order stochastic process. Results in the full dataset and technology & consumer goods sector highlight positive effects of firm inclusion performance, indicating that a more inclusive workplace contributes positively to the firm technology level. Board cultural diversity stands out in the full dataset, implying that a more culturally diverse composition of board members can drive TFP growth of the firm. Diverse perspectives among leadership may lead to more comprehensive decision-making and company strategies. Surprisingly, training hours can bring down the TFP level, as shown in the full dataset and industrial and services sector. One explanation is that an increase in employee training hours might create a temporal inefficiency due to the workforce disruption caused by reallocating time from work to training, or the adaption period for workers to incorporate their training into their tasks. However, these results need more scrutiny of the potential reverse causality issues, which might lead to a flawed estimation of the fixed-effect specification.

Table 4.2 Results of Fixed-effect Models

Variable	Variable Description	All Sectors	Industrial & Services	Technology & Consumer Goods
ln_TFP_lag 1	First Lag of TFP	0.265***	0.242***	0.325***
		(0.023)	(0.030)	(0.037)
ln_DI	Diversity	0.018	0.012	0.039
		(0.032)	(0.039)	(0.053)
ln_IN	Inclusion	0.019**	0.014	0.029**
		(0.008)	(0.239)	(0.013)
ln_BGDI	Board Gender Diversity	0.008	0. 014	-0.000
		(0.018)	(0.567)	(0.026)
ln_BCDI	Board Cultural Diversity	0.051*	0. 042	0.053
		(0.029)	(0.036)	(0.049)
ln_EGDI	Executive Gender Diversity	-0.024	-0.024	-0.011
		(-0.020)	(0.026)	(0.032)
ln_ECDI	Executive Cultural Diversity	-0.015	-0.014	-0.015
		(-0.021)	(0.267)	(0.035)
ln_TRtotal	Training Hours	-0.035**	-0.048**	-0.007
		(0.18)	(0.024)	(0.026)

$p < 10\%$*, $p < 5\%$**, $p < 1\%$***

4.2 Reverse causality

Reverse causality tests provide further evidence that technology likely follows the form of a first-order stochastic process. Insignificant results of training hours indicate that it can be an exogenous variable and hence serve as a valid control variable. This implies exogeneity might come from the fact that employee training policies are often determined as a part of company's HR policy or guidelines in advance and seldom adjusted in response to productivity performance.

Diversity and inclusion both suffer from reverse causality and should be estimated dynamically using GMM in Arellano-Bond model. Even though they are not all tested significant in the two sub-datasets, the p-values only exceed the 10% threshold marginally. At Table 4.3, all four interaction terms of diversity score with board and executive diversity also have causality issues in the full dataset, though the 10% threshold is not satisfied to qualify for significant estimates. Both interaction terms of diversity score with board gender diversity and executive gender diversity are tested significant and positive on Industrial & Services sector, meaning that a higher TFP in the previous financial year can amplify the interaction of board and executive gender diversity with firm diversity performance. In the Technology & Consumer Goods sector, the interaction term of diversity score with board cultural diversity has a positive coefficient and shows reverse causality.

Table 4.3 Reverse Causality Tests

Variable	Variable Description	Full Dataset	Industrial & Services	Technology & Consumer Goods
ln_TFP	TFP	0.267***	0.240***	0.341***
		(0.023)	(0.029)	(0.036)
ln_DI	Diversity	0.041**	0.038	0.052
		(0.020)	(0.024)	(0.036)
ln_IN	Inclusion	0.154**	0.106	0.295**
		(0.075)	(0.087)	(0.147)
ln_BDI_G	Board Gender Diversity*Diversity	0.070	0.097*	0.010
		(0.048)	(0.058)	(0.085)
ln_BDI_C	Board Cultural Diversity*Diversity	0.051	0.020	0.137***
		(0.036)	(0.047)	(0.052)
ln_EDI_G	Executive Gender Diversity*Diversity	0.0696	0.124**	-0.067
		(0.044)	(0.054)	(0.071)
ln_EDI_C	Executive Cultural Diversity*Diversity	-0.009	0.009	-0.048
		(0.041)	(0.052)	(0.065)
ln_TRtotal	Training Hours	0.051	0.048	0.062
		(0.033)	(0.038)	(0.067)

p < 10%*, p < 5%**, p < 1%***

4.3 Arellano-Bond model

The first lag of TFP remains significant across datasets at all levels, with only marginal violation of the statistical significance at the 10% level in the Industrial & Services sector. Coinciding with the fixed-effect model, inclusion score is significant in the full dataset, confirming that a more inclusive workplace drives the firm productivity.

Industrial & Services sector highlights a positive effect of diversity instead, as opposed to the insignificant result in the fixed-effect model. A potential explanation is that in industrial and service-based firms, which based on our selection criteria rely less on R&D and sell products directly to customers, diversity may enhance problem-solving capability and teamwork within their sales and production teams and also enable better communication with customers from all backgrounds, leading to improved TFP performances. The interaction term of board cultural diversity with diversity score shows significant and negative result in Industrial & Services sector. This suggests that higher board cultural diversity can somewhat offset the positive effect of better diversity score on productivity. It's probably because culturally diverse perspectives are unnecessary among board members in traditional and mature sectors like Industrial & Services where business models are standardised and stable. A diverse board composition might only increase miscommunication, inefficiency, or even conflicts among the leadership.

In Technology & Consumer Goods sector, although diversity itself does not have a significant effect on productivity, its interaction terms with *ECDI* have a significant and positive influence, meaning that executive cultural diversity enhances the impact of firm diversity on TFP. Given the nature of Technology & Consumer Goods sector, companies in this sector have higher reliance on their R&D team in designing new products and has very standard sales channels simply through online or offline retail. A more culturally diverse executive team encourage creativity in the workplace, allowing R&D teams to develop more popular products. The significant and positive training hours further support this narrative. It means better-trained workers are better at facilitating innovation and product development process.

Additionally, the Arellano-Bond AR(1) test confirms first-order serial correlation in the residual has been properly accounted for. The AR(2) test shows further that there is no second-order serial correlation, confirming the validity of the instruments. Sargan and Hansen test on the full dataset are significant, indicating overidentification of the instruments. This issue is accounted for in both sub-datasets as Sargan and Hansen tests are insignificant in both cases. Hausman test shows no more correlation between variables in the fixed-effect model and the error term than the Arellano-Bond model. However, it doesn’t sabotage the validity of Arellano-Bond model, as the endogeneity issue is mainly contributed by reverse causality.

Table 4-4 Results of Arellano-Bond Models

Variable	Variable Description	Full Dataset	Industrial & Services	Technology & Consumer Goods
ln_TFP_lag1	First Lag of TFP	0.273*	0.391	0.590**
		(0.144)	(0.241)	(0.233)
ln_DI	Diversity	0.175	2.163**	-0.143
		(0.226)	(0.996)	(0.417)
ln_IN	Inclusion	0.027*	-0.014	0.054
		(0.015)	(0.035)	(0.056)
ln_BDI_G	Board Gender Diversity*Diversity	-0.096	0.175	-0.228
		(0.055)	(0.196)	(0.203)
ln_BDI_C	Board Cultural Diversity*Diversity	-0.029	-1.257*	-0.174
		(0.092)	(0.731)	(0.165)
ln_EDI_G	Executive Gender Diversity*Diversity	-0.011	-0.059	0.117
		(0.056)	(0.133)	(0.169)
ln_EDI_C	Executive Cultural Diversity*Diversity	0.026	-0.358	0.429*
		(0.127)	(0.515)	(0.248)
ln_TRtotal	Training Hours	0.015	-0.027	0.027*
		(0.013)	(0.067)	(0.016)
Arellano-Bond AR(1) test p-value		0.015**	0.020**	0.016**
Arellano-Bond AR(2) test p-value		0.216	0.364	0.303
Sargan test p-value		0.041	0.691	0.721
Hansen test p-value		0.057	0.736	0.325

$p < 10\%$*, $p < 5\%$**, $p < 1\%$***

5. Conclusion and Further Research

The results show that the overall diversity has a limited relationship with firm's productivity. The gender diversity in both boards and executives are irrelevant to TFP. Our results align with (Carter et al. 2010). Moreover, we tested the reverse causality which previous studies had mentioned less. The increase in productivity may lead to an increase in some diversity variables at the company level. It is worth noting that while diversity drives TFP in Industrial & Services sector, board cultural diversity may negatively moderate this effect. While our findings show that diversity score has no significant impact on productivity in Technology & Consumer Goods sectors, executive cultural diversity has demonstrated interesting interactions with a positive influence on productivity.

There remain several areas for further research that could address our research limitations. Firstly, the AB model suffers from including weak instruments in short panels (T=8) and limited firm observations (n=268). Experimenting more complex methods like system GMM will be meaningful. Secondly, most of the current research on diversity topics focus on developed countries such as European countries and the US. The effect of diversity among top management levels in developing countries lacks discussion. Thirdly, our research only focuses on Industiral & Services sector and Technology & Consumer Goods sector. Although diversity has limited influence on TFP in the two traditional sectors selected, it may still stimulate innovation in other companies like tech firms or newly listed start-ups. Analysis across wider industries might reveal a different landscape. Lastly, our research paper looks into the overall firm's productivity, but it will be interesting to investigate how diversity at the top management level affects employee productivity according to gender. For instance, whether more female executives or board members would increase the productivity of female employees. Exploring these areas in future research would provide a more comprehensive understanding of the influence of diversity in the workplace.

Word Count: 2820

6. Bibliography

Berliant, M., & Fujita, M. (2012). Culture and diversity in knowledge creation. Regional Science and Urban Economics, 42(4), 648–662. https://doi.org/10.1016/j.regsciurbeco.2012.02.008

Carter, D. A., D'Souza, F., Simkins, B. J., & Simpson, W. G. (2010). The gender and ethnic diversity of US boards and board committees and firm financial performance. Corporate Governance: An International Review, 18(5), 396–414. https://doi.org/10.1111/j.1467-8683.2010.00809.x

Fassio, C., Kalantaryan, S., & Venturini, A. (2019). Foreign Human Capital and Total Factor Productivity: A Sectoral approach. Review of Income and Wealth, 66(3), 613–646. https://doi.org/10.1111/roiw.12426

Fassio, C., Montobbio, F., & Venturini, A. (2018). Skilled migration and innovation in European industries. Research Policy, 48(3), 706–718. https://doi.org/10.1016/j.respol.2018.11.002

Hamilton, B. H., Nickerson, J. A., & Owan, H. (2003). Team Incentives and Worker Heterogeneity: An empirical analysis of the impact of teams on productivity and participation. Journal of Political Economy, 111(3), 465–497. https://doi.org/10.1086/374182

Leszczensky, L., & Wolbring, T. (2019). How to deal with reverse causality using panel data? Recommendations for researchers based on a simulation study. Sociological Methods & Research, 51(2), 837–865. https://doi.org/10.1177/0049124119882473

Ozgen, C. (2021). The economics of diversity: Innovation, productivity and the labour market. Journal of Economic Surveys, 35(4), 1168–1216. https://doi.org/10.1111/joes.12433

Trax, M., Brunow, S., & Suedekum, J. (2015). Cultural diversity and plant-level productivity. Regional Science and Urban Economics, 53, 85–96. https://doi.org/10.1016/j.regsciurbeco.2015.05.004

7. Appendix

Table 1: DEI score components

Diversity Score Components	Inclusion Score Components
Board gender diversity	Flexible Working Hours(Y/N)
Board cultural diversity	Day Care Services(Y/N)
Women employee percentage	Employees with Disabilities(Y/N)
New women employee percentage	HRC Corporate Equality Index
Women executive employee percentage	HIV/AIDS programmes(Y/N)
Women managers percentage	
Implementation of diversity process(Y/N)	
Implementation of diversity objectives(Y/N)	

Table 2: Panel Data Structure

n = 268, T = 8

Distribution of years	min	5%	25%	50%	75%	95%	max
	8	8	8	8	8	8	8