BOOSTING PRODUCTIVITY GROWTH BY CREATING EQUAL WORKPLACE OPPORTUNITIES FOR ALL

WORKFORCE DIVERSITY AND FIRM PRODUCTIVITY IN NEW ZEALAND

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ABOUT THIS RESEARCH PROGRAMME

Workplace diversity significantly impacts productivity and economic growth. Better talent allocation could boost productivity and increase long-term output growth per person. In NZ, labour is highly segregated, with women and ethnic minorities concentrated in lower-paid industries, driving gender and ethnic pay gaps that affect financial, health, and wellbeing outcomes. This programme analyses how workplace diversity affects productivity and equity. Using various data sources, we will estimate NZ’s productivity gains from diversity, assess workplace policies and leadership, and evaluate public policies. A key focus is Māori and Pacific businesses, exploring recruitment, pay transparency, and workplace culture. Māori and Pacific-led research will provide insights into workplace barriers, enablers, and values

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Workforce Diversity and Firm Productivity in New Zealand

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1 Introduction

In many countries, the workforce is becoming more diverse. Migration, shifting population composition and changing gender norms have altered who is in the workforce and how workplaces are organised. New Zealand is a clear example. It has a high share of foreign-born workers, an ethnically diverse population, a high female labour force participation rate, and comparatively flexible labour market institutions. These features raise an important question: does workforce diversity support firm performance?

Economic theory offers competing predictions. Diverse teams may benefit from a wider set of perspectives, skills and networks, which can support problem-solving and innovation. But diversity can also increase communication costs and create frictions if workers struggle to coordinate or if discrimination affects team dynamics. The empirical literature reflects this tension. For example, in Denmark, Parrotta, Pozzoli, and Pytlikova (2014) find that ethnic diversity lowers productivity, while educational diversity has mixed effects. In contrast, Trax, Brunow, and Suedekum (2015) show that cultural diversity raises productivity in German manufacturing. Austrian evidence also suggests positive effects from birthplace diversity (Böheim, Horvath, and Mayr, 2012). Other studies point to negative effects: linguistic diversity in Norway reduces productivity unless migrants have strong host-country language skills (Dale-Olsen and Finseraas, 2020). Recent work highlights deeper mechanisms. Cultural human capital can explain persistent productivity differences across origin groups, even within the same educational categories (Ek, 2024). Macro-level work emphasises talent allocation. Hsieh, Hurst, Jones, and Klenow (2019) show that the improved allocation of women and minorities across high-productivity occupations accounts for a sizeable share of long-run US growth.

The New Zealand setting provides a useful contrast to the countries studied in this literature. New Zealand combines one of the highest foreign-born shares in the OECD with longstanding skilled migration policies and flexible labour market institutions. These features mean that many firms operate with a global and multi-ethnic workforce, and they may help reduce some of the coordination costs that otherwise arise in diverse teams. At the same time, the persistence of gender and ethnic inequalities in wages and progression suggests that inclusion and talent allocation remain important challenges. Industry-level evidence reinforces this point. Iusitini, Meehan, and Pacheco (2024) document sizeable gender and ethnic pay gaps across industries in Aotearoa New Zealand, even after accounting for observable worker and job characteristics. These patterns indicate that firms and industries differ in how they recognise, reward and allocate talent, and provide further motivation for examining how workforce composition relates to productivity.

There is also relevant New Zealand evidence using linked employer–employee data. Sin, Stillman, and Fabling (2022) show that women earn less than men even when employed in the same firms, and that only a small share of this gap can be explained by gender differences in measured productivity. Other New Zealand studies use the same productivity data to examine topics such as broadband adoption and migration. Together, these papers demonstrate the value of rich administrative data for understanding how workforce composition relates to output in the New Zealand context.

This paper applies these ideas to New Zealand using matched employer–employee data from the Longitudinal Business Database and the productivity dataset described in Fabling and Maré (2015) and Fabling and Maré (2019). We follow an approach that is commonly used in this literature, first estimating industry-specific production functions to recover firm-level total factor productivity (TFP; see, e.g., Parrotta, Pozzoli, and Pytlikova (2014) and Fabling and Grimes (2021)). We then relate TFP to two dimensions of diversity: gender and ethnicity. Diversity is measured using a fractionalisation index constructed from all employees on the payroll in each year. Our specification includes detailed controls for labour composition by group, as well as year-by-industry fixed effects.

The New Zealand evidence we present makes two contributions. First, we document that both ethnic and gender diversity are positively associated with firm-level productivity across the economy. These effects are statistically significant and economically large: for all firms combined, a 0.1 increase in fractionalisation is associated with a rise in TFP of roughly 16-17 % for ethnic diversity and 10-11 % for gender diversity. These results place New Zealand within the upper range of elasticities seen in the international literature. Second, the positive relationship appears consistently across the five largest industries we examine, although the magnitude varies. This pattern differs from some overseas findings (for example, positive effects only in manufacturing in Germany) and suggests that the New Zealand institutional and labour market settings may support the productivity-enhancing channels more strongly.

We interpret our findings through both micro and macro mechanisms raised in the literature. At the micro level, the New Zealand results are more consistent with the positive channels dominating. Firms with more diverse workforces may be drawing on richer skill mixes, complementary experiences and broader networks. They may also be better at recognising and allocating talent internally. At the macro level, the results may reflect inclusion and the allocation of talent. If high-productivity firms are more successful at attracting or retaining diverse workers, then these firms are making better use of the available talent pool. This aligns with the argument of Hsieh, Hurst, Jones, and Klenow (2019) that removing barriers for under-represented groups raises output by allowing talent to move into more productive firms and occupations.

Overall, the evidence suggests that diversity is associated with higher productivity in New Zealand, and that both gender and ethnic diversity contribute to this relationship. This supports a view of diversity not only as a labour market or equity concern, but also as an aspect of firm capability and talent use.

2 Data and methods

We draw on linked employer–employee microdata to estimate firm-level productivity and examine its relationship with gender and ethnic diversity. This section outlines how the productivity dataset is constructed, how diversity is measured, how total factor productivity is estimated, and how we relate the two in our regression framework.

2.1 Productivity data

The productivity data are based on the firm-level production dataset developed from the Longitudinal Business Database (LBD) by Fabling and Maré (2015) and updated in Fabling and Maré (2019). This dataset provides annual measures of firm output and the main productive inputs for all market-sector employing firms. It combines financial information from the Annual Enterprise Survey (AES), administrative tax data from IR10 returns, Goods and Services Tax (GST) returns, and monthly pay-as-you-earn (PAYE) payroll data. These sources are harmonised to construct a single firm-year panel with consistent definitions across time and across data sources.

Following Fabling and Maré (2015) and Fabling and Maré (2019), gross output is measured from firm revenues and related income items, and is deflated using industry-specific producer price indices to obtain a real output measure. Inputs are grouped into three standard categories: capital, labour and intermediate inputs. Capital input is derived from information on fixed assets in AES and IR10 and converted into a real capital-services measure using industry-level price indices. Labour input is based on an annualised full-time-equivalent (FTE) measure, which adjusts for part-time work, working proprietors and multiple-job holding. Intermediate inputs are constructed from expenditure on goods and services used up in production and deflated using industry-level input price indices. The resulting dataset is an annual panel from 2001–2023 covering private, for-profit employing firms in market-sector industries (broadly, those producing output sold at market prices).

2.2 Diversity

We measure workforce diversity using all employees who received salary or wage payments in a given year, based on PAYE (Employer Monthly Schedule, EMS) data. For each firm-year we compute gender and ethnic diversity using a standard fractionalisation index:

$$D_{it}^{h} = 1 - \sum_{j=1}^{N} s_{jit}^{2} \tag{1}$$

where s_j is the share of group j in the firm i in year t, and N is the number of groups along the dimensions gender (h=g) and ethnicity (h=e). For gender, we use two groups; for ethnicity we use five: European, Māori, Asian, Pacific, and Other.

The diversity index increases when a workforce is more diverse, and provides the probability that two randomly drawn individuals in a firm belong to different groups. It has a minimum value of 0 if only one category is represented and a maximum of $1-1/N$ if all groups are equally represented (so the maximum is 0.5 for gender with $N = 2$ and 0.8 for ethnicity with $N = 5$). It is widely used in the firm-level diversity literature, including Parrotta, Pozzoli, and Pytlikova (2014) and related studies.

We restrict the sample to firms with at least five employees, to avoid cases where diversity is mechanically capped by workforce size.

2.3 Productivity estimation

Estimating firm-level productivity from observed inputs and outputs is challenging because firms adjust their input choices in response to shocks in productivity, and because unobserved factors such as management quality may affect both inputs and output. If these issues are ignored, conventional OLS estimates of production functions can be biased. A range of semi-parametric control-function approaches has been proposed to address these concerns, using investment, intermediate inputs or other proxies for unobserved productivity (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2006).

We follow Wooldridge (2009), which provides a control-function method that addresses endogeneity in input choices, and is the approach adopted in several studies using the LBD dataset (such as Fabling and Grimes, 2021). We estimate the production function separately for each of the 39 industries used in the productivity data, allowing technologies to differ across industries and interpreting TFP only within industries. This industry-specific estimation strategy is standard in the firm-level productivity literature (see, for example, Fabling and Maré, 2015; Parrotta, Pozzoli, and Pytlikova, 2014).

We estimate a gross-output Cobb–Douglas production function of the form:

$$\ln Y_{it} = \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_M \ln M_{it} + a_{it}, \tag{2}$$

where Y_{it} is deflated gross output, K_{it} is capital services, L_{it} is labour input, M_{it} is intermediate consumption, and a_{it} is the resulting TFP measure for firm i in year t.

2.4 Diversity regression

We then regress firm-level productivity on gender diversity (D^g) and ethnic diversity (D^e):

$$TFP_{it} = \alpha D^g_{it} + \beta D^e_{it} + \gamma X_{it} + \epsilon_{it}, \tag{3}$$

where X is a vector including year×industry fixed-effects and the shares of the workforce belonging to each category included in the diversity indices, which should account to some extent for differences in labour quality (following Parrotta, Pozzoli, and Pytlikova (2014)).

We report estimates for the full sample and separately for the five largest industries.

2.5 Descriptive statistics

Table 1 summarises the characteristics of all firms in our analysis and, for comparison, the five largest industries: accommodation and food services; construction services; other retailing; professional, scientific and technical services; and wholesale trade. These industries together account for 36 % of the workforce and 45 % of firms in our analysis sample, and exhibit a wide range of technologies, workforce structures and diversity levels.

Across all firms, average employment is relatively small, but there is wide dispersion in size, output and input use. The five largest industries differ systematically. Accommodation and food services and other retailing tend to be smaller and more labour-intensive, whereas professional, scientific and technical services and wholesale trade have larger workforces and higher capital intensity. Construction services sits between these patterns, reflecting the mixed labour and capital requirements of the industry.

The shares of gender and ethnic groups also vary across industries. In accommodation and food services and in other retailing, firms employ comparatively higher proportions of Māori, Pacific and Asian workers. Construction services also shows a more mixed ethnic composition than the economy as a whole. In contrast, professional, scientific and technical services and wholesale trade have higher shares of European workers and lower representation of some other ethnic groups. Gender composition also varies across industries, with accommodation and food services and retail having higher shares of women, and construction services having a markedly lower share.

These differences in group shares are reflected in the diversity indices. Ethnic diversity is higher in accommodation and food services, construction services and retailing, and lower in professional services and wholesale trade. Gender diversity is also highest in industries with more balanced male–female representation, and lowest in construction services where the workforce is predominantly male. Table 1 summarises these patterns and shows how differences in workforce composition translate into variation in the diversity measures across industries.

Table 1: Firm characteristics

	All firms	Accommod. and food services	Construction services	Other retailing	Professional, scientific, and tech services	Wholesale trade
Production data						
ln(K)	11.71	11.58	11.05	11.67	11.50	12.00
ln(L)	1.80	1.48	1.87	1.73	2.05	2.11
ln(M)	13.01	12.47	13.43	12.18	12.81	13.17
ln(Y)	13.97	13.35	14.18	13.33	14.20	14.34
Employment						
Employees	32.21	27.68	16.22	32.62	25.50	28.28
FTE	15.33	7.91	8.85	15.28	15.44	17.15
Working proprietors	0.93	0.69	1.14	0.85	1.19	0.74
Group shares						
European	0.66	0.53	0.67	0.73	0.75	0.71
Māori	0.15	0.15	0.19	0.10	0.08	0.10
Pacific people	0.04	0.03	0.05	0.02	0.02	0.04
Asian	0.12	0.26	0.06	0.13	0.13	0.12
Other	0.03	0.03	0.03	0.03	0.03	0.03
Male	0.58	0.34	0.86	0.36	0.46	0.62
Female	0.42	0.66	0.14	0.64	0.54	0.38
Diversity						
Ethnic diversity	0.33	0.38	0.35	0.28	0.29	0.32
Gender diversity	0.31	0.35	0.21	0.28	0.34	0.35

Notes: Table reports means of firm-year observations for all firms in the sample and for the five largest industries by employment. The sample comprises private, for-profit employing firms in market-sector industries observed between 2001 and 2023, restricted to firms with at least five employees.

Figure 1 shows how diversity has changed over time. Ethnic diversity increases steadily from around 0.30 in the early 2000s to above 0.37 by the early 2020s. Gender diversity rises more slowly, from roughly 0.30 to around 0.32–0.33 over the same period. These trends reflect broader demographic changes in the New Zealand labour market, including sustained migration flows and gradual shifts in occupational gender composition (Meehan, Pacheco, and Schober, 2025).

3 Results

This section presents the main regression results linking workforce diversity to firm-level productivity and examines how these associations vary across industries.

3.1 Main regression results

Table 2 presents the estimated association between workforce diversity and firm-level productivity. Both ethnic and gender diversity are positively related to TFP. For the full sample, the coefficient on ethnic diversity is 1.55, implying a 0.1 increase in ethnic fractionalisation is associated with a 16.8 % increase in productivity. For gender, the coefficient is 1.00, implying that a 0.1 increase in gender fractionalisation is associated with a 10.5 % increase in productivity.

These effect sizes are large compared with many international studies, but remain within the range documented in the broader literature on diversity and firm performance. For example,

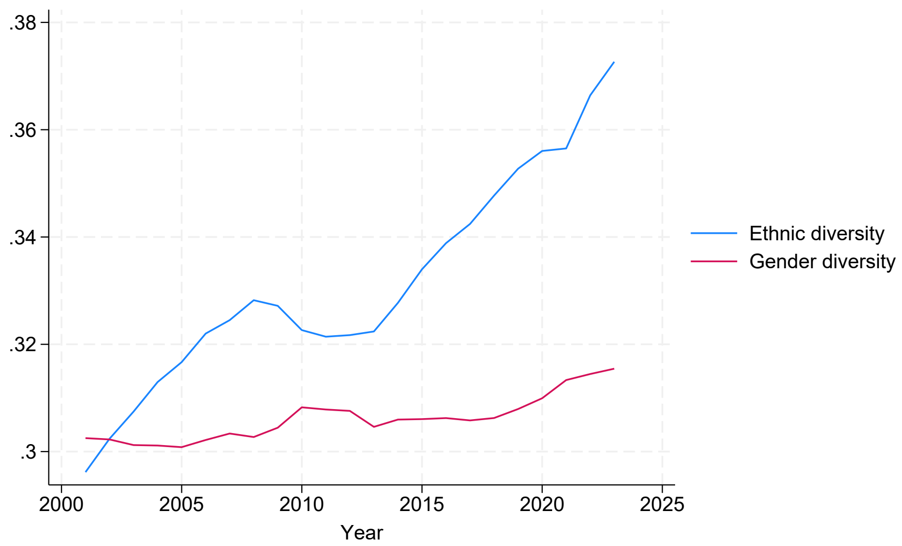

Figure 1: Diversity over time

Trax, Brunow, and Suedekum (2015) estimate that a 0.1 increase in cultural fractionalisation raises productivity in German manufacturing by around 3 %, while other studies report effects ranging from small negative associations to increases of up to 20 % depending on the diversity measure and outcome considered (Ozgen, 2021).

3.2 Industry heterogeneity

The positive associations between diversity and productivity are not confined to the aggregate sample. Across the five largest industries, ethnic diversity is positively associated with productivity in all cases. The coefficients range from 0.88 in accommodation and food services to 2.27 in wholesale trade, which correspond to increases in productivity of about 9 % and around 26 %, respectively, for a 0.1 increase in ethnic fractionalisation. Gender diversity is also positively associated with productivity across industries, although the magnitude varies more. The coefficients range from 0.81 in professional, scientific and technical services to 1.61 in construction services, implying increases of around 8 % and about 18 %, respectively, for a 0.1 increase in gender fractionalisation.

This cross-industry variation is consistent with differences in production technologies, workforce structures and task requirements. Industries with more homogeneous workforces (such as construction services) may experience larger marginal gains from additional diversity, while sectors with already balanced workforces show smaller associations. Customer-facing industries such as wholesale trade exhibit some of the strongest associations for ethnic diversity, although we do not attempt to identify the specific mechanisms.

3.3 Interpretation and comparison with the literature

The results suggest a robust positive relationship between workforce diversity and firm productivity in New Zealand. These findings align with studies showing that diverse teams can benefit from complementarities in skills, networks, and problem-solving approaches (e.g., Trax, Brunow, and Suedekum, 2015; Böheim, Horvath, and Mayr, 2012). The consistent sign and significance

Table 2: Productivity and diversity

	All firms	Accommod. and food services	Construction services	Other retailing	Professional, scientific, and tech services	Wholesale trade
Ethnic diversity	1.55	0.88	1.69	1.95	1.72	2.27
	(0.02)***	(0.03)***	(0.05)***	(0.08)***	(0.05)***	(0.07)***
Gender diversity	1.00	1.37	1.61	1.00	0.81	1.18
	(0.01)***	(0.04)***	(0.08)***	(0.05)***	(0.05)***	(0.07)***
N	1226331	165537	107076	96522	103122	84387

Notes: Dependent variable is log total factor productivity (TFP). Each column reports coefficients from OLS regressions of firm-level TFP on ethnic and gender diversity, with both indices included simultaneously. All specifications include year×industry fixed effects and controls for the shares of each ethnic and gender group in employment. Robust standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

across industries imply that the relationship is not driven by a single sector but reflects a broader pattern across the New Zealand economy.

The positive association contrasts with the negative results reported for Denmark (Parrotta, Pozzoli, and Pytlikova, 2014). One interpretation is that institutional and labour market settings can influence whether the productivity-enhancing or productivity-reducing channels of diversity dominate. In New Zealand—characterised by high migration inflows, long-standing skilled-migration policies and comparatively flexible labour markets—coordination costs may be lower or more easily managed, enabling the positive mechanisms to dominate.

3.4 Limitations

These results should be interpreted with care. First, the estimates describe correlations rather than causal effects. Firms that value innovation or adopt particular management practices may both attract more diverse workers and achieve higher productivity, and our controls may not fully capture these differences. Second, the diversity measures reflect broad group shares and do not capture within-group variation in skills, experience or language proficiency. Third, although we estimate production functions by industry, measurement error in inputs or outputs may still affect the resulting TFP measures. Finally, we do not explore alternative specifications or robustness checks, so the stability of the results across different modelling choices has not been tested. These considerations mean that the results should be interpreted as descriptive patterns rather than causal estimates.

4 Discussion and conclusion

This paper provides new evidence on the relationship between workforce diversity and firm productivity in New Zealand. Using linked employer–employee data and industry-specific production functions, we find consistent positive associations between productivity and both ethnic and gender diversity. These results hold at the aggregate level and across the five largest industries in the measured sector. The magnitudes are economically meaningful and sit toward the upper end of those reported in the international literature.

Several mechanisms may help explain these findings. At the micro level, diverse teams may draw on a wider range of skills, experiences and networks, supporting problem-solving and adaptability. This is consistent with the positive associations documented in studies such as Trax, Brunow, and Suedekum (2015) and Böheim, Horvath, and Mayr (2012). The larger coefficients in industries with historically low gender diversity, such as construction services, are also consistent with the idea that firms with more homogeneous workforces may experience greater marginal gains when their teams become more diverse. At the macro level, the results may reflect differences in the allocation and recognition of talent across firms. If firms that attract and retain more diverse workers are better at identifying talent or adopting inclusive practices, then diversity may be a marker of better internal allocation. This interpretation aligns with recent work on the role of inclusion and talent allocation in shaping economic performance (Hsieh, Hurst, Jones, and Klenow, 2019).

The New Zealand institutional and labour market context may also contribute to the positive associations we observe. New Zealand has one of the highest foreign-born shares in the OECD, long-standing skilled migration settings and comparatively flexible labour markets. These features may help reduce some of the coordination costs that can arise in diverse teams, potentially supporting the productivity-enhancing mechanisms identified in the literature. At the same time, persistent gender and ethnic gaps in wages and progression suggest that inclusion remains incomplete (e.g. Iusitini, Meehan, and Pacheco, 2024; Sin, Stillman, and Fabling, 2022), and that firms differ in the extent to which they recognise and fully utilise available talent.

The findings should be interpreted with care. The analysis documents correlations rather than causal effects, and the controls available cannot fully capture management practices, workplace culture, or unobserved differences in worker skills. The diversity measures rely on broad group classifications and do not reflect variation within groups, including differences in experience, qualifications or language proficiency. Measurement error in inputs and outputs may also affect the estimated productivity levels, despite the detailed construction of the productivity data. Finally, we did not explore alternative specifications or robustness checks, so the sensitivity of the results to different modelling choices remains an important area for future work.

Despite these limitations, the results provide a clear descriptive pattern: in New Zealand, firms with more diverse workforces - both ethnically and by gender - tend to have higher productivity. This relationship is evident across a wide range of industries and is consistent with mechanisms that highlight the benefits of diverse teams and the importance of effective talent allocation. The findings suggest that diversity is not only a matter of fairness or representation but may also be an aspect of firm capability with relevance for productivity and performance.

Future research could explore the channels behind these associations in more detail, including the role of management practices, team composition within firms, or differences between domestic and migrant workers. Linking diversity to productivity dynamics, innovation outcomes or worker wellbeing may also deepen our understanding of how inclusive workplaces contribute to economic performance.

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