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IZA DP No. 18206

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ABSTRACT

Firms and Ethnic Wage Differences

We examine the contribution to ethnic earnings gaps of differences in the firms where different ethnic groups work. We use linked employer-employee data to estimate worker and firm pay premiums (fixed effects), adapting existing methods to deal with multiple-response ethnicities and weighting. The sorting of workers across firms contributes 10-26 percent of within-ethnicity gender gaps but affects average earnings for men or women within ethnic groups by less than 1 percent, in the face of average ethnic earnings gaps of up to 14 percent. We conclude that within-firm earnings differences are the dominant source of ethnic earnings gaps.

JEL Classification: J15, J30, J42, J71

Keywords: earnings, ethnicity, sorting, two-way fixed effects, linked employer employee data

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1 Introduction

We examine the extent to which inter-ethnic pay differences reflect differences in the firms in which different ethnic groups work. Specifically, we ask whether some ethnic groups are more likely than others to work in high-paying firms and if so, what this contributes to average earnings differences among ethnic groups. We also look at whether the degree of sorting of high-earning workers into high-paying firms varies across ethnicities. Answering these questions sheds light on the mechanisms that create and perpetuate ethnic pay gaps, and helps focus efforts to address labour market inequities.

The analysis complements insights from related papers that are also part of the WERO (Working to End Racial Oppression) work programme, including a worker-based analysis of ethnic wage gaps (Benison & Maré, 2025), and analysis of ethnic wage and productivity differences (Fabling & Maré, 2025; Maré & Fabling, 2025).

The primary contribution of this paper is to provide a detailed New-Zealand-specific analysis of ethnic and gender matching and sorting across high- and low-paying firms. We adapt methods to deal with sex-specific and ethnicity-specific worker and firm fixed effects, addressing challenges associated with multiple ethnicity responses and FTE-weighting. We report on the sensitivity of findings to alternative assumptions and normalisations being used for estimating firm premiums.

We find that unequal sorting of workers into well-paying firms can account for around 15% of the gender earnings gap, and between 10% and 26% of gender earnings gaps within ethnic groups. However, such sorting has a more limited impact on ethnic gaps for women or ethnic gaps for men. We estimate that average earnings are raised or lowered by less than 1 percent by firm sorting, in the face of ethnic earnings gaps of up to 14 percent. The additional impact of workers sorting into firms that pay workers of their sex relatively well is of secondary importance.

We also look at ethnic differences in the likelihood of high-earning workers working in well-paying firms. We report modest ethnic differences in the strength of this correlation, and a trend decline in correlations for all groups since around 2015.

Section 2 summarises recent studies that have documented the growing role played by firms differences in explaining changes in wage inequality and accounting for gender and ethnic pay differences. Section 3 documents our empirical strategy, and is followed by a discussion of the data sources we use in section 4. Section 5 presents our main findings on ethnic wage

variation, the role of firms, and ethnic differences in sorting across firms. The paper concludes with a summary and discussion in section 6.

2 Related studies

Differences between firms in average wages paid account for a substantial proportion of overall wage variation, even among subsets of jobs defined by industry, location, firm size, or worker demographics (Song et al., 2019). Criscuolo et al. (2020) report that between-firm variation accounts for between 30 percent and 60 percent of wage variation, based on analysis across 14 countries, including New Zealand. Furthermore, increases in between-firm wage inequality have been the dominant source of increasing wage inequality in recent decades (Barth et al., 2016; Card et al., 2013; Criscuolo et al., 2020; Schaefer & Singleton, 2020; Song et al., 2019). In New Zealand, the contribution of between-firm differences to overall wage inequality (32%) is at the lower end of the range internationally, but still an important dimension of wage inequality, with the potential to contribute to ethnic earnings gaps.

Average wages in a firm are in part a result of differences in the mix of workers. Firms employing disproportionately skilled workers are likely to pay above-average wages, although they may not pay a high premium controlling for their employee mix. Identifying whether a firm pays a low or high premium requires controlling for employee composition, which is typically achieved through regression methods. Equation (1) summarises the general pattern of such regressions.

$$\ln w_{ijt} = x_{ijt}\beta + \lambda_i + \phi_j + \varepsilon_{ijt} \quad (1)$$

The log of wages for worker *i*, who is working for firm *j* at time *t* depend on observed worker or job characteristics, x_{ijt} (such as age, gender), a 'worker effect' (λ_i) that captures unobserved and time-invariant wage-related characteristics of worker *i*, and a 'firm effect' (ϕ_j) that captures whether firm *j* pays relatively high wages, relative to other firms, for the workers it employs. A residual term (ε_{ijt}) captures remaining idiosyncratic wage variation due to, eg, the effect of firm-specific demand or productivity shocks on wages. Identifying both worker and firm effects requires linked employer-employee data and specialised estimation methods (Abowd et al., 1999, 2002). Firm effects can, and often are, estimated in the absence of worker effects, relying on observed worker and job characteristics to control for the influence of within-firm employee composition on average earnings differences, to estimate firm-specific premiums, which tends to overestimate the contribution of firm effects to wage variance due to the correlation between

unobserved worker and firm effects. Criscuolo et al. (2020) find that firm effects account for around two-thirds of between-firm wage inequality when only observed worker composition is controlled for, and substantially less when estimation includes worker effects.

Card et al. (2018) reports that two-way (worker and firm) fixed effects models typically find that firm effects account for 15 to 20 percent of the variance of wages. For New Zealand, Maré & Hyslop (2006) report a firm effects contribution of 10 to 15 percent.[1] Firms that pay high wage premiums (firm effects) tend to be more productive and/or profitable. Premiums are suggestive of rent-sharing by firms, although the elasticity of individual wages with respect to firm performance is relatively weak (0.02 to 0.15) (Allan & Maré, 2021; Card et al., 2018).

We quantify the impact that working in firms paying different premiums has on ethnic pay gaps in New Zealand. Using the notation in equation (1), we focus on whether average firm fixed effects, conditional on worker characteristics $\left(E\left[\phi_j \middle| x_{ijt}, \lambda_i\right]\right)$, differ across ethnicities. Pendakur and Woodcock (2010) characterise such differences as "glass doors" – invisible constraints, such as arise from discrimination, on the ability of some groups to secure jobs in well-paying firms.

Previous studies have found evidence that glass doors contribute significantly to gender wage gaps. Card (2016) reports that variation in firm fixed effects (estimated for men) accounts for 15 to 20 percent of the gender wage gap – in proportion to the contribution to overall wage inequality. A similar pattern is also evident in New Zealand, with Sin et al (2022) reporting a contribution of 28 percent to the gender pay gap. Jewell et al (2020) notes that the contribution of sorting by firm fixed effects to the gender wage gap in the UK (16 percent) is three times as large as the contribution of occupational sorting. These studies find not only that women are less likely to work in firms that pay high firm-specific premiums but also that they receive smaller premiums than men do in the same firms.

Findings on the impact of inter-firm sorting on ethnic pay gaps is more mixed. Carrington and Troske (1998) report that sorting of whites and non-whites across firms in the United States is effectively random, contributing minimally to observed ethnic gaps. Furthermore, they find that within-firm wage gaps are largely accounted for by differences in observable worker characteristics. Also for the United States, Hellerstein and Neumark (2008) find that Blacks work in higher fixed effect firms than do Whites, narrowing the ethnic pay gap, although sorting into low paying firms contributes about 10 to 15 percent of the Hispanic-White gap.

[1] Criscuolo et al (2020) report a 29% between-firm variance contribution based on estimates that control for worker age and gender, but not for worker fixed effects.

In the United Kingdom, Forth et al. (2023) find that estimated White-non-White ethnic gaps are larger when firm fixed effects are controlled for, indicating that Whites are employed disproportionately in low-paying firms. They conclude that ethnic pay gaps are primarily a within-firm phenomenon. Phan et al. (2025) document variation in this pattern for different ethnic groups in the UK. They report that Black African employees tend to work in firms with low firm-specific wage effects, but that sorting into high firm-effect firms favours Indian, Chinese and Black Caribbean workers, with no contribution for Pakistani workers. Benison and Maré (2025) also report variation in the estimated impacts of firm sorting for different ethnic groups. Some effects are positive and some negative, although the impacts are generally small, accounting for only 5 percent to 10 percent of ethnic pay gaps. Fabling and Maré (2025) examine the impacts of firm-sorting for Māori workers, finding that Māori men and women work in low-paying firms throughout most of their working lives, with a lack of age-related 'upgrading' to better paying firms evident for Māori women in particular.

Gerard et al. (2021) find more substantial contributions of firm sorting to White-non-White wage gaps in Brazil. Firm fixed effects account for 21 percent of the (17%) ethnic gap for men, and 25 percent of the (24%) gap for women. Barth et al. (2012) examine pay gaps for immigrants to Norway and find similarly large contributions of firm sorting, accounting for 40 percent of the native-immigrant wage gap. Barth et al. also document that native workers move to increasingly well-paying firms over time – a pattern that is not evident for immigrant workers.

Pendakur and Woodcock (2010) examine sorting for immigrants and visible minorities in Canada. They find strong contributions of sorting to immigrant pay gaps– accounting for one quarter to one half of the pay gap. The contributions and the proportions are higher for recent (less than 10 years) than for longer-settled immigrants, and are small for visible minorities who are not immigrants.

The effects of firm sorting vary substantially across different ethnic groups and across countries. It is therefore vital to obtain context-specific estimates rather than rely on insights from international studies alone. We turn now to our estimation of effects for ethnic groups in New Zealand.

3 Identification

Our empirical strategy aims to identify the extent to which workers' earnings reflect employer pay practices or workers' own inherent earning capacity. This involves three key measurement

choices – earnings-adjustment, averaging, and normalisation. We adjust annual earnings information to remove lifecycle age-earnings patterns, and aggregate year-to-year variation. A worker thus has high adjusted earnings in a year if their earnings are high relative to other workers with the same characteristics. Initially, we control simply for age-earnings profiles. In some specifications, we control for sex-specific age-earnings profiles, or separate age-earnings profiles by sex and ethnicity.

We estimate a two-way fixed effect model of adjusted earnings to separately identify each worker's average adjusted earnings (a worker fixed effect), and, for each employing firm, whether the firm on average pays relatively well or poorly (a firm fixed effect). In some specifications, we estimate a separate sex-specific firm fixed effect to allow for firms paying different premiums to men and women, or a sex- and ethnicity-specific firm fixed effect to estimate differing sex-ethnicity premiums.

We estimate the relationship shown in equation (1) in two stages. The two-step estimating approach is summarised in equations (2) and (3).[2] The adjusted earnings measure $\left(\widetilde{w}_{ijt}\right)$ is the residual from a regression of the log of real earnings $\left(w_{ijt}\right)$ for person *i* working in firm *j* in year *t* on a full set of age (α_a) and year (τ_t) intercepts.[3] In the second stage, averaging is achieved by estimating a time-invariant worker fixed effect (λ_i) for each worker, and a time-invariant firm fixed effect $\left(\phi_j\right)$ for each firm. Each of these sets of fixed effects is normalised to have zero mean overall. Although, by construction, the adjusted earnings has mean zero in each year and therefore the sum of worker and firm effects has mean zero, the mean worker and firm fixed effects can vary over time.

First stage – earnings adjustment

$$\mathrm{w_{ijt}} = \alpha_a \mathrm{a_{it}} + \tau_t + \widetilde{w}_{ijt} \qquad (2)$$

Second stage – worker and firm fixed effects

$$\widetilde{w}_{ijt} = \lambda_i + \phi_j + \varepsilon_{ijt} \qquad (3)$$

By estimating the worker and firm fixed effects in two stages, the age profiles in the first stage capture the average impact of life-cycle sorting of workers across firms paying different premiums $\left(\phi_j\right)$. Time-invariant worker and firm fixed effects are identified in the second stage by time-averaging, conditional on the average patterns that are partialled out in the first stage (Kline,

[2] See Kline (2024) for a detailed discussion of alternative specifications and identification issues.

[3] One age intercept (a=30) and one time intercept (t=2000) are omitted.

2024). Given our estimation approach, the estimated worker effects cannot be interpreted as a proxy for worker skill but instead capture the combined effects of relative skill levels and discriminatory pay practices. We are able to identify the contribution of sorting across firms on ethnic earnings gaps but we cannot separate the contributions of ethnic-related pay discrimination from ethnic differences in skill.

Our main analysis is stratified by sex, with equations (2) and (3) estimated separately by sex. Sex-specific coefficients in equation (2) yield adjusted earnings estimates that have zero mean for each sex – a high-earning worker is one whose earnings are high relative to other workers of the same sex and age. Sex-specific estimation of equation (3) yields separate firm fixed effect estimates for each sex $\left(\phi_j^s\right)$ – capturing sex-specific earnings premiums, and worker fixed effects, normalised to be zero mean by sex (λ_i^s).

Equations (2) and (3) can also be estimated to incorporate ethnicity-specific age and year effects, and to provide estimates of ethnicity-specific earnings premiums for each firm. The data we use can record multiple ethnic identities for each worker. To obtain ethnicity-specific coefficients, we therefore interact ethnic share variables[4] (σ_i^e) with covariates in equations (2) and (3) – as shown in equations (4) and (5). The resulting ethnicity-specific firm fixed effects $\left(\phi_j^e\right)$ are normalised to have zero mean for each ethnicity, as are the worker fixed effects (λ_i^e). Equations (4) and (5) can also be estimated separately by sex, to identify whether adjusted earnings are high or low relative to workers of the same sex, ethnicity and age (λ_i^{se}), and whether firms pay workers of a given sex and ethnicity relatively well $\left(\phi_j^{se}\right)$. In this case, worker and firm fixed effects are normalised to each have mean of zero for each sex-ethnicity combination.

Ethnicity-specific first stage – earnings adjustment

$$\mathrm{w_{ijt}} = \sum_{e=eth} \sigma_{\mathrm{i}}^{\mathrm{e}} \left(\alpha_{\mathrm{a}}^{\mathrm{e}} \mathrm{a_{it}} + \tau_t\right) + \widetilde{w}_{ijt}^e \tag{4}$$

Ethnicity-specific second stage – worker and firm fixed effects

$$\widetilde{w}_{ijt}^e = \lambda_i^e + \sum_{e=eth} \sigma_{\mathrm{i}}^{\mathrm{e}} * \phi_j^e + \varepsilon_{ijt}^e \tag{5}$$

Statistical identification of the worker and firm fixed effects relies on worker movement between firms, with biases arising for workers or firms with few job changes (Abowd et al., 2002; Andrews et al., 2008; Kline, 2024; Maré & Hyslop, 2006). Consequently, we iteratively remove

[4] Ethnicity responses are inversely weighted by the number of responses that each person gives (see section 4.1).

workers and firms with only one connection to the rest of the worker-firm network (Correia, 2017; Koutis et al., 2014). Furthermore, we retain only the largest connected set of firms and workers, which removes a relatively small proportion of jobs. We require that workers belong to the largest connected subgroup for each of their ethnicities, dropping the worker if they do not.

Table 1 summarises the combinations of first stage and second stage specifications that we consider. We focus initially on specification [1], which does not differentiate firm or worker effects by sex or ethnicity. Specification [2a] estimates sex-specific firm effects, based on variation in earnings adjusted for aggregate age-earnings profiles. Given the important sex-related differences in pay that we document, we also estimate specifications that adjust for sex-specific age-earnings profiles, allowing for sex-specific worker effects (specification [2b]) and additionally firm effects that differ by sex (specification [3]) or by sex and ethnicity (specification [4a]). We report some results that allow for differences in worker and firm fixed effects by sex and ethnicity ([4b] and [5]).[5]

Contributions of firm sorting to ethnic pay gaps

We examine the contributions of firm sorting to ethnic pay gaps in two ways – first, decomposing the difference between the average earnings of ethnic groups (overall or by sex) and the overall average level of earnings, and second, by decomposing sex-specific ethnic earnings gaps (relative to sex-specific average earnings). These decompositions are summarised in equations (6) and (7) respectively, for relative earnings of an ethnic group *G* separately by sex *s*.

DECOMPOSITION OF ETHNIC/SEX EARNINGS GAP RELATIVE TO OVERALL MEAN:

$$E[\mathrm{w_{it}} - \bar{w}|G,s] = \underbrace{E[\phi|G,s]}_{Firm-sorting} + \underbrace{E[\phi^s - \phi|G,s]}_{\substack{firm-sorting \\ by\ sex\ premium}} + \underbrace{\mathrm{E}[\alpha_a \mathrm{a_{it}} + \tau_t - \bar{w}|G,s]}_{Age\ Adjustment} + \underbrace{E[\lambda_i + \varepsilon_{it}|G,s]}_{Remainder} \quad (6)$$

The first decomposition (equation (6)) highlights the combined effects of gender and ethnic pay gaps. Age adjustment in the first stage of estimation uses pooled age and time effects. Two sets of firm effects are estimated in the second stage – either pooled (ϕ: specification [1]) or sex-specific (ϕ_s: specification [2a]). The second decomposition (equation (7)) adjusts raw earnings by sex-specific age and time effects, resulting in a different set of pooled and age specific firm effects (specifications [2b] and [3]). For each decomposition, the earnings gap is decomposed into four

[5] Given the substantial sex-based differences in age-earnings profiles, we do not present results that are differentiated by ethnicity but not by sex.

parts – two related to firm sorting, one accounting for age-adjustment, and a final remainder that captures differences in skills and in pay discrimination.

DECOMPOSITION OF SEX-SPECIFIC ETHNIC EARNINGS GAP (RELATIVE TO SEX-SPECIFIC MEAN)

$$E[\mathrm{w_{it}} - \overline{w}^{s}|G,s] = \underbrace{E[\phi|G,s] - E[\phi|s]}_{Firm-sorting} + \underbrace{E[\phi^{s} - \phi|G,s] - E[\phi^{s} - \phi|s]}_{\substack{firm-sorting \\ by\ sex\ premium}} \quad (7)$$

$$+ \underbrace{\mathrm{E}\left[\alpha_{a}^{s}\mathrm{a_{it}} + \tau_{\mathrm{t}}^{\mathrm{s}} - \overline{w}^{s}\middle|G,s\right]}_{Age\ Adjustment} + \underbrace{E[\lambda_{i} + \varepsilon_{it}|G,s] - E[\lambda_{i} + \varepsilon_{it}|s]}_{Remainder}$$

4 Data

We use data on employment and earnings from the Fabling-Maré labour tables, derived from the Integrated Data Infrastructure and the Longitudinal Business Database (Fabling & Maré, 2015).[6] The core information on which these tables are built is the confidentialised EMS (Employer Monthly Schedule) record of monthly wage and salary earnings provided by firms to Inland Revenue, summarising all payments with tax deducted at source. The labour tables include an estimated measure of full-time-equivalent (FTE) employment, which is used to calculate an FTE earnings measure, excluding earnings of working proprietors. Earnings measures are reported as real earnings, deflated to the average CPI over the year to March 2023 (referred to as $2023). A "job" is a continuous monthly spell of wage and salary payments from an employer to an employee (treating one-month earnings gaps as continuous).

Table 2 documents the restrictions we apply to the data for the current study. Over our study period of 2000 – 2024, there are an average of 3.231m distinct jobs each year, with aggregate annual real earnings of $118b. Earnings from the first or last month of a job is an unreliable measure of the full-month earnings rate due to part-month employment as well as atypical initial or final pay associated with signing bonuses, lump sum annual leave payouts, or redundancy.

We drop all start and end months, which eliminates around 20% of annual jobs – being short-term jobs for which we have no mid-spell months. As shown in Table 2, these omitted jobs account for about 6% of earnings. Restricting attention to 18-64 year olds lowers the coverage rate for earnings to 90% and for jobs to 74%. We create an annual dataset of earnings, analysing

[6] We use the October 2024 instance of these databases.

average monthly earnings for each worker's main job each March year.[7] With this restriction, we retain 87% of aggregate earnings, and lower the coverage of jobs to 60%. Finally, dropping workers with missing ethnicity data and restricting attention to the largest connected subgroup of workers and firms have relatively minor effects on data coverage. The largest connected subgroup contains 97.9% of selected jobs with non-missing ethnicity, and 99.1% of earnings. Our final analytical dataset covers 86% of earnings and 58% of all jobs between 2000 and 2024.[8]

4.1 Ethnic classification

Workers' ethnicities are identified from a combination of administrative and survey sources. We use data as it appears in the *personal_details* table of Statistics New Zealand's Integrated Data Infrastructure (IDI). The primary source of ethnicity data is the Census of Population and Dwellings. Where census data are not available for an individual, source-ranked administrative ethnicity information is used, with preference given to sources that have been found to be most consistent with Census. Each person can identify with more than one ethnicity, with responses coded to five broad categories (European, Māori, Pacific, Asian, Middle-Eastern/Latin American/African).[9] Coded in this way, an individual can identify with up to five distinct ethnicities. Over 90 percent of individuals identify with only one ethnic group (the total number of ethnicity responses is around 11% greater than the number of individuals).

We use two distinct approaches to calculating summary statistics by ethnicity.[10] The first (*total response*) approach calculates ethnicity-specific measures based on all individuals who identify with a particular ethnicity. Thus, individuals identifying as Māori and European would be included in the calculation of statistics for the Māori ethnic group as well as in the calculation of statistics for the European ethnic group. The alternative approach (*response-weighted*) ensures that an individual identifying with multiple ethnicities receives the same weight as a single-ethnicity individual when calculating overall shares, sums, and means. This is achieved by using an individual's 'share of ethnicity responses' in place of a binary (0/1) ethnicity indicator. In this

[7] Main job is the employer-employee combination that accounts for the highest mid-spell real earnings in a year. This could be in multiple jobs with the same employer. In a very small number of cases, two jobs have the same maximum earnings and one is chosen arbitrarily.

[8] There is some variation in coverage over time, with smaller losses due to dropping start and end months (jobs coverage of 76% in 2000 rising to 81% in 2024; earnings coverage rising from 92% to 95%) and slightly larger losses over time due to applying the 18-64 age restriction (2% to 3% larger losses in 2024 than in 2000).

[9] "Other ethnicities" are grouped with European as detailed Census responses suggest this is the most consistent classification.

[10] A third option, which we do not pursue in this study, is to treat each different combination of ethnicities as a distinct category (e.g., 'Māori & European' is treated as different from Māori and different from European).

case, an individual identifying as both Māori and European would contribute a half-measure to the count of or average for Māori and a half-measure to the count of or average for Europeans. This reweighting ensures that the sum of response-weighted variables equals the actual sum across all individuals. This approach is, therefore, desirable for statistical purposes. It is not intended as a measure of the strength or importance of multiple ethnic identities.[11] The (total response) alternative gives more weight to individuals with multiple responses.[12]

4.2 Mean Characteristics

Table 3 summarises the ethnic composition of our analytical sample. It shows each ethnic group's share of FTE employment, and of average monthly FTE earnings within main job. Shares are constructed so that they add to 100% (that is, response-weighted).

Employment of Māori workers has grown over time at about the same rate as overall employment. The Māori share of employment has remained at 10% throughout the period. There has been slight growth in the share of FTE employment accounted for by Pacific Peoples (from 5% to 7%) and MELAA workers (from 1% to 2%). The most significant changes in the ethnic composition of employment are for European workers, whose response-weighted share dropped from 80 percent in 2000 to 62 percent in 2024, and Asian workers, whose share rose from 4 percent to 20 percent. Ethnic group shares of earnings are similar to the employment shares, though slightly higher for European workers (74% compared with 70% of employment), and lower for other groups, reflecting relatively high earnings rates for Europeans.

Mean real monthly earnings are shown for each group, together with an earnings gap measure – the percentage deviation of average monthly earnings from the pooled (all ethnicities) average. Because Europeans are 70% of the analytical sample, their average earnings are similar to the overall average (4% above). All other ethnic groups have lower-than-average monthly earnings, ranging from –2% for MELAA workers, to larger gaps for Asian (–6%), Māori (–13%) and Pacific (–17%) workers.

The table also shows the size of the gender gap within each ethnic group. There are sizeable gender gaps for all ethnic groups, with relatively large gaps for ethnic groups with high average earnings. Compared with an overall gender gap in monthly FTE earnings of –26%, ethnicity-specific gender gaps range from –12% (for Pacific Peoples) to –30% (for Europeans).

[11] Houkamau & Sibley (2019, p. 131) find that "Māori with multiple ethnic identities may not necessarily have a weaker sense of cultural identity compared with those identifying as solely Māori"

[12] Appendix Table 1 summarises the formulae and properties of total-response and response-weighted counts, shares, sums and means.

The final block of Table 3 shows the sex-composition of the five ethnic groups. Men account for more than half of fulltime equivalent workers within each ethnic group. The share accounted for by women is highest among European workers (48%), and relatively low among MELAA (43%) and Asian (44%) workers. Although the ethnic differences in sex-shares are modest, they are relevant for explaining ethnic earnings gaps due to the interaction with the substantial gender gaps.

Our focus is on the role of firms in accounting for ethnic earnings differences. Given the substantial gender differences that exist for all ethnic groups, we stratify our analysis by sex. Table 4 summarises the composition of employment and earnings by sex and ethnicity – analogously to the summaries in Table 3. Consistent with the modest differences across ethnic groups in the gender mix, the sex-specific composition patterns shown in Table 4 are similar to the Table 3 patterns for men and women combined. The sex-specific earnings differences across ethnicities are, however, more distinct. The 'mean monthly FTE earnings' blocks in Table 4 show average earnings for each sex-ethnicity group expressed as a proportion of overall mean earnings (labelled as 'Relative to overall mean'), and also relative to the sex-specific mean ('ethnic gap for women' and 'ethnic gap for men'). Relative to the overall mean, women's average earnings by ethnicity are –12% to –23% below average. Almost all male ethnic group averages are higher than the average of the highest paid group of women by ethnicity (European women, with an average of –12%). The only exception is that Pacific men have earnings that are slightly below that of European women. Ethnic gaps for men are more pronounced than are ethnic gaps for women, ranging from +6% above the all-male average for European men to –22% for Pacific men (final row of panel b). For women, ethnic gaps range from 2% above the all-women average, to –10% for Pacific women (final row of panel a).

Mean monthly FTE earnings differences by ethnicity and sex have been relatively stable over 2000-2024 (Figure 1). Average earnings by ethnicity are plotted relative to overall mean earnings each year, with a value of zero indicating average earnings. The ordering of relative earnings by ethnicity is consistent over time within each panel, with the exception of MELAA women, whose average earnings were higher than those of European women between 2000 and 2005. The earnings of European men were around 20% above average for most of the period, with some relative decline since 2018 – but still over 15% above average in 2024. Across the board, there has been growth in the relative earnings of women over the period.

A further advantage of stratifying our analysis of ethnic earnings differences by sex is that we can more easily take into account sex differences in life-cycle earnings patterns. The first panel

of Figure 2 shows the patterns of (log) average earnings by age for men and for women. Men's average earnings continue to rise beyond age 30, peaking in their late 40s. The age profile of earnings for women is similar to that of men until around 30 years of age, after which the average changes very little until around 50, after which it declines. The distinction between men's and women's age earnings profiles is evident in panels (b) and (c) of Figure 2, which shows ethnicity-specific profiles. Each profile is plotted relative to earnings at age 30, which removes differences in the levels of earnings by ethnicity and sex.

Although age earnings profiles by sex look similar across ethnicities, we control in some of our subsequent analyses for ethnicity-specific and sex-specific profiles to take account of pronounced differences in the age distributions of workers by sex and ethnicity (shown in the second column of Figure 2). Pacific and MELAA workers are more likely than average to be young, with peak densities at ages around 30 to 35. In contrast, European workers have a modal age of around 50. These differences contribute to ethnic earnings gaps.

5 Findings

5.1 Earnings and employment in high-paying firms

The equations documented in section 3 are estimated based on the log of real earnings, which is a common approach to analysing earnings gaps, with log differences being approximately equal to ratios of group earnings. However, ethnicity and gender earnings gaps measured as differences in log earnings differ from those presented in Table 3 and Table 4, which are based on ratios of mean earnings. Mean (log) real earnings by gender and ethnicity are presented in Table 5 together with the implied ethnicity and gender gaps.[13]

Overall ethnic gaps range from -0.139 (for Pacific Peoples) to 0.034 (for Europeans). However, as shown in Table 4 there are substantial earning differences between men and women within each ethnic group. For women (panel b of Table 5), the (log) earnings gaps by ethnicity, relative to the overall mean log(earnings) of 8.63, range from –0.106 to –0.205, which are slightly smaller than the –13% to –23% gaps reported in Table 4. Ethnic gaps measured relative to the mean for all women range from –0.081 to 0.018, with ethnic differences for women slightly less pronounced than for all workers. For men (panel (c)), (log) earnings gaps by ethnicity of –0.088 to

[13] The means and gaps in Table 5, and in subsequent tables, are based on response-weighted means, as discussed in section 4.1 and summarised in Appendix Table 1.

0.165 correspond to –13% to 19% in Table 4. When measured relative to gender-specific mean earnings, there is greater variation across ethnicities for men than for women (panel c). European men earn 0.055 more than men on average, whereas the gap for Pacific men is –0.197. European women earn 0.014 more than the average woman, whereas the gaps for Māori and Pacific women are –0.076 and –0.081 respectively.

5.1.1 Contributions of firm pay premiums to ethnic wage gaps

Table 6 summarises the contributions of firm pay premiums to the earnings gaps measured relative to overall mean earnings, as shown in Table 5. Earnings gaps are decomposed using the formula shown in equation (6), which separately quantifies the contributions of age differences, firm pay premiums, sex-specific firm pay premiums, and the combined effect of skill differences and pay discrimination. Age adjustment is done based on a common (men and women combined) age-earnings profile, with firm effects estimated from (pooled) age-adjusted earnings (ie, estimation approach [1]).

Based on differences in age distributions, we would expect Asian and MELAA men and women to have higher average earnings. For Asian women, earnings would be higher by 0.042, meaning that their earnings gap of –0.106 would be 40% larger if they had the same age profile as workers overall. Asian men also have an age profile associated with higher average earnings. Age adjustment contributes 0.036 to their expected earnings, which is larger than their earnings gap of 0.032. MELAA workers also have favourable age profiles, which partially account for the 0.076 positive earnings gap for MELAA men and reduce the earnings gap for MELAA women. Age adjustment of earnings for – relatively young – Māori and Pacific men accounts for 69% and 17% respectively of their negative earnings gaps.

Sorting into high-paying firms has a positive effect for all groups of men, accounting for 15% of the positive overall male earnings gap. For women, the contributions are uniformly negative, meaning that women are sorted into less-well-paying firms, and this accounts for 15% of the overall female earnings gap of –0.124. The positive contribution of firm sorting for men is stronger than average for Pacific men (0.023), European men (0.019) and MELAA men (0.018). Among women, the effect of sorting into lower-paying firms is strongest for Māori women (–0.030) and European women (–0.020). Panel (c) of Table 6 summarises the impact of age adjustment and firm sorting on the gender gap within each ethnic group. Firm sorting accounts for 10% to 26% of ethnic-specific gender gaps.

Each panel of Table 6 also contains a summary of the impact of sorting into firms with sex-specific firm premiums that differ from their overall firm premiums (ie, estimation approach [2a]). Women from ethnic groups other than European are sorted into firms where women are paid relatively well compared with what women are generally paid. However for no group does the benefit from this outweigh the effect of working in firms with low overall firm effects. Among men, only European men are positively sorted into firms that pay men relatively well. For Asian men, the small advantage of working in firms with higher than average premiums (0.003) is more than offset by the disadvantage of working in firms that pay men less well (–0.006).

For most ethnic and gender groups, the 'remainder' component of the decomposition has the same sign, and is of a similar size to the raw gap, meaning that the combined effect of age adjustment and firm sorting is of secondary importance in understanding ethnic and gender gaps. The combined effect of differences in skill and differences in discriminatory pay practices account for between 53% (for MELAA men) and 134% (Asian women) of earnings gaps, apart from the case of Asian men, where there is a remainder contribution of only –0.002, or –5% of the small 0.032 earnings gap.

Table 7 presents an alternative decomposition of earning gaps, focusing on ethnic earnings gaps for men and women separately. The decomposition is based on equation (7), which incorporates sex-specific age adjustment (using estimation approaches [2b] for ϕ and [3] for ϕ^s). The patterns generally reflect the inter-ethnic variation shown in Table 6, but mask the mean earnings differences between men and women. Panel (a) summarises the decomposition of ethnic earnings gaps for women, panel (b) shows the decomposition for men, and panel (c) contains an FTE-weighted average of the effects for men and women combined.

As in Table 6, age adjustment makes a positive contribution to ethnic earnings gaps for Asian and MELAA workers. Without their favourable age structures, the small positive ethnic earnings gaps for Asian and MELAA women would become negative, and the negative ethnic earnings gaps for Asian and MELAA men would be magnified.

The earnings benefits of working in firms that generally pay relatively well were largest for Pacific women (0.013) and MELAA women (0.010). In contrast, Asian men (–0.014) and Māori women (–0.011) worked disproportionately in relatively poor-paying firms. The size of these contributions is, however, small relative to the size of ethnic earnings gaps. The impact on average ethnic earnings gaps is never greater than 1 percent, in the face of ethnic earnings gaps of up to 14 percent.

The additional effects of working in firms that pay workers of their own sex relatively well is of secondary importance for all ethnic-gender groups (using estimation approach [3]). The average 'remainder' components of the decompositions are negative (–0.038 to –0.143) for all groups other than Europeans (0.038), and are large compared with the size of ethnic earnings gaps. Sorting across firms is not a large component of ethnic earnings gaps.

The relatively small incremental contributions from sex-specific premiums suggests that correlations are high between overall firm pay premiums (ϕ_j) and sex-specific premiums (ϕ_j^s). In Table 8, we summarise these correlations, and the correlation with premiums by sex and ethnicity(ϕ_j^{se}). Correlations are calculated from specifications in which fixed effects are calculated on the same basis as earnings adjustments (specifications [1],[3] and [5] in Table 1). The correlation of overall and sex-specific premiums is 0.96 for men and 0.94 for women, indicating that high-paying firms generally pay both men and women relatively well.[14] The correlations are similar (0.95 and 0.93) when comparing overall and sex*ethnicity premiums, suggesting that the effect of ethnicity-specific pay levels within firms is small. This is confirmed by the 0.99 correlation between sex-specific and sex*ethnicity-specific premiums. The lower panel of Table 8 examines this correlation within each ethnic group. The lowest correlations between (ϕ_j^s) and (ϕ_j^{se}) are seen for Māori, Pacific and MELAA employees (0.93 to 0.95). While still high, this is suggestive of some degree of within-firm pay differentiation by ethnicity, which could be a result of (positive or negative) discrimination.

5.1.2 Mean FFE for subgroups

In Table 9, we summarise the variation in firm premiums by ethnicity for selected subsets of workers, based on within-sex firm premiums (ϕ_j^s, estimation approach [3]) It is worth reiterating that sex-specific firm premiums have a mean of zero for each sex, so that the mean earnings and premiums presented in Table 9 exclude gender gaps. The first row compares mean within-sex premiums across ethnicities. As shown in Table 5, Asian and Māori workers are in firms that pay lower-than-average wages to workers of their sex (–0.005 and –0.006 respectively). These patterns of sorting into well-paying firms vary by location, worker birthplace and education, and

[14] Correlations are based on firm-level averages of fixed effects, weighted by the response-weighted FTE of their employees. Correlations are mechanically higher for firms with low workforce diversity. Correlations for the subset of firms with higher ethnic diversity are lower.

by industry. For each of these dimensions, subgroups in Table 9 are ordered from lowest-paid to highest paid.[15]

By location, sex-adjusted earnings ($\widetilde{w}_s$) in non-metropolitan areas are –0.08 below average, compared with 0.043 above average in metropolitan areas. The firm premium contributions to these earnings differences are –0.027 (34%) in non-metropolitan areas and 0.014 (33%) in metropolitan areas. These locational differences in mean firm fixed effects are not experienced equally by all ethnic groups. In non-metropolitan areas, Māori, Pacific and MELAA workers are in relatively well-paying firms – with mean firm premium of only –0.005 to –0.007, below the overall mean of –0.027. In metropolitan areas, Asian workers work in firms that pay only 0.001 above average, compared with 0.010 to 0.018 for other groups.

Although New Zealand-born workers are, on average, working in low-paying firms ($\bar{\phi}_j^s = -0.002$), this is not true for New Zealand-born Pacific, Asian, and MELAA workers (0.018, 0.030 and 0.011 above the –0.002 average). Among non-New Zealand-born workers, Asian workers (–0.012) and Māori workers (–0.008) work in firms with below-average firm effects, despite an average premium of 0.005 for non-New Zealand-born workers generally.

There is a clear firm-premium gradient by education, with more highly qualified workers being employed in higher paying firms. Post-graduate workers on average work in firms paying 0.031 above average. In contrast, firms employing workers without qualifications on average pay –0.026 below average. The qualification gradient is not evident for Māori and Pacific workers, particularly for women (appendix table 3).

Variation in firm premiums across industries is pronounced, with similar patterns evident for all ethnic groups. Industries with high adjusted wages tend to have high-paying firms. An exception is the Public Administration, Education and Health industries, where wages are high, despite lower-than-average firm premiums. This pattern reflects the relatively high qualification levels among public sector workers. Conversely, workers in the manufacturing, construction and utilities industries receive low adjusted wages but from firms that pay relatively well.

5.1.3 Employment in high-paying firms: Age variation

The overall inter-ethnic differences in mean firm fixed effects capture average differences over time and across all ages (Table 5). There is, however, also a pronounced age profile in mean firm fixed effects, reflecting a process of workers sorting into higher paying firms as they age. These

[15] Appendix Table 2 shows the employment shares by ethnicity for each subgroup. Appendix Table 3 and Appendix Table 4 present results analogous to Table 9, separately for women and men respectively.

age profiles are shown in Figure 3. The first panel compares age profiles of firm fixed effects by sex. It is notable that the general shape of the age profiles of fixed effects resembles the age-earnings profiles shown in Figure 2, even though the fixed effects are estimated from sex-specific age-adjusted earnings. This suggests that there is lifecycle variation in access to well-paying firms – a feature we return to in the next section – although the scale of fixed effect variation in Figure 3 (-0.10 to 0.04) is small relative to the earnings variation in Figure 2 (-0.50 to 0.20).

Overall fixed effects (ϕ_j from specification [2b] in Table 1) are uniformly higher for men than for women, with differences increasing between ages 25 and 40. The figure also shows sex-specific firm fixed effects (ϕ_j^s from specification [3] in Table 1). These have the same age-pattern as the overall fixed effects, differing mainly due to the normalisation of having mean of zero by sex. These normalised sex-specific firm fixed effects are plotted for each ethnic group in panels (b) and (c) of Figure 3.

Mean firm fixed effects for European and Pacific women peak at around age 30, whereas for Asian and MELAA women, mean firm fixed effects keep rising until their late 30s as they on average move to higher-paying firms. Māori women experience rising firm fixed effects until they are in their early 20s, after which there is essentially no net movement into higher-paying firms. Prime-aged (30-60) European men have the highest mean firm fixed effects of any male ethnic group, peaking at 0.02 above average in their early 40s. In contrast, Asian men are in lower-than-average paying firms at almost all ages, with particularly low mean firm fixed effects while in their 20s.

5.2 Correlations of worker and firm fixed effects

There are clearly systematic differences between ethnicities in access to jobs in high-paying firms and in patterns of access across the life-cycle, although these differences make only modest contributions to overall ethnic earnings gaps. The magnitude of ethnic differences in Figure 3 are generally between 0.02 and 0.05 at various ages, compared with inter-ethnic earnings gaps of 0.05 to 0.25 for men and up to 0.09 for women. Further insights into ethnic differences in access to good (well-paying) jobs can be obtained by examining the correlation between worker fixed effects and firm fixed effects – that is, whether high-earning workers are employed in firms that pay relatively well. A low correlation could reflect a degree of labour market stratification by ethnicity, limiting the opportunities for even high-earning worker to secure well-paid jobs and career advancement.

Table 10 shows the strength of positive worker-firm sorting by sex and ethnicity. The first column shows how strongly high-earning men or high-earning women are sorted into firms that generally pay well. The overall correlation for men (0.182) is stronger than for women (0.167), indicating greater positive assortative matching for men. The correlations are positive for all ethnic groups, and particularly strong for Asian and MELAA men and women, and for European men. The correlations in the second column show the strength of sorting into firms with high within-sex pay premiums. These are all positive and similar to the correlations in the first column (as we might expect from the results in Table 8). They are, however, generally slightly weaker, indicating that each sex by ethnicity group is more strongly sorted into firms that generally pay well than they are into firms that pay workers of their sex well. The one exception is that Pacific women are slightly more strongly sorted into firms that pay women relatively well.

The third and fourth columns of Table 10 correspond to specifications [4b] and [5] in Table 1. Worker premiums for each worker are measured relative to other workers of the same sex and ethnicity. The third column shows the correlation of worker premiums with firms' sex-premiums, whereas the final column shows whether high-premium workers are sorted into firms that pay workers of the same sex and ethnicity well. It appears that firm premiums by sex group are more strongly related to worker premiums than are firms' relative pay to sex by ethnicity groups. Compared with the within-sex averages in the third column, only Asian and European workers have higher than average sorting on the basis of sex by ethnicity firm effects (fourth column). The correlations in the final column are less precisely estimated because firm fixed effects by sex and ethnicity are in some cases estimated across a relatively small number of firms.[16]

5.2.1 Changes in worker-firm sorting over time

The overall correlations discussed in the previous section provide a representative summary of inter-ethnic sorting differences. They do not, however, reveal changes over time that have been occurring since 2000. These changes are shown in Figure 4, based on the correlation between worker premiums within sex by ethnicity groups and firm sex premiums (specification [4b]). Worker-firm sorting was relatively strong for Asian men and women until around 2015, when it started weakening. For Asian women, the strength of sorting has converged to the same level as that of European women. The strength of sorting among Pacific women diverged from that of European and Māori women in 2008 and subsequently followed a post-2015 decline, leaving

[16] Estimates for European men and women are each based on around 17m job-year observations over 24 years. Estimates for MELAA men and women are based on around 0.4m job-year observations.

Pacific women with the lowest sorting strength of any group in 2024 (0.05). The post-2015 decline in sorting is also evident for men, with relatively strong declines for Māori, Pacific and Asian men and a less pronounced drop for European men. For Asian men, the decline reversed their initially high sorting strength to below the level for European men, and to the same level as Māori and Pacific men. Changes in sorting strength for the smallest (MELAA) ethnic group are similar for men and women. They experienced a rise in sorting strength between 2008 and 2015 and, despite experiencing the common subsequent decline, continued to have the highest sorting strength of any group by 2024 (0.18 for men and 0.17 for women).

To investigate the patterns of sorting more fully, Table 11 and Table 12 report the correlation between worker and firm fixed effects for selected groups of workers and firms. For this analysis, we focus on the correlation of worker effects by sex and ethnicity and the sex-based firm fixed effects of the firms in which they work (specification [4b]).

Sorting of (low-) high-earnings workers into (low-) high-paying firms is generally stronger for overseas-born workers than for New Zealand-born workers. As shown in Table 11, this is true for men and women, and for each ethnic group other than Māori women, for whom the correlation is stronger for those born in New Zealand.[17] Sorting correlations are relatively weak (0.09 to 0.13) for Pacific women, Māori and Pacific men, and for New Zealand-born Asian workers.

Patterns of qualification-related worker-firm sorting differ notably between men and women. For men, sorting correlations are low among workers with low levels of highest qualification (no qualifications or school qualifications only) – generally below 0.1, and highest for men with graduate or postgraduate qualifications (up to 0.23). For low-qualification European and Asian women, sorting correlations are low, but for Māori and Pacific women, correlations are lowest for highly qualified women (consistent with Appendix Table 3). Sorting of high-earning women into high-paying firms is strongest for women with post-school or graduate qualifications.

Table 12 presents analogous summaries of worker-firm sorting by location and by industry. Sorting is generally stronger in metropolitan than in non-metropolitan areas. Apart from MELAA workers, sorting correlations in non-metropolitan areas are at or below 0.11, whereas correlations in metropolitan areas are generally above 0.11. Exceptions to the general pattern are that sorting among Pacific men is stronger in non-metropolitan than in metropolitan areas, and sorting for MELAA workers is high in both metropolitan and non-metropolitan areas.

[17] Overseas-born Māori is a small group (Appendix Table 2).

Industry sorting patterns differ between men and women. For women, sorting is strongest within public administration, education and health industries (0.14 to 0.18), whereas for men it is strongest within 'other service' industries (0.13 to 0.21). There is relatively weak sorting within the 'retail, accommodation and hospitality' industry for both men and women, and also within the higher-paid 'telecommunications, finance and insurance and professional services' industries. (Low-) High-earning women employed in 'agriculture and mining' industries tend to be in (higher-) lower-paying firms, whereas the opposite is true for men. Within manufacturing industries worker-firm sorting is weak for European and Māori workers and for Pacific men (but not Pacific women).

6 Summary and discussion

Overall, our study finds that sorting of different ethnic groups into firms that pay different earnings premiums does contribute to ethnic pay gaps but that the contribution is not large. Overall, only European workers have average earnings above the overall average, with a log difference of 0.034 (approximately 3.5%). Average earnings for Māori and Pacific workers are relatively low, with log-difference ethnic gaps of –0.112 (-10.6%) and –0.139 (-13.0%) respectively. There are smaller negative gaps for Asian (–0.032, or 3.1%) and MELAA (–0.003 or –0.3%) workers.

These gaps are generally smaller than the gender gaps within ethnic groups, which range in size between –0.117 to –0.274. Only for Pacific Peoples is the ethnic gap (–0.139) more pronounced than the within-ethnicity gender gap (–0.137). Much of our analysis focuses on ethnic gaps separately for women and for men, measured relative to sex-specific means, while acknowledging the substantial gender differences in pay both within and between firms.

Ethnic gaps are more pronounced for men than for women. European men are paid, on average, 0.055 more than the average man. In contrast, Māori, Pacific and Asian men are paid –0.078 to –0.197 lower than average and MELAA men are paid –0.034 below average. For women, the ethnic gap in favour of Europeans is only 0.014, similar to that of Asian (0.018) and MELAA (0.015) women. The positive gap for Asian and MELAA women is more than accounted for by their favourable age structure. Average earnings of Māori and Pacific women are below the average for women generally (-0.076 and -0.081 respectively)

Our primary research question relates to how strongly sorting across firms that pay different premiums contributes to ethnic earnings gaps. As is the case for earnings gaps,

differences in firm pay premiums has a greater impact on gender gaps than it does on ethnic gaps. Using mean firm fixed effects (ϕ_j) as the measure of firm pay premiums, we find that women are on average employed in firms that pay –0.019 below average, whereas men work in firms that pay 0.016 above average – a combined contribution of –0.035, equating to about 15% of the gender earnings gap. The largest sex-specific ethnic earnings gap is between Pacific men (–0.197) and European men (0.055), a difference of 0.252. For this pair, there is only a 0.005 difference in average firm premiums, equivalent to about 2% of the earnings gap. The strongest contribution of firm premium differences for men is between Pacific men (0.007) and Asian men (–0.014), implying that the Pacific-Asian inter-ethnic gap for men would be 0.021 (31%) larger if it were not for the fact that Pacific men are in better-paying firms.

Among women, the most pronounced difference in firm premiums is between Pacific women (0.013) and Māori women (–0.011). This difference of 0.024 is larger than the small 0.005 earnings gap between Māori and Pacific women. However, the contribution of firm premiums to larger earnings gaps is small. The largest female earnings gap is between Pacific and European women (0.095 higher for European). Mean firm premiums are higher for Pacific women, by 0.014, meaning that their inter-ethnic gap would be 0.014 larger were it not for the different firm premiums.

Overall, the contributions of firm premiums to sex-specific earnings gaps are generally relatively small and are highly variable in their impact, magnifying some inter-ethnic gaps, and offsetting others. The contribution of firm sorting to ethnic earnings gaps is generally smaller than the contributions of gender earnings gaps or age-structure differences. The additional effect of men and women working in firms where sex-specific firm premiums (ϕ_j^s) are more (or less) favourable than overall firm premiums is of secondary importance. Women other than European women are positively sorted into firms that pay women relatively well, though the magnitude of the effect is small (less than 0.004). Pacific, Asian and MELAA men work disproportionately in firms that pay men relatively poorly, with effects of –0.002 to –0.005.

Although the impacts of firm premiums on ethnic gaps are relatively small and variable, they are nevertheless systematic. There is a clear age profile of firm premiums, which differs across ethnicities. This suggests that lifecycle patterns of sorting into better-paying firms contributes to earnings growth, with differing contributions by ethnicity. Relatively strong sorting is evident for young Pacific men. For Māori women, there is no evidence of such sorting between ages 25 and 55. The contributions of firm premiums by age vary between -0.10 and 0.03 (Figure 3), which is about a fifth of the age earnings variation (-0.50 to 0.20: Figure 2).

There are also ethnic differences in sorting correlations – the degree to which (low-) high-earning workers are employed in (low-) high-paying firms. A low correlation could arise for an ethnic group if racism or other forms of discrimination leads to an undervaluation or non-recognition of the skills of highly skilled workers, preventing them from securing jobs in well-paying firms. It could also reflect labour market segmentation along ethnic lines, whereby workers from an ethnic group are able to secure jobs in only a subset of firms, a pattern that can reflect the effects of systemic racism. Worker-firm correlations are positive for all sex-by-ethnicity groups, although the relative strength of sorting across ethnic groups appears to have changed since about 2015. Correlations were relatively strong for Asian men and women prior to 2015. Since then, correlations have declined for all groups. Among both men and women, declines have been somewhat slower than average for European workers. The decline for Asian men has been relatively strong. Since 2015, the strength of correlation has been highest for the small MELAA group.

While there is convincing evidence that racism and discrimination affect labour market choices, options and outcomes for different groups of workers (see Tan et al., 2024), our findings indicate that differential sorting across firms can at most account for only a small proportion of ethnic earnings gaps. The greater part of ethnic earnings gaps is due to within-firm earnings variation between ethnic groups. Our empirical approach was tailored to provide a credible measure of the effect of firm sorting. A limitation of the approach is that we are unable to separate remaining ethnic earnings differences arising from differences in skills from those resulting from differences in how skills are paid within firms. In related work, Benison & Maré (2025) find that substantial ethnic pay gaps remain even after controlling for observable worker and job characteristics, including firm pay premiums.

Reducing the impact of racism and discrimination in recruitment, retention and hiring could improve average earnings for racialised groups that are unable to secure jobs in well-paying firms. However, greater reductions are likely from measures that reduce within-firm inequities.

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Statistics New Zealand Disclaimer

These results are not official statistics. They have been created for research purposes from the IDI which is carefully managed by Stats NZ. For more information about the IDI, please visit https://www.stats.govt.nz/integrated-data/. The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes and is not related to the data's ability to support Inland Revenue's core operational requirements. Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Data and Statistics Act 2022. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers.

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Tables and Figures

Table 1: Estimation approaches

	Two-way fixed effect estimation (equations 3 & 5)		
	Pooled (eq 3)	By sex (eq 3)	By sex & ethnicity (eq 5)
	$E[\phi] = 0$	$E[\phi \mid s] = 0$	$E[\phi \mid s, e] = 0$
Earnings adjustment			
Pooled (eq 2)	[1]	[2a]	
$E[\widetilde{w}] = 0$	λ_i ; ϕ_j	λ_i ; ϕ_j^s	
$E[\lambda] = 0$			
By sex (eq 2)	[2b]	[3]	[4a]
$E[\widetilde{w} \mid s] = 0$	λ_i^s ; ϕ_j	λ_i^s ; ϕ_j^s	λ_i^s ; ϕ_j^{se}
By sex & ethnicity (eq 4)		[4b]	[5]
$E[\widetilde{w} \mid s, e] = 0$		λ_i^{se} ; ϕ_j^s	λ_i^{se} ; ϕ_j^{se}

Note: $\widetilde{w}$ refers to the age and year adjusted earnings, as described in section 3. λ_i refers to a worker-specific fixed effect for worker i. ϕ_j refers to a firm-specific fixed effect for firm j. Superscripts (s=sex; e=ethnicity) indicate group-specific normalisation.

Table 2: Coverage of employment and earnings

	Employment (# jobs)	Total Earnings ($2023b)
All jobs (average 2000-2024)	3,231,275	118.35
Mid-spell months only	80%	94%
Ages 18-64	74%	90%
Main job only	60%	87%
Non-missing ethnicity	59%	87%
Largest connected subgroup	58%	86%
Final sample (average 2000-2024)	1,876,029	101.63

Table 3: Composition of employment and earnings (by ethnicity)

	All	European	Māori	Pacific	Asian	MELAA
FTE employment share						
• 2000	100%	80%	10%	5%	4%	1%
• 2024	100%	62%	10%	7%	20%	2%
• Average (2000 – 2024)	100%	70%	10%	6%	12%	1%
Aggregate earnings share						
• 2000	100%	83%	9%	4%	4%	1%
• 2024	100%	65%	9%	6%	19%	2%
• Average (2000 – 2024)	100%	74%	9%	5%	11%	1%
Mean monthly FTE earnings						
• 2000	$5,515	$5,666	$4,746	$4,525	$5,287	$5,603
• 2024	$7,237	$7,556	$6,389	$6,066	$6,927	$7,202
• Average (2000 – 2024)	$6,377	$6,629	$5,554	$5,280	$6,005	$6,257
• Ethnic earnings gap	0%	4%	-13%	-17%	-6%	-2%
• Gender Gap within ethnicity	-26%	-30%	-17%	-12%	-15%	-21%
% women (FTE weighted)						
• 2000	47%	47%	45%	45%	49%	42%
• 2024	48%	49%	48%	46%	47%	46%
• Average (2000 – 2024)	47%	48%	46%	44%	47%	43%

Note: Employment and earnings shares are response-weighted by $\frac{1}{N_{eth}}$ (section 4.1). Monthly earnings are real (CPI-indexed to March 2023 year) and total response based. The ethnic earnings gap is the percentage deviation of average monthly earnings by ethnicity from the pooled (all-ethnicities) average $[Gap = (w_e - \overline{w})/\overline{w}]$. The within-ethnicity gender gap is the deviation between men's and women's earnings as a proportion of the average earnings by ethnicity $\left[Gender\ gap_e = \left(w_{fe} - w_{me}\right)/\overline{w}_e\right]$ where e=ethnicity, m=male, f=female. The overall gender gap in monthly FTE earnings is 26%.

Table 4: Composition of employment and earnings (by sex and ethnicity)

	All	European	Māori	Pacific	Asian	MELAA
			(a) Women			
FTE employment share						
• 2000	100%	81%	10%	5%	4%	1%
• 2024	100%	63%	10%	6%	19%	2%
• Average	100%	71%	10%	6%	12%	1%
Aggregate earnings share						
• 2000	100%	82%	9%	4%	4%	1%
• 2024	100%	64%	9%	6%	19%	2%
• Average	100%	73%	9%	5%	12%	1%
Mean monthly FTE earnings						
• 2000	$4,518	$4,588	$4,123	$4,056	$4,542	$4,696
• 2024	$6,569	$6,728	$6,044	$5,822	$6,507	$6,517
• Average	$5,499	$5,601	$5,054	$4,923	$5,511	$5,527
• Relative to overall mean	-14%	-12%	-21%	-23%	-14%	-13%
• Ethnic gap for women	0%	2%	-8%	-10%	0%	1%
			(b) Men			
FTE employment share						
• 2000	100%	79%	11%	5%	4%	1%
• 2024	100%	61%	10%	7%	20%	2%
• Average	100%	69%	11%	7%	12%	1%
Aggregate earnings share						
• 2000	100%	83%	9%	4%	3%	1%
• 2024	100%	66%	8%	6%	19%	2%
• Average	100%	74%	9%	5%	11%	1%
Mean monthly FTE earnings						
• 2000	$6,391	$6,633	$5,257	$4,904	$6,000	$6,269
• 2024	$7,850	$8,338	$6,711	$6,270	$7,302	$7,776
• Average	$7,154	$7,563	$5,988	$5,565	$6,437	$6,815
• Relative to overall mean	12%	19%	-6%	-13%	1%	7%
• Ethnic gap for men	0%	6%	-16%	-22%	-10%	-5%

Note: Employment and earnings shares are weighted by $\frac{1}{N_{eth}}$. Monthly earnings are real (CPI-indexed to March 2023 year) and total response based. The ethnic gap by sex is the percentage deviation of average monthly earnings by sex from the pooled (all-ethnicities) average by sex. $[ethnic\ gap_{se} = (w_{se} - \overline{w}_s)/\overline{w}_s]$*. The average relative to the overall mean is the percentage deviation of average monthly earnings by sex and ethnicity from the pooled (all-ethnicities) average* $[Relative\ to\ overall\ mean_{se} = (w_{se} - \overline{w})/\overline{w}]$ *where e=ethnicity, s=sex.*

Table 5: Mean log earnings and earnings gaps (by sex and ethnicity)

	All	Europ	Māori	Pacific	Asian	MELAA
			(a) All workers			
Mean log(real monthly earnings)	8.634	8.669	8.522	8.495	8.602	8.631
Earnings gap (rel to overall mean)		0.034	-0.112	-0.139	-0.032	-0.003
			(b) Women			
Mean log(real monthly earnings)	8.511	8.525	8.434	8.429	8.528	8.526
Earnings gap (rel to overall mean)	-0.124	-0.110	-0.200	-0.205	-0.106	-0.108
Earnings gap (rel to female mean)	0.000	0.014	-0.076	-0.081	0.018	0.015
			(c) Men			
Mean log(real monthly earnings)	8.744	8.799	8.596	8.547	8.666	8.710
Earnings gap (rel to overall mean)	0.109	0.165	-0.038	-0.088	0.032	0.076
Earnings gap (rel to male mean)	0.000	0.055	-0.148	-0.197	-0.078	-0.034

Note: weighted by FTE and ethnicity-response-weighted (section 4.1).

Table 6: Contributions of firm pay premiums to gender and ethnic earnings gaps

	All	European	Māori	Pacific	Asian	MELAA
			(a) Women			
Earnings gap (cf overall mean)	-0.124	-0.110	-0.200	-0.205	-0.106	-0.108
Contributions						
(Pooled) Age adjustment	0.006	0.002	-0.004	-0.007	0.042	0.017
(% of earnings gap)	(-4%)	(-1%)	(2%)	(3%)	(-40%)	(-16%)
Mean ϕ	-0.019	-0.020	-0.030	-0.006	-0.011	-0.008
(% of earnings gap)	(15%)	(18%)	(15%)	(3%)	(10%)	(8%)
Additional effect of Mean ϕ^s		-0.002	0.004	0.005	0.005	0.002
(% of earnings gap)		(2%)	(-2%)	(-2%)	(-4%)	(-2%)
Remainder	-0.111	-0.090	-0.169	-0.198	-0.142	-0.120
(% of earnings gap)	(89%)	(82%)	(85%)	(96%)	(134%)	(110%)
			(b) Men			
Earnings gap (cf overall mean)	0.109	0.165	-0.038	-0.088	0.032	0.076
Contributions						
(Pooled) Age adjustment	-0.005	-0.008	-0.026	-0.015	0.036	0.020
(% of earnings gap)	(-4%)	(-5%)	(69%)	(17%)	(114%)	(27%)
Mean ϕ	0.016	0.019	0.012	0.023	0.003	0.018
(% of earnings gap)	(15%)	(11%)	(-32%)	(-26%)	(10%)	(24%)
Additional effect of Mean ϕ^s		0.002	0.000	-0.004	-0.006	-0.003
(% of earnings gap)		(1%)	(1%)	(5%)	(-20%)	(-4%)
Remainder	0.098	0.152	-0.024	-0.091	-0.002	0.040
(% of earnings gap)	(89%)	(93%)	(62%)	(104%)	(-5%)	(53%)
			(c) Gender gap (Women – Men)			
Gender earnings gap	-0.233	-0.274	-0.161	-0.117	-0.137	-0.184
Contributions						
(Pooled) Age adjustment	0.010	0.010	0.022	0.008	0.006	-0.003
(% of earnings gap)	(-4%)	(-4%)	(-14%)	(-7%)	(-4%)	(2%)
Mean ϕ	-0.035	-0.038	-0.042	-0.028	-0.014	-0.027
(% of earnings gap)	(15%)	(14%)	(26%)	(24%)	(10%)	(14%)
Additional effect of Mean ϕ^s		-0.003	0.004	0.009	0.011	0.006
(% of earnings gap)		(1%)	(-2%)	(-8%)	(-8%)	(-3%)
Remainder	-0.208	-0.242	-0.145	-0.107	-0.140	-0.160
(% of earnings gap)	(89%)	(88%)	(90%)	(91%)	(102%)	(87%)

Note: weighted by FTE and ethnicity-response-weighted (section 4.1). Age adjustment for this table is based on pooled (men and women) age-earnings profiles. See equation (6). Specifications (see Table 1): ϕ is from [1]; ϕ^s is from [2a].

Table 7: Contributions of firm pay premiums to ethnic earnings gaps

	European	Māori	Pacific	Asian	MELAA
			(a) Women		
Ethnic earnings gap for women	0.014	-0.076	-0.081	0.018	0.015
Contributions					
Age adjustment for women	-0.008	-0.008	-0.003	0.054	0.029
(% of ethnic earnings gap)	(-58%)	(11%)	(4%)	(303%)	(189%)
Mean ϕ (diff from female mean)	-0.001	-0.011	0.013	0.007	0.010
(% of ethnic earnings gap)	(-6%)	(15%)	(-16%)	(41%)	(63%)
Additional effect of Mean ϕ^S	-0.002	0.003	0.004	0.004	0.002
(% of ethnic earnings gap)	(-11%)	(-4%)	(-5%)	(23%)	(13%)
Remainder	0.025	-0.060	-0.095	-0.048	-0.025
(% of ethnic earnings gap)	(175%)	(79%)	(117%)	(-267%)	(-166%)
			(b) Men		
Ethnic earnings gap for men	0.055	-0.148	-0.197	-0.078	-0.034
Contributions					
Age-adjusted for men	0.002	-0.026	-0.020	0.022	0.014
(% of ethnic earnings gap)	(3%)	(18%)	(10%)	(-29%)	(-40%)
Mean ϕ (diff from male mean)	0.002	-0.004	0.007	-0.014	0.002
(% of ethnic earnings gap)	(4%)	(3%)	(-3%)	(18%)	(-5%)
Additional effect of Mean ϕ^S	0.001	0.000	-0.003	-0.005	-0.002
(% of ethnic earnings gap)	(2%)	(0%)	(2%)	(6%)	(7%)
Remainder	0.050	-0.117	-0.180	-0.081	-0.047
(% of ethnic earnings gap)	(90%)	(79%)	(91%)	(104%)	(139%)
			(c) Average		
Average ethnic earnings gap	0.034	-0.112	-0.139	-0.032	-0.003
Contributions					
Age-adjustment	-0.003	-0.018	-0.013	0.037	0.020
(% of ethnic earnings gap)	(-8%)	(16%)	(9%)	(-111%)	(-159%)
Mean ϕ (diff from male mean)	0.001	-0.007	0.009	-0.004	0.005
(% of ethnic earnings gap)	(2%)	(6%)	(-6%)	(12%)	(-40%)
Additional effect of Mean ϕ^S	0.000	0.001	0.000	-0.001	0.000
(% of ethnic earnings gap)	(-0%)	(-1%)	(0%)	(2%)	(3%)
Remainder	0.038	-0.091	-0.143	-0.066	-0.038
(% of ethnic earnings gap)	(106%)	(79%)	(98%)	(197%)	(296%)

Note: weighted by FTE and ethnicity-response-weighted (section 4.1). Age adjustment for this table is sex-specific. See equation (7). Specifications (see Table 1): ϕ is from [2b]; ϕ^S is from [3].

Table 8: Correlation of alternative firm fixed effects (by sex and ethnicity)

	Group	Specifications (see Table 1)	Women	Men
$Corr(\phi, \phi^s)$	All	[1],[3]	0.94	0.96
$Corr(\phi, \phi^{se})$	All	[1],[5]	0.93	0.95
$Corr(\phi^s, \phi^{se})$	All	[3],[5]	0.99	0.99
			By ethnicity	
$Corr(\phi^s, \phi^{se})$	European	[5]*,[5]	0.98	0.98
$Corr(\phi^s, \phi^{se})$	Māori	[5]*,[5]	0.93	0.94
$Corr(\phi^s, \phi^{se})$	Pacific Peoples	[5]*,[5]	0.94	0.95
$Corr(\phi^s, \phi^{se})$	Asian	[5]*,[5]	0.99	0.99
$Corr(\phi^s, \phi^{se})$	MELAA	[5]*,[5]	0.93	0.94

*Note: correlations are weighted by FTE and ethnicity-response-weighted. ϕ has zero mean overall. ϕ^s has zero mean by sex. ϕ^{se} has zero mean for each sex*ethnicity group. Specification [5]* is an ethnicity-share weighted average of ϕ^{se} for a firm from specification [5].*

Table 9: Mean firm pay premiums – by ethnicity (sex-specific premium: ϕ^s)

	Adj earn ($\tilde{w}^s$)	Mean FFE ($\bar{\phi}^s$: specification [3])					
	All	All	Europ	Māori	Pacific	Asian	MELAA
Mean ϕ^s	0.000	0.000	0.001	-0.006	0.009	-0.005	0.005
By Location							
• Non-Metro	-0.080	-0.027	-0.028	-0.005	-0.007	-0.031	-0.006
• Metro	0.043	0.014	0.018	0.010	0.014	0.001	0.011
By birthplace							
• Non-NZ-born	-0.005	0.005	0.015	-0.008	0.001	-0.012	0.000
• NZ-born	0.004	-0.002	-0.002	-0.004	0.018	0.030	0.011
By highest qualification							
• No qualifications	-0.229	-0.026	-0.030	-0.004	0.008	-0.049	-0.033
• School	-0.099	-0.008	-0.008	-0.002	0.012	-0.030	-0.014
• Post-school	-0.032	-0.007	-0.005	-0.001	0.017	-0.031	-0.015
• Graduate	0.103	0.011	0.015	-0.013	0.008	0.002	0.017
• Post-graduate	0.279	0.031	0.030	-0.012	0.005	0.025	0.024
By Industry (ANZSIC06)							
• Retail/Accomm/hospitality (G,H)	-0.217	-0.107	-0.106	-0.043	-0.023	-0.076	-0.060
• Agric & Mining (A,B)	-0.141	-0.048	-0.047	-0.032	-0.064	-0.030	0.003
• Services n.e.c. (F,I,L,N,R,S)	-0.044	-0.014	-0.012	-0.020	-0.010	-0.013	-0.015
• Manuf/const/utilities (C,D,E)	-0.012	0.032	0.027	0.030	0.041	0.019	0.035
• Public Adm/educ/health (O,P,Q)	0.058	-0.001	-0.001	-0.011	0.004	0.003	0.002
• Telco/fin/insur/profserv (J,K,M)	0.237	0.094	0.089	0.029	0.062	0.077	0.081

Note: weighted by FTE and ethnicity-response-weighted (section 4.1). Metropolitan areas are identified based on Statistics New Zealand Functional Urban Areas (2023), and include Auckland, Hamilton, Tauranga, Wellington, Christchurch and Dunedin. 'Services not elsewhere included' covers: F: Wholesale Trade; I: Transport, Postal and Warehousing; L: Rental, Hiring and Real Estate Services; N: Administrative and Support Services; R: Arts and Recreation Services; S: Other Services.

Table 10: Sorting – correlation between worker and firm fixed effect [corr(λ, ϕ)] (by sex and ethnicity)

Worker premium	λ^s		λ^{se}	
	high earner within sex		high earner within sex&ethnicity	
Firm premium	ϕ	ϕ^s	ϕ^s	ϕ^{se}
	overall	sex-specific	sex-specific	within sex&eth
Specification (see Table 1)	[2b]	[3]	[4b]	[5]
			(a) Women	
All ethnicities	0.167	0.151	0.152	0.118
• European	0.172	0.156	0.151	0.131
• Māori	0.154	0.147	0.152	0.060
• Pacific	0.107	0.111	0.121	0.039
• Asian	0.189	0.180	0.177	0.139
• MELAA	0.199	0.194	0.195	-0.058
			(b) Men	
All ethnicities	0.182	0.159	0.157	0.122
• European	0.192	0.167	0.159	0.142
• Māori	0.115	0.102	0.139	0.042
• Pacific	0.112	0.094	0.147	0.035
• Asian	0.202	0.158	0.172	0.125
• MELAA	0.228	0.200	0.202	-0.084

Note: weighted by FTE and ethnicity-response-weighted (section 4.1).

Table 11: Sorting correlations – by birthplace and highest qualification (by sex and ethnicity)

	Birthplace		Highest qualification				
	Overseas-born	New Zealand-born	None	School	Post-school	Graduate	Post-graduate
			(a) Women				
	Corr(λ^{se}, ϕ^{s}): age profiles by sex*ethnicity; firm gender premium						
All ethnicities	0.162	0.148	0.082	0.115	0.122	0.130	0.109
• European	0.162	0.152	0.078	0.114	0.124	0.142	0.124
• Māori	0.137	0.147	0.142	0.150	0.165	0.135	0.089
• Pacific	0.109	0.085	0.122	0.124	0.129	0.040	0.043
• Asian	0.180	0.121	-0.042	0.099	0.092	0.150	0.130
• MELAA	0.199	0.162	0.151	0.140	0.138	0.157	0.143
			(b) Men				
	Corr(λ^{se}, ϕ^{s}): age profiles by sex*ethnicity; firm gender premium						
All ethnicities	0.190	0.146	0.072	0.104	0.129	0.193	0.151
• European	0.194	0.156	0.072	0.113	0.131	0.185	0.155
• Māori	0.126	0.101	0.099	0.072	0.113	0.159	0.163
• Pacific	0.103	0.083	0.082	0.080	0.108	0.101	0.143
• Asian	0.156	0.107	0.076	0.078	0.031	0.138	0.146
• MELAA	0.208	0.142	0.116	0.103	0.135	0.234	0.139

Note: Estimates are based on specification [4b] in Table 1

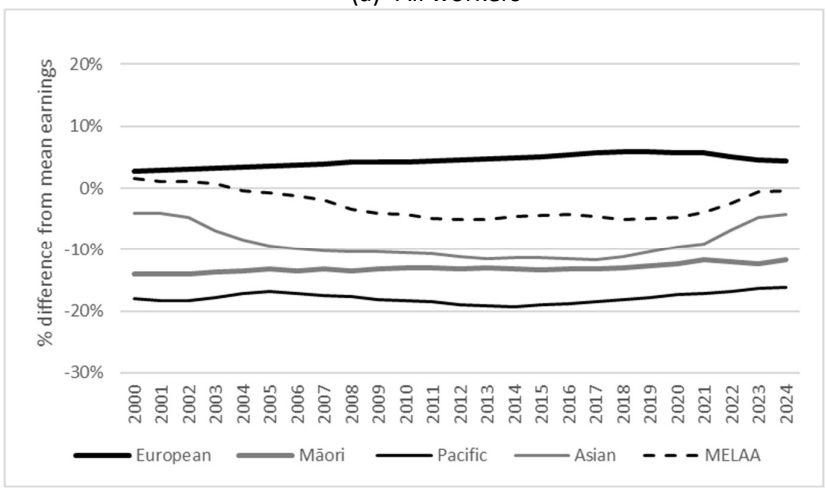
Table 12: Sorting correlations – by location and industry (by sex and ethnicity)

	Location		Industry					
	Non-metro	Metro	Retail, accom & hospitality (G,H)	Agric & mining (A,B)	Services (not elsewhere included)	Manuf, constr & util (C,D,E)	Public admin, educ & health (O,P,Q)	Telecoms, fin&insur, &prof serv (J,K,M)
(a) Women								
Corr(λ^{se}, ϕ^{s}): age profiles by sex*ethnicity; firm gender premium								
All ethnicities	0.079	0.154	0.011	-0.074	0.117	0.065	0.144	0.060
• European	0.078	0.155	0.032	-0.075	0.126	0.077	0.141	0.075
• Māori	0.097	0.155	0.031	-0.028	0.128	0.059	0.163	0.073
• Pacific	0.076	0.111	-0.022	-0.020	0.094	0.121	0.136	0.051
• Asian	0.078	0.183	-0.046	-0.010	0.116	0.124	0.169	0.047
• MELAA	0.151	0.193	-0.019	0.110	0.178	0.155	0.179	0.061
(b) Men								
Corr(λ^{se}, ϕ^{s}): age profiles by sex*ethnicity; firm gender premium								
All ethnicities	0.086	0.181	0.033	0.116	0.180	0.065	0.089	0.087
• European	0.091	0.183	0.027	0.110	0.187	0.087	0.071	0.096
• Māori	0.065	0.126	0.015	0.145	0.162	-0.004	0.160	0.119
• Pacific	0.111	0.091	-0.024	0.105	0.144	0.045	0.118	0.077
• Asian	0.075	0.166	0.025	-0.013	0.126	0.107	0.096	0.060
• MELAA	0.178	0.201	0.031	0.172	0.211	0.140	0.144	0.093

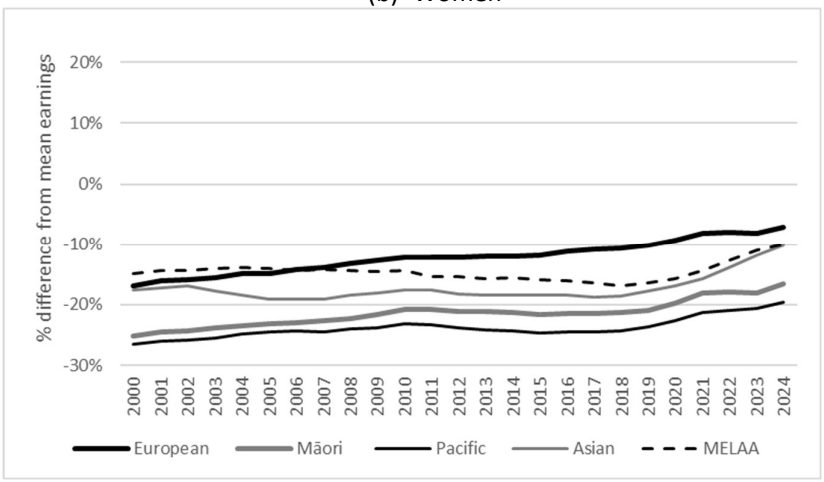
Note: Estimates are based on specification [4b] in Table 1

Figure 1: Relative real earnings by year (by sex and ethnicity)

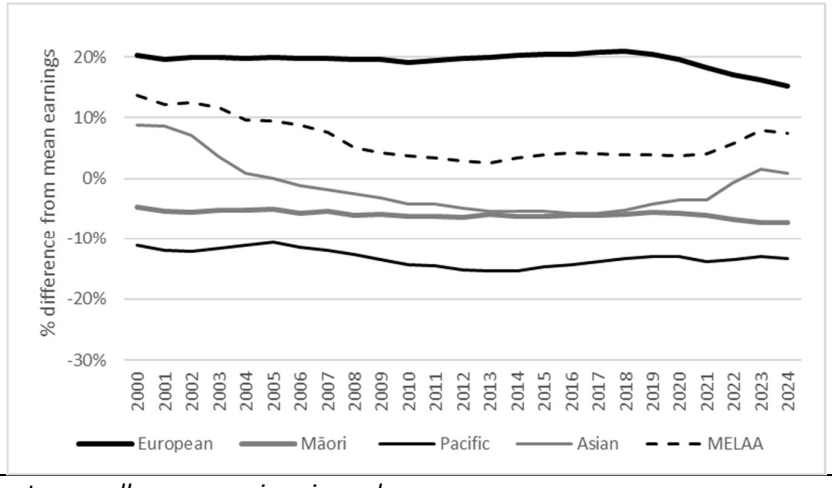
(a) All workers



(b) Women

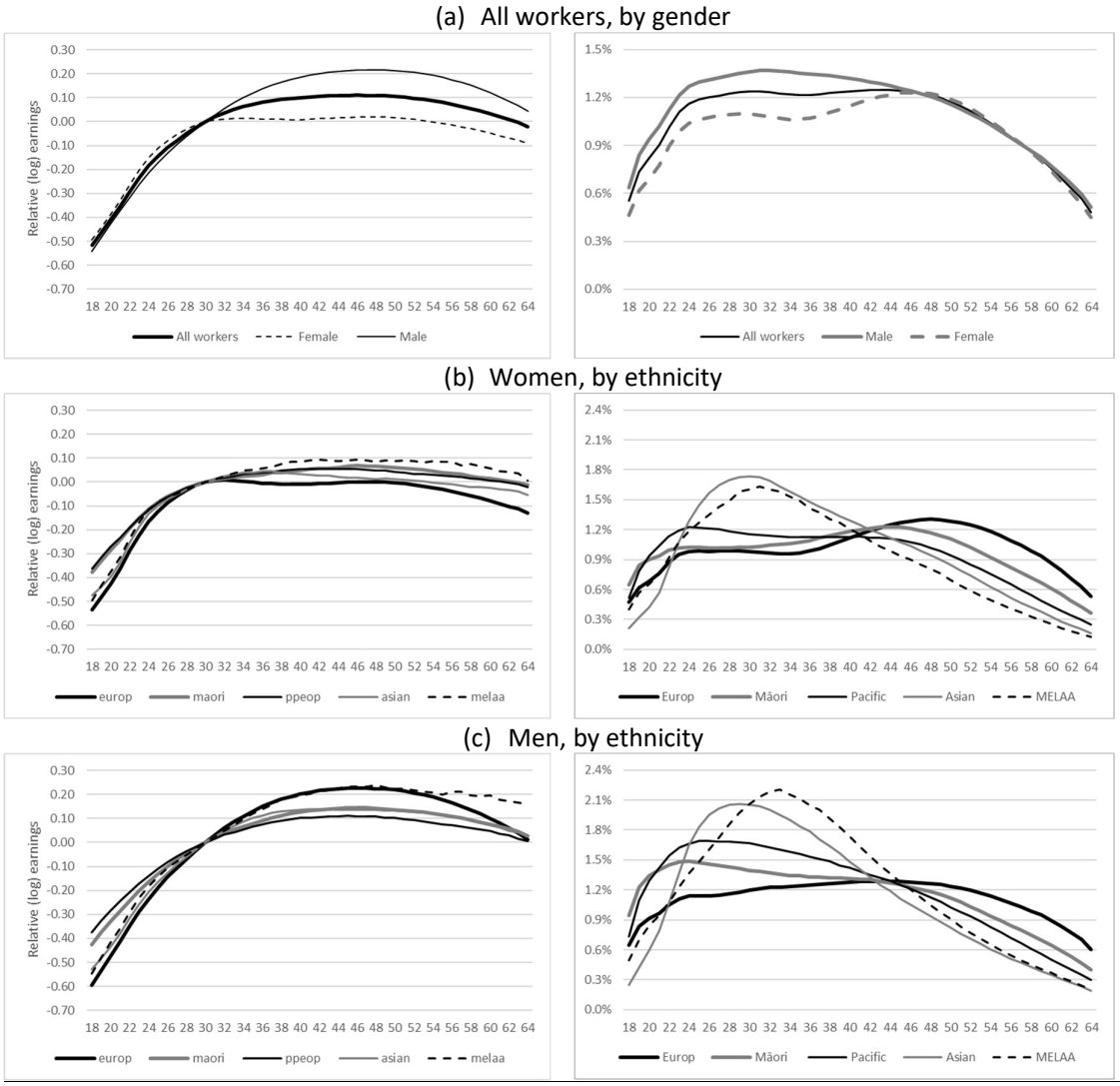


(c) Men



Note: Relative to overall mean earnings in each year.

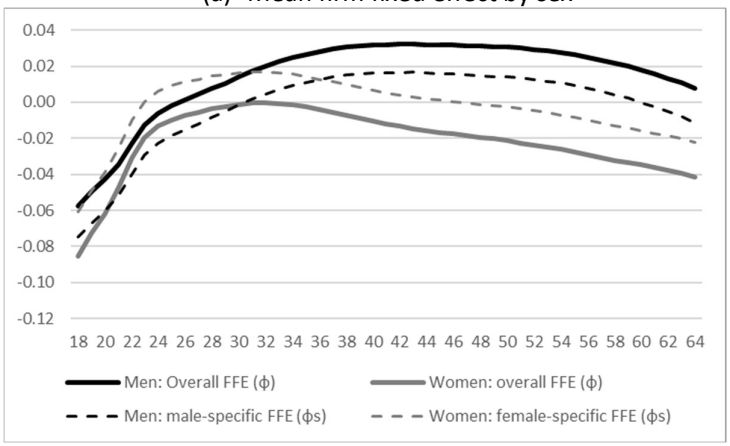
Figure 2: Age-distributions and age-earnings profiles (by sex and ethnicity)



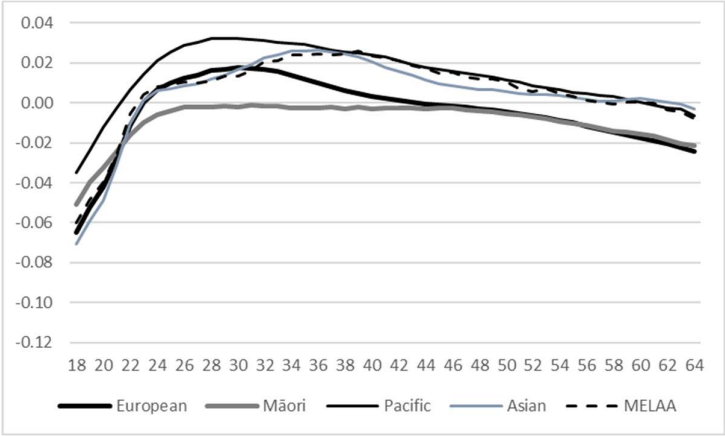
Note: Relative earnings are measured as mean log-difference, relative to earnings at age 30, estimated from a regression that includes year-specific intercepts.

Figure 3: Mean firm fixed effect by age (by sex and ethnicity)

(a) Mean firm fixed effect by sex



(b) Mean firm fixed effect for women, by ethnicity (female-specific FFE)



(c) Mean firm fixed effect for men, by ethnicity (male-specific FFE)

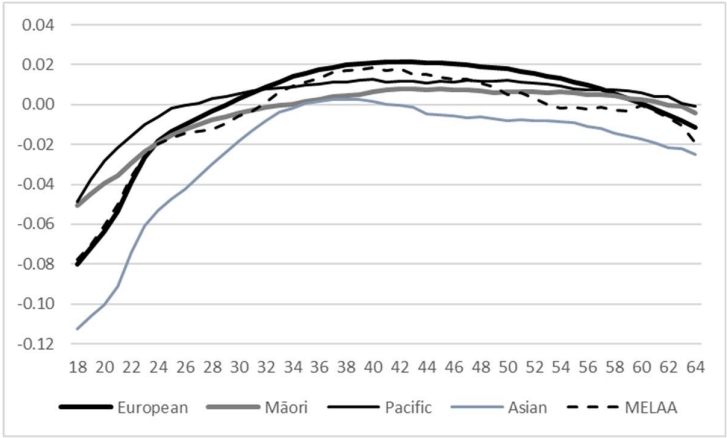
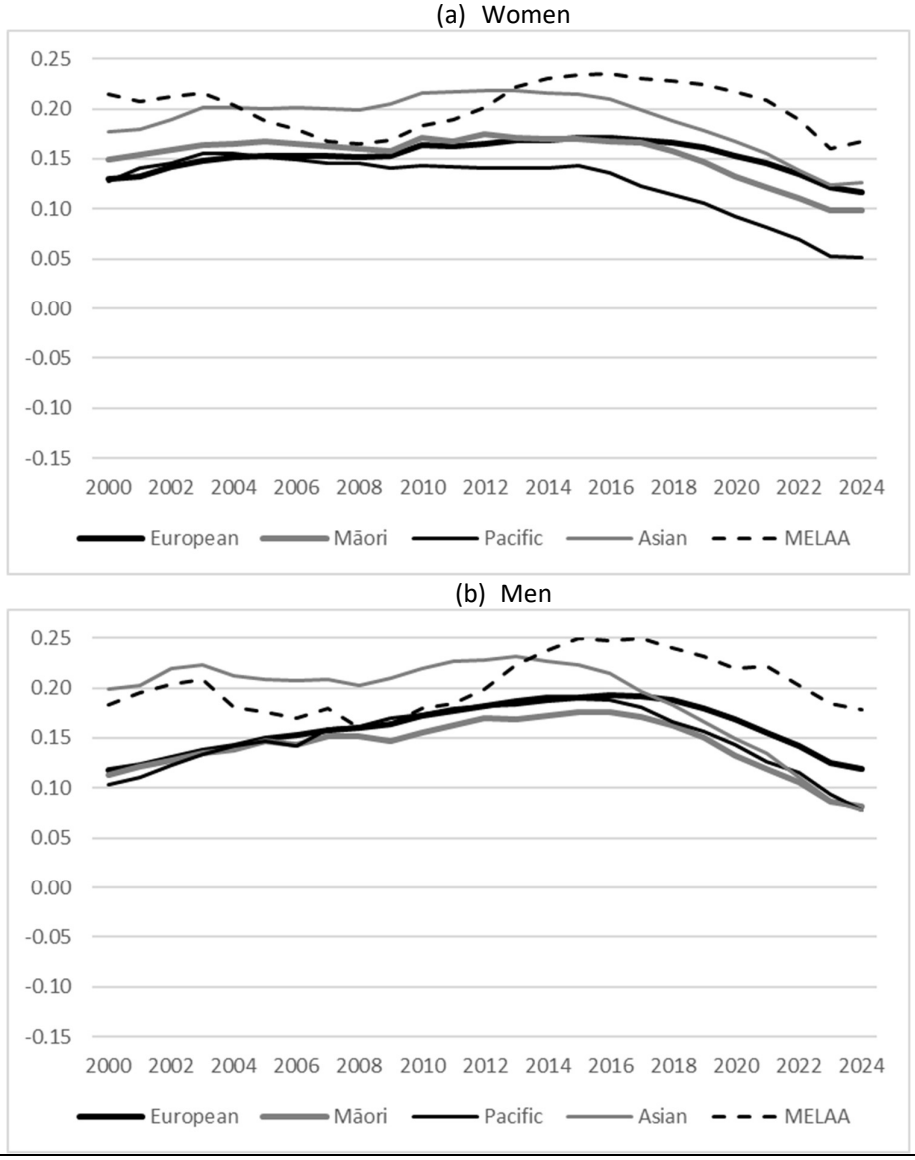


Figure 4: Sorting correlations by year: Corr(λ^{se}, ϕ^{s}) (by sex and ethnicity)



Note: Worker and firm fixed effects are based on specification [4b] in Table 1.

Appendix Table 1: Weighting of ethnicity responses

	Formula	Total Response	Response-weighted
Weight	$[\omega_i]$	$\omega_i = 1$	$\omega_i = \frac{1}{\sum_e I_i^e}$
Ethnicity measure	$[\tilde{I}_i^e = \omega_i * I_i^e]$	$\sum_e \tilde{I}_i^e \geq 1$	$\sum_e \tilde{I}_i^e = 1$
Weighted ethnicity count	$\left[N_e^\omega = \sum_i \omega_i * I_i^e\right]$	$\sum_e N_e^\omega \geq N$	$\sum_e N_e^\omega = N$
Weighted ethnicity share	$\left[\theta_e^\omega = \frac{N_e^w}{N}\right]$	$\sum_e \theta_e^\omega \geq 1$	$\sum_e \theta_e^\omega = 1$
Weighted sum of x (by ethnicity)	$\left[X_e^\omega = \sum_i \tilde{I}_i^e * x_i^e\right]$	$\sum_e X_e^\omega \geq \sum_i x_i$	$\sum_e X_e^\omega = \sum_i x_i$
Weighted mean of *x* (by ethnicity)	$\left[\bar{x}_e^\omega = \frac{X_e^\omega}{N_e^\omega}\right]$	Indeterminate relationship with $\bar{x}$	$\sum_e \lambda_e^\omega * \bar{x}_e^\omega = \frac{\sum_i x_i}{N} = \bar{x}$

Note: The notation ω for weights should not be confused with w (FTE-adjusted earnings). 'i' denotes individual; 'e' denotes ethnicity. I_i^e is an indicator that equals 1 if individual i identifies with ethnicity e, and 0 otherwise.

Appendix Table 2: FTE employment shares – by ethnicity and subgroup

	All	European	Māori	Pacific	Asian	MELAA
			Share of total FTE			
Total FTE	100%	70%	10%	6%	12%	1%
			Share of Group FTE (column percentage)			
By Location						
• Non-Metro	34%	38%	51%	13%	12%	20%
• Metro	66%	62%	49%	87%	88%	80%
By birthplace						
• Non-NZ-born	29%	19%	2%	59%	92%	87%
• NZ-born	71%	81%	98%	41%	8%	13%
By highest qualification						
• No qualifications	8%	8%	13%	14%	3%	3%
• School	30%	30%	36%	48%	18%	21%
• Post-school	29%	30%	32%	24%	20%	24%
• Graduate	20%	18%	13%	10%	38%	30%
• Post-graduate	14%	14%	6%	4%	21%	21%
By Industry (ANZSIC06)						
• Retail/Accomm/hospitality (G,H)	13%	12%	11%	11%	22%	17%
• Agric & Mining (A,B)	4%	4%	6%	3%	3%	3%
• Services n.e.c. (F,I,L,N,R,S)	20%	20%	20%	26%	18%	19%
• Manuf/const/utilities (C,D,E)	22%	21%	28%	31%	18%	20%
• Public Adm/educ/health (O,P,Q)	28%	29%	28%	22%	23%	26%
• Telco/fin/insur/profserv (J,K,M)	13%	14%	6%	6%	16%	15%

Note: Shares are based on ethnicity-response weighted FTE (section 4.1)

Appendix Table 3: Mean sex-specific firm pay premiums - subgroups of women

	Adj earn ($\widetilde{w}^s$)	Mean FFE ($\bar{\phi}^s$: specification [3])					
	All	All	Europ	Māori	Pacific	Asian	MELAA
Mean ϕ^s	0.000	0.000	-0.002	-0.008	0.017	0.011	0.012
By Location							
• Non-Metro	-0.090	-0.035	-0.036	0.005	0.016	-0.002	0.013
• Metro	0.046	0.018	0.018	0.015	0.021	0.017	0.020
By birthplace							
• Non-NZ-born	0.005	0.009	0.010	-0.010	-0.002	0.000	0.002
• NZ-born	-0.001	-0.004	-0.005	-0.004	0.034	0.042	0.021
By highest qualification							
• No qualifications	-0.222	-0.035	-0.040	0.009	0.030	-0.014	-0.002
• School	-0.103	-0.006	-0.008	0.001	0.027	-0.011	-0.002
• Post-school	-0.065	-0.008	-0.011	0.001	0.027	-0.003	-0.002
• Graduate	0.085	0.006	0.004	-0.019	0.008	0.012	0.010
• Post-graduate	0.260	0.030	0.027	-0.017	0.004	0.016	0.014
By Industry (ANZSIC06)							
• Retail/Accomm/hospitality (G,H)	-0.214	-0.094	-0.098	0.000	0.025	0.007	0.014
• Agric & Mining (A,B)	-0.182	-0.068	-0.075	0.009	0.029	0.028	0.041
• Services n.e.c. (F,I,L,N,R,S)	-0.040	-0.007	-0.009	-0.011	0.013	0.018	0.006
• Manuf/const/utilities (C,D,E)	-0.006	0.049	0.039	0.022	0.032	0.004	0.023
• Public Adm/educ/health (O,P,Q)	0.049	0.000	-0.001	-0.008	0.008	0.010	0.012
• Telco/fin/insur/profserv (J,K,M)	0.178	0.086	0.078	-0.004	0.042	0.035	0.028

Note: weighted by FTE and ethnicity-response-weighted (section 4.1).

Appendix Table 4: Mean sex-specific firm pay premiums - subgroups of men

	Adj earn ($\widetilde{w}^s$)	Mean FFE ($\bar{\phi}^s$: specification [3])					
	All	All	Europ	Māori	Pacific	Asian	MELAA
Mean ϕ^s	0.000	0.000	0.004	-0.004	0.003	-0.019	-0.001
By Location							
• Non-Metro	-0.071	-0.020	-0.020	-0.014	-0.020	-0.053	-0.020
• Metro	0.040	0.011	0.018	0.005	0.008	-0.014	0.004
By birthplace							
• Non-NZ-born	-0.014	0.001	0.020	-0.006	0.003	-0.021	-0.001
• NZ-born	0.008	0.000	0.000	-0.004	0.005	0.019	0.004
By highest qualification							
• No qualifications	-0.233	-0.020	-0.023	-0.010	-0.002	-0.079	-0.046
• School	-0.096	-0.009	-0.008	-0.004	0.002	-0.046	-0.021
• Post-school	-0.011	-0.006	-0.002	-0.003	0.009	-0.047	-0.022
• Graduate	0.125	0.018	0.030	-0.003	0.007	-0.007	0.024
• Post-graduate	0.302	0.032	0.034	-0.002	0.005	0.034	0.033
By Industry (ANZSIC06)							
• Retail/Accomm/hospitality (G,H)	-0.220	-0.122	-0.116	-0.113	-0.094	-0.147	-0.128
• Agric & Mining (A,B)	-0.127	-0.041	-0.037	-0.045	-0.085	-0.049	-0.010
• Services n.e.c. (F,I,L,N,R,S)	-0.046	-0.018	-0.014	-0.026	-0.024	-0.033	-0.029
• Manuf/const/utilities (C,D,E)	-0.014	0.027	0.024	0.033	0.044	0.025	0.038
• Public Adm/educ/health (O,P,Q)	0.078	-0.004	-0.001	-0.017	-0.005	-0.012	-0.014
• Telco/fin/insur/profserv (J,K,M)	0.298	0.102	0.101	0.074	0.094	0.114	0.119

Notes: weighted by FTE and ethnicity-response-weighted (See section 4.1).