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ABSTRACT

Ethnic Wage Differences in Aotearoa New Zealand

Ethnic wage gaps are a substantial and persistent issue in New Zealand. Understanding the drivers of such gaps is key to understanding the economic, social, and institutional factors that contribute to labour market inequality and to identifying measures to reduce gaps. Using household survey data from 2009 to 2023, this study implements a version of the Oaxaca-Blinder decomposition method to examine the sources of ethnic wage gaps in New Zealand. Our results confirm the pattern of disadvantage previously documented for non-European ethnic groups. Differences in demographic, educational, and job characteristics account for substantial portions of the wage gaps for Māori, Pacific, and European groups. After accounting for differences in mean characteristics, sizeable wage gaps remain, providing insight into the degree of ethnic labour market disadvantage that is due to unobservable characteristics or broader systemic factors.

JEL Classification: J15, J30, J71

Keywords: ethnicity, wages, decomposition, Aotearoa New Zealand

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1 Introduction

There are well-documented, substantial, and persistent ethnic wage gaps in New Zealand (Alexander et al., 2001; Cochrane & Pacheco, 2022; Iusitini et al., 2024; Maani, 2004; Treasury, 2018). Little progress has been made in reducing ethnic wage gaps over time, with recent estimates suggesting that Māori, Pacific, Asian, and MELAA workers earn between 10 and 19 percent less than European workers (Iusitini et al., 2024). Understanding the drivers of these wage gaps is a key step in understanding the economic, social, and institutional factors that contribute to labour market inequality, and in identifying and addressing inequity.

Wage gaps may result from differences in worker and job characteristics, from differences in how those characteristics are rewarded in the labour market, or from broader systemic factors that result in different pay on the basis of ethnicity, such as discrimination and racism. Systemic factors and inequities outside the labour market can also contribute to ethnic differences in characteristics (e.g. educational attainment) and to ethnic differences in the returns to those characteristics.

This study examines the relative importance of various sources of ethnic wage gaps in New Zealand. Using data from the New Zealand Household Labour Force Survey (Income) for the years 2009 to 2023, we implement a version of the commonly used Oaxaca-Blinder decomposition method to explore how differences in observable characteristics contribute to wage gaps in New Zealand. Ethnic groups differ in their educational levels, household characteristics, the places they live, and the jobs they work in, all of which help to account for group differences in average wages. However, after accounting for these factors, unexplained differences in wages remain, which we conclude must be due to factors uncorrelated with the observable characteristics we include in our analysis. Discrimination and racism likely play a role.

This study makes three contributions to the literature. First, we decompose wage gaps for 13 different ethnic groups, providing a more detailed and differentiated analysis of ethnic wage gaps than is available from existing studies that rely on high-level aggregations (European, Māori, Pacific, Asian, and MELAA). Given that each person can identify with more than one ethnicity, we define gaps by comparing wages for each ethnic group with wages of everyone who does not identify with that ethnic group (the "complement" group). Second, our version of the Oaxaca-Blinder decomposition method yields a measure of the wage gap that would remain even if both groups had the same average characteristics. This provides an indication of structural differences in wages caused by unobserved characteristics and systemic factors. Third, we incorporate a measure of firm-level pay premiums as a job characteristic – a factor that is unavailable in most wage gap decompositions, and which captures the uneven distribution of workers ("sorting") across lower- and higher-paying firms.

We estimate relatively large, positive wage gaps (higher wages) for the European ethnic groups and relatively large, negative wage gaps for Māori and Pacific groups. The wage gaps for most Asian groups are negative, albeit smaller in magnitude than the Pacific wage gaps. A relatively small negative wage gap is estimated for the MELAA group. Differences in characteristics explain a substantial portion of Māori and Pacific wage gaps and partially explain some of the European gaps. Sorting across lower- and higher-paying firms plays a relatively minor role in explaining wage gaps compared to demographic, educational, household, and job characteristics. Differences in returns to characteristics are also relevant sources of wage gaps. Our estimates indicate that even if all differences in observable characteristics were eliminated, sizeable wage gaps would remain due to differences in returns or pay differences independent of characteristics. This suggests that there are unobservable characteristics or broader systemic factors not captured by the variables in our model that are contributing to wage gaps in New Zealand.

The rest of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the data we use and presents a descriptive examination of ethnic wage disparities. Section 4 outlines our methodology. Section 5 presents the wage gap decomposition results. Section 6 concludes.

2 Literature review

Early studies of ethnic disparities in the New Zealand labour market focus mostly on employment and income (rather than wage) gaps between Māori and non-Māori. Historically, the labour market experience of Māori has been characterised by lower employment rates, higher unemployment rates, and lower average incomes compared with non-Māori (Maré, 1995). Such differences are still evident in more recent data.[1] A key question is how much of these disparities can be explained by differences in observable characteristics between Māori and non-Māori. It is well documented that the Māori population has observable characteristics associated with poorer labour market outcomes, including a younger age profile, lower rates of educational attainment, and a relatively high concentration living in areas with high rates of unemployment (Chapple & Rea, 1998; Chapple, 2000; Maré, 1995). Poorer labour market outcomes may also be attributable

[1] MBIE (2022): Annex three: Overview of Māori employment outcomes in Aotearoa New Zealand.

to differences in health status (Chapple, 2000), occupation (Chapple, 1999; Maré, 1995), and hours worked (Maani, 2004).

There is considerable variation in outcomes within as well as between ethnic groups (Dixon & Maré, 2005). Chapple (2000) shows that there is considerable overlap between the Māori and non-Māori earnings distributions, and that poor outcomes for Māori with low literacy, poor education, working in blue-collar occupations, and working in primary industries contribute to the between-group differences (Chapple, 1999, 2000).

Recent research has drawn attention to the significant pay gaps between NZ European and Māori, Pacific, and Asian workers (The Treasury, 2018; Cochrane & Pacheco, 2022; Iusitini et al., 2024). From a policy perspective, it is important to understand whether such pay gaps arise from characteristic or skill differences between ethnic groups (possibly due to discrimination outside the labour market), or whether there exist differential returns possibly arising from discrimination within the labour market (Alexander et al., 2001). Treasury (2018) employs the Oaxaca-Blinder decomposition method and finds that differences in characteristics account for 68-73% (depending on gender) of the Māori-European wage gap and 39-55% of the Pacific-European wage gap. Differences in educational level and occupation make the largest contributions to explaining these wage gaps. Cochrane and Pacheco (2022) apply the same method, incorporating an adjustment for selection bias arising from differential employment rates. They find that differences in characteristics explain about 70% of the pay gap for Māori, between 27-38% for Pacific, and –22% for Asian.[2] Like Treasury (2018), the authors show that differences in job-related characteristics are key contributors to wage gaps, particularly for Māori and Pacific males. Differences in region are also important. For example, Pacific peoples are heavily concentrated in Auckland, where wages are relatively high, which helps to reduce the Pacific-European wage gap.

Iusitini et al. (2024) report considerable variation in ethnic pay gaps across industries in New Zealand. For example, the Māori pay gap in 2022 ranged from 2% in Hospitality to 20% in Logistics. Compared with European workers, Māori and Pacific workers are underrepresented in high-pay occupations (Managers; Technicians and Trade workers) and underrepresented in high-pay industries (Professional Services; Media & Finance). Asian workers are overrepresented in high-pay industries (Professional Services; Media & Finance) but are also overrepresented in the low-pay industries (Hospitality; Retail). Decomposition analysis corroborates the results from previous studies - differences in characteristics explain a greater proportion of the pay gap for Māori than for Pacific workers, and a negative proportion for Asian workers.

[2] The negative explained proportion for Asian indicates that Asian workers have characteristics associated with relatively good labour market outcomes. If they had the same characteristics as European workers, the wage gap would be even bigger.

The wage gap literature shows that ethnic wage gaps in New Zealand cannot be fully explained by differences in observable characteristics. Part of the gaps remain unexplained, especially for Pacific workers, suggesting that there are significant differences in returns to characteristics in the labour market. Historically, differences in returns to characteristics have been attributed to labour market discrimination (Alexander et al., 2001). However, differential returns could be caused by differences in unmeasured characteristics, such as field of qualification, English language proficiency, or firm-specific skills and experience (Treasury, 2018). Other plausible causes include ethnic differences in preferences for non-pecuniary elements of jobs and unconscious bias (Cochrane & Pacheco, 2022). Although it is not possible to identify which of these causes are driving the unexplained gaps, the existence of unexplained gaps suggests that non-European ethnic groups may be receiving smaller labour market rewards for the same set of skills and characteristics.

A strand of the broader wage gap literature looks at the role of firms in explaining wage disparities between different demographic groups. Economics studies of gender differences have identified two firm-related channels that may generate gender wage disparities: a sorting channel whereby women sort into lower-paying firms, and a bargaining channel whereby women receive lower firm-specific premiums than men at the same firm (Card et al., 2016). Card et al. (2016) show that these sorting and bargaining channels explain about 20% of the gender wage gap in Portugal. Sin et al. (2022) similarly demonstrate the relevance of such channels in explaining gender wage gaps in New Zealand. They show that sorting across firms explains 5% to 9% of the gender wage gap. The remaining within-firm gap is attributed to women being less willing to bargain or less successful at bargaining to capture firm-specific rents. They conclude that taste discrimination is likely an important factor in explaining why gender wage gaps persist.

A few recent studies have examined the role of sorting across firms in explaining ethnic wage gaps. Gerard et al. (2021) measure the effects of firm policies on ethnic pay differences in Brazil and find that non-Whites tend to be employed disproportionately in lower-premium firms compared to White workers of similar skill levels. In a similar vein, Phan et al. (2022) find that firm-specific wage effects account for a significant portion of the wage gaps between white and ethnic-minority workers in Britain, both at the mean and along other points of the wage distribution. Accounting for firm-specific wage effects reduces the contributions to the wage gaps made by other personal and job-related characteristics, suggesting that previous studies that do not account for the influence of firm-specific wage effects are prone to bias. Carrington and Troske (1998) decompose the black and white wage gap in the U.S. manufacturing industry and find that the gap is primarily a within-firm phenomenon, rather than a result of black and white workers sorting into low- and high-paying firms. Forth et al. (2023) present a similar argument. They observe considerable segregation of white and non-white employees across workplaces in Britain but show that such inter-workplace segregation does not contribute to aggregate wage penalties for ethnic minorities. Instead, the wage penalties are mostly explained by within-firm differences in wage setting.

3 Data

Data Source

The main data source for this study is the Household Labour Force Survey (HLFS). Designed to produce a range of official statistics on employment, the HLFS collects quarterly employment data for a representative sample of around 15,000 households (representing roughly 30,000 individuals). The survey also collects data on a wide range of individual, household, and job-related characteristics relevant to employment decisions and labour market outcomes. Detailed income, earnings, and hours worked data are collected in the Income Survey in the June quarter of each year.[3] We use income data from the June 2009 to June 2023 quarters and link them with the demographic data provided in the HLFS. We pool the data over the 15 years and deflate our wage measure to 2023 NZ dollars. All analyses are weighted using survey sample weights.

Measures of firm-specific wage premiums ("firm effects") are derived from administrative data on monthly earnings of employees (Fabling & Maré, 2015). The firm effects are estimated from a two-way fixed effect specification (Abowd et al., 2002; Kline, 2024; Maré & Hyslop, 2006). There is an imperfect match between jobs that are reported in the HLFS and corresponding jobs in the administrative data. Data from the HLFS are linked to monthly job records for each individual in the month of interview where available, or to the prior, or subsequent month. Where employees have multiple jobs in a month, the average firm effect is used.

Sample restrictions

We restrict our sample to the working population aged 16 to 64. We identify a worker as an individual who is employed, works a positive number of hours, and earns a positive amount of income. We focus on the earnings of wage and salary employees, excluding self-employed and family workers whose earnings are less directly determined in the labour market. We trim the top

[3] The Income Survey has existed in various forms as the Income Supplement to the HLFS and is currently referred to as HLFS (Income).

and bottom 1 percent of hourly wages to remove the influence of measurement error and outliers on our estimates. This gives us an initial sample size of 207,500 workers.

We include imputed and proxy observations within our sample. Imputed observations are those in which missing values have been replaced with the values of a respondent with similar characteristics. Proxy observations are those in which responses to survey questions were provided by another household member on behalf of the individual.

When merging our sample with the data containing firm premium measures, we successfully match 188,565 workers and fail to match 18,935 workers. Our descriptive and regression analyses use the restricted sample of 188,565 workers. Demographic, educational, and household characteristics of the full sample of 207,500 workers are almost identical to those of the restricted sample, with some small differences in employment status.

Ethnicity groups

Ethnicity is self-reported in the HLFS and coded to a detailed (6-digit) level. Most studies of ethnic wage gaps in New Zealand focus on 1-digit level ethnicities (European; Māori; Pacific; and Asian) excluding MELAA and other ethnic groups due to small sample sizes (Cochrane & Pacheco, 2022; Iusitini et al., 2024; Treasury, 2018). An advantage of pooling the Income Survey data across years is that it gives us the statistical power to analyse wage gaps for more narrowly defined ethnic groups. As detailed in Table 1, we disaggregate the 1 digit-level European, Māori, Pacific, Asian, and MELAA ethnicities into 13 distinct ethnic groups.[4] This allows us to see if the labour market experiences differ for ethnicities which are usually grouped together, such as NZ European and Other European.

Respondents in the HLFS can identify with more than one ethnicity. Unlike previous studies that use prioritised ethnicity to create mutually exclusive ethnic groups, we use total response ethnicity. For each of the 13 ethnic groups in Table 1, we divide the sample into two disjoint groups – workers who list that ethnic group as one of their ethnicities, and a "complement" group who do not. An individual can thus be included in more than one ethnic group. Since our ethnic groups are not mutually exclusive, we cannot directly compare each ethnicity with a common comparison group. For example, we cannot compare the mean wage of each ethnicity directly with the mean wage of NZ Europeans. We therefore compare the mean wage of each ethnic group with that of the complement group. For example, we compare NZ Europeans with non-NZ Europeans, Māori with non-Māori, Samoan with non-Samoan, and so on.

[4] To create the groups, we begin with the 3-digit ethnicities and combine small 3-digit ethnicities into 2-digit groups, with remaining small 2-digit groups combined into 1-digit groups.

Key variables

Appendix Table 1 provides the definitions of the variables used in our analysis. Our outcome of interest, wages, is measured as actual total hourly earnings from main job, before tax and deflated to 2023 dollars using the Consumer Price Index. Total hourly earnings include regular earnings plus extra income, such as from allowances, bonuses, and commissions. Main job is defined as the job the individual worked the most hours in. Throughout the rest of this paper, we refer to total hourly earnings as wages.

We use the natural log of wages as the dependent variable in our regressions. In our regressions, we control for the influence of household resources on an individual's wage. An issue with using the standard measure of household income as an explanatory variable is that it is highly correlated with an individual's wage and can lead to reverse causality. To avoid this endogeneity, we construct a measure of household income that removes the influence of an individual's own income. Specifically, for each individual, we sum up the income of the other members in the individual's household. We then equivalise the values (based on total household size) and classify them by decile. Our household income decile variable therefore acts as a proxy for household resources without being inherently linked to our dependent variable.

To capture the impact of firm-specific wage premiums on wages, we include a firm premium variable that is normalised to have a mean of zero across all jobs and is approximately equal to the proportional difference of the premium paid by each firm from the overall average.

3.1 Descriptive statistics

In this section, we explore ethnic differences in observable characteristics relevant to labour market outcomes. Table 2 provides descriptive profiles of our 13 ethnic groups of interest, alongside a comparison profile that combines all ethnicities. After implementing the sample restrictions discussed above, we find that 64% of our sample of workers identify as NZ European and 13% identify as Māori. The remaining ethnic group sizes are around 1 to 5% of the sample, with Tongan being the smallest group that we examine. Owing to multiple responses, the sum of shares exceeds 100%.

The European and Asian groups have similar proportions of multiple-ethnicity workers to the average, whilst Māori and the Pacific workers are between two to five times more likely to report having multiple ethnicities. Mixed-ethnicity individuals have been shown to have labour market outcomes different from those of sole-ethnicity individuals in New Zealand (Chapple, 1999; Dixon & Maré, 2005), highlighting the importance of controlling for multiple ethnicity status within our decomposition analysis.

Thirty percent of our sample are migrants. A relatively small proportion of NZ European and Māori are migrants. Amongst the remaining European groups and Asian groups, a large majority are migrants. For the Pacific groups, the proportion of migrants varies from 28% for Cook Islands Māori to 60% for Tongan.

The education profiles of NZ European and MELAA groups are similar to the profile for all ethnicities. The Pacific groups are substantially more likely to have no qualification and less likely to have a degree. For example, the proportion of Tongan with no qualification is double the proportion for all ethnicities, and the proportion with a degree is half of that for all ethnicities. Conversely, the Asian groups are substantially less likely to have no qualification and substantially more likely to have a degree. Māori follow a similar pattern to the Pacific groups, whereas British and Irish and Other European follow a similar pattern to the Asian groups.

The Pacific and Asian groups are more likely to be in the Auckland urban area. For example, 73% of Tongan workers live in Auckland, compared with 32% for all ethnicities. The remaining ethnic groups are less concentrated in Auckland.

In terms of household characteristics, the Pacific ethnicities are more likely to have dependent children and live in larger households. Average household income decile is lower than average for Chinese and Tongan and higher than average for British and Irish and Filipino.

There are relatively similar rates of workers within the primary sector across the different ethnic groups. Māori and Pacific workers are more likely to work in the secondary sector whilst Indian, Chinese, Other Asian and British and Irish are more likely to work in the services sector. In regard to occupations, Māori and Pacific workers are less likely to be in higher-paying occupations (managers; professionals) and more likely to be in lower-paying occupations (sales workers; machinery operators and drivers; labourers). The converse is true for British and Irish and Other European workers.

There is limited variation across ethnic groups in the average firm effects of the firms in which they are employed. The average across all ethnicities is –0.01, indicating that the sample we are using is employed in firms that pay slightly below the average (–1%) across all firms. Māori and Other Asian workers are in slightly lower-paying firms (–2% and –3% respectively), whereas British and Irish workers are in firms that pay 2% above average.

3.2 Ethnic wage variation

The focus of this paper is on ethnic wage gaps and how such gaps can be explained by differences in observable characteristics. Table 3 first summarises the employment rates and wages for each ethnicity, and how each ethnic group’s wage compares with the wage of their complement group (“wage gap”). Employment rates vary substantially by ethnicity. Tongan, Cook Islands Māori, and Chinese have relatively low employment rates, approximately 15pp below the rate of 70% for all ethnicities. Filipino, British and Irish, Indian, Other European, and NZ European have higher-than-average employment rates. There is also substantial variation in hourly wage rates, with the lowest rate of $28.83 for Cook Islands Māori being roughly $10 less than the highest rate of $39.18 for British and Irish.

When comparing the wage rate of each ethnicity with the wage rate of their complement group, three patterns emerge. First, there are relatively large, positive wage gaps for British and Irish and Other Europeans (11 to 13%), and a modest positive wage gap of 5.9% for NZ Europeans. Second, in stark contrast to the European wage gaps, there are relatively large, *negative* wage gaps for Māori and the four Pacific groups (ranging from –11 to –15%). The third pattern involves the moderately negative wage gaps for the Other Asian, Filipino, and Indian groups. The only non-European wage gap that isn't negative is the Chinese wage gap, which is relatively small and positive.

To visualise these ethnic wage disparities, Figure 1 presents kernel density estimates (spread over three panels) of each ethnicity's wage distribution. For comparison, each panel shows the distribution for all ethnicities combined, labelled All ethnicities. On the X axis is log hourly wages in 2023 dollars. The labels have been converted from log to dollar values to aid interpretation.

Panel A presents the wage distributions for the European groups and MELAA. The curves for the NZ European and MELAA distributions closely follow the curve for the All ethnicities distribution, with wages clustering at around $20 to $26 per hour. The British and Irish and Other European curves are flatter, with a higher proportion of workers earning relatively high wages. It is clear from Figure 1 that the average differences between groups are small relative to the extent of variation within each group. This is also evident in Table 3, which shows that the size of wage gaps between groups (–$6 to +$5) is considerably smaller than the within-group standard deviation of real wages ($11 to $18).

Panel B presents the wage distributions for the Māori and Pacific groups, which are all similar in shape and peak density. Although the distributions have similar modal wages to the All ethnicities distribution, the wages of Māori and Pacific workers are less dispersed and more clustered around the modal point. Moreover, there is a relatively low proportion of Māori and Pacific workers earning above $33 per hour, indicating that the Māori, Samoan, Cook Islands Māori, Tongan, and Other Pacific groups are less represented in the upper end of the wage distribution (and therefore over-represented at lower or mid-level wages) compared to the All ethnicities group.

Panel C presents the wage distributions for the Asian groups. The curve for Chinese employees is similar to All ethnicities curve, whereas the other curves are somewhat less dispersed and are concentrated more at the lower end of the wage distribution compared to the All ethnicities comparison group.

Overall, we find significant inequalities in wages across ethnicities. In line with previous literature, we observe that the European groups earn relatively higher wages while the Māori, Pacific, and Asian groups earn relatively lower wages. Furthermore, kernel density estimates reveal that wages are less dispersed and concentrated more in the lower end of the distribution for the Māori and Pacific groups, and also most Asian groups. For all ethnic groups, within-group wage variation is considerably larger than the mean differences between groups. We now turn to understanding the drivers of the mean ethnic wage differences through the lens of decomposition analysis.

4 Method

4.1 Oaxaca-Blinder decomposition

We employ a variation of the decomposition method introduced by Oaxaca (1973) and Blinder (1973) to decompose the wage gap between different ethnicities. This approach divides wage gaps into a component (statistically) accounted for by differences in worker and job characteristics, a component that captures the wage difference if all workers had average characteristics, and a component that is due to how differences in returns to characteristics interact with differences in mean characteristics.[5]

We begin by de-meaning our explanatory variables by subtracting from each data point the overall sample mean, as follows:

$$\tilde{X}_i = X_i - \bar{X}$$

where *i* indexes individuals and X_i is a vector of explanatory variables.

Consider two ethnicity groups, where group A is the ethnicity group of interest (e.g. Māori) and group B is the complement group (e.g. non-Māori). The wage gap that we decompose is the difference in mean log wages $\left(\overline{\ln(w^A)} - \overline{\ln(w^B)}\right)$. We estimate (log) wage regressions separately for group A and group B.

$$\ln(w_i^A) = \alpha^A + \beta^A \tilde{X}_i^A + \varepsilon_i^A \quad (1)$$

$$\ln(w_i^B) = \alpha^B + \beta^B \tilde{X}_i^B + \varepsilon_i^B \quad (2)$$

[5] A graphical illustration of the decomposition method is included as Appendix A: Graphical depiction of decomposition

The A and B superscripts denote the ethnicity groups. $\tilde{X}_i$ is the vector of de-meaned explanatory variables. β's are vectors of coefficients to be estimated, and α's are intercept terms. Since the explanatory variables have been de-meaned, the intercept term represents the expected wage for an individual with mean characteristics (where $(X_i - \bar{X}) = 0$). The same β coefficients would be estimated if equations (1) and (2) were estimated with non-de-meaned variables.

Given the linear wage models above, the mean wage gap can be expressed as the difference in the linear predictions of the two models at the group-specific means of the explanatory variables.

$$\overline{\ln(w^A)} - \overline{\ln(w^B)} = (\hat{\alpha}^A + \hat{\beta}^A \bar{\tilde{X}}^A) - (\hat{\alpha}^B + \hat{\beta}^B \bar{\tilde{X}}^B) \tag{3}$$

In our results section, we decompose both positive and negative wage gaps. We define a positive contribution to the wage gap as a contribution that raises group A's mean wage relative to group B's mean wage. A positive contribution therefore increases the size of positive gaps and decreases the size of negative gaps. Conversely, a negative contribution to the wage gap is a contribution that lowers group A's wage relative to group B's wage. A negative contribution therefore decreases the size of positive gaps and increases the size of negative gaps.

To identify the contribution of differences in observable characteristics and differences in returns to characteristics to the wage gap, equation (3) can be rearranged as:

$$\overline{\ln(w^A)} - \overline{\ln(w^B)} = \underbrace{(\bar{\tilde{X}}^A - \bar{\tilde{X}}^B)\hat{\beta}^*}_{\substack{Composition \\ effect}} + \underbrace{(\hat{\beta}^A - \hat{\beta}^*)\bar{\tilde{X}}^A + (\hat{\beta}^* - \hat{\beta}^B)\bar{\tilde{X}}^B}_{Interaction\,effect} + \underbrace{(\hat{\alpha}^A - \hat{\alpha}^B)}_{\substack{Returns \\ effect}} \tag{4}$$

Equation (4) splits the wage gap into three components: the composition effect, returns effect, and the interaction effect.

The composition effect is the part of the wage gap that is attributable to differences in mean (observable) characteristics between the two groups. Differences in mean characteristics are evaluated using a set of non-discriminatory benchmark returns to characteristics, denoted β^*. Therefore, the composition effect shows how differences in observable characteristics affect the wage gap if both groups received the same benchmark returns to characteristics. A well-documented concern with implementing Oaxaca-Blinder decompositions is that the choice of β^* can lead to significant variation in the decomposition results. A common approach is to set β^* as group B's regression coefficients, with group B being the comparison or dominant group. This assumes that group B's wage structure is unaffected by discrimination and would prevail in the labour market in the absence of discrimination (Treasury, 2018).[6] In the context of ethnic wage gaps, there is no reason to assume that the wage structure of one ethnic group is non-discriminating and would prevail over the other. It is possible that while the wage structure of the minority ethnic group may be subject to negative discrimination, the majority group may be subject to positive discrimination. Thus, if there were no discrimination in the labour market, the counterfactual wage structure would be a combination of the wage structures of the two groups. We follow the approach of Neumark (1988) and use the coefficients from a pooled regression of both group A and group B for β^*. This approach relies on the more relaxed assumption that the non-discriminatory wage structure is some weighted average of group A's and group B's coefficients. Interpreting the composition effect is relatively straightforward. A positive composition effect indicates that group A has more of the characteristics that are generally rewarded in the labour market and/or less of the characteristics that are generally penalised, compared to group B. For conciseness and ease of interpretation, we will refer to a positive composition effect as the group having favourable characteristics and a negative composition effect as the group having unfavourable characteristics.[7]

The returns effect is the difference in predicted wages for the two groups, evaluated where both groups have characteristics that match the overall sample averages. This difference in predicted wages is driven by differences in the group-specific returns to (the same) characteristics, plus any wage difference due to factors independent of the measured characteristics. It is measured as the difference in intercepts of equations (1) and (2).[8]

The interaction effect captures the interaction between differences in returns and how each group's characteristics deviate from the sample mean characteristics. When group-specific returns differ, the effect of group differences in characteristics may be larger or smaller than what is captured by the composition effect, which evaluates the contribution of group differences using pooled returns. The interaction of differences in group-specific returns with group differences can therefore either reinforce or offset the effect of having below or above mean characteristics (i.e. the composition effect). The first term in the 'interaction effect' expression in equation (4) captures the interaction between group A having returns different from the pooled returns $\left(\hat{\beta}^A - \hat{\beta}^*\right)$ and group A's deviation from sample mean characteristics $(\bar{\bar{X}}^A)$. The second term

[6] In the gender wage gap literature, it is common for the men's wage structure to be used for β^*, which assumes that wage discrimination is directed only against women and not towards men.

[7] Note we are not suggesting that the favourable characteristics are intrinsically better or more desirable than others, only that they lead to higher wages relative to the unfavourable characteristics.

[8] The intercept in a wage equation with mean-deviated covariates is the expected wage at mean values of covariates. It thus captures both intercept and slope (return) effects.

captures the interaction between group B having returns different from the pooled returns $\left(\hat{\beta}^{*} - \hat{\beta}^{B}\right)$ and group B's deviation from the mean ($\bar{\bar{X}}^{B}$).

To illustrate, consider the case where group A has below-average education ($\bar{X}^{A} < \bar{X}$). Since education is positively rewarded in the labour market ($\hat{\beta}^{*} > 0$), having below-average education lowers group A's expected wage. This is picked up by the composition effect as a negative contribution to the wage gap. Assume also that group A has a relatively higher return to education ($\hat{\beta}^{A} > \hat{\beta}^{*}$). This means group A's expected wage is lower than what is implied by the pooled return. In other words, the higher return amplifies the penalty (or opportunity cost) of having below-average education. This is picked up by the interaction effect as a negative contribution to the wage gap, which reinforces the negative composition effect.

If, instead, group A has a relatively lower return to education ($\hat{\beta}^{A} < \hat{\beta}^{*}$), since group A does not have much education, their lower return means that their expected wage is higher than what is implied by the pooled return. The reduced penalty of below-average education due to having a lower return shows up as a positive contribution to the wage gap, which offsets the negative composition effect.

The two interaction terms reflect the fact that interactions for each group contribute to the overall wage difference. A positive combined interaction effect indicates that the pattern of interactions across the two groups contributes to higher relative wages for group A. Conversely, a negative interaction effect indicates that the pattern of interactions contributes to lower relative wages for group A.

In summary, group A's expected wage is higher when they have relatively higher returns to characteristics they have high levels of, or relatively lower returns to characteristics they have low levels of. Differences in returns can therefore either reinforce or offset the composition effect of differences in mean characteristics. This means that the total effect of differences in characteristics on the wage gap is the sum of the composition effect and the interaction effect.

A useful feature of the Oaxaca-Blinder decomposition method is that the composition and interaction effects can be further decomposed to show the contributions of specific variables to the wage gap. For example, we can show how differences in mean age contribute to the gap, or how differences in returns to education (evaluated at mean deviations) contribute to the gap. Rather than showing the contribution of each variable individually, we group variables into the following domains: demographic (individual) characteristics, migrant status, educational attainment, urban area, household characteristics, industry, job-related characteristics, and firm premium. See Appendix Table 2 for the list of variables that fall under each domain. In our results section we show how these domains contribute to the wage gap through the composition and interaction effects.

4.2 Adjusting for selection bias

Wages are observed only for people who are employed and employed workers are more likely to have characteristics associated with higher wages. Individuals with relatively low education or skills may be less likely to be employed due to their inability to secure acceptably well-paid jobs. This means the wages are observed disproportionately for higher paid workers, so the average wage is overestimated. Furthermore, if the factors that affect an individual's likelihood of working are correlated with the factors that affect wages, the coefficients from a wage equation estimated via OLS will be biased.

To correct our results for selection bias, we apply the Heckman correction technique (Heckman, 1979). This involves estimating a (probit) selection equation that models the factors that influence employment (i.e. the factors that influence selection into our sample of observed wages). The selection equations for groups A and B are given by:

$$worker_i^A = \gamma^A Z_i^A + u_i^A \tag{4}$$
$$worker_i^B = \gamma^B Z_i^B + u_i^B \tag{5}$$

where $worker_i$ is a dummy variable that equals 1 for workers (employed) and 0 for non-workers (unemployed, not in the labour force).[9] Z is a vector of explanatory variables (including an intercept term), u_i is the error term, and γ is the vector of parameters to be estimated.

We use a Maximum Likelihood approach to jointly estimate the selection equations (4) and (5) and the wage equations (1) and (2), allowing for a correlation (ρ) between the error terms (u_i and ε_i). If ρ is statistically significantly different from zero, selection bias is present, and the Maximum Likelihood estimation automatically corrects the regression coefficients and predicted mean wages for such bias. Our wage gap decomposition is conducted on selection-adjusted wages, which are the expected wages if everyone in the full HLFS sample (i.e. workers and non-workers) participated in the labour force.

Ideally, we would include a variable that affects selection into employment but does not directly affect wages. Including such a variable in the model would strengthen identification, reduce multicollinearity, and provide a more reliable estimate of ρ. However, we are unable to

[9] We drop self-employed and family workers completely from the sample, so they do not appear in either of the worker or non-worker groups.

identify any valid exclusion restrictions. All explanatory variables in X of the wage equations appear in Z of the selection equations. We find that variables that may have theoretical justifications for influencing employment but not wages, such as having dependent children or being a sole parent, have a statistically significant impact on wages and therefore cannot validly be excluded from the wage equations. The lack of an exclusion restriction means our model identification is relatively weak because it relies solely on distributional assumptions. Identification is achieved because the variables enter non-linearly into the probit equation but linearly into the wage equation. This reliance on distributional assumptions for model identification is problematic but preferable to omitting relevant variables from the wage equations.

5 Results

5.1 Decomposition of wage gaps

Table 4 summarises our Oaxaca-Blinder decomposition results.[10] The first ("wage gap") section of the table presents the raw and selection-adjusted wage difference between the given ethnicity and their complement group. As highlighted in section 3.1, there are relatively large positive wage gaps for the European ethnicities, large negative wage gaps for Māori and the Pacific ethnicities, and moderately negative gaps for Indian, Filipino, and Other Asian.

The adjusted wage differences show that adjusting for selection typically causes the wage gap estimate to increase in absolute value (i.e. the gap gets wider).[11] For example, the NZ European wage gap widens from 5.9% to 9.9% while the Māori wage gap widens from –11% to –16%. This suggests that unadjusted wage gaps may understate the true severity of ethnic wage disparities, especially for Māori, Cook Islands Māori, Tongan, and Other Asian. Adjusting for selection has a different effect on the Indian, Filipino, and Chinese wage gaps. For the Indian wage gap, selection adjustment narrows the gap from –4.2% to –0.6%. For the Filipino and Chinese gaps, the signs are reversed: the Filipino wage gap goes from negative to positive (although statistically insignificant) and the Chinese wage gap goes from positive to negative. Overall, these results highlight that adjusting for selection is not a trivial exercise. Selection adjustment does not affect

[10] Appendix Table 3 presents our estimates of the pooled returns.

[11] Using the Heckman selection adjustment method outlined in section 4.2, we estimate a positive correlation between the error terms of the wage equation and the selection equation. This means that we estimate a positive selection into employment, where higher-earnings-potential individuals select into the labour market. Thus, we expect the mean wage to decrease for each ethnicity when adjusting for labour market selection. Ethnic wage gaps will change when adjusting for selection if the mean wage decrease for a given ethnicity differs from the mean wage decrease of their complement group.

all wage gap estimates in the same way, and for some ethnicities the adjusted wage gap suggests that the advantage or disadvantage experienced in the labour market is greater than what is suggested by the raw gap.

The second section of Table 4 presents the estimated composition, interaction, and returns effects. The remaining section presents the variable domain contributions that make up the composition and interaction effects.

Beginning with the largest group (NZ European), the positive composition effect indicates that NZ Europeans have favourable characteristics overall. This effect is driven largely by a positive migrant contribution, which reflects that NZ European are less likely to be migrants, a characteristic with a negative pooled return (Appendix Table 3). This positive migrant contribution to the composition effect, however, is offset by a negative migrant contribution to the interaction effect. Since NZ European have a positive migrant return, the pooled return overstates their expected wage at their below-average migrant level, which the interaction effect adjusts for. Since the interaction effect dominates the composition effect, we would expect NZ European to earn slightly less than non-NZ European given the differences in characteristics. However, there is a relatively large, positive returns effect, indicating that a significant amount of the wage premium NZ Europeans experience would remain even if differences in characteristics were eliminated.

Like the NZ European group, the British and Irish and Other European groups each have a positive composition effect. However, these effects are due to favourable education, job, and demographic characteristics, rather than favourable migrant characteristics. This reflects that, compared to their respective complement groups, British and Irish and Other European have higher education levels, are more likely to work in high-paying occupations, and are older (Table 2). Furthermore, while NZ Europeans have a small, negative firm premium contribution, British and Irish and Other European have a moderately-sized positive firm premium contribution. This suggests that part of the reason British and Irish and Other European earn more is because they are disproportionately employed in higher-paying firms. In contrast to the NZ European group, the British and Irish and Other European groups have positive interaction effects, which are driven by relatively large migrant contributions. Hence, the interaction effects reinforce the positive composition effects for these two groups . Lastly, the returns effects for both groups are relatively small compared to the composition and interaction effects, indicating that the British and Irish and Other European wage gaps are mainly driven by differences in characteristics (and how such differences interact with group-specific returns).

The Māori, Samoan, Tongan, Cook Islands Māori, and Other Pacific wage gap patterns are in stark contrast to the European wage gap patterns. First, the Māori and Pacific groups have relatively large negative composition effects, indicating unfavourable characteristics. The largest contribution under the composition effect is education, reflecting that Māori and Pacific have significantly lower education levels on average compared with their complement groups. The other significant contributions are from the job, demographic, and household domains, which likely reflect that these ethnic groups are more likely to work in low-paying occupations, are younger, and live in bigger households, all of which are associated with lower wages. The firm premium contribution is negative for Māori, but positive for the Pacific groups. The latter is possibly due to the Pacific groups being more likely to live in Auckland, benefiting from the urban wage premium. However, the magnitudes of these firm premium contributions are dwarfed by the contributions from the other domains. The negative composition effects for the Māori and Pacific groups are partially offset by positive interaction effects (except for Tongan), particularly for Other Pacific and Cook Islands Māori. Looking at the domain contributions, it appears that group-specific returns to demographic characteristics alleviate the penalty from having unfavourable demographic characteristics, as do job characteristics for the Pacific groups. Despite this, the returns effects show that large wage differences would remain even if differences in characteristics were eliminated. Therefore, the negative wage gaps for the Māori and Pacific groups are being driven by both differences in characteristics and differences in returns.

The Asian wage gap patterns are more complex. The Indian, Chinese, and Filipino groups have positive composition effects, while Other Asian have a negative composition effect. For all four groups, education provides the biggest positive contribution, likely driven by such groups being significantly more likely to have a degree. The biggest negative contribution comes from the migrant domain since a very large majority of the individuals in these groups are migrants. For the Other Asian group, there is a moderately sized negative firm premium contribution, suggesting that working for lower-paying firms plays a role in explaining the group's wage gap. There is a positive interaction effect for Indian, Filipino, and Other Asian, driven by positive contributions from the migrant and demographic domains. Thus, the penalty for being a migrant is reduced by offsetting group-specific returns (lower penalties) for these three groups. In contrast, the migrant contribution is negative for Chinese because they face a greater penalty than is captured by the pooled return. Finally, the returns effect is negative for all four groups, and bigger in magnitude than the composition and interaction effects combined.

The pattern of wage decomposition for the MELAA group differs from that of other groups. The composition and interaction effects are effectively zero, with the returns effect being the only statistically significant component of the wage gap. The domain contributions to the composition effect suggest that MELAA have favourable demographic and education characteristics, but these are offset by unfavourable migrant and job characteristics. The domain contributions to the interaction effect are mostly statistically insignificant. This suggests that reducing differences in characteristics may have no effect on the wage gap, and that differences in returns is the key driver behind the gap.[12]

To summarise, NZ Europeans experience a positive wage gap that would remain in the absence of differences in characteristics. The British and Irish and Other European groups experience positive wage gaps because of favourable characteristics and reinforcing returns. Conversely, the Māori and Pacific groups experience negative wage gaps because of unfavourable characteristics and large negative returns effects. Some Asian groups have favourable characteristics, but the relatively large returns effects suggest that the wage gaps are predominantly driven by factors that would remain even if differences in characteristics were eliminated.

5.2 Decomposition of wage gaps by sex

We repeat our decomposition analysis for males and females separately to see if the patterns observed in the previous section change when stratifying by sex. Appendix Table 4 shows that the patterns are broadly similar when looking across ethnicities. For both the male and female subgroups, the NZ European and MELAA wage gaps stem mainly from returns effects. For the Other European group, the wage gap comprises positive composition and interaction effects, with minimal influence from the returns effect. Among the Māori and Pacific groups, negative composition and returns effects account for most of the wage gaps for both men and women. For the Asian groups, there is variation with the composition and interaction effects but a consistently negative returns effect across sexes.

For the European, Māori, Pacific and MELAA groups, the decomposition patterns across sexes are very similar. The composition, interaction, and returns effects tend to have the same sign, varying only in magnitude. One anomaly is the female British and Irish wage gap, which has a substantially large returns effect compared to the equivalent for the male British and Irish gap. The domain contributions patterns (under the composition effect) are also largely the same across sexes. The only noticeable difference is that the household domain appears to play a bigger role in explaining the wage gap for females.

For the Asian groups, the decompositions are not similar across sexes. For example, the composition and interaction effects are statistically insignificant for the male Indian and male

[12] The lack of a statistically significant composition and returns effect does not appear to be due to a lack of statistical power. Pooling the income survey data from 2009 to 2023 gives us a sample count of 5,472 for MELAA, which is double the size of our smallest ethnic group (Tongan, with 2,295).

Other Asian wage gaps, but statistically significant for the female equivalent gaps. Despite these differences, the domain contribution patterns appear similar across sexes. For example, the education domain is positive and the migrant domain is negative for males and females across the four Asian groups. Thus, the differing composition and interaction effects may be the result of differing domain contribution magnitudes, rather than underlying structural differences between the males and females of these ethnic groups.

Overall, we conclude that the decomposition patterns stratified by sex are broadly similar to the decomposition patterns for all sexes and do not offer substantially different insights into ethnic wage differences in New Zealand.

6 Conclusion

This study investigates the drivers of ethnic wage gaps in New Zealand. It extends the existing literature by analysing wage gaps for a larger number of ethnic groups and incorporating a measure of firm pay premiums to detect the effects of worker sorting across firms. Employing a variant of the Oaxaca-Blinder decomposition method and adjusting our results for sample selection bias, we decompose wage gaps into three components: differences in observable characteristics (composition effect), the interaction of differences in returns with differences in characteristics (interaction effect), and the predicted difference in wages if groups had mean characteristics (returns effect).

Our results confirm the pattern of wage advantage for European ethnic groups, and wage disadvantage previously documented for non-European ethnic groups. We estimate positive wage gaps (higher wages) for the NZ European, British and Irish, and Other European groups, and sizeable negative wage gaps for the Māori, Samoan, Cook Islands Māori, Tongan, and Other Pacific groups. Negative wage gaps are also estimated for the Chinese, Other Asian, and MELAA groups.

There is an ethnic pattern to the contributions to wage gaps from differences in observable characteristics. Composition effects are strongly positive for the British and Irish and Other European ethnic groups due to favourable educational, job, and demographic characteristics. In contrast, composition effects are strongly negative for Māori and for Pacific ethnic groups, reflecting inequalities determined outside the labour market, such as lower education levels. For high-migrant groups, the migrant contribution to the composition effect is typically negative, reflecting that migrants are generally paid less. However, for migrants identifying as Indian, Chinese, Other Asian, Filipino, this is partially or fully offset by a positive education contribution, particularly for Indian and Chinese, whose higher qualification levels more than compensate for the migrant penalty. This likely reflects the stratified nature of regulated migration flows, whereby policy settings favour skills and education, with a differential effect on inequality within and across ethnicities (Collins, 2020). Firm sorting, as captured by our firm premium variable, does not play a major role in explaining ethnic wage gaps. While the firm premium domain contributes modestly to the wage gap through the composition effect for some groups – such as British and Irish, Other European, Samoan, and Other Asian – the contribution is generally less substantial than that of other domains. The education, migrant, demographic, and household domains provide much bigger contributions to the wage gaps.

In most cases, the interaction effect makes a positive contribution to wage gaps, offsetting negative gaps or magnifying positive gaps. This suggests that there are relatively high marginal returns to wage-enhancing characteristics for groups with relatively low levels of those characteristics. One implication of this is that reducing differences in characteristics may have a greater impact on reducing wage gaps than would be expected based on calculations using average returns.

Our decomposition results, however, highlight the importance of factors that are *not* captured by the measured characteristics incorporated in our estimation. There are clearly ethnic differences in the 'returns effect', which captures the wage gap that would remain even if differences in observable characteristics were eliminated. NZ European workers would earn 10.4% higher wages, with small positive level effects for British and Irish and Other European groups. Wages would be substantially lower for Other Asian (–13.5%), Cook Islands Māori (–11.9%), Other Pacific (–8.8%), Chinese (–8.7%), and Māori (–7.1%). Negative returns effects are also evident for the remaining ethnic groups (–3.5% to –6.3%). Such returns effects provide insight into the degree of ethnic labour market disadvantage that is not related to differences in the broad range of measured characteristics included in our analysis. The patterns are consistent with existing qualitative evidence on patterns of racism and employment in New Zealand (Tan et al., 2024). The patterns may also reflect ethnic differences in other employment-related factors such as access to jobs due to residential location or access to employment-related networks.

Overall, the decomposition of ethnic wage gaps highlights the multi-faceted nature of wage differences and the many avenues through which inequalities are created and sustained. Some of the wage differences reflect the impact of inequality and possible inequity in the education system, housing market, and migration policy. Some reflect the impact of different job characteristics, including different occupations and to a small extent differences in securing work in high-paying firms. Despite identifying these sources of ethnic wage gaps, our decomposition has not pinpointed an obvious mechanism for reducing ethnic wage gaps. Inequality, inequity, and discrimination are perpetuated across multiple domains and mechanisms, meaning that ethnic wage gaps cannot be eliminated by action within the labour market alone. The clear ethnic pattern in returns effects points to the significant component of wage gaps that would remain between workers who differ only in their ethnicity.

A key continuing challenge for future research in this area is to better understand the mechanisms that perpetuate the sustained unexplained wage differences. Better measurement of characteristics such as literacy and numeracy skills, work experience, or on-the-job learning may account for some of the unexplained gaps (Treasury, 2018), but our expectation is that this would have a relatively small effect on our results. Our finding of small contributions from firm-level pay premiums may be because wage gaps are more pronounced within firms, rather than being a result of sorting across firms (Carrington & Troske, 1998; Forth et al., 2023). An examination of within-firm ethnic wage gaps would be a useful extension. A closer examination of how ethnic wage gaps differ over the life cycle and differ across the wage distribution would also provide insights into the mechanisms that perpetuate ethnic wage gaps and actions that could reduce inequities.

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Statistics New Zealand Disclaimer

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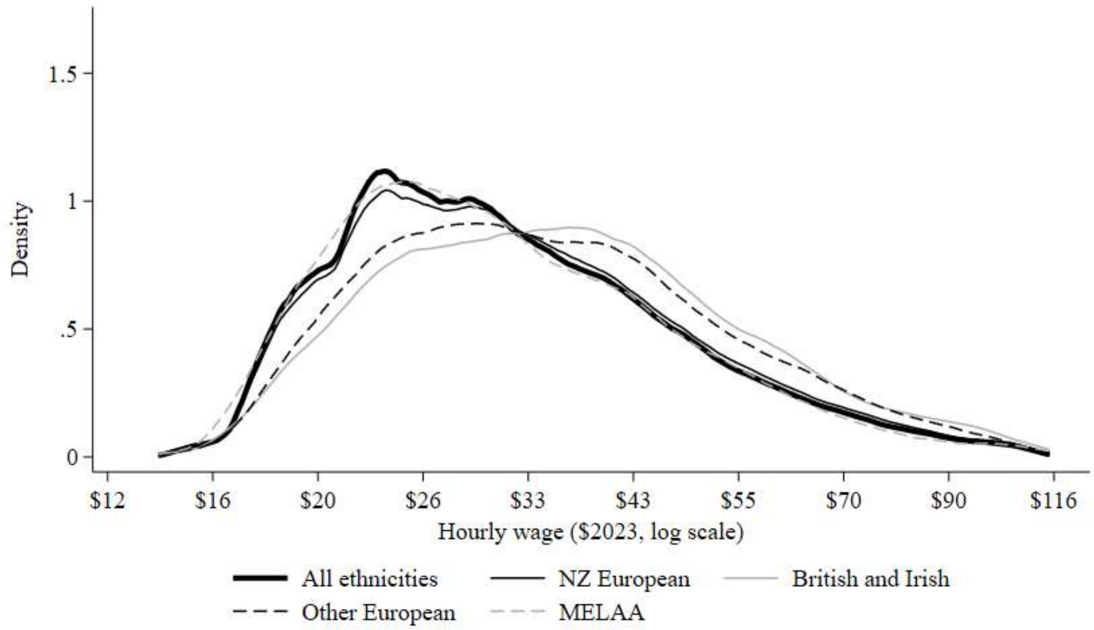
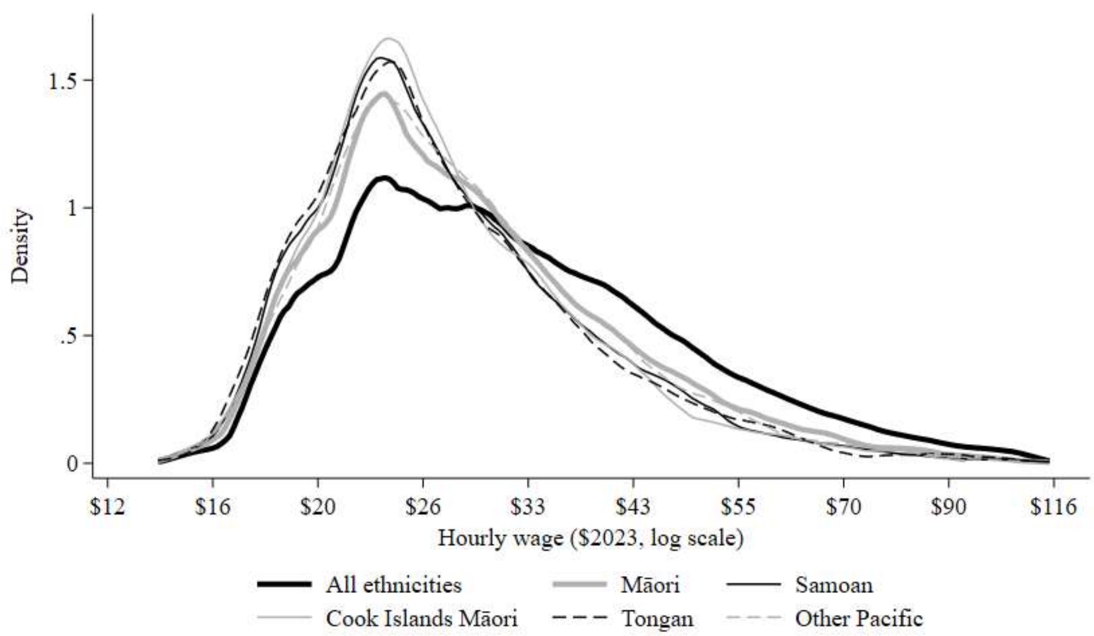
Tables & figures

Figure 1: Hourly wage distributions (by ethnicity)

Panel A



Panel B



(continued)

(continued) Figure 1: Hourly wage distributions (by ethnicity)

Panel C

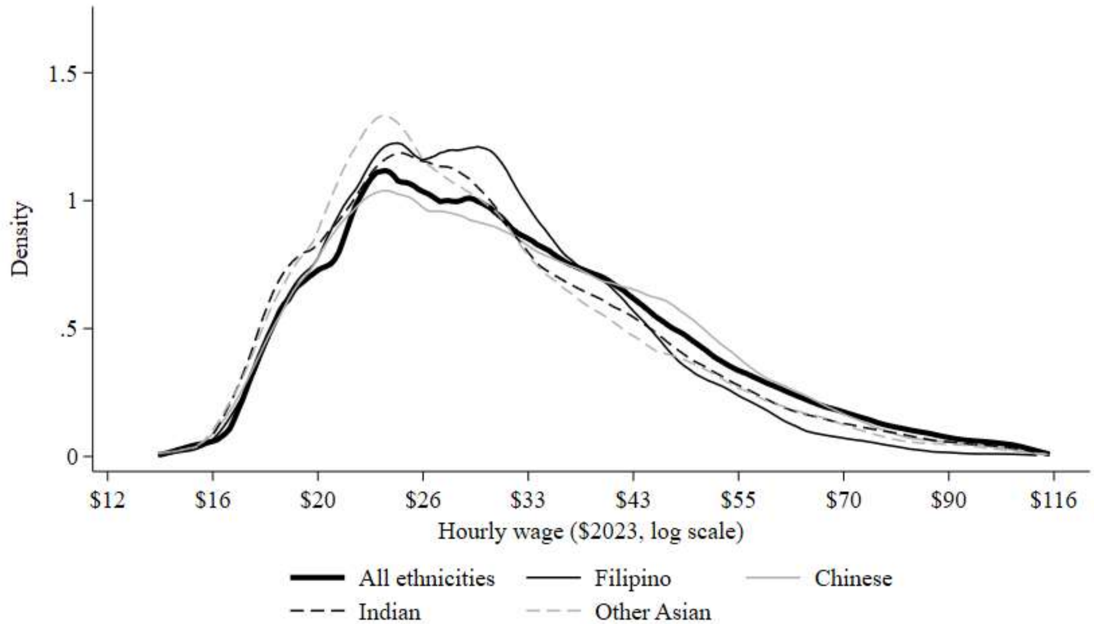


Table 1: Classification of ethnicities

1-digit ethnic groups	Disaggregated ethnic groups
European	NZ European
	British and Irish
	Other European
Māori	Māori
Pacific	Samoan
	Cook Islands Māori
	Tongan
	Other Pacific
Asian	Filipino
	Chinese
	Indian
	Other Asian
MELAA	MELAA

Table 2: Descriptive profiles

	All ethnicities	NZ European	Māori	Indian	Other European	Samoan	MELAA
Demographic							
Male	0.51	0.50	0.51	0.57	0.50	0.52	0.53
Female	0.49	0.50	0.49	0.43	0.50	0.48	0.47
Mean age	39.60	40.24	37.83	35.27	39.82	36.38	40.46
Multiple ethnicity	0.09	0.12	0.48	0.07	0.13	0.29	0.10
Single ethnicity	0.91	0.88	0.52	0.93	0.87	0.71	0.90
Migrant							
Migrant	0.30	0.10	0.02	0.92	0.90	0.47	0.45
NZ born	0.70	0.90	0.98	0.08	0.10	0.53	0.55
Education							
No qualification	0.12	0.12	0.22	0.04	0.05	0.24	0.10
School	0.28	0.30	0.32	0.19	0.23	0.41	0.27
Post school	0.27	0.28	0.28	0.23	0.29	0.20	0.28
Degree	0.33	0.30	0.18	0.53	0.43	0.15	0.35
Urban							
Auckland urban area	0.32	0.23	0.20	0.66	0.39	0.65	0.30
Main urban area	0.46	0.50	0.48	0.28	0.43	0.30	0.49
Secondary urban area	0.05	0.06	0.07	0.03	0.05	0.02	0.04
Minor urban area	0.07	0.07	0.12	0.02	0.05	0.02	0.07
Rural area	0.11	0.13	0.13	0.02	0.09	0.01	0.11
Household							
Sole parent	0.03	0.03	0.05	0.01	0.02	0.02	0.03
Not sole parent	0.97	0.97	0.95	0.99	0.98	0.98	0.97
Have dependent children	0.39	0.36	0.48	0.42	0.39	0.59	0.36
Don’t have dependent children	0.61	0.64	0.52	0.58	0.61	0.41	0.64
Mean household size	3.26	3.09	3.54	3.51	3.10	4.59	3.04
Mean household income decile	5.81	5.92	5.41	5.84	5.93	5.73	5.60
Industry							
Primary sector	0.04	0.04	0.06	0.03	0.03	0.02	0.04
Secondary sector	0.20	0.20	0.25	0.15	0.18	0.27	0.21
Services sector	0.76	0.76	0.69	0.82	0.79	0.72	0.75
Job							
High-wage occupation	0.40	0.41	0.29	0.39	0.49	0.23	0.38
Medium-wage occupation	0.34	0.35	0.34	0.32	0.35	0.34	0.36
Low-wage occupation	0.26	0.24	0.37	0.29	0.16	0.43	0.26
Full-time	0.83	0.81	0.83	0.86	0.85	0.87	0.81
Part-time	0.17	0.19	0.17	0.14	0.15	0.13	0.19
Firm premium							
Mean firm premium	-0.01	-0.01	-0.02	0.00	0.01	0.01	-0.01
Observations	188,565	122,232	24,282	10,383	9,075	6,213	5,472
(percent of sample)	(100%)	(65%)	(13%)	(6%)	(5%)	(3%)	(3%)

Source: Household Labour Force Survey 2009-2023

Notes: HLFS Sample aged 16 to 64. Variable definitions provided in Appendix Table 1.

(continued)

(continued) Table 2: Descriptive profiles

	Chinese	British and Irish	Other Asian	Filipino	Other Pacific	Cook Islands Māori	Tongan
Demographic							
Male	0.47	0.52	0.51	0.52	0.52	0.53	0.56
Female	0.53	0.48	0.49	0.48	0.48	0.47	0.44
Mean age	36.73	41.44	36.32	38.23	36.85	36.81	36.76
Multiple ethnicity	0.10	0.14	0.09	0.05	0.40	0.39	0.22
Single ethnicity	0.90	0.86	0.92	0.95	0.60	0.61	0.78
Migrant							
Migrant	0.84	0.92	0.92	0.95	0.63	0.28	0.60
NZ born	0.16	0.08	0.08	0.05	0.37	0.72	0.40
Education							
No qualification	0.05	0.06	0.09	0.07	0.17	0.30	0.30
School	0.19	0.22	0.24	0.27	0.36	0.35	0.36
Post school	0.13	0.30	0.18	0.17	0.28	0.23	0.19
Degree	0.62	0.43	0.49	0.49	0.19	0.12	0.15
Urban							
Auckland urban area	0.68	0.30	0.56	0.47	0.60	0.54	0.73
Main urban area	0.29	0.49	0.35	0.40	0.30	0.34	0.18
Secondary urban area	0.01	0.05	0.03	0.03	0.03	0.05	0.03
Minor urban area	0.01	0.05	0.03	0.04	0.04	0.04	0.03
Rural area	0.01	0.10	0.03	0.06	0.02	0.03	0.02
Household							
Sole parent	0.01	0.02	0.01	0.01	0.02	0.04	0.02
Not sole parent	0.99	0.98	0.99	0.99	0.98	0.96	0.98
Have dependent children	0.37	0.36	0.40	0.47	0.57	0.53	0.65
Don’t have dependent children	0.64	0.64	0.60	0.53	0.43	0.47	0.35
Mean household size	3.21	3.03	3.46	3.93	4.24	4.20	4.84
Mean household income decile	5.27	6.03	5.40	6.29	5.61	5.61	5.20
Industry							
Primary sector	0.01	0.02	0.03	0.06	0.03	0.03	0.03
Secondary sector	0.14	0.17	0.17	0.24	0.24	0.27	0.32
Services sector	0.85	0.82	0.80	0.69	0.73	0.70	0.65
Job							
Occupation group 1	0.47	0.51	0.38	0.34	0.25	0.21	0.20
Occupation group 2	0.32	0.34	0.35	0.37	0.39	0.36	0.33
Occupation group 3	0.21	0.14	0.27	0.29	0.36	0.43	0.47
Full-time	0.82	0.85	0.79	0.88	0.86	0.85	0.87
Part-time	0.18	0.15	0.21	0.12	0.14	0.15	0.13
Firm premium							
Mean firm premium	0.00	0.02	-0.03	0.00	0.00	0.00	0.00
Observations	5,454	5,358	4,974	3,873	3,048	2,355	2,295
(percent of sample)	(3%)	(3%)	(3%)	(2%)	(2%)	(1%)	(1%)

Source: Household Labour Force Survey 2009-2023

Notes: HLFS Sample aged 16 to 64. Variable definitions provided in Appendix Table 1.

Table 3: Wage summary statistics

	Observations	Employment rate	Wage	Std dev of wage	Wage gap	Proportional wage gap
All ethnicities	188,565	70%	$34.42	(15.63)		
NZ European	122,232	74%	$35.25	(16.15)	$2.33	5.9%
Māori	24,282	60%	$30.72	(12.74)	-$4.29	-11%
Indian	10,383	75%	$32.47	(14.51)	-$2.07	-4.2%
Other European	9,075	74%	$38.03	(17.03)	$3.81	11%
Samoan	6,213	59%	$29.13	(11.49)	-$5.44	-15%
MELAA	5,472	65%	$33.92	(15.39)	-$0.51	-1.5%
Chinese	5,454	55%	$34.23	(14.88)	-$0.20	1.1%
British and Irish	5,358	79%	$39.18	(17.56)	$4.91	13%
Other Asian	4,974	59%	$31.67	(13.85)	-$2.83	-6.6%
Filipino	3,873	80%	$31.22	(11.51)	-$3.27	-6.3%
Other Pacific	3,048	65%	$30.00	(11.78)	-$4.49	-12%
Cook Islands Māori	2,355	55%	$28.83	(11.03)	-$5.65	-15%
Tongan	2,295	52%	$28.96	(11.66)	-$5.52	-15%

Source: Household Labour Force Survey 2009-2023

Notes: HLFS Sample aged 16 to 64. Wage measures are for the restricted sample of 188,565 employees (see section 3). Wage gap and proportional wage gap are relative to the complement group. Proportional wage gap is the log wage gap estimated using regression analysis, as found in the results section.

Table 4: Wage gap decomposition results

	NZ European	Māori	Indian	Other European	Samoan	MELAA	Chinese
Wage gap							
Wage difference	5.9**	-11.0**	-4.2**	11.0**	-15.0**	-1.5**	1.1*
Adjusted wage difference	9.9**	-16.2**	-0.6	13.1**	-17.5**	-3.7**	-5.4**
Decomposition							
Composition effect	3.2**	-10.4**	1.8**	6.5**	-14.4**	0.3	5.3**
Interaction effect	-3.8**	1.3**	2.0**	5.9**	3.2**	0.0	-2.0*
Returns effect	10.4**	-7.1**	-4.3**	0.7	-6.3**	-3.9**	-8.7**
Composition effect contributions							
Demographic	-1.0**	-3.0**	-0.5**	1.6**	-2.4**	1.5**	-0.9**
Migrant	4.1**	2.3**	-4.9**	-4.7**	-1.6**	-0.8**	-4.1**
Education	-0.8**	-4.4**	5.3**	3.7**	-5.4**	0.7**	6.2**
Urban	0.1*	-0.1**	-0.1	0.0	-0.1	0.0*	-0.1
Household	1.0**	-1.3**	0.0	0.9**	-2.7**	0.1	-0.1
Industry	0.1**	-0.5**	-0.1**	0.4**	-0.1	-0.2**	0.5**
Job	1.2**	-2.9**	0.3**	2.6**	-3.9**	-0.5**	1.9**
Firm premium	-0.4**	-0.7**	0.4**	1.1**	1.0**	-0.1	0.3*
Year	-1.1**	0.2**	1.4**	0.8**	0.7**	-0.4**	1.6**
Interaction effect contributions							
Demographic	-0.1**	2.6**	1.3**	0.2**	1.4**	-0.1*	1.7**
Migrant	-3.5**	-2.1**	2.3**	5.9**	0.2	-0.2	-2.3**
Education	0.0**	-0.5**	-1.2**	-0.7**	0.3	0.0	-1.3**
Urban	0.0	0.2**	-0.1	0.2**	-1.1**	0.0	0.4
Household	-0.1**	0.0	-0.3**	-0.3**	1.1**	0.2*	-0.3**
Industry	0.0**	0.1**	-0.1	0.1	-0.2	0.1	-0.7**
Job	-0.1**	0.8**	0.1	0.4**	1.4**	0.0	0.5**
Firm premium	0.0**	0.1**	0.0	0.1	-0.2**	0.0	0.0
Year	-0.1**	0.1**	0.1	0.0	0.3**	0.1	0.1
Observations	122,232	24,282	10,383	9,075	6,213	5,472	5,454

Source: Household Labour Force Survey 2009-2023

*Notes: HLFS Sample aged 16 to 64. **p<0.05, *p<0.1.*

(continued)

(continued) Table 4: Wage gap decomposition results

	British and Irish	Other Asian	Filipino	Other Pacific	Cook Islands Māori	Tongan
Wage gap						
Wage difference	13.0**	-6.6**	-6.3**	-12.0**	-15.0**	-15.0**
Adjusted wage difference	17.7**	-11.6**	1.1	-12.9**	-21.6**	-22.6**
Decomposition						
Composition effect	6.9**	-2.3**	2.3**	-11.4**	-15.7**	-17.7**
Interaction effect	8.1**	4.2**	2.3	7.3**	6.0**	-0.3
Returns effect	2.7*	-13.5**	-3.5*	-8.8**	-11.9**	-4.5**
Composition effect contributions						
Demographic	2.5**	-0.6**	2.0**	-1.7**	-2.8**	-0.7*
Migrant	-4.7**	-4.8**	-5.0**	-2.6**	-0.1	-2.6**
Education	3.5**	3.2**	3.8**	-3.2**	-6.7**	-6.2**
Urban	0.1**	0.0	0.0	-0.1	-0.1	-0.2**
Household	0.9**	-0.4**	-0.5**	-2.0**	-2.4**	-3.6**
Industry	0.6**	-0.4**	-0.3**	-0.1	-0.3**	-0.2**
Job	2.9**	-0.6**	-1.0**	-3.2**	-4.3**	-4.8**
Firm premium	1.5**	-1.4**	0.5**	0.3*	0.4**	0.6**
Year	-0.3**	2.7**	2.7**	1.1**	0.5**	0.1
Interaction effect contributions						
Demographic	-0.1	1.3**	0.2	2.9**	2.1**	1.4**
Migrant	8.5**	2.5**	3.3*	2.1**	0.1	1.0
Education	-0.5**	-0.7**	-2.3**	0.3	1.4**	-0.6
Urban	-0.1	-0.4	0.5**	0.0	-0.4	-3.0**
Household	-0.4**	-0.5**	-0.5*	0.9**	0.4	-0.3
Industry	0.0	-0.1	0.5**	-0.1	0.2	-0.6**
Job	0.5**	0.2**	0.4**	0.8**	2.1**	2.0**
Firm premium	0.2*	0.2**	-0.1*	-0.1	-0.1	-0.2**
Year	0.0	1.8**	0.3	0.5**	0.3**	0.1
Observations	5,358	4,974	3,873	3,048	2,355	2,295

Source: Household Labour Force Survey 2009-2023

*Notes: HLFS Sample aged 16 to 64. **p<0.05, *p<0.1.*

Table 5: Wage gap decomposition results, by sex

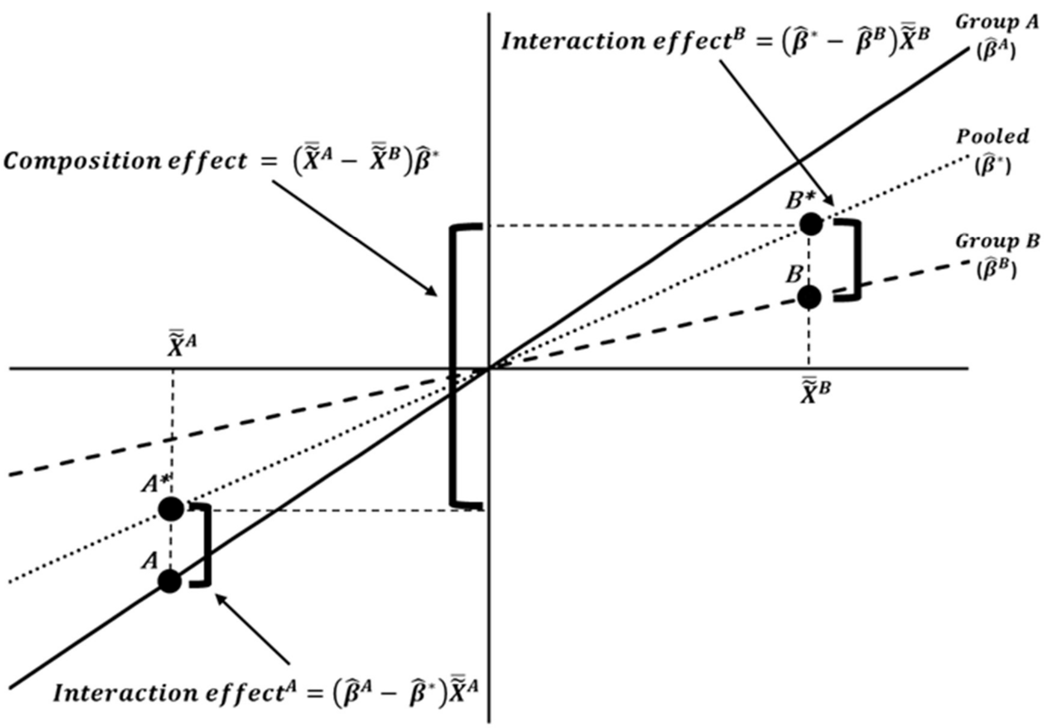
	NZ European	Māori	Indian	Other European	Samoan	MELAA	Chinese
				Male			
Wage gap							
Wage difference	7.4**	-13.0**	-6.8**	13.0**	-19.0**	0.0	-0.1
Adjusted wage difference	10.3**	-18.2**	-3.1**	16.3**	-22.3**	-2.4**	-4.8**
Decomposition							
Composition effect	3.3**	-12.0**	-0.5	8.4**	-16.4**	0.8	6.1**
Interaction effect	-4.1**	3.3**	2.2	6.4**	4.4**	0.1	-0.4
Returns effect	11.1**	-9.5**	-4.8**	1.5	-10.3**	-3.3**	-10.5**
Observations	58,443	11,565	5,658	4,467	3,117	2,808	2,481
				Female			
Wage gap							
Wage difference	5.0**	-8.9**	-2.5**	8.7**	-10.0**	-3.8**	2.7**
Adjusted wage difference	10.2**	-14.0**	0.0	9.9**	-13.2**	-5.6**	-4.3**
Decomposition							
Composition effect	4.0**	-9.0**	1.7**	5.1**	-12.8**	-1.1	5.1**
Interaction effect	-3.3**	-0.5	2.9**	4.9**	2.9**	0.0	-3.1**
Returns effect	9.5**	-4.5**	-4.6**	0.0	-3.3**	-4.5**	-6.4**
Observations	63,792	12,720	4,728	4,605	3,096	2,664	2,973

	British and Irish	Other Asian	Filipino	Other Pacific	Cook Islands Māori	Tongan
				Male		
Wage gap						
Wage difference	14.0**	-6.6**	-7.7**	-14.0**	-17.0**	-19.0**
Adjusted wage difference	19.6**	-8.3**	4.0**	-14.9**	-22.2**	-23.9**
Decomposition						
Composition effect	8.4**	-0.8	3.1**	-11.5**	-17.1**	-18.6**
Interaction effect	7.6**	1.6	-1.9	9.1**	7.0**	1.6
Returns effect	3.6*	-9.1**	2.9	-12.5**	-12.2**	-6.8**
Observations	2,721	2,412	1,917	1,521	1,203	1,257
				Female		
Wage gap						
Wage difference	11.0**	-6.5**	-5.0**	-10.0**	-14.0**	-12.0**
Adjusted wage difference	29.0**	-15.1**	2.4**	-11.3**	-21.8**	-22.2**
Decomposition						
Composition effect	5.4**	-3.7**	0.8	-11.9**	-15.5**	-17.6**
Interaction effect	0.5	6.1**	6.6**	5.6**	5.4**	-0.8
Returns effect	23.1**	-17.4**	-5.0**	-5.0**	-11.8**	-3.9*
Observations	2,637	2,562	1,956	1,527	1,152	1,038

Source: Household Labour Force Survey 2009-2023
*Notes: HLFS Sample aged 16 to 64. **p<0.05, *p<0.1.*

Appendix A: Graphical depiction of decomposition

Appendix Figure 1: Graphical illustration of wage gap decomposition



$$\overline{\ln(w^A)} - \overline{\ln(w^B)} = \underbrace{(\bar{\bar{X}}^A - \bar{\bar{X}}^B)\hat{\beta}^*}_{\substack{Composition \\ effect}} + \underbrace{(\hat{\beta}^A - \hat{\beta}^*)\bar{\bar{X}}^A}_{Interaction\ effect^A} + \underbrace{(\hat{\beta}^* - \hat{\beta}^B)\bar{\bar{X}}^B}_{Interaction\ effect^B} + \underbrace{(\hat{\alpha}^A - \hat{\alpha}^B)}_{Returns\ effect}$$

Appendix Figure 1 provides a graphical illustration of our version of the Oaxaca-Blinder decomposition with de-meaned explanatory variables. The Y-axis corresponds to wages and the X-axis corresponds to a given explanatory variable (X) that has been de-meaned. The regression lines represent the relationship between wages and variable X for group A, group B, and the pooled group. In this example, group A has a below-average level of X ($\bar{\bar{X}}^A$ < 0) and a higher relative return to X ($\hat{\beta}^A > \hat{\beta}^*$). Conversely, group B has an above-average level of X ($\bar{\bar{X}}^B$ > 0) and a lower relative return to X ($\hat{\beta}^B < \hat{\beta}^*$).

For illustrative purposes, the wage variable has been de-meaned and groups A and B are assumed to have the same expected wage at mean characteristics (i.e. $\hat{\alpha}^A - \hat{\alpha}^B = 0$). Our actual decomposition uses non-de-meaned wages, providing an estimate of inter-group wage differences in the absence of differences in X. By removing the influence of different intercepts in Appendix Figure 1, we can directly compare the slopes of the regression lines, which is useful for interpreting the interaction effect.

Composition effect

The composition effect is the difference in mean wages that is due to differences in X, evaluated at pooled returns. On Appendix Figure 1, it is the vertical distance between points A* and B*. The figure shows that, given the positive slope of the pooled slope ($\hat{\beta}^*$), group A's below-average level of X lowers their expected wage relative to group B. Group A earn less than group B because they have less of X. The composition effect makes a negative contribution to the wage gap.

Interaction effect

The interaction effect captures the interaction between differences in returns and differences in X. It consists of two components: the group A component captures the contribution from group A having relatively high returns, evaluated at $\bar{\bar{X}}^A$. The group B component captures the contribution from group B having relatively low returns, evaluated at $\bar{\bar{X}}^B$.

The group A component of the interaction effect is the vertical distance between points A and A*. Given their below-average level of X, group A's higher relative return means that their expected wage is lower than what is implied by the pooled return. This is shown by A being below A* when X = $\bar{\bar{X}}^{\mathrm{A}}$. Thus, group A's relatively high return amplifies the penalty of having a below-average level of X. The interaction effect for group A makes a negative contribution to the wage gap.

The group B component of the interaction effect is represented by the vertical distance between points B and B*. Given their above-average level of X, group B's lower relative return means that their expected wage is lower than what is implied by the pooled return. This is shown by B being below B* at X = $\bar{\bar{X}}^{\mathrm{B}}$. Thus, group B's relatively low return lessens the reward of having an above-average level of X. The interaction effect for group B makes a positive contribution to the wage gap (recall the wage gap is from the perspective of group A).

The net contribution of the interaction effect to the wage gap depends on the relative sizes of the two group components. In this example, the two components appear to cancel each other out. If the group A component were relatively bigger in magnitude, the interaction effect would contribute negatively to the wage gap (and thus reinforce the composition effect). Conversely, if the group B component was bigger, the interaction effect would contribute positively to the wage gap.

Appendix B: Tables

Appendix Table 1: Variable definitions

Variable	Definition
Wage	Actual total hourly earnings from main job, before tax and deflated to 2023 dollars
Female	Dummy variable. Equals 1 if female, 0 if male
Age	Age in years
Multiple ethnicities	Dummy variable. Equals 1 if reports having more than one ethnicity, 0 if reports only one ethnicity
Migrant status	Dummy variable. Equals 1 if born overseas, 0 if born in New Zealand
Highest qualification	Categorical variable. Highest qualification attained: no school, school, post-school certificate, degree
Urban area	Categorical variable. The urban area the individual lives in: Auckland urban area, main urban area (excl. Auckland), secondary urban area, minor urban area, rural area
Sole parent status	Dummy variable. Equals 1 if one parent with dependent child(ren) only, 0 otherwise
Dependent children	Dummy variable. Equals 1 if has a dependent child or more, 0 otherwise
Household size	Number of individuals in the household
Household income decile	Equivalised household income decile ranging from 1 to 10. Household income is measured as total household income minus the individual's income (i.e. the sum of the income of the other household members)
Industry	Categorical variable. The ANZSIC Level 1 industry the individual works in: Agriculture, forestry and fishing, and mining; Manufacturing; Electricity, gas, water and waste services; Construction; Wholesale trade; Retail trade; Accommodation and food services; Transport, postal, and warehousing; Information media and telecommunications; Financial and insurance services; Rental, hiring, and real estate services; Professional services; Administrative and support services; Public administration and safety; Education and training; Health care and social assistance; Arts and recreation services; Other services
Primary sector	Dummy variable. Equals 1 if the individual works in Agriculture, forestry and fishing. 0 otherwise
Secondary sector	Dummy variable. Equals 1 if the individual works in: Manufacturing; Electricity, gas, water, and waste services; Construction. 0 otherwise
Services sector	Dummy variable. Equals 1 if the individual works in: Wholesale trade; Retail trade; Accommodation and food services; Transport, postal, and warehousing; Information media and telecommunications; Financial and insurance services; Rental, hiring, and real estate services; Professional services; Administrative and support services; Public administration and safety; Education and training; Health care and social assistance; Arts and recreation services; Other services. 0 otherwise

(continued)

(continued) Appendix Table 1: Variable definitions

Variable	Definition
Occupation	Categorical variable. The ANZSCO Level 1 occupation of the individual: Manager; Professional; Technicians and trade worker; Community and personal service worker; Clerical and administrative worker; Sales worker; Machinery operators and driver; Labourer
High-wage occupation	Dummy variable. Equals 1 if the individual's occupation is: Manager; Professional. 0 otherwise
Medium-wage occupation	Dummy variable. Equals 1 if the individual's occupation is: Technician and trade worker; Community and personal service worker; Clerical and administrative worker. 0 otherwise
Low-wage occupation	Dummy variable. Equals 1 if the individual's occupation is: Sales worker; Machinery operator and driver; Labourer. 0 otherwise
Full-time/part-time status	Dummy variable. Equals 1 if working part-time, 0 if working full-time
Firm premium	The firm premium (firm fixed effects) variable is normalised to have a mean of zero across all jobs and is approximately equal to the (log-difference) proportional difference of the premium paid by each firm from the overall average.

Appendix Table 2: Domains for the wage decomposition

Domain	Variable
Demographic	Age, age squared, multiple ethnicities
Migrant	Migrant
Education	School, post-school, degree
Urban	Main urban, secondary urban, minor urban, rural area
Household	Sole parent, dependent children, household size, household income decile
Industry	Industry
Job	Occupation, part-time
Firm premium	Firm premium
Year	Year dummies for 2010 through to 2023

Appendix Table 3: Pooled wage regression results

	(1) Selection equation DV = Worker n = 270,609		(2) Wage equation DV = Log hourly wage n = 188,565	
	Coefficient	SE	Coefficient	SE
Demographic				
Female	-0.43**	0.0061	-0.15**	0.0019
Age	0.15**	0.0014	0.051**	0.00046
Age squared	-0.0017**	0.000018	-0.00055**	0.0000057
Multiple ethnicities	-0.066**	0.0099	-0.024**	0.0030
Migrant				
Migrant	-0.19**	0.0070	-0.073**	0.0021
Education				
School	0.38**	0.0082	0.13**	0.0026
Post school	0.55**	0.0087	0.20**	0.0027
Degree	0.89**	0.0098	0.33**	0.0032
Urban				
Main urban area	0.070**	0.0073	0.0089**	0.0022
Secondary urban area	0.089**	0.014	0.0045	0.0040
Minor urban area	0.0076	0.012	-0.022**	0.0036
Rural area	0.038**	0.012	0.0021	0.0036
Household				
Sole parent	-0.47**	0.015	-0.15**	0.0051
Have dependent children	-0.028**	0.0079	0.042**	0.0023
Household size	-0.076**	0.0025	-0.027**	0.00077
Household income decile	0.013**	0.0044	-0.014**	0.0013
Household income decile squared	0.0021**	0.00040	0.0022**	0.00012
One person household	-0.17**	0.015	-0.079**	0.0046
Industry				
Manufacturing			0.054**	0.0041
Electricity			0.088**	0.0082
Construction			0.074**	0.0045
Wholesale trade			0.078**	0.0049
Retail trade			0.014**	0.0043
Accommodation			0.034**	0.0044
Transport			0.062**	0.0049
Information			0.050**	0.0073
Financial			0.13**	0.0061
Rental			0.074**	0.0072
Professional services			0.13**	0.0049
Administrative			0.037**	0.0049
Public administration			0.12**	0.0049
Education			0.035**	0.0046
Health care			0.062**	0.0044
Arts and recreation			0.063**	0.0062
Other services			0.050**	0.0051

Source: Household Labour Force Survey 2009-2023

*Notes: HLFS Sample aged 16 to 64. **p<0.05, *p<0.1.*

(continued)

(continued) Appendix Table 3: wage regression results

	(1) Selection equation Worker n = 270,609		(2) Wage equation Log hourly wage n = 188,565	
	Coefficient	SE	Coefficient	SE
Job				
Professionals			0.0080**	0.0030
Technicians and trade workers			-0.13**	0.0029
Community workers			-0.20**	0.0031
Clerical workers			-0.14**	0.0030
Sales workers			-0.17**	0.0030
Machinery operators and drivers			-0.23**	0.0034
Labourers			-0.23**	0.0029
Part-time			-0.041**	0.0017
Firm premium				
Firm premium			0.62**	0.0074
Year				
2010	-0.0077	0.012	0.0072*	0.0039
2011	-0.017	0.014	-0.023**	0.0043
2012	-0.027*	0.014	-0.015**	0.0043
2013	0.0041	0.014	0.012**	0.0043
2014	0.025*	0.014	0.016**	0.0042
2015	0.043**	0.014	0.047**	0.0043
2016	0.040**	0.014	0.082**	0.0041
2017	0.031**	0.014	0.090**	0.0041
2018	0.055**	0.014	0.12**	0.0041
2019	0.046**	0.014	0.13**	0.0040
2020	-0.0092	0.014	0.15**	0.0040
2021	0.0040	0.013	0.17**	0.0040
2022	0.048**	0.014	0.16**	0.0041
2023	0.092**	0.014	0.17**	0.0041
Constant	0.72**	0.0035	3.30**	0.00098

Source: Household Labour Force Survey 2009-2023
*Notes: HLFS Sample aged 16 to 64. **p<0.05, *p<0.1.*

Appendix Table 4: Wage gap decomposition results, by sex

	NZ European	Māori	Indian	Other European	Samoan	MELAA	Chinese
				Male			
Wage gap							
Wage difference	7.4**	-13.0**	-6.8**	13.0**	-19.0**	0.0	-0.1
Adjusted wage difference	10.3**	-18.2**	-3.1**	16.3**	-22.3**	-2.4**	-4.8**
Decomposition							
Composition effect	3.3**	-12.0**	-0.5	8.4**	-16.4**	0.8	6.1**
Interaction effect	-4.1**	3.3**	2.2	6.4**	4.4**	0.1	-0.4
Returns effect	11.1**	-9.5**	-4.8**	1.5	-10.3**	-3.3**	-10.5**
Composition effect contributions							
Demographic	-0.7**	-4.0**	-1.9**	2.6**	-3.2**	1.8**	-0.3
Migrant	3.8**	2.2**	-4.5**	-4.2**	-1.6**	-0.7**	-3.6**
Education	-0.7**	-4.7**	5.3**	3.5**	-5.7**	0.9**	5.9**
Urban	0.3**	0.1	-0.4**	0.0*	-0.4**	0.0	-0.4**
Household	0.1**	-0.2**	0.5**	0.8**	-0.8**	-0.4**	0.1
Industry	0.2**	-0.7**	-0.4**	0.7**	-0.2*	-0.3**	0.7**
Job	1.4**	-4.1**	0.4**	3.3**	-5.1**	-0.3	2.5**
Firm premium	-0.1	-0.8**	-0.6**	1.3**	0.3	0.0	-0.2
Year	-1.0**	0.2**	1.2**	0.6**	0.4**	-0.4**	1.5**
Observations	58,443	11,565	5,658	4,467	3,117	2,808	2,481
				Female			
Wage gap							
Wage difference	5.0**	-8.9**	-2.5**	8.7**	-10.0**	-3.8**	2.7**
Adjusted wage difference	10.2**	-14.0**	0.0	9.9**	-13.2**	-5.6**	-4.3**
Decomposition							
Composition effect	4.0**	-9.0**	1.7**	5.1**	-12.8**	-1.1	5.1**
Interaction effect	-3.3**	-0.5	2.9**	4.9**	2.9**	0.0	-3.1**
Returns effect	9.5**	-4.5**	-4.6**	0.0	-3.3**	-4.5**	-6.4**
Composition effect contributions							
Demographic	-0.7**	-1.8**	-0.6**	0.9**	-1.8**	0.6**	-0.3
Migrant	4.2**	2.3**	-5.1**	-5.0**	-1.5**	-0.9**	-4.4**
Education	-0.9**	-4.1**	5.0**	3.7**	-4.7**	0.3	6.1**
Urban	-0.2**	-0.3**	0.3**	0.1**	0.4**	0.0	0.4**
Household	2.1**	-2.6**	-0.8**	1.1**	-4.6**	0.5**	-0.5**
Industry	0.1**	-0.4**	0.1	0.3**	-0.1	-0.1	0.4**
Job	1.1**	-1.9**	0.1	2.1**	-2.9**	-0.7**	1.2**
Firm premium	-0.6**	-0.6**	1.1**	1.0**	1.5**	-0.4**	0.8**
Year	-1.2**	0.2**	1.6**	1.0**	0.9**	-0.4**	1.6**
Observations	63,792	12,720	4,728	4,605	3,096	2,664	2,973

Source: Household Labour Force Survey 2009-2023

*Notes: HLFS Sample aged 16 to 64. **p<0.05, *p<0.1.*

(continued)

(continued) Appendix Table 4: Wage gap decomposition results, by sex

	British and Irish	Other Asian	Filipino	Other Pacific	Cook Islands Māori	Tongan
			Male			
Wage gap						
Wage difference	14.0**	-6.6**	-7.7**	-14.0**	-17.0**	-19.0**
Adjusted wage difference	19.6**	-8.3**	4.0**	-14.9**	-22.2**	-23.9**
Decomposition						
Composition effect	8.4**	-0.8	3.1**	-11.5**	-17.1**	-18.6**
Interaction effect	7.6**	1.6	-1.9	9.1**	7.0**	1.6
Returns effect	3.6*	-9.1**	2.9	-12.5**	-12.2**	-6.8**
Composition effect contributions						
Demographic	3.3**	-0.8**	2.4**	-2.2**	-4.7**	-1.8**
Migrant	-4.3**	-4.2**	-4.5**	-2.4**	0.1	-2.5**
Education	3.3**	3.5**	3.1**	-3.2**	-6.4**	-6.5**
Urban	0.1**	-0.3**	-0.2**	-0.4**	-0.3**	-0.5**
Household	0.7**	0.1	0.0	-0.7**	-0.8**	-1.5**
Industry	0.8**	-0.5**	-0.7**	-0.1	-0.4**	-0.3**
Job	3.2**	0.4*	-0.5*	-3.8**	-5.1**	-5.7**
Firm premium	1.7**	-1.7**	0.5**	0.2	-0.3	0.5*
Year	-0.4**	2.6**	2.9**	1.0**	0.6**	-0.3
Observations	2,721	2,412	1,917	1,521	1,203	1,257
			Female			
Wage gap						
Wage difference	11.0**	-6.5**	-5.0**	-10.0**	-14.0**	-12.0**
Adjusted wage difference	29.0**	-15.1**	2.4**	-11.3**	-21.8**	-22.2**
Decomposition						
Composition effect	5.4**	-3.7**	0.8	-11.9**	-15.5**	-17.6**
Interaction effect	0.5	6.1**	6.6**	5.6**	5.4**	-0.8
Returns effect	23.1**	-17.4**	-5.0**	-5.0**	-11.8**	-3.9*
Composition effect contributions						
Demographic	1.3**	-0.1	1.6**	-1.4**	-1.8**	-1.2**
Migrant	-5.0**	-5.2**	-5.3**	-2.8**	-0.4**	-2.5**
Education	3.6**	2.5**	4.3**	-2.9**	-6.6**	-5.3**
Urban	0.1*	0.3**	0.2**	0.2**	0.2**	0.3*
Household	1.4**	-0.8**	-1.2**	-3.7**	-4.2**	-5.7**
Industry	0.4**	-0.4**	-0.1	-0.1	-0.4**	-0.2**
Job	2.7**	-1.7**	-1.4**	-2.7**	-3.6**	-3.9**
Firm premium	1.1**	-1.2**	0.4*	0.3	0.8**	0.4
Year	-0.2	2.7**	2.4**	1.3**	0.5*	0.6**
Observations	2,637	2,562	1,956	1,527	1,152	1,038

Source: Household Labour Force Survey 2009-2023

*Notes: HLFS Sample aged 16 to 64. **p<0.05, *p<0.1.*