Gender and ethnic pay gaps:

An industry-level portrait of Aotearoa

NEW ZEALAND POLICY RESEARCH INSTITUTE
TE KĀHUI RANGAHAU MANA TAURITE

Manatū Wāhine
Ministry for Women

Authors
Leon Iusitini, Lisa Meehan and Gail Pacheco

Acknowledgements
This project was commissioned by Ministry for Women. We would like to thank members of the ministry for their feedback and input throughout the research planning process. Additionally, we had input from Leilani Tamu (MBIE), Ella Henry (AUT), Geoff Simmons (previously Toi Moi), Brett O'Riley (EMA), Maria Uluilelata on the research plan and a draft version of this report.

Published
New Zealand Policy Research Institute, Auckland, New Zealand

ISBN (PDF): 978-1-99-101118-3

2024

Suggested citation: Iusitini., L., Meehan, L., & Pacheco, G. (2024). *Gender and ethnic pay gaps: An industry-level portrait of Aotearoa,* New Zealand Policy Research Institute, Auckland.

Disclaimer

Executive Summary

This report provides a descriptive examination of gender and ethnicity pay gaps at the industry level in Aotearoa New Zealand (NZ). We employ survey and administrative data to estimate industry pay gaps between 2016 and 2022, and then explore the structural and contextual factors driving these gaps.

Pay gap estimates (with survey data):

- At the industry level, these estimates are relevant for benchmarking and monitoring purposes.
- The aggregate (all industries) gender pay gap was 9.4% in 2022. This varied from a small negative gap in the Construction industry to a 15% gap in the Media & Finance and Professional Services industries.
- The aggregate (all industries) ethnic pay gaps in 2022 were 14.6% for Māori-European; 10.2% for Asian-European; and the largest one was 18.8% for the Pacific-European gap.
- Across industries, the Māori pay gap in 2022 ranged from 2% in Hospitality to 20% in Logistics, the Pacific pay gap ranged from 3% in Professional Services to 27% in Media & Finance, and the Asian pay gap ranged from 0.4% in Hospitality to 16% in the Wholesale industry.
- In terms of intersectional pay gaps, the ethnic pay gaps in aggregate (all industries) are 13%, 14%, and 8% for Māori, Pacific and Asian women respectively relative to European women. For men, the aggregate pay gaps are 16%, 23%, and 13% for Māori, Pacific and Asian men respectively relative to European men. When gender and ethnic pay gaps are combined, the pay gaps compound. The aggregate pay gap for Māori women versus European men is 23%, for Pacific women versus European men is 24%, and for Asian women versus European men is 18%.

Exploring pay gap estimation with administrative data:

- Currently, only around 40% of employees have hours information in the administrative data.
- Pay gap estimates using administrative data tend to be larger than estimates using survey data. However, relative pay gaps across industries are generally similar between the two sources, with some exceptions (e.g. the Healthcare industry).

Workforce composition by industry:

- Women and non-Europeans are more likely to work in lower-paid industries (such as Hospitality and Retail) compared with men and Europeans.
- European workers are most overrepresented in Education (an average-pay industry) and Professional Services (a high-pay industry).

- Māori are underrepresented in the two highest paying industries (Professional Services and Media & Finance), and overrepresented in Agriculture and Administrative Services.
- Pacific workers are also underrepresented in the high-pay industries of Professional Services and Media & Finance, as well as Education and Hospitality.
- Asian workers are overrepresented in the high-pay industries of Professional Services and Media & Finance, but they are also overrepresented in the low-pay industries of Hospitality and Retail.

Earnings distribution by industry:

- Within an industry, women and non-Europeans are overrepresented among lower earning deciles and underrepresented in higher deciles.
- In all industries, more than 30% of women fall in the bottom three earnings deciles, and less than 30% of women fall in the top three deciles.
- Māori workers are overrepresented in the bottom three earnings deciles in all industries.
- While Pacific workers are generally overrepresented in the bottom deciles, they tend to fall disproportionately into the middle-earnings deciles and are underrepresented in the top deciles.
- Unlike Māori and Pacific workers, Asian workers are underrepresented in the bottom deciles in half of the industries, but also tend to be underrepresented at the very top of the earnings distribution.

Occupation distribution by industry:

- In aggregate (all industries), women are less likely than men to work in high-pay occupations, such as Managers and Technicians and Trades Workers, and more likely to work in low-pay occupations such as Community and Personal Service Workers and Sales Workers.
- Women are more likely to work as Professionals, which is a high-pay occupation on average, but this is driven by the overrepresentation of women who work as Professionals in Education and Healthcare.
- Relative to Europeans, Māori and Pacific workers are underrepresented in high-pay occupations such as Managers and Professional workers, and overrepresented in low-pay occupations such as Labourers.
- The occupation distribution of Asians more closely resembles that of Europeans, but they are underrepresented as Managers and overrepresented as Professionals, as well as Labourers in some industries.

Pay gap decompositions highlight that pay gaps are mostly unexplained, with some ethnic differences:

- Pay gaps are decomposed into explained and unexplained components.

- Note that discrimination can exist in both the explained and unexplained components. For example, pay gaps may be partly explained by group differences in educational attainment, yet these educational differences may themselves arise from unfair disparities or discrimination.
- In all industries except Professional Services, very little of the gender pay gap is explained. In many industries, some characteristics, particularly educational and job characteristics, make a negative contribution to the explained component of the pay gap. That is, women have lower average pay than men despite having higher average education levels, or more favourable job characteristics such as occupation.
- This negative-explained phenomenon is even more marked for Asian pay gaps, which have negative explained components in every industry except Education. That is, we would expect Asian workers to have higher wages given their high average education levels.
- The explained component for Māori pay gaps is 50% or higher in nearly all industries, with job-related characteristics generally making the largest contribution, followed by educational attainment.
- For Pacific pay gaps, the unexplained component is also the largest component in almost all industries, with job-related characteristics generally accounting for the largest share of the explained component.

Contents

1 Introduction 10
2 Data 11
2.1 Data sources 11
Part A: Pay gaps using Household Labour Force Survey data 11
Part A: Pay gaps using Inland Revenue data 11
Part B: Analysis of structural drivers 13
2.2 Variables 13
2.3 Sample selection 17
3 Method 18
4 Part A Results 21
4.1 Pay gaps in 2022 21
Gender pay gaps 21
Ethnic pay gaps 22
Intersectional pay gaps 23
4.2 Exploratory analysis of pay gaps using IR data 26
4.3 Industry pay gaps over time 30
Gender pay gaps over time 30
Māori pay gaps over time 32
Pacific pay gaps over time 34
Asian pay gaps by industry over time 36
5 Part B Results 38
5.1 Workforce compositions by industry 39
5.2 Differences in the earnings distribution 41
5.3 Occupation distribution by industry 48
5.4 Firm distribution by industry 54
5.5 Decomposition of pay gaps 55
The Blinder-Oaxaca decomposition method 56
Decomposition results: How much of the pay gaps are ‘explained’? 58
Decomposition results: Gender pay gaps 59
Decomposition results: Ethnic pay gaps 61
References 66
Appendix A: IR hours data coverage 67
Appendix B: Median wage pay gaps 68
Appendix C: Industry pay gaps over time 69
Appendix D: Sample descriptives table 83
Appendix E: Blinder-Oaxaca decomposition results 86

List of Figures

Figure 1. Gender pay gaps by industry, 2022 22
Figure 2. Ethnic pay gaps by industry, 2022 23
Figure 3. Ethnic pay gaps by industry, 2022: Women versus women 24
Figure 4. Ethnic pay gaps by industry, 2022: Men versus men 24
Figure 5. Ethnic pay gaps by industry, 2022: Women versus men 25
Figure 6. Mean hourly earnings by industry: IR versus HLFS 27
Figure 7. Gender pay gaps by industry: IR versus HLFS 28
Figure 8. Ethnic pay gaps by industry: IR versus HLFS 29
Figure 9. Gender pay gaps by industry over time 31
Figure 10. Māori pay gaps by industry over time 33
Figure 11. Pacific pay gaps by industry over time 35
Figure 12. Asian pay gaps by industry over time 37
Figure 13. Mean hourly pay by industry, 2022 38
Figure 14. Share of female employees (%) by industry 39
Figure 15. Share of employees by ethnicity and industry 41
Figure 16. Share of female employees by decile of gross annual earnings, by industry 43
Figure 17. Share of European employees by decile of gross annual earnings, by industry 44
Figure 18. Share of Māori employees by decile of gross annual earnings, by industry 45
Figure 19. Share of Pacific employees by decile of gross annual earnings, by industry. 46
Figure 20. Share of Asian employees by decile of gross annual earnings for year ended June 2022, by industry. 47
Figure 21. Average annual earnings for the year ended February 2018, by occupation. 48
Figure 22. Distribution of men and women across occupations as at March 2018, by industry 49
Figure 23. Distribution of Māori and Europeans across occupations as at March 2018, by industry 51
Figure 24. Distribution of Pacific peoples and Europeans across occupations as at March 2018, by industry 52
Figure 25. Distribution of Asians and Europeans across occupations as at March 2018, by industry 53
Figure 26. Correlation between firms' share of male employees and average annual earnings paid to their employees, by industry 54
Figure 27. Correlation between firms' share of European employees and average annual earnings paid to their employees, by industry 55
Figure 28. Proportion of 'all industries' pay gaps explained by group differences in observed characteristics from Blinder-Oaxaca decomposition 59

Figure 29. Proportion of gender pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition 61
Figure 30. Proportion of Māori pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition 62
Figure 31. Proportion of Pacific pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition 63
Figure 32. Proportion of Asian pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition 64

Appendix:

Figure A.1. IR data - Share of employees with hours information by industry, June 2021 67
Figure B.1. Gender pay gaps by industry, median wages, 2022 68
Figure B.2. Ethnicity pay gaps by industry, median wages, 2022 68
Figure C.1. Agriculture 69
Figure C.2. Manufacturing 70
Figure C.3. Construction 71
Figure C.4. Wholesale 72
Figure C.5. Retail 73
Figure C.6. Hospitality 74
Figure C.7. Logistics 75
Figure C.8. Media & Finance 76
Figure C.9. Professional services 77
Figure C.10. Administrative services 78
Figure C.11. Public administration 79
Figure C.12. Education 80
Figure C.13. Healthcare 81
Figure C.14. Arts & Recreation 82

List of Tables

Table 1. 13 pay gaps estimated for 14 industries in each of six pooled years.. 14
Table 2. Definitions of variables used in Part A (pay gaps) and Part B (decompositions) 15

Appendix:

Table D.1. Descriptive statistics of HLFS sample used in Blinder-Oaxaca decompositions 83
Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction).................................... 86

1 Introduction

This technical report provides a descriptive examination of gender and ethnic pay gaps at the industry level in Aotearoa New Zealand (NZ). We utilise survey and administrative data sources in Stats NZ's Integrated Data Infrastructure (IDI). The analysis is split into two components: (A) Estimation of pay gaps at the industry level over the period 2016 to 2022, and (B) Exploration of structural and contextual factors that may be driving these pay gaps.

In Part A we estimate both gender and ethnic pay gaps, including applying an intersectional lens, at the industry level in NZ using both survey and administrative data. Thus, we build on existing NZ research, particularly Pacheco et al. (2017) and Cochrane and Pacheco (2022). These estimates can be used by organisations within an industry to benchmark their own pay gaps against the industry average, as well as providing an understanding of sectoral differences across NZ.

In Part B we examine a number of structural drivers within industries. This includes delving into gender and ethnic differences in the firms, occupations and industries in which people work. We also quantify how much of each pay gap in each industry can be accounted for by group differences in a range of individual, household, regional, educational, and job-related characteristics and how much of each gap is left unexplained by such differences.

It is imperative that the results from Parts A and B are used in a complementary fashion. Pay gaps are a complex and multi-faceted issue within industries and it is necessary to view all elements of the puzzle together, rather than in isolation. This is why our analysis has examined a number of perspectives to provide a helicopter view of each industry sector.

The report proceeds as follows. Section 2 details the data used in estimating pay gaps by industry in NZ; Section 3 describes the methodology; Section 4 presents results for industry-level gender and ethnic pay gaps over time (i.e., results for Part A), and Section 5 presents the results of the structural analysis (i.e., Part B).

2 Data

This section describes the survey and administrative data from Stats NZ's Integrated Data Infrastructure that is used in this report, the variables used, and the sample selection. It includes discussion of the data for the estimation of pay gaps using both survey and administrative data (Part A) and the analysis of structural drivers of pay gaps (Part B).

2.1 Data sources

Part A: Pay gaps using Household Labour Force Survey data

To estimate pay gaps, our main analysis uses data from the Household Labour Force Survey (HLFS). The HLFS is run by Stats NZ every quarter with a nationally representative sample of about 15,000 households (equating to about 30,000 individuals). It collects information on labour market outcomes as well as demographic and socioeconomic characteristics of respondents and their households. The HLFS target population is the usually resident non-institutionalised population of New Zealanders aged 15 years and over. We use the June quarter HLFS over the years 2016 to 2022, because the surveys in this quarter collect additional information on income received from various sources and hours worked over the reference week of the HLFS, including hourly earnings. [1] The HLFS has a rotating panel design in which the same respondents are interviewed over a set number of consecutive quarters and then replaced (on a rotating basis) by a new set of respondents, such that the entire panel is turned over in an eight-quarter period.

HLFS data are included in Stats NZ's Integrated Data Infrastructure (IDI), which is a large research database that holds de-identified administrative and survey microdata about people, households, and businesses linked across a range of life domains for the whole population of NZ (including data from Inland Revenue (IR) and the Census).

Part A: Pay gaps using Inland Revenue data

IR data available in the IDI includes earnings data but, until recently, has not included information on employment hours. This has limited the usefulness of IR data for measuring pay gaps which ideally use hourly earnings measures. However, recently IR data on hours paid has become available.

[1] Where necessary, Stats NZ imputes missing responses from a random 'donor' respondent with similar characteristics, with imputation rates for job income (for example) ranging between nine and 13 percent.

The advantage of using an administrative source such as IR data to calculate pay gaps is that it overcomes the sample-size issues encountered with HLFS data when examining sub-groups and industries. For example, our industry analysis using HLFS is undertaken for 14 industries only, yet still runs into small sample-size issues within some industries for certain pay gap groups. For example, very few Pacific female workers are employed in the Agriculture industry, making pay gap estimates based on survey data potentially unreliable due to a small number of underlying observations. However, using administrative data is more limited in terms of the availability of a wide range of demographic and work characteristics. These characteristics are useful for examining structural reasons behind pay gaps, particularly via Blinder-Oaxaca decompositions.

There are also some specific limitations relating to the IR hours information. In particularly, it is not compulsory for organisations to provide this information to IR, and in June 2021, about 41% of employees had hours information, varying from 25% in Retail to 76% in the Education industry (see Appendix A for more information on IR hours coverage by industry, and for details of an adjustment made to recorded hours in the Education industry). More important than the coverage rate, however, is whether those organisations that provide information to IR are representative of organisations in their industry. As a hypothetical example, if only large organisations within the Logistics industry provide this information to IR, and these large organisations also have smaller gender pay gaps on average than smaller organisations, say, then using the IR data to estimate pay gaps will result in an underestimation of this industry's aggregate gender pay gap. Thus, since the use of IR data to calculate hourly earnings gaps has not been attempted previously, we provide exploratory results in this report, with comparisons with HLFS results to get a sense of how representative the IR data are. In order to be able to make these comparisons of HLFS and IR pay gap results, the same methodology and data definitions is used for the IR analysis as is used for the HLFS analysis (see Sections 2.2, 2.3 and 3).

IR employee data includes information on taxable income, the source of the taxable income (e.g. benefit payments, wages and salaries etc.) and hours paid. Information on each employee's employer is also available, allowing us to identify the employer's industry. We restrict attention to wage and salary earnings. We examine earnings and industry of employment from a person's main job, which we define as the job in which they earned the highest income in the given month.

For exploratory purposes, we limit attention to June 2021, to match the HLFS June 2021 time period in order to make comparisons. This is the latest June date with available IR data with all the necessary information (in particular, industry of employment was not available for June 2022 IR data at the time of analysis).

It should be noted that IR hours information is on hours paid, whereas HLFS is on hours worked. In contrast to hours worked, hours paid excludes unpaid overtime and includes some hours that are not actually worked, such as paid leave and statutory holidays. For example, if someone who is employed 40 hours a week is on annual or sick leave in the entire week of interest, their hours paid would still be 40, but their hours worked would be zero.

Gender and ethnicity data are from Stats NZ's personal details table. This table derives this information based on numerous IDI sources. Individuals may give different responses to an ethnicity question depending on the context (e.g. filling out a census form versus making an ACC claim etc.). As a result, there tend to be more individuals who are recorded as having multiple ethnicities in the IDI than in the HLFS. Using the same prioritisation method as with the HLFS data, therefore, results in a lower share of individuals identifying as European and a higher share identifying as belonging to other ethnic groups.

Part B: Analysis of structural drivers

In Part B we use data from the HLFS, Inland Revenue's Employer Monthly Schedule, and the 2018 Census (all sources can be linked via a confidentialised unique identifier attached to each individual). Data from the HLFS is used in a Blinder-Oaxaca decomposition that apportions each pay gap into 'explained' and 'unexplained' components. Data from Inland Revenue's Employer Monthly Schedule and the 2018 Census is used for a descriptive analysis of structural gender and ethnic differences in firm, occupation, and industry distribution.

2.2 Variables

For Part A's pay gap derivation using HLFS data, hourly earnings are defined as total hourly earnings from the respondent's main job or business in real terms (deflated to 2016 Q2 dollars using the Consumer Price Index). 'Total' earnings encompass regular earnings plus extra income such as allowances, bonuses, and commissions. Past research suggests that men benefit more than women from performance pay systems (e.g. profit sharing, bonuses etc.) (Fabling et al., 2012), which highlights that using regular earnings alone would likely underestimate pay gaps. Gender is defined as male or female. Ethnic group is defined at level 1 of Stats NZ's Ethnicity Standard Classification 2005, assigning respondents to one ethnic group based on the following prioritisation hierarchy: Māori, Pacific, Asian, Middle Eastern/Latin American/African (MELAA), Other ethnicity, European. This classification of ethnicity creates mutually exclusive ethnic categories which are necessary for the decomposition used in Part B. Industry is the respondent's industry of their main job defined at level 1 (division) of the Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006.

HLFS data from 2016 to 2022 are used to estimate pay gaps. In order to mitigate small numbers for some gender and ethnic groups within some industries in some years, we do two things. First, we pool data over two consecutive years, i.e., data are pooled over the 2016 and 2017 HLFS surveys, the 2017 and 2018 surveys, etc. This results in six pooled samples: 2016/17, 2017/18, 2018/19, 2019/20, 2020/21, and 2021/22. Henceforth we refer to each of these pooled samples as a 'year', and refer to the second year (e.g., 2021/22 is referred to as 2022). Second, we collapse the industry variable from the original 19 categories of ANZSIC down to 14 industry groupings. [2] For the sake of brevity, we refer to resulting long industry names by the industry with the most workers (e.g., 'Electricity, Gas, Waste & Water Services and Construction' is referred to as 'Construction') or a shortened name (e.g., 'Education and training' is referred to as 'Education') – see Table 2 for full information on the coverage of each industry grouping.

Pay gaps are estimated by gender, ethnicity, and combinations thereof (i.e., intersectional pay gaps). Due to small sample sizes for MELAA and Other ethnic groups, ethnic pay gaps are estimated only for Māori, Pacific and Asian populations (versus the European population). In total, 13 pay gaps are estimated for each of the 14 industry groupings across each of the six pooled-sample years, as shown in Table 1.

Table 1. 13 pay gaps estimated for 14 industries in each of six pooled years

Pay gap	Industry
Gender pay gap	
➢ Women vs. men	➢ Agriculture
Ethnic pay gaps	➢ Manufacturing
➢ Māori vs. European	➢ Construction
➢ Pacific vs. European	➢ Wholesale
➢ Asian vs. European	➢ Retail
Intersectional pay gaps	➢ Hospitality
➢ Māori women vs. European women	➢ Logistics
➢ Pacific women vs. European women	➢ Media & Finance
➢ Asian women vs. European women	➢ Professional Services
➢ Māori men vs. European men	➢ Administrative Services
➢ Pacific men vs. European men	➢ Public Administration
➢ Asian men vs. European men	➢ Education
➢ Māori women vs. European men	➢ Healthcare
➢ Pacific women vs. European men	➢ Arts & Recreation
➢ Asian women vs. European men	

Definitions of all variables used in the Part A analysis using HLFS and the decomposition in Part B are listed in Table 2. As shown in the table, for the Blinder-Oaxaca decompositions we make use of data on

[2] Some small underlying cell sizes (<100) remain for Pacific peoples and Asians in some industries in some years.

individual (age, sex, ethnicity, country of birth), household (sole parent status, partnership status, number of children, household income decile), geographical (region of NZ), educational (highest qualification attained), and job-related (occupation, part-time employment, permanent job, job tenure, employment continuity, union membership) characteristics. It was also necessary to collapse some categories to mitigate the issue of small cell numbers. For example, region was collapsed from six categories to five.

Table 2. Definitions of variables used in Part A (pay gap estimates) and Part B (decompositions)

Variable	Definition
Pay	
Total hourly earnings	Total hourly earnings from main job (includes allowances, bonuses, commissions, etc.), deflated to 2016 Q2 NZ dollars
Log total hourly earnings	Natural logarithm of total hourly earnings
Industry (abbreviated name)	
Agriculture	Dummy variable: 1 = Industry of main job is Agriculture, Forestry, Fishing and Mining; 0 otherwise
Manufacturing	Dummy variable: 1 = Industry of main job is Manufacturing; 0 otherwise
Construction	Dummy variable: 1 = Industry of main job is Electricity, Gas, Water, Waste Services and Construction; 0 otherwise
Wholesale	Dummy variable: 1 = Industry of main job is Wholesale Trade; 0 otherwise
Retail	Dummy variable: 1 = Industry of main job is Retail Trade; 0 otherwise
Hospitality	Dummy variable: 1 = Industry of main job is Accommodation and Food Services; 0 otherwise
Logistics	Dummy variable: 1 = Industry of main job is Transport, Postal and Warehousing; 0 otherwise
Media & Finance	Dummy variable: 1 = Industry of main job is Information Media and Telecommunications, Financial and Insurance Services, Rental, Hiring and Real Estate Services; 0 otherwise
Professional Services	Dummy variable: 1 = Industry of main job is Professional, Scientific and Technical Services; 0 otherwise
Administrative Services	Dummy variable: 1 = Industry of main job is Administrative and Support Services; 0 otherwise
Public Administration	Dummy variable: 1 = Industry of main job is Public Administration and Safety; 0 otherwise
Education	Dummy variable: 1 = Industry of main job is Education and Training; 0 otherwise
Healthcare	Dummy variable: 1 = Industry of main job is Health Care and Social Assistance; 0 otherwise
Arts & Recreation	Dummy variable: 1 = Industry of main job is Arts, Recreation and Other Services; 0 otherwise
Individual characteristics	
Sex	1 = Female; 0 = Male
Age	Age in years
Age-squared	Age in years squared
European	Dummy variable: 1 = European prioritised ethnicity; 0 otherwise
Māori	Dummy variable: 1 = Māori prioritised ethnicity; 0 otherwise

Table 2. Definitions of variables used in Part A (pay gap estimates) and Part B (decompositions) continued.

Individual characteristics	
Pacific	Dummy variable: 1 = Pacific prioritised ethnicity; 0 otherwise
Asian	Dummy variable: 1 = Asian prioritised ethnicity; 0 otherwise
MELAA and Other	Dummy variable: 1 = Middle Eastern, Latin American, African or Other prioritised ethnicity; 0 otherwise
NZ born	Dummy variable: 1 = born in NZ; 0 otherwise
Household characteristics	
Sole parent	Dummy variable: 1 = Sole parent with dependent child(ren); 0 otherwise
Partnered	Dummy variable: 1 = Partnered; 0 = Not partnered
Number of dependent children	Number of dependent children in family
Household income	Household weekly income decile
Region characteristics	
Auckland	Dummy variable: 1 = Auckland region; 0 otherwise
Waikato	Dummy variable: 1 = Waikato region; 0 otherwise
Wellington	Dummy variable: 1 = Wellington region; 0 otherwise
Rest of the North Island	Dummy variable: 1 = Rest of the North Island; 0 otherwise
South Island	Dummy variable: 1 = South Island; 0 otherwise
Education characteristics	
Bachelor's degree or higher	Dummy variable: 1 = Highest qualification is Level 7 (bachelor's degree, graduate certificate, or level 7 diploma) or higher (e.g. Masters, PhD); 0 otherwise
Post-school qualification	Dummy variable: 1 = Highest qualification is a post-school qualification (e.g. Level 1-4 certificates, Level 5-6 Diplomas); 0 otherwise
School qualification	Dummy variable: 1 = Highest qualification is a secondary school qualification; 0 otherwise
No qualification	Dummy variable: 1 = No qualification; 0 otherwise
Job-related characteristics	
Managers and professionals	Dummy variable: 1 = Occupation in main job is Manager or Professional; 0 otherwise
Technical, trade, community, and personal service workers	Dummy variable: 1 = Occupation in main job is Technical, Trade, Community or Personal Service worker; 0 otherwise
Clerical, administrative, and sales workers	Dummy variable: 1 = Occupation in main job is Clerical, Administrative or Sales worker; 0 otherwise
Machinery operators, drivers, and labourers	Dummy variable: 1 = Occupation in main job is Machinery Operator, Driver or Labourer; 0 otherwise
Part-time employment	Dummy variable: 1 = In part-time employment (<30 hours per week); 0 = In full-time employment ($\geq$30 hours per week)
Permanent job	Dummy variable: 1 = Main job is permanent; 0 otherwise
Job tenure	Number of weeks working in main job, ranging from 1 = Less than 1 month up to 7 = 10 years or more
Employment continuity of 1 to 4 months	Dummy variable: 1 = Employed for 1 to 4 months in the past 12 months; 0 otherwise
Employment continuity of 5 to 8 months	Dummy variable: 1 = Employed for 5 to 8 months in the past 12 months; 0 otherwise
Employment continuity of 9 to 11 months	Dummy variable: 1 = Employed for 9 to 11 months in the past 12 months; 0 otherwise
Employment continuity of 12 months	Dummy variable: 1 = Employed for 12 months in the past 12 months; 0 otherwise
Union member	Dummy variable: 1 = Member of a union; 0 otherwise

2.3 Sample selection

For each pooled sample, the following sample selection criteria are applied: HLFS respondents are restricted to those aged between 16 and 64 years who are paid employees (not an employer, self-employed, or an unpaid worker in a family business) with non-negative hourly earnings. We trim our sample by dropping individuals who fall into the top or bottom one percent of the distribution of positive hourly earnings in each pooled year. Due to the HLFS's rotating panel design, generally between one half and two-thirds of respondents will be present in two consecutive June HLFS surveys, and hence be represented twice in each pooled sample. However, they are retained to ensure that the representativeness of the sample to the underlying population of usual residents is maintained. Each pooled sample has a sample size of approximately 45,000 respondents.

For the description of structural gender and ethnic differences in firm, occupation and industry distribution in Part B, analysis is again restricted to individuals aged 16 to 64 years and the top and bottom one percent of the earnings distributions in each year are trimmed (as in Part A). Individuals who have multiple employers during any given year are assigned to the employer with whom they had the highest annual earnings. Individuals with employers that have multiple ANZSIC (industry) codes in a given year are assigned to the industry code in which they had the highest annual earnings. For analyses at the firm level, enterprises with multiple ANZSIC codes in any given year are assigned to the ANZSIC code in which the enterprise paid out the highest wages and salaries summed over all their employees. In each year, firms paying a mean wage (averaged over all their employees) that falls in the top and bottom one percent of the distribution of mean wage are dropped, as are firms with fewer than six employees.

3 Method

In Part A of our analysis, pay gaps for each industry in each year are estimated as follows (using the gender pay gap as an example):

$$\frac{\text{Men's mean real hourly earnings} - \text{women's mean real hourly earnings}}{\text{Men's mean real hourly earnings}} \times 100$$

The pay gaps are estimated using each group's mean (rather than median) hourly earnings because mean earnings are able to be used in the Blinder-Oaxaca decomposition employed in Part B. Moreover, while mean earnings are more sensitive to extreme values, we mitigate this issue by dropping individuals who fall into the top or bottom 1% of the earnings distribution (as described in Section 2). HLFS sample weights are applied when estimating pay gaps.

Having estimated the pay gaps, the next step is to understand what explanatory factors contribute to the gaps by using the standard decomposition approach in the literature for studying mean differences in outcomes between groups introduced by Oaxaca (1973) and Blinder (1973). This Blinder-Oaxaca decomposition technique quantifies how much of the pay gap can be 'explained' by group differences in productivity characteristics, and how much remains as a residual 'unexplained' component that cannot be accounted for by such differences in earnings determinants. The first step is to estimate wage equations for each group being compared – group A (e.g., men, Europeans) in equation (1) and group B (e.g., women, Māori) in equation (2):

$$\ln\left(w_{i,j,t}^{A}\right) = \beta^{A} X_{i,j,t}^{A} + \varepsilon_{i,j,t}^{A} \tag{1}$$

$$\ln\left(w_{i,j,t}^{B}\right) = \beta^{B} X_{i,j,t}^{B} + \varepsilon_{i,j,t}^{B} \tag{2}$$

where A and B superscripts denote the two groups being compared, the i subscript denotes the i^{th} wage earner, the j subscript denotes the j^{th} industry, the t subscript denotes the year, $\ln(w)$ denotes the natural logarithm of total hourly earnings, and X represents a vector of explanatory variables including individual, household, geographical, educational, and job-related characteristics.

The pay gap is calculated in equation (3) and decomposed in equation (4):

$$\overline{\ln(w^{A})} - \overline{\ln(w^{B})} = \widehat{\beta^{A}}\overline{X^{B}} - \widehat{\beta^{B}}\overline{X^{B}} \tag{3}$$

$$\overline{\ln(w^{A})} - \overline{\ln(w^{B})} = \beta^{*}\left(\overline{X^{A}} - \overline{X^{B}}\right) + \left\{\left(\widehat{\beta^{A}} - \beta^{*}\right)\overline{X^{A}} + \left(\beta^{*} - \widehat{\beta^{B}}\right)\overline{X^{B}}\right\} \tag{4}$$

where β^* is the coefficient vector from a pooled regression over both groups which is used to weight the differences in group characteristics[3], $\hat{\beta}$ represents the vector of coefficients estimated in the wage equations, and $\bar{X}$ is a vector of mean explanatory variable values. The first term on the right-hand side of equation (4) is the part of the pay gap that is explained by group differences in average characteristics (based on the explanatory variables outlined in Table 2). This 'explained' component can be further broken down to show the contribution of different groupings of characteristics to the overall gap (these groupings are also shown in Table 2). The second component on the right-hand side of (4) is the part of the pay gap left unexplained. This reflects differences in the returns to characteristics in the labour market and is more problematic to interpret. Why are there unexplained differences? There are several possible reasons. These include: (i) unobserved group differences in characteristics not captured in the current data; (ii) group differences in the non-pecuniary elements of jobs; (iii) discriminatory behaviour; (iv) unconscious bias, etc.

The Blinder-Oaxaca decompositions of each pay gap in each industry (and all industries combined) use data *pooled across all years* (2016 to 2022). HLFS sample weights are applied and standard errors are clustered at the individual level to account for individuals appearing more than once in each pooled sample.

A known issue with the Blinder-Oaxaca decomposition is that the results it produces can be affected by sample selection bias (Heckman, 1979), given that hourly earnings are only observed for employed individuals in our sample (the earnings of people who are not currently participating in the labour market are not observed). To correct our estimates for sample selection bias, we apply the Heckman correction procedure, which deducts the selection effects from the overall pay gap and then applies the decomposition equations to the adjusted pay gap. We do this correction for both groups being compared. The procedure requires one additional step before equations (1) to (4) above. This is to separately estimate probit models of labour force participation for group A (e.g., men, Europeans) in equation (5) and group B (e.g., women, Māori) in equation (6):

$$LFP^A = \varphi^A Z^A \tag{5}$$

$$LFP^B = \varphi^B Z^B \tag{6}$$

where A and B superscripts denote the two groups being compared and where the full HLFS sample (pooled across all years) is utilised, i.e., we do not restrict the analysis to waged employees (as was done

[3] Use of the coefficients from a pooled regression assumes that in the absence of discrimination, the 'wage structure' (or returns to productivity characteristics) that would prevail would be some amalgam of group A's and group B's coefficients.

for the estimation of pay gaps in Part A) but rather include individuals of all labour force statuses. In equations (5) and (6) LFP stands for labour force participation (equal to 1 for wage earners, the self-employed, the unemployed, and others in the labour force; and equal to 0 for those not in the labour force) and Z represents the vector of explanatory variables shown in Table 1 except for job-related characteristics. Then for each member of group A in equation (7) and group B in equation (8), the probability of participating in the labour force is predicted as:

$$\widehat{LFP_j^A} = \widehat{\gamma_1^A} Z_{1j}^A + \widehat{\gamma_2^A} Z_{2j}^A + \cdots + \widehat{\gamma_k^A} Z_{kj}^A \tag{7}$$

$$\widehat{LFP_j^B} = \widehat{\gamma_1^B} Z_{1j}^B + \widehat{\gamma_2^B} Z_{2j}^B + \cdots + \widehat{\gamma_k^B} Z_{kj}^B \tag{8}$$

where k and j subscripts denote the k^{th} explanatory variable and the j^{th} member of group A or group B in the sample.

A selection-correction parameter for each member of group A in equation (9) and group B in equation (10) is generated as:

$$Mills_j^A = \frac{(normalden(-\widehat{LFP^A}))_j}{1-(normal(-\widehat{LFP^A}))_j} \tag{9}$$

$$Mills_j^B = \frac{(normalden(-\widehat{LFP^B}))_j}{1-(normal(-\widehat{LFP^B}))_j} \tag{10}$$

where $normalden$ and $normal$ denote the standard normal density function and the cumulative normal distribution function, respectively. The selection-correction indices – inverse Mills ratios $Mills_j^A$ for group A and $Mills_j^B$ for group B – are added as additional variables into the decomposition procedure shown in equations (1) to (4), yielding the decomposition results corrected for selection bias.

4 Part A Results

In this section we present pay gaps across industries as evident from most recent HLFS data in 2021 and 2022. We then undertake exploratory analysis of pay gaps using 2021 IR data. We also use HLFS data to examine longitudinal trends over the last seven years.

4.1 Pay gaps in 2022

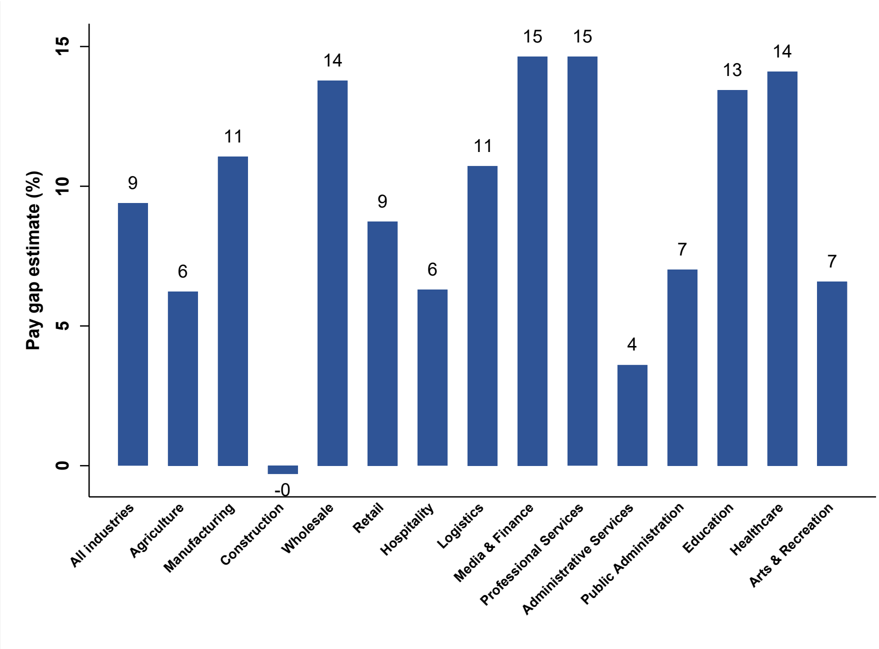
In 2022, the aggregate (all industries) gender pay gap was 9.4%. In terms of aggregate ethnic pay gaps, the Māori-European gap was 14.6%, the Pacific-European gap was 18.8%, and the Asian-European gap was 10.2%.

Gender pay gaps

Across industries, gender pay gaps vary considerably (Figure 1). There is a small negative gender pay gap in the Construction industry. However, this is also the industry with the lowest share of female workers (as evident in Section 5). At the other end of the spectrum, the gender pay gap is highest in Media & Finance (15%), Professional Services (15%), Healthcare (14%), Wholesale (14%), and Education (13%). Some of these industries with high gender pay gaps are male-dominated (e.g., Wholesale), but others are female-dominated (e.g., Healthcare and Education).

Note that in Appendix B we also provide *median* pay gaps by industry for completeness. These are provided for both gender and ethnic pay gaps. The median pay gaps are sometimes a little higher, sometimes a little lower compared to the mean pay gaps (shown in Figures 1 and 2 below). Importantly, the patterns are very similar, which is the key take out from these comparisons.

Figure 1. Gender pay gaps by industry, 2022



Source: Authors' calculations using pooled June 2021 and 2022 HLFS data

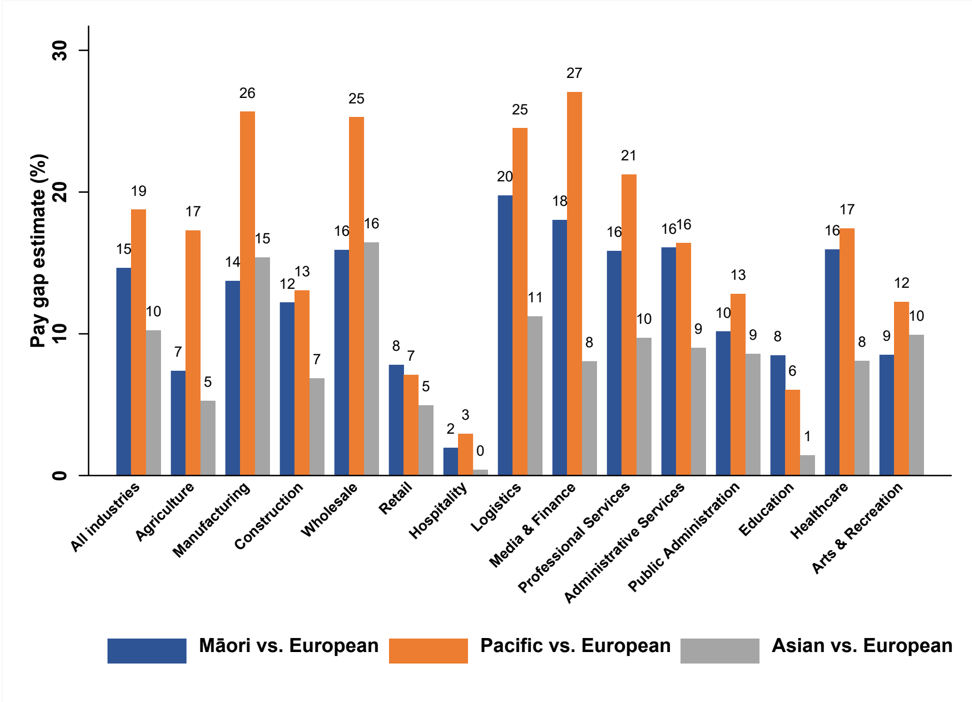
Ethnic pay gaps

Turning to ethnic pay gaps (Figure 2) and examining the Māori pay gaps by industry, these range from 2% in Hospitality to 20% in Logistics – a ten-fold difference. It should also be kept in mind, however, that for industries that have lower average pay rates, such as Hospitality, a relatively small pay gap is likely in part due to a compressed wage scale, leaving less room for pay differences across different groups of workers. It is worth noting that both of these industries have a relatively high share of Māori workers (as shown in Section 5).

The Pacific pay gap also has an almost ten-fold difference between the industry with the smallest pay gap (3% for Hospitality) and largest pay gap (27% for Media & Finance). Both of these industries have a relatively small share of Pacific workers (e.g. Pacific peoples account for less than 3% of workers in the Professional Services industry, as shown in Section 5). Overall, the Pacific pay gap is larger than the Māori pay gap in all industries except Retail.

The Asian pay gap by industry is generally smaller than the Māori and Pacific pay gaps. It is smallest in the Hospitality industry (0.4%) and largest in the Wholesale industry (16%).

Figure 2. Ethnic pay gaps by industry, 2022



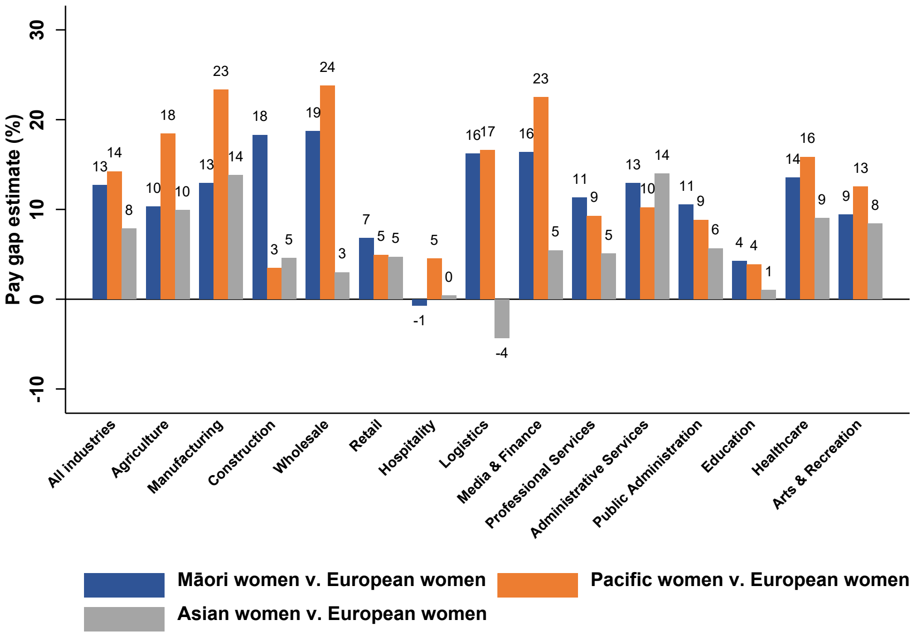
Source: Authors' calculations using pooled June 2021 and 2022 HLFS data

Intersectional pay gaps

We next look at results by gender and ethnicity. A caveat to be kept in mind with these results is that they may be more volatile due to a small number of workers in some categories. Recall that the year 2022 in our analysis refers to pooled 2021 and 2022 data, where pooling was undertaken to increase the sample size. For example, just 1,100 Pacific women worked in the Agriculture industry in 2021 and 2022. Note that this is the population weighted count, with the underlying number of survey respondents this represents being less than 10. Therefore, this result may not reliable due to it being based on a very small number of underlying individuals.

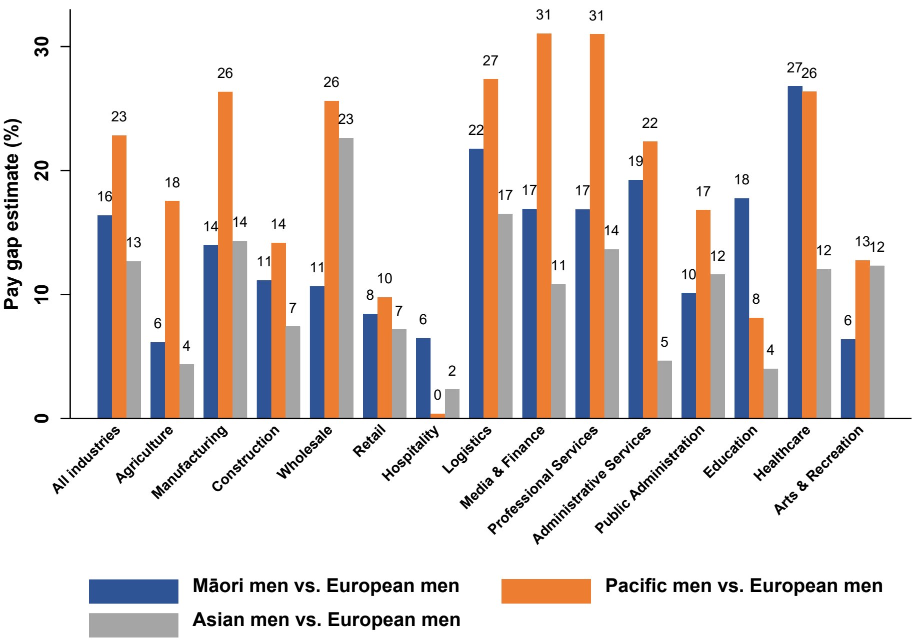
Figures 3 and 4 provide ethnic pay gaps within gender (for women and men respectively), while Figure 5 provides the ethnic pay gaps for women relative to men. As Figure 3 illustrates the ethnic pay gaps for women across all industries are 13%, 14%, and 8% for Māori, Pacific and Asian women relative to European women. When the same comparison is done for men in Figure 4, the aggregate (all industries) pay gaps are 16%, 23%, and 13% for Māori, Pacific and Asian men respectively relative to European men. As expected, when gender and ethnic pay gaps are combined, i.e. comparing ethnic women to European men (Figure 5), the pay gaps compound. The aggregate (all industries) pay gap for Māori women versus European men is 23%, for Pacific women versus European men is 24%, and for Asian women versus European men is 18%.

Figure 3. Ethnic pay gaps by industry, 2022: Women versus women



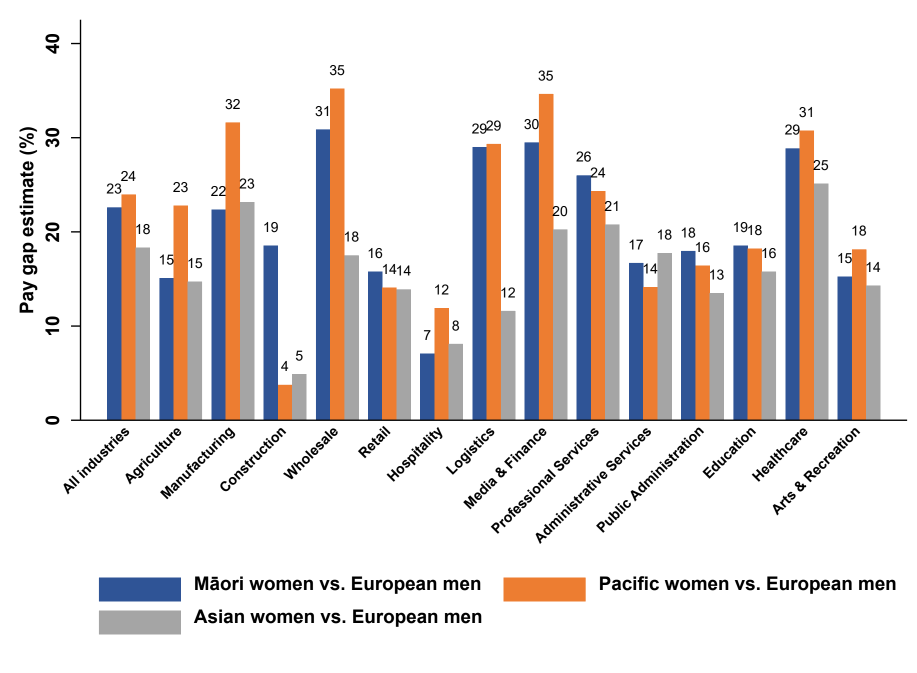
Source: Authors' calculations using pooled June 2021 and 2022 HLFS data

Figure 4. Ethnic pay gaps by industry, 2022: Men versus men



Source: Authors' calculations using pooled June 2021 and 2022 HLFS data

Figure 5. Ethnic pay gaps by industry, 2022: Women versus men



Source: Authors' calculations using pooled June 2021 and 2022 HLFS data

Figure 3 shows that the pay gaps for Māori, Pacific and Asian women compared with European women are small (under 5%) in industries such as Education. This is in contrast to the ethnic pay gaps in this industry when comparing women to men (Figure 5), where the pay gap rises to above 15%. This signals that the pay gaps in Figure 5 for this industry are largely driven by gender. In general, the pay gaps for Māori, Pacific and Asian women compared with European women are large in industries such as Wholesale and Media & Finance, with these industries having both sizeable gender and ethnicity pay gaps.

When examining ethnic pay gaps for men in Figure 4 we find that for Māori men, the pay gap is lowest in Agriculture (6%), and largest in Healthcare (27%). For Pacific men, it is smallest in Hospitality (0.4%), and largest in Media & Finance (31%). For Asian men, it is smallest in Hospitality (2%) and largest in the Wholesale industry (23%).

There is substantial variation in the pay gaps shown in Figures 3, 4 and 5. For example, in Figure 5, for Māori women, the pay gap with European men ranges from 7% in Hospitality to 31% in Wholesale. For Pacific women, the pay gap with European men ranges from 4% in Construction to 35% in Wholesale. For Asian women, the pay gap with European men ranges from 5% in Construction to 25% in Healthcare.

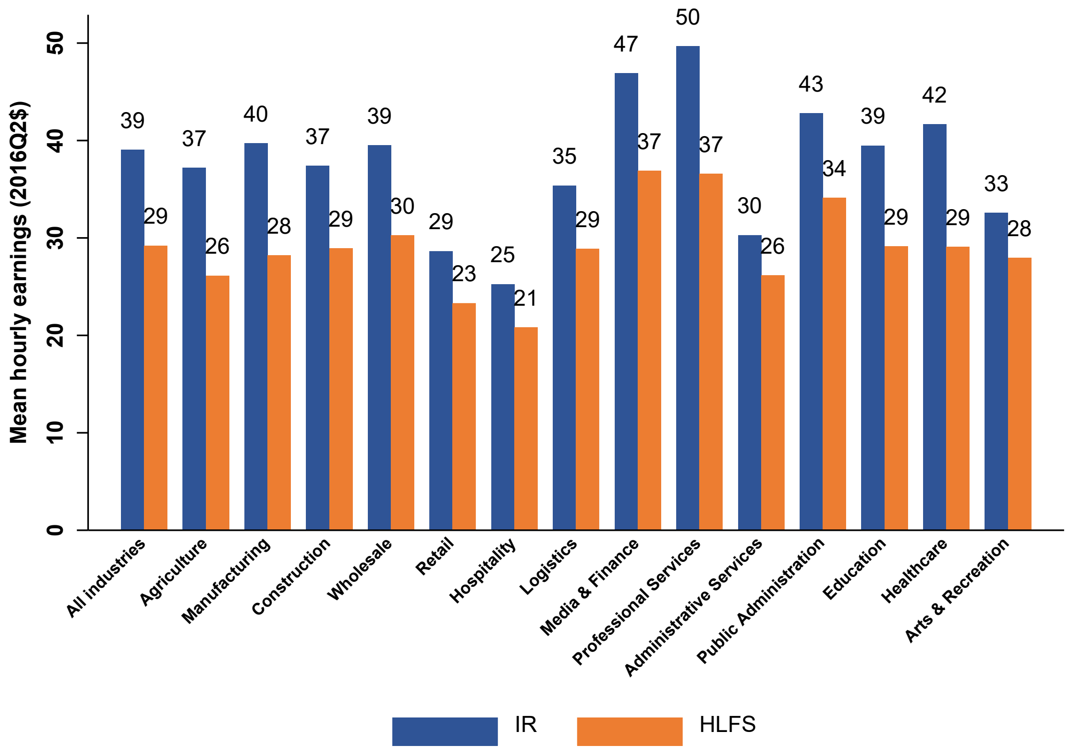
In summary, in some industries, such as Education and Hospitality, the ethnic pay gaps within gender are relatively small, whereas the ethnic pay gaps across gender are substantively larger – this signals that the pay gaps for Māori/Pacific/Asian women relative to European men are mostly driven by gender pay disparities. In contrast, in other industries, such as Administrative Services and Construction, the ethnic pay gaps within gender are relatively similar to the ethnic pay gaps across gender, indicating that the pay gaps for Māori/Pacific/Asian women relative to European men in this sector are predominantly driven by ethnic pay disparities.

4.2 Exploratory analysis of pay gaps using IR data

This subsection looks at pay gaps calculated using IR administrative data for June 2021. As mentioned in Section 2.1, June 2021 was chosen as the latest time period with the necessary data (in particular, industry of employment). Note that for comparisons with HLFS data, the time periods do not exactly match, as the HLFS data is a combination of 2021 and 2022 data.

Before examining pay gaps using IR data, we look at mean hourly earnings by industry calculated using IR versus HLFS data (Figure 6). In all industries, mean hourly earnings calculated using IR data are higher than those calculated using HLFS. It is unclear why this is. One possibility is that IR uses hours paid information while HLFS uses hours worked. However, hours paid is not necessarily systematically lower than hours worked. Hours paid can be higher than hours worked (e.g., due to periods of paid leave), or can be lower (e.g., due to unpaid overtime). In addition, the difference between hours paid and hours worked is unlikely to be of a magnitude that would account for the difference in mean hourly earnings. Another possibility is that HLFS underestimates mean hourly earnings due to an undersampling of high-income earners, which is a known issue with household surveys (Lustig, 2019). A further possibility is that IR data only includes about 40% of employees who have recorded hours information. Those who have hours information may not be representative of all employees in the relevant industry. For example, a greater share of large firms provide IR with hours information for their employees (Najam & Allan, forthcoming). It may be that the higher average pay in the IR data reflects that coverage is better for larger firms, who also tend to have higher average pay than smaller firms. While the latter possibility seems the more likely candidate given the magnitude of the differences, further investigation would be required to determine this.

Figure 6. Mean hourly earnings by industry: IR versus HLFS

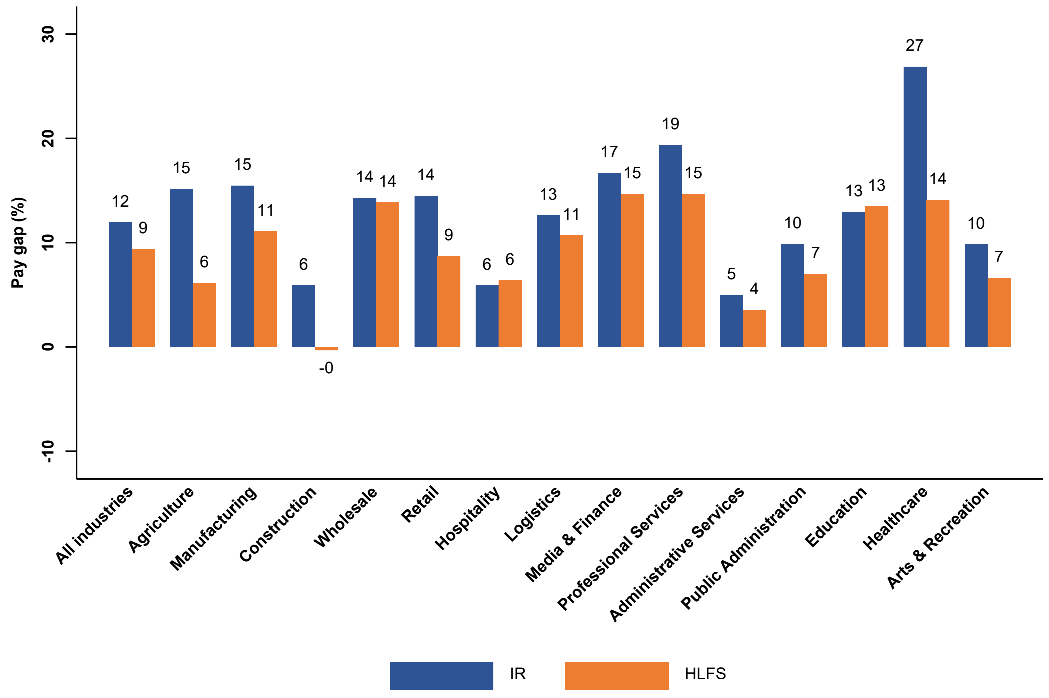


Source: Authors' calculations using pooled June 2021 and 2022 HLFS data and June 2021 IR data.

Turning to pay gaps and first examining gender pay gaps by industry, estimates using IR data are larger than HLFS estimates in all industries except Hospitality and Education (Figure 7). Some of these differences are small (e.g., in Wholesale), but some are very large. The largest differences are in Healthcare, with an IR gender pay gap estimate of 27% versus an HLFS estimate of 14%, and Agriculture, with an IR estimate of 15% versus an HLFS estimate of 6%. Other sizeable differences include Retail (14% versus 9%), Manufacturing (15% versus 11%), Professional Services (19% versus 15%) and Construction (6% versus -0.3%).

Understanding why these differences between IR and HLFS results arise would require further investigation. It may have something to do with larger firms being more likely to have hours information, as firm size may also be correlated with the magnitude of pay gaps. The difference in healthcare may be particularly large because there are a relatively small number of large employers in this industry (namely, District Health Boards during the time period being investigated). Large employers in this industry also are more likely to have hours information in the IR data. However, further investigation would be needed to more firmly establish the reasons behind these differences.

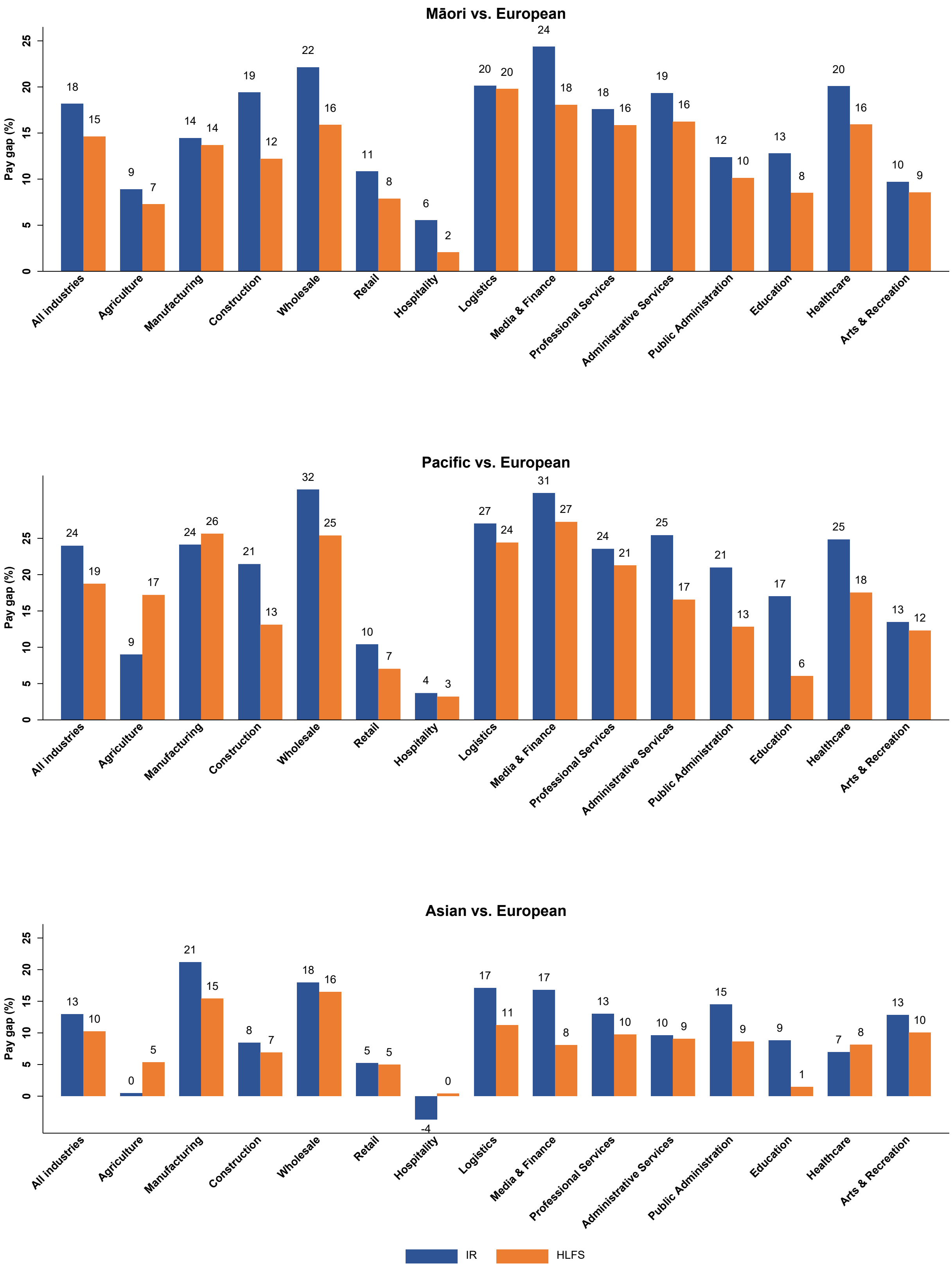
Figure 7. Gender pay gaps by industry: IR versus HLFS



Source: Authors' calculations using pooled June 2021 and 2022 HLFS data and June 2021 IR data.

In terms of ethnic pay gaps (Figure 8), as with gender pay gaps, the IR-estimated pay gaps are again generally larger than the HLFS-estimated pay gaps. Also similar to gender pay gaps, Māori and Pacific pay gaps in Healthcare are particularly large when measured using IR rather than HLFS (20% versus 16% and 25% versus 18% respectively). There are also large differences between the IR and HLFS pay gaps in Construction for Māori and Pacific pay gaps. Also for Māori and Pacific pay gaps, there are also large differences between IR and HLFS measures in Wholesale, whereas there are almost no difference in the gender pay gap in this industry.

Figure 8. Ethnic pay gaps by industry: IR versus HLFS



Source: Authors' calculations using pooled June 2021 and 2022 HLFS data and June 2021 IR data.

4.3 Industry pay gaps over time

This section continues the helicopter view of industry pay gaps, with a longitudinal lens, using HLFS data. The specific focus is on gender and ethnic pay gaps. Key findings are provided with respect to illustrating the industries with increases (or decreases) in gender and/or ethnic pay gaps over the years 2017 to 2022. For another perspective that focuses on each industry separately and includes the intersectional results, see a full summary of trends in all pay gaps in Appendix C.

Gender pay gaps over time

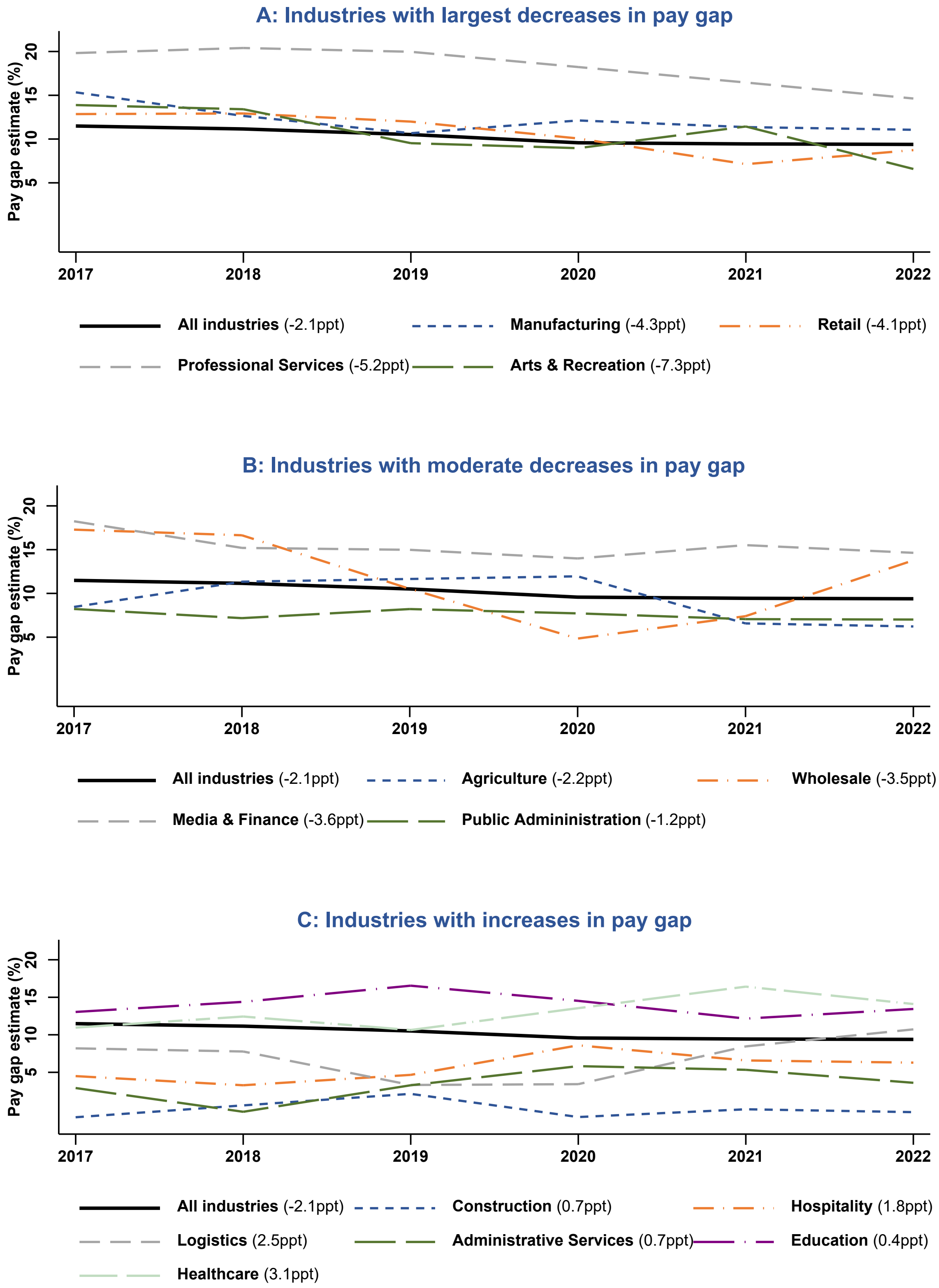
Figure 9 presents gender pay gaps by industry over the time period of our sample. Panel A presents industries that had a large decrease in their pay gaps (in percentage point (ppt) terms), Panel B presents industries that had small to moderate decreases in their pay gaps, and Panel C presents industries that had an increase in their pay gaps. The threshold level splitting moderate and large decreases in pay gaps was -4 ppt.[4] All results are presented relative to the 'all industries' average trend.

In aggregate (all industries), the gender pay gap has decreased by 2ppt, or 18% (from 11% in 2017 to 9% in 2022). By industry, the largest decrease was in Arts & Recreation (-7ppt or -53%, from 14% to 7%). The Professional Services industry also experienced a large decrease (-5ppt or -26%, from 20% to 15%). However, this large percentage point decrease was possibly because of the high starting point, with this industry having the largest pay gap in 2017 (20%). By 2022, it had the second largest pay gap (14.63%), which was slightly smaller than the pay gap in Media & Finance (14.64%).

The industry with the largest percentage point increase in their gender pay gap was Healthcare (3ppt or 29%, from 11% in 2017 to 14% in 2022). Hospitality had a lower starting pay gap than Healthcare (5% versus 13%), and experienced a larger percentage increase (40%), but a smaller percentage point increase (2ppt). Education also experienced a small increase. The government is a large employer in both the Healthcare and Education industries. Any ongoing and further initiatives towards improving pay parity in healthcare and education (e.g. increasing the pay of nurses working in places like aged-care facilities and Māori and Pacific health organisations to be on pay with hospital nurses; recent and future pay equity settlements in health and education) will be important to monitor with respect to the gender and ethnic pay gaps in this sector.

[4] This threshold was adjusted to -3 ppt when analysing many of the ethnic pay gaps, due to smaller changes over our sample period.

Figure 9. Gender pay gaps by industry over time



Source: Authors' calculations using 2016-2022 HLFS data
Notes: Numbers in parentheses refer to percentage point change between 2017 and 2022.

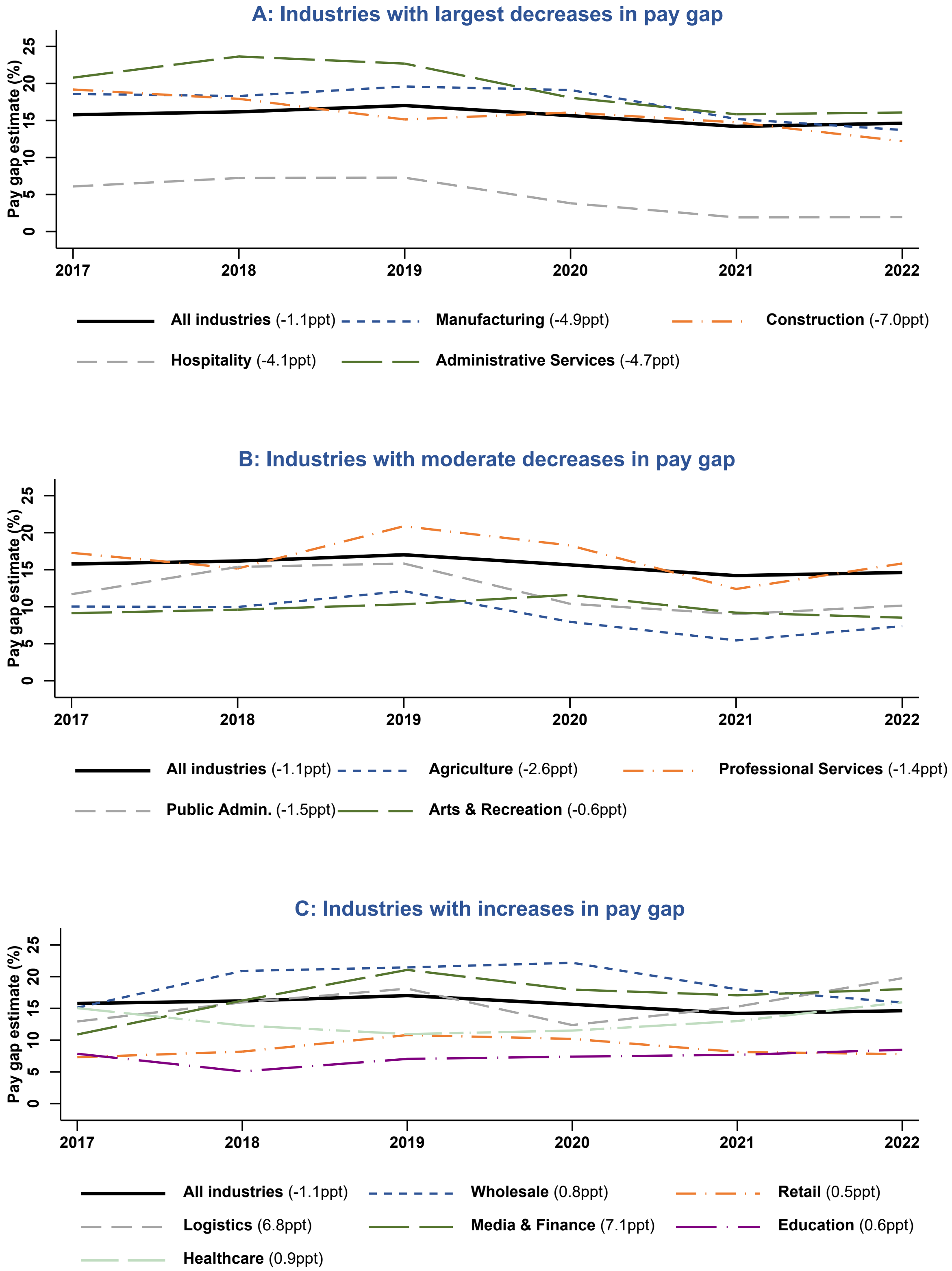
Māori pay gaps over time

The aggregate (all industries) Māori pay gap has reduced marginally from 16% in 2017 to 15% in 2022 (-1ppt or -7%) (Figure 10). Recall that the comparison group for all ethnic pay gaps is the European population. Not only is the 2017 Māori pay gap starting point of 16% higher than the starting point for the gender pay gap (11%), it has failed to decrease by as much over time (-2ppt decrease for the gender pay gap versus -1ppt for the Māori pay gap).

The Construction industry experienced the largest percentage point decrease in the Māori pay gap (Figure 10 Panel A), with the gap decreasing by 7ppt or 36% (from 19% to 12%). Additionally, Hospitality had a large decrease in percentage terms, going from 6% to 2%, a 69% decrease.

At the other end of the spectrum, the Māori pay gap grew between 2017 and 2022 in six industries (Figure 10 Panel C). The pay gap in the Media & Finance industry increased from 11% to 18% (7ppt or 66%). This contrasts with the gender pay gap in this industry, which decreased from 18% to 15% over the same time period (Figure 9 Panel B). Similarly, while the gender pay gap in Professional Services, which is another high-wage industry, decreased from 20% to 15%, the Māori pay gap in this industry decreased much less (from 17% to 16%). However, like the gender pay gaps, the Māori pay gaps in the Education and Healthcare industries have increased over time, the former increasing from 8% to 9%, and the latter increasing from 15% to 16%. While the pay equity settlements relate to gender-based pay undervaluation in female-dominated occupations and do not cover ethnic disparities, recent and upcoming pay settlements in health and education may work to improve ethnic pay gaps in these industries. Moreover, the government health sector pay parity initiatives (e.g. to achieve parity for community nurses with currently higher-paid hospital nurses) may also contribute to reducing ethnic pay gaps if Māori and Pacific nurses are more likely to work in community health roles (e.g. Māori and Pacific health organisations, aged-care facilities, etc.). In addition, the government has recently proposed pay equity settlements for specialist Māori educator roles (kaiārahi i te reo) and increased the pay of kōhanga reo kaiako to achieve pay parity with other early learning centres and kindergartens teachers.

Figure 10. Māori vs. European pay gaps by industry over time



Source: Authors' calculations using 2016-2022 HLFS data.
Notes: Numbers in parentheses refer to percentage point change between 2017 and 2022.

Pacific pay gaps over time

The aggregate (all industries) Pacific pay gap decreased from 21% in 2017 to 19% in 2022 (Figure 11). While this is a similar percentage point decrease to the gender pay gap over the same period, it is smaller in percentage terms (-11% versus -18%) because the Pacific pay gap is larger.

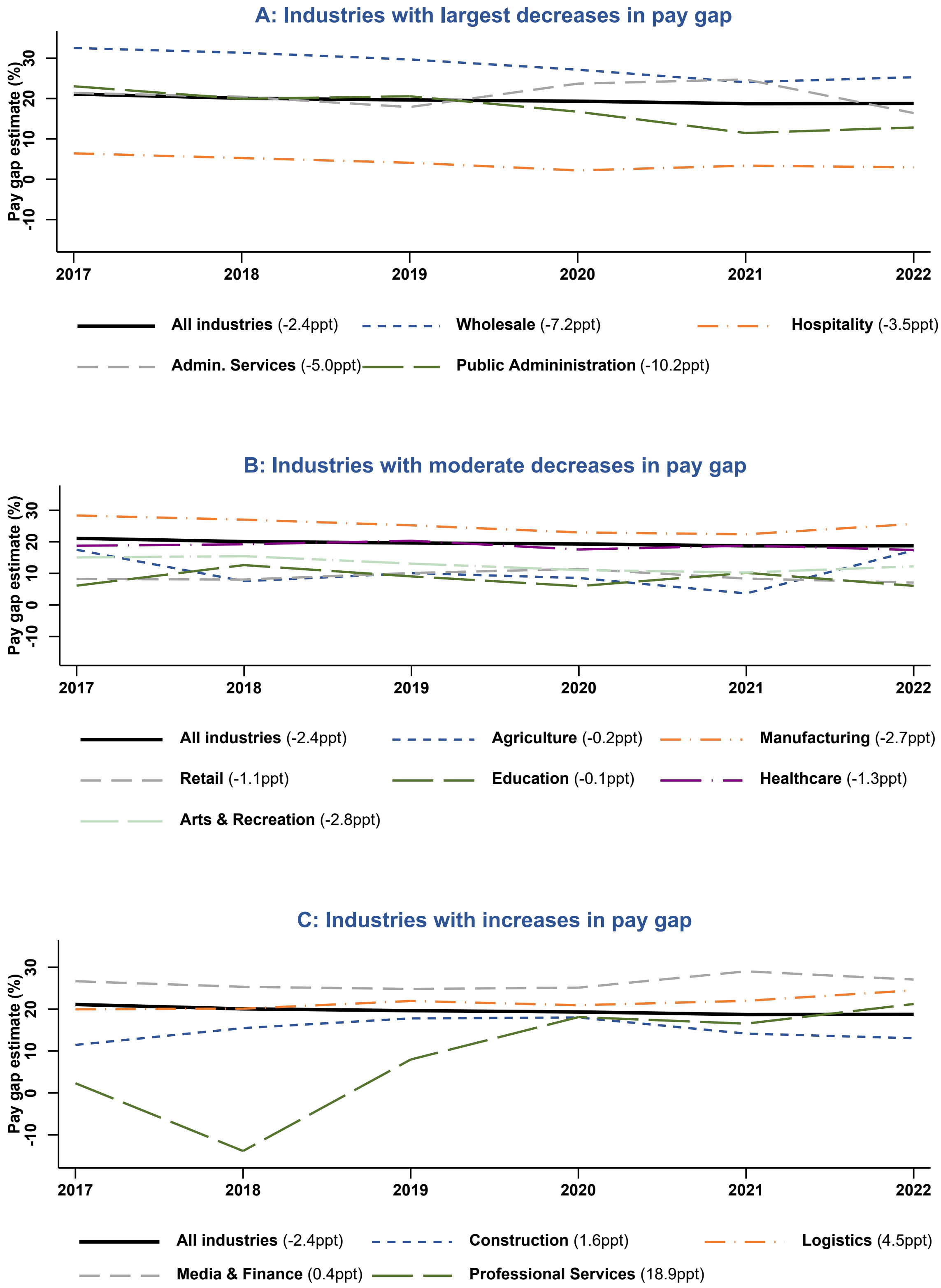
When interpreting the Pacific pay gap estimates displayed in Figure 11, some caution should be taken as there are a small number of Pacific workers in several industries, which then results in small HLFS sample size. For example, there are only 5,600 Pacific workers in our population of interest who are employed in the Professional Services industry, with information for this group being based on the underlying HLFS data of 40 unweighted counts. This is likely why the pay gaps for this industry are volatile, ranging from -14% to 19% over the 2017 to 2022 period. Similarly, there are very few Pacific workers in the Agriculture industry. [5]

The industries with the largest percentage point decrease in the Pacific pay gap between 2017 and 2022 are Public Administration (-10ppt or -44%, from 23% to 13%) and Wholesale Trade (-7ppt or -22%). More progress has been made in the Pacific pay gap than the Māori pay gap in the Public Administration industry (which decreased by 5ppt from 21% to 15%), resulting in the Pacific pay gap now being slightly lower than the Māori pay gap in this industry. The industry with the largest increase in this pay gap over the same time period (excluding Professional Services due to the reason given above) is Logistics (5ppt or 23%).

Also of note, the Pacific pay gap is high in the Manufacturing industry, where Pacific workers are also overrepresented (see Section 5.1). While the Māori pay gap in Manufacturing has decreased from 19% in 2017 to 14% in 2022, there has been a smaller decrease for the Pacific pay gap, despite a higher starting point (from 28% in 2017 to 26% in 2022). On a more positive note, while the gender and Māori pay gaps in the Education and Healthcare industries increased between 2017 and 2022, the Pacific pay gaps in these industries have decreased. Nonetheless, there is enough volatility in these series that a longer time series would allow a more definitive finding regarding the trends in these sectors.

[5] Note that the target population of HLFS is those usually resident in NZ, and therefore would not necessarily include Recognised Seasonal Employer (RSE) workers, who are recruited from eligible Pacific countries and only allowed to stay in NZ for a limited time.

Figure 11. Pacific vs. European pay gaps by industry over time



Source: Authors' calculations using 2016-2022 HLFS data
Notes: Numbers in parentheses refer to percentage point change between 2017 and 2022.

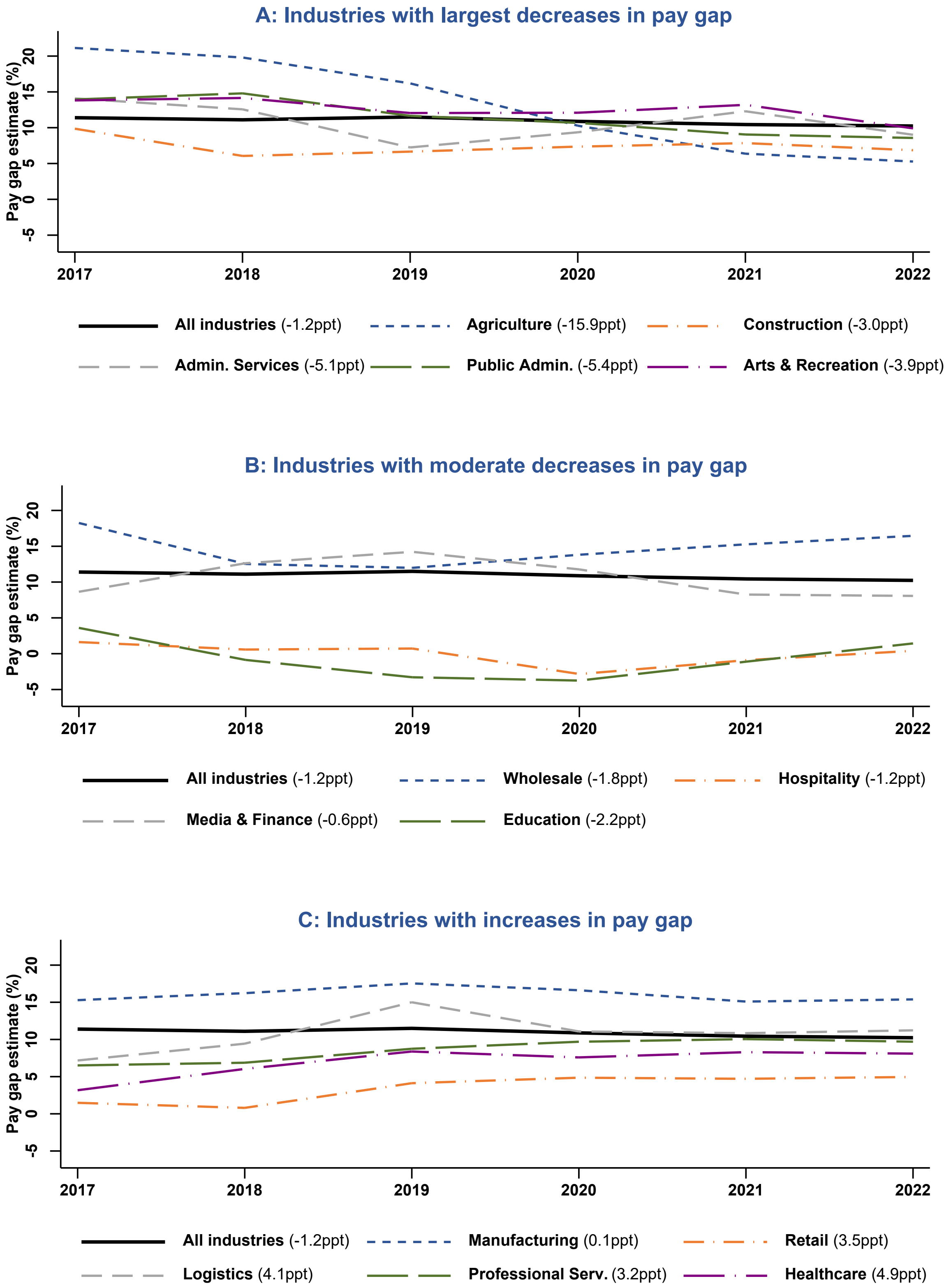
Asian pay gaps over time

Figure 12 presents Asian pay gaps by industry over time, relative to the comparison population of Europeans. In aggregate (all industries), the Asian pay gap was 11% in 2017 and decreased marginally to 10% by 2022.

The industry with the largest percentage point decrease is Agriculture (-16ppt or -75%, from 21% in 2017 to 5% in 2022). However, as with Pacific workers, there is a small underlying HLFS sample of Asian workers in this industry, so the trend in this particular sector should be interpreted with caution.

As Figure 12, Panel A shows there were also large decreases in Public Administration (-5ppt or -38%, from 14% to 9%) and Administrative Services (-5ppt or -36%, from 14% to 9%). At the other end of the spectrum, as Figure 12 Panel C shows, the Asian pay gap increased (in percentage point terms) the most in the Healthcare industry (5ppt or 155%, from 3% to 8%). It also increased in Retail (by 235% to 5%, albeit from a low starting point of 1.5%), Logistics, Professional Services and Manufacturing.

Figure 12. Asian vs. European pay gaps by industry over time



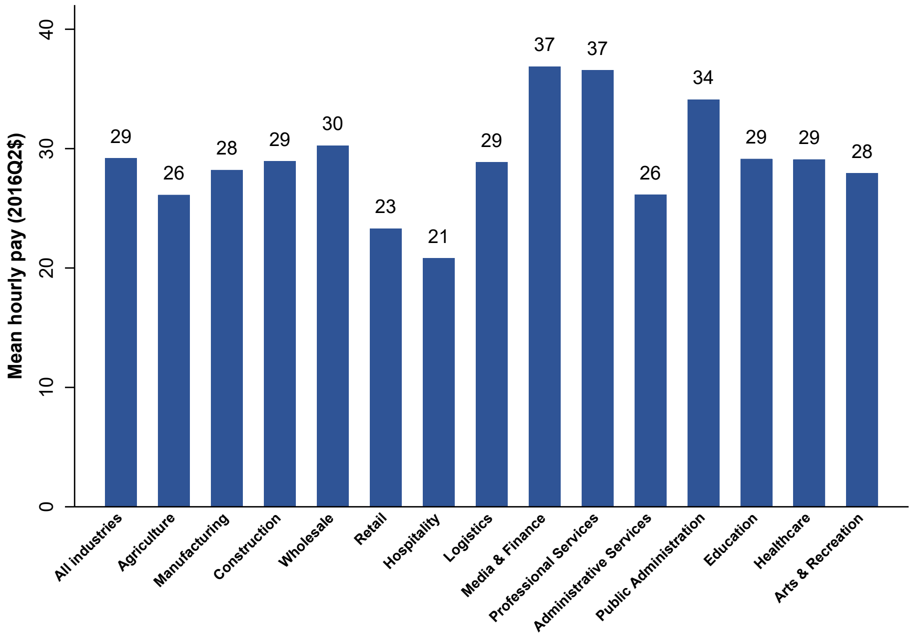
Source: Authors' calculations using 2016-2022 HLFS data
Notes: Numbers in parentheses refer to percentage point change between 2017 and 2022.

5 Part B Results

This section examines structural issues that can contribute to pay gaps. This includes delving into gender and ethnic differences in the firms, occupations and industries in which people work.

Before delving into these structural issues, we present some context on the mean hourly pay by industry in 2022 (Figure 13). Media & Finance and Professional Services have the highest average hourly pay rates ($37 in 2016Q2$). Conversely, Hospitality ($21) and Retail ($23) have the lowest average hourly pay rates.

Figure 13. Mean hourly pay by industry, 2022



Source: Authors' calculations using June 2022 HLFS data

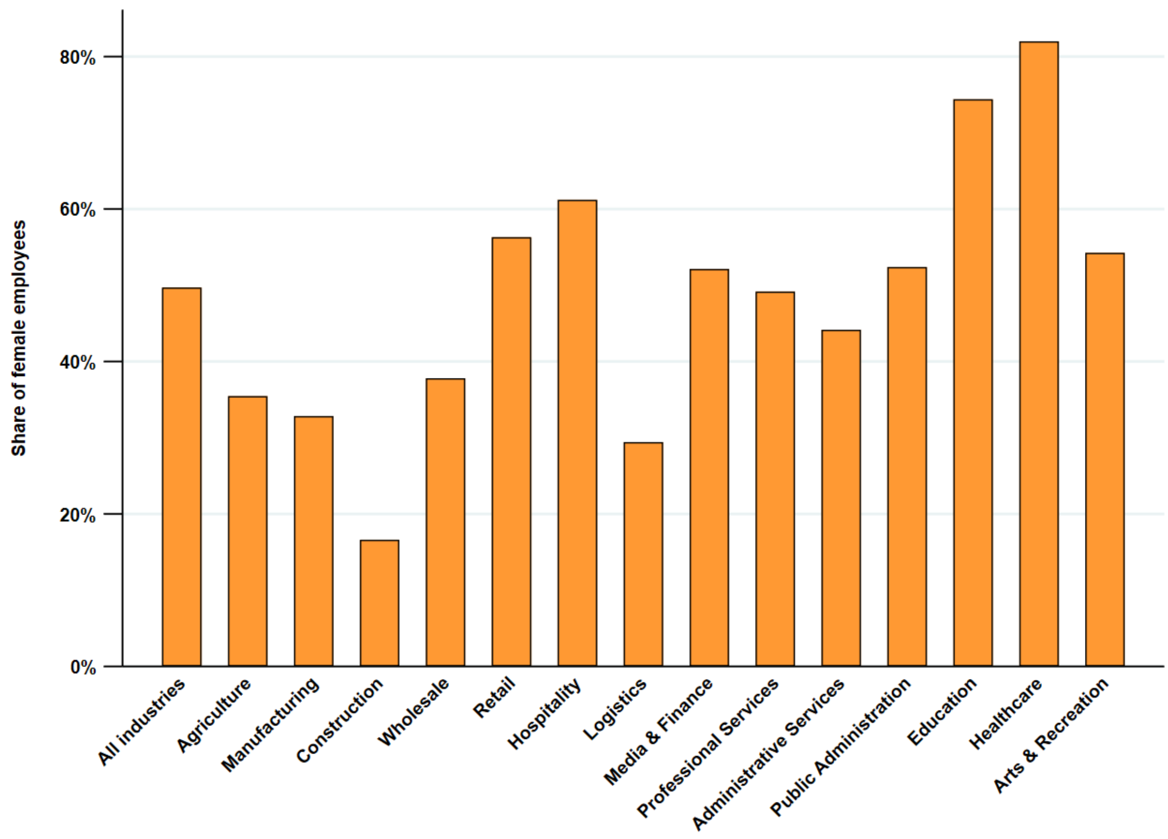
In the remaining descriptive analysis, note that we use population-wide administrative data from Inland Revenue and the 2018 Census rather than HLFS data. As such, earnings for an individual are defined as gross annual wages and salaries summed over all employers across the 12 months ended 30 June for the respective year. Occupational analysis uses 2018 Census data. Occupation is defined at level 1 (major group with eight categories) of the Australian and New Zealand Standard Classification of Occupation (ANZSCO) 2006. Note also that the variables for gender, ethnicity, and industry are defined the same in this section as in Part A (see Section 2).

5.1 Workforce compositions by industry

While Part A focuses on within-industry pay gaps, it is important to keep in mind that aggregate pay gaps can in part be driven by women and/or non-Europeans being more likely to work in lower-paying industries. Therefore, this subsection examines the gender and ethnic distribution of workers by industry – see Figures 14 and 15. For example, for gender, we examine the number of female employees as a share of all employees within each industry.

In aggregate (all industries), the share of female employees is 49.7% (noting that this is total employee count, unadjusted for hours). Females are overrepresented in low-pay industries such as Hospitality (61%) and Retail (56%). Females are most overrepresented in Education (74%) and Healthcare (82%), which have similar mean hourly pay rates as the aggregate (all industries) rate. Females are most underrepresented in Construction, where they account for 17% of employees, followed by Logistics (29%), Manufacturing (33%) and Agriculture (35%). The two highest-paying industries, Media & Finance and Professional Services, have about the same shares of female employees as the aggregate share (52% and 49% respectively).

Figure 14. Share of female employees by industry



Source: Authors' calculations using IR LEED data, year ended June 2021

Turning to ethnicity, across all industries, Europeans account for 54% of workers, Māori account for 16%, Pacific 7% and Asians 19%. Europeans are most overrepresented in the Education (accounting for 64% of workers) and Professional Services (65%) industries, and most underrepresented in Administrative Services (36%) and Hospitality (42%).

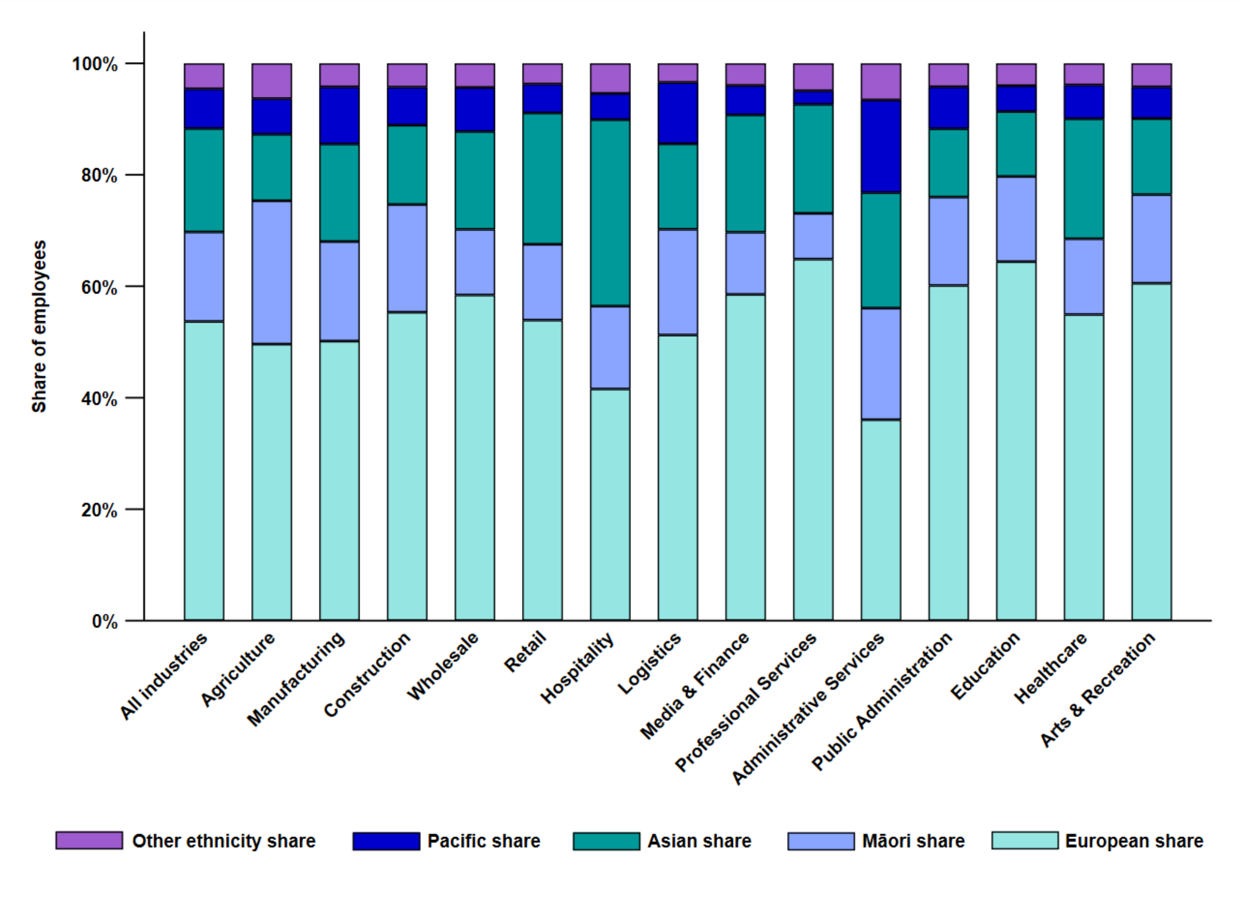
The high share of Europeans in Education also raises potential issues in terms of intergenerational transmission of ethnic pay gaps via educational outcomes. International research finds that students generally have better academic outcomes when they have a teacher who is more similar to them in terms of ethnicity and gender (e.g. Dee, 2005; Redding, 2019). For NZ, research highlights that teachers are also more likely to underestimate the abilities of Māori students compared with European students and that Māori students perceive their schools to have lower academic aspirations for them than their European counterparts (Hynds et al., 2017; Rubie-Davies et al., 2006; Rubie-Davies & Peterson, 2016).

Māori are most overrepresented in Agriculture (accounting for 26% of workers) and Administrative Services (20%). Māori are most underrepresented in the two highest paying industries: Professional Services (8%) and Media & Finance (11%). They are also somewhat underrepresented in Healthcare (14%) and Education (15%).

Pacific workers are most overrepresented in Administrative Services (17%), Logistics (11%) and Manufacturing (10%). Like Māori, they are underrepresented in the high-paying industries of Professional Services (2%) and Media & Finance (5%), as well as Education (5%) and Hospitality (5%).

Asian workers are overrepresented in Hospitality (accounting for 33% of workers), Retail (24%) and Healthcare (22%). They are also overrepresented in the high-wage industries of Media & Finance (21%) and Professional Services (20%). They are most underrepresented in Agriculture (12%) and Education (12%).

Figure 15. Share of employees by ethnicity and industry



Source: Authors' calculations using IR LEED data, year ended June 2021

5.2 Differences in the earnings distribution by industry

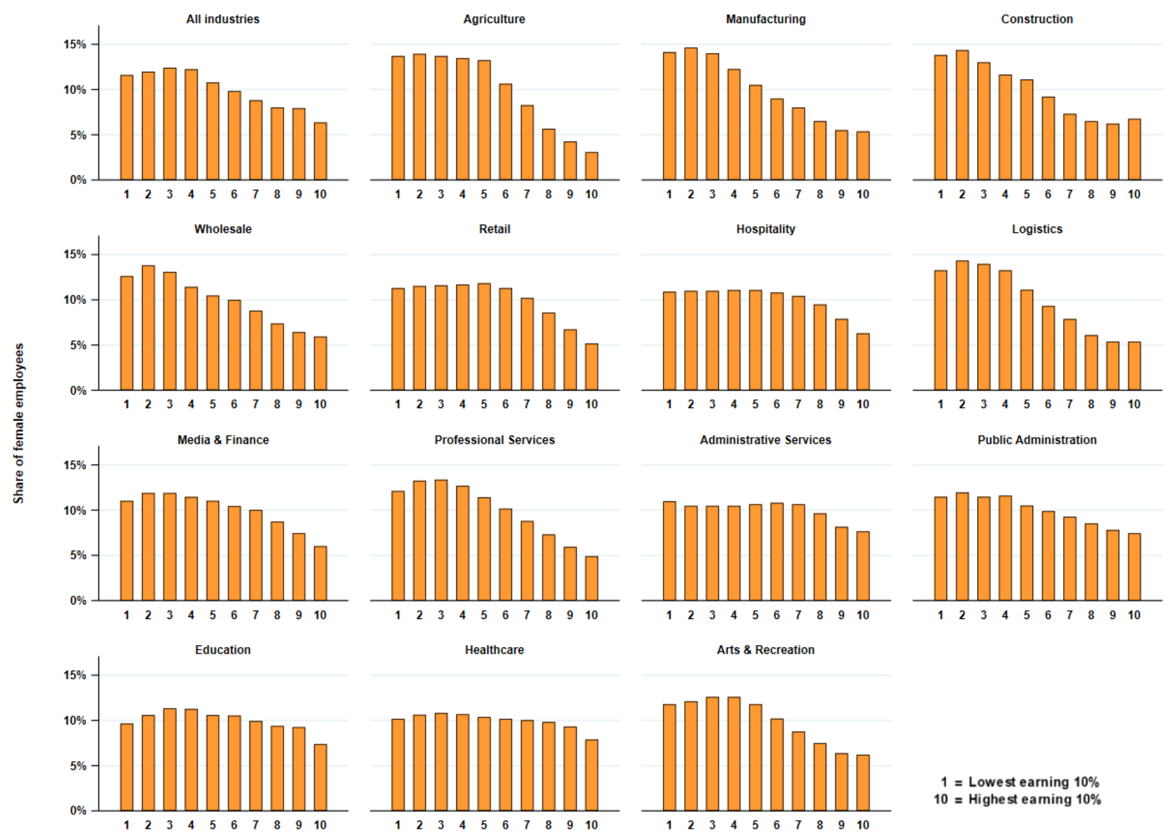
This subsection looks at gender and ethnic differences in the earnings distribution in more detail. It examines gross *annual* earnings for the year ended June 2021 from IRD data, rather than hourly pay from HLFS due to issues of small cell sizes for some industry and gender/ethnicity combinations. Thus, it does not adjust for hours or part-year work. It includes all those with positive wage or salary earnings.

Figure 16 examines the share of women who fall into each earnings decile by industry. For example, the earnings of all workers (both men and women) in Agriculture are split so that 10% of workers are in each decile. We then examine what share of women fall into each decile. If men and women had an equal earnings distribution, we would expect that 10% of women would fall into each decile. However, for most industries there is a clear pattern whereby women are more likely to fall into the lower earning deciles and less likely to fall into the higher earning deciles. Indeed, all industries have more than 30% of women falling in the bottom three deciles, and less than 30% of women falling in the top three deciles. The industries with the highest share of women in the bottom three deciles are Manufacturing (43%) and

Agriculture (41%), and the industries with the lowest share are Healthcare and Administrative Services (both 32%).

There are some apparent discrepancies between the gender pay gaps in Figure 1 and the annual earnings distributions shown in Figure 16. For example, the gender pay gap in Construction is close to zero, but the earnings distribution shows women are much more likely to be in the bottom earnings deciles than men. However, this appears to be due to differences in the IRD versus HLFS data. The distribution of *hourly* earnings in Construction using HLFS data is much flatter, with women more evenly distributed across the hourly earnings deciles (not shown, graphs available upon request). It may be, for example, that women in the Construction industry are much more likely to work part-time than men, resulting in a more skewed distribution of annual earnings, but a flatter distribution for hourly earnings. The annual earnings distribution for Healthcare (Figure 16) is relatively flat given how large the pay gap in this industry is (Figure 1). The hourly earnings distribution (not shown) is also relatively flat, although women are more underrepresented in the top deciles.

Figure 16. Share of female employees by decile of gross annual earnings, by industry



Source: Authors' calculations using IR LEED data, year ended June 2021

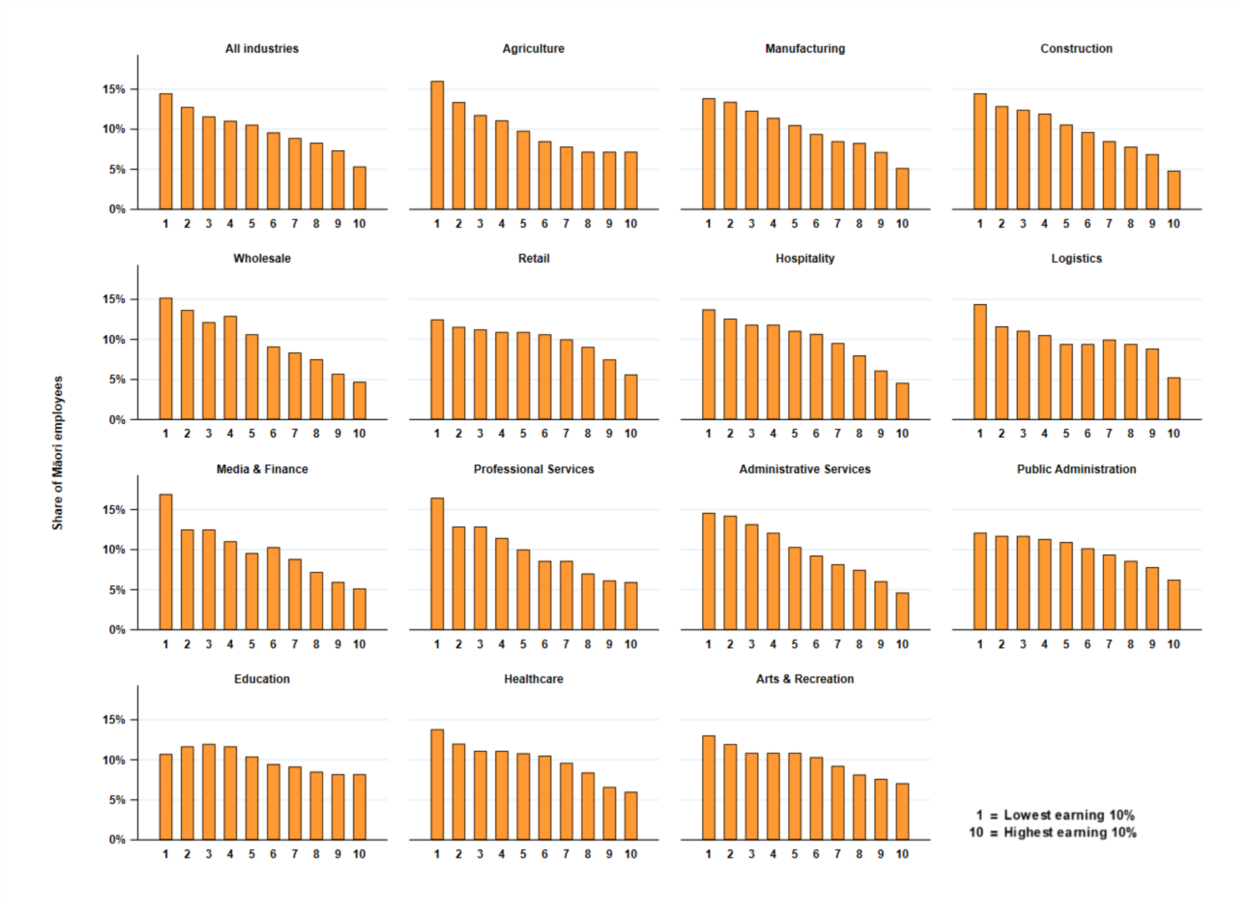
Figure 17. Share of European employees by decile of gross annual earnings, by industry

Source: Authors' calculations using IR LEED data, year ended June 2021

Looking at ethnicity, for all industries, less than 30% of European workers fall in the bottom three deciles of the annual earnings distribution, except the Hospitality and Healthcare industries, where 32% and 31% of European employees fall into the bottom three deciles, respectively (Figure 17). Correspondingly, more than 30% of European workers fall into the top three deciles in all industries except Hospitality, with 27% of European workers.

As Figure 18 shows, more than 30% of Māori workers fall into the bottom three earnings deciles in all industries. Professional Services, Administrative Services, and Media & Finance have the highest shares of Māori workers falling into the bottom three deciles (all 42%). The Education and Retail industries have the lowest shares (34% and 35% respectively).

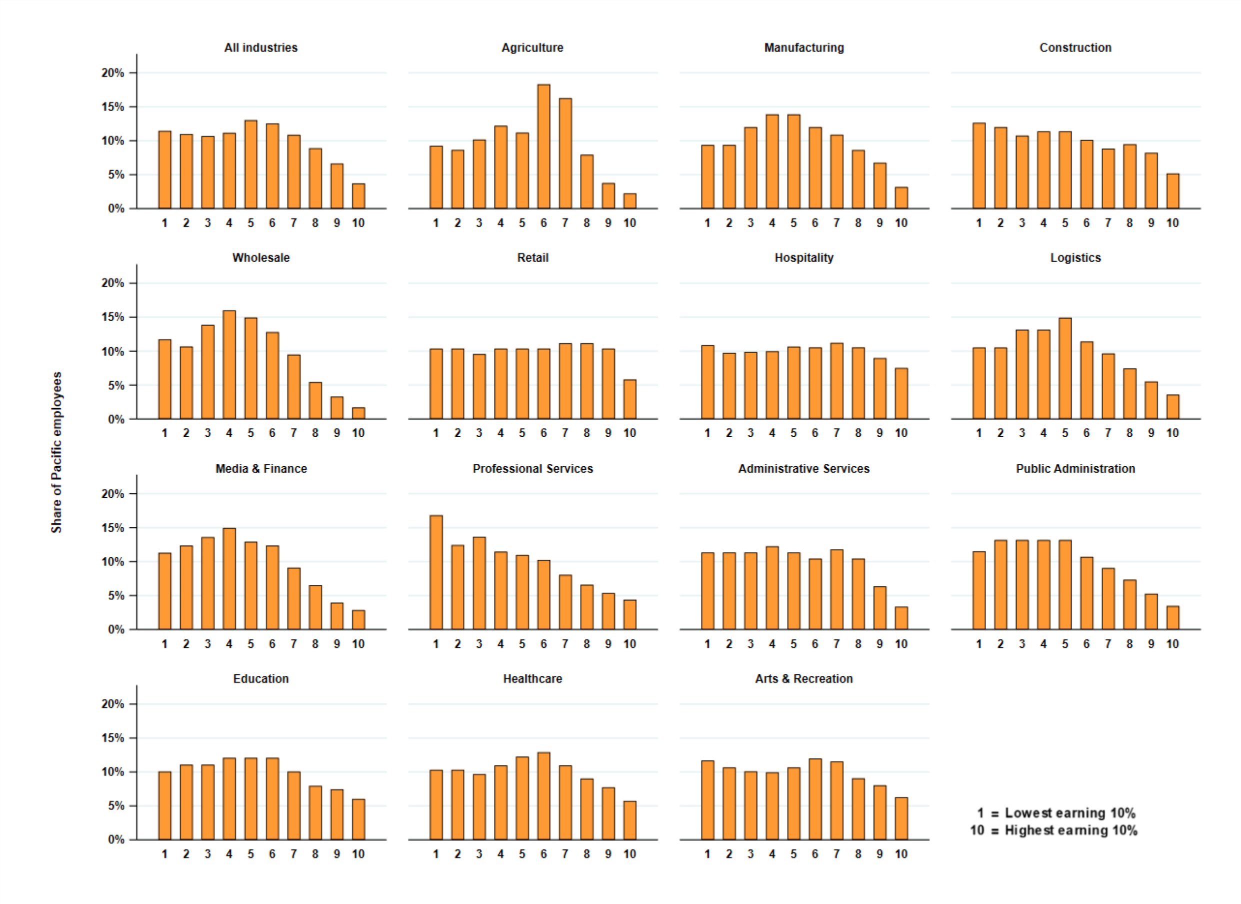
Figure 18. Share of Māori employees by decile of gross annual earnings, by industry.



Source: Authors' calculations using IR LEED data, year ended June 2021

For Pacific workers (Figure 19), the industries with the highest share of workers in the bottom three deciles are Professional Services (43%) and Public Administration (38%). There are some industries where Pacific workers tend to disproportionately fall into the middle-earnings deciles rather than the lowest ones. For example, Agriculture and Wholesale. However, there are still a disproportionately small share of Pacific workers who fall in the high earnings deciles in these industries. Just 10% of Pacific workers are in the top three earnings deciles in Wholesale and 14% in Agriculture.

Figure 19. Share of Pacific employees by decile of gross annual earnings, by industry.



Source: Authors' calculations using IR LEED data, year ended June 2021

Unlike Māori and Pacific workers, Figure 20 shows that less than 30% of Asian workers are in the bottom three earnings deciles in all but three industries, and more than 30% are in the top three earnings deciles in six industries. The Education industry has the highest share of Asian workers in the bottom three deciles (36%), followed by Public Administration (34%) and Wholesale (32%). Less than one-quarter of Asian workers fall into the bottom three deciles in the Agriculture, Administrative Services, Hospitality, and Healthcare industries. However, Asian workers are also underrepresented in the very top of the earnings distribution. For example, they account for less than 10% of the top earnings decile in all but two industries - 13% of Asian workers are in the top decile of Hospitality and 11% are in the top decile of Healthcare.

Despite the moderate Asian pay gap in the Agriculture, Construction, Retail, Administrative Services and Healthcare industries (Figure 1), Figure 20 suggests Asian employees are overrepresented in the higher annual earnings deciles in these industries. However, the *hourly* earnings distribution based on HLFS data (not shown) suggests they are underrepresented in the higher deciles. Also, there is a small Asian pay gap in Hospitality despite Asian employees being overrepresented in the higher annual deciles in this industry. However, there is a more even distribution across deciles in hourly earnings for Asian workers in this industry. It may be that Asian employees in these industries work, on average, longer hours, leading to these discrepancies in the distribution of annual and hourly earnings.

Figure 20. Share of Asian employees by decile of gross annual earnings, by industry.

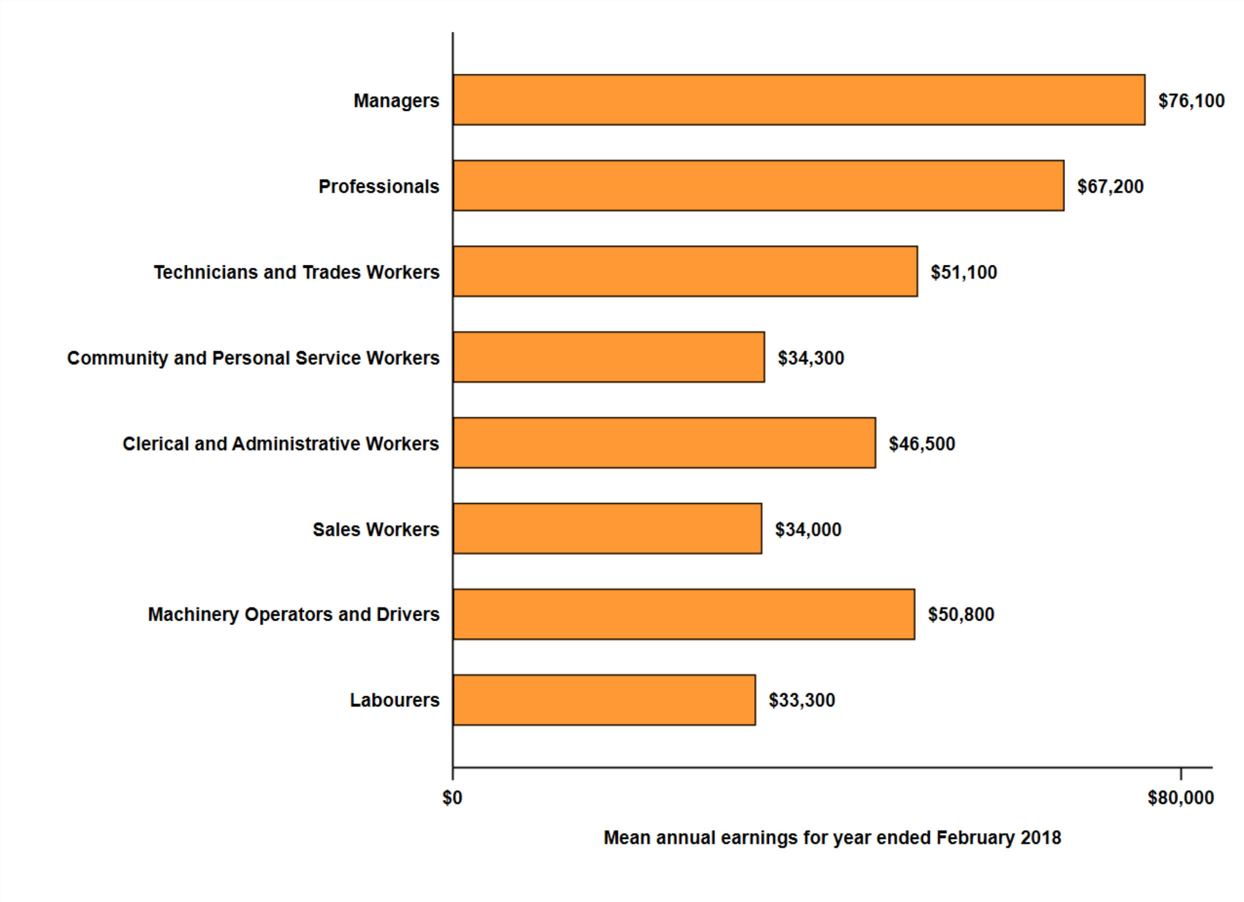
Source: Authors' calculations using IR LEED data, year ended June 2022

There are several factors which may be driving the finding that women and non-Europeans tend to be in the lower end of the earnings distribution within industries. It may be that they work in lower-paying occupations. For example, in the health sector, doctors are generally paid more than nurses and nursing is a female-dominated profession, whereas traditionally, most doctors were European men (although diversity has increased in this profession). It may also be that women and non-Europeans work in lower-paying firms within an industry. For example, lawyers at one law firm may be paid more, on average, than lawyers at another firm. To gain more insights into these earnings distributions, the next two subsections therefore explore the distribution of occupations and firm pay levels within industries.

5.3 Occupation distribution by industry

This section examines the occupational distribution of workers by gender and ethnicity, which can affect pay gaps if women and non-Europeans are more likely to work in lower-paying occupations. We begin by describing differences in pay between occupations. Figure 21 displays the mean annual earnings of people in each occupation, where occupation data is for people's main job as reported in the 2018 Census coded to level 1 (eight categories) of the Australian and New Zealand Standard Classification of Occupations and earnings data is from IR's Employer Monthly Schedule for the year ended February 2018 (i.e., wages and salaries earned over approximately the 12 months prior to the Census). Figure 21 shows that Managers have the highest average annual earnings of all occupations, followed (in descending order) by Professionals, Technicians and Trades Workers, Machinery Operators and Drivers (whose annual earnings are roughly the same as Technicians and Trades Workers), Clerical and Administrative Workers, Community and Personal Service Workers, Sales Workers (roughly the same as the former), and finally Labourers, who have the lowest annual earnings.

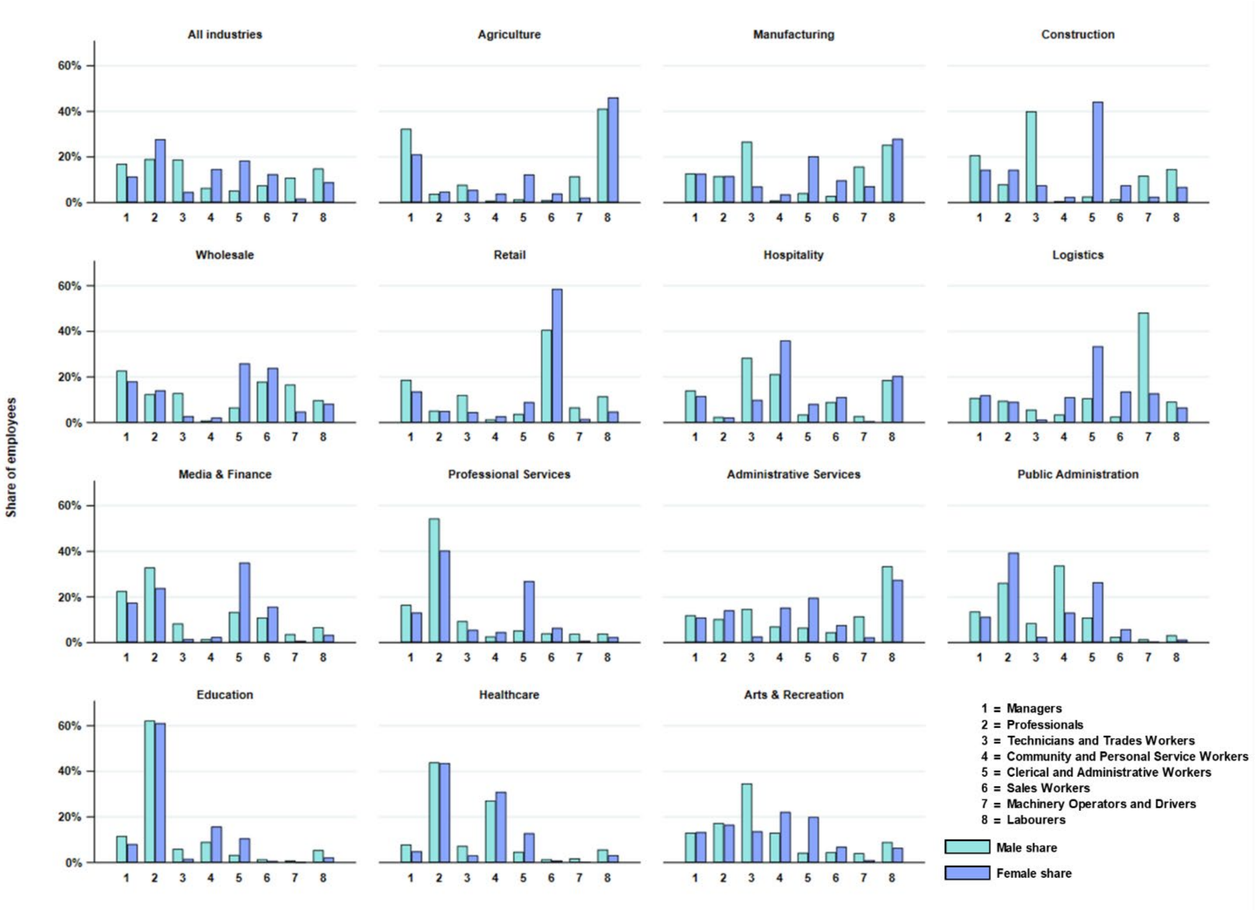
Figure 21. Average annual earnings for the year ended February 2018, by occupation.



Source: Authors' calculations using 2018 Census data and IR LEED data for year ended February 2018.

Figure 22 displays the distribution of men and women across occupations by industry. For each industry displayed in Figure 22, the bars show the share of men and share of women across each of the eight occupations in that industry (so the bars for men total to 100% and the bars for women also total to 100%). Figures 23, 24, and 25 likewise display the distribution of Māori, Pacific and Asian employees (respectively, compared to European employees) across the eight occupations, by industry.

Figure 22. Distribution of men and women across occupations as at March 2018, by industry



Source: Authors' calculations using 2018 Census data.

In aggregate (all industries), 14% of employees are employed as Managers (17% of male employees are Managers, and 11% of female employees), 23% as Professionals (19% male, 28% female), 12% as Technicians and Trades Workers (19% male, 5% female), 11% as Community and Personal Service Workers (6% male, 15% female), 12% as Clerical and Administrative Workers (5% male, 18% female), 10% as Sales Workers (8% male, 12% female), 6% as Machinery Operators and Drivers (11% male, 2% female), and 12% as Labourers (15% male, 9% as female). The relatively high share of women who are employed as Professionals in aggregate reflects the high share of Professionals in the large, female-dominated industries of Education and Healthcare (discussed below).

The distribution of occupations varies by industry and is in line with expectations. For example, the Agriculture industry is dominated by Labourers and Managers, the Retail industry is dominated by Sales Workers, the Education industry is dominated by Professionals, and the Healthcare industry is dominated by Professionals and Community and Personal Service Workers.

Figure 22 shows that, relative to men, women are most underrepresented in Technicians and Trades occupations. This is the case in every industry, but the underrepresentation is particularly large in Construction, Arts & Recreation, Manufacturing, and Hospitality. Women are also underrepresented as Machinery Operators and Drivers (in every industry, but especially in Logistics and Wholesale), as Labourers (in all industries except Agriculture, Manufacturing, and Hospitality), and as Managers (in all industries – especially Agriculture – except Manufacturing and Arts & Recreation where they are equally represented and Logistics where they are more likely than men to be Managers). The underrepresentation of women as Technicians and Trades Workers, Machinery Operators and Drivers, and Managers is likely to contribute to the gender pay gap given that these three occupations constitute three of the four highest-earning occupations as shown in Figure 21.

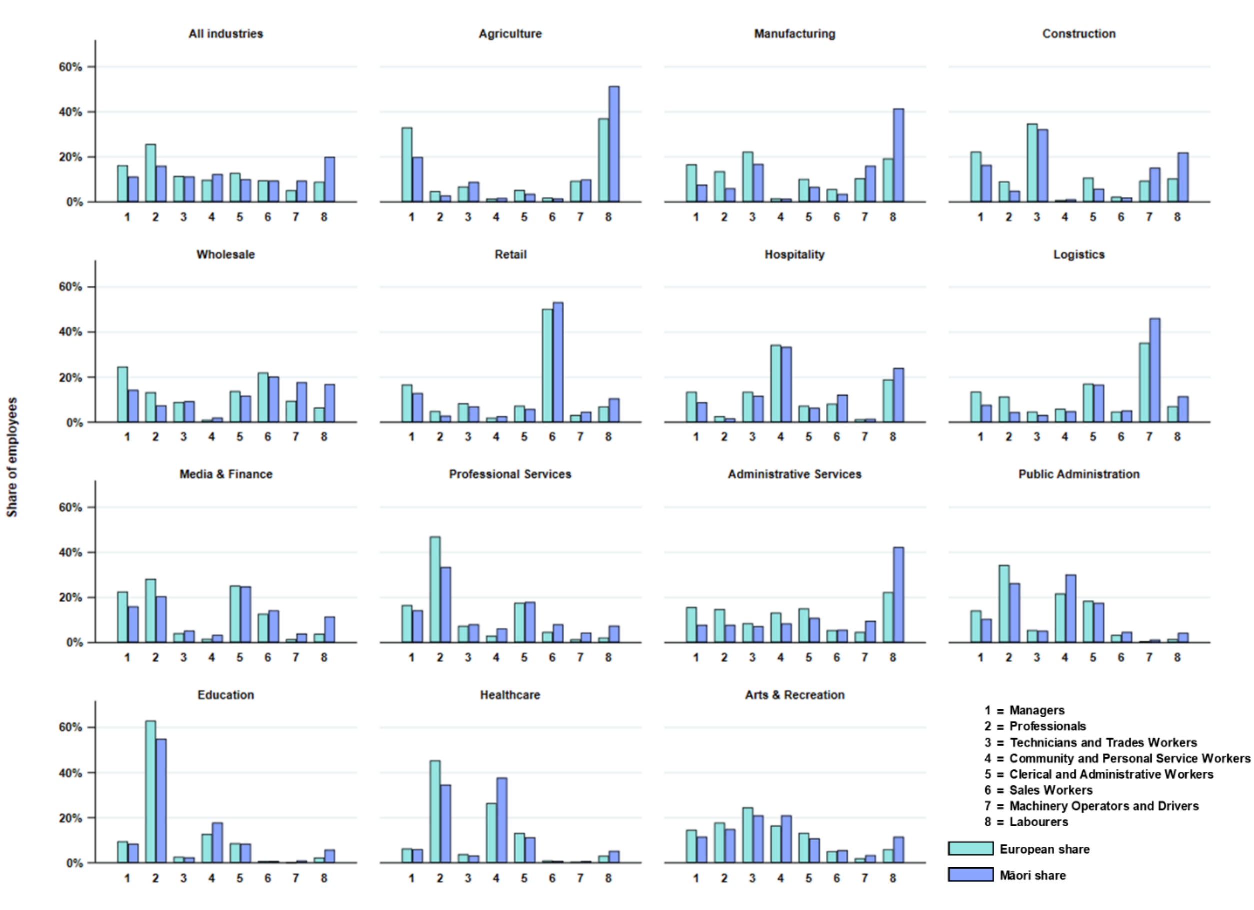
Relative to women, men are most underrepresented in Clerical and Administrative occupations. This is the case in every industry, but especially Construction, Logistics, Professional Services, Media & Finance, and Wholesale. In aggregate, men are underrepresented as Professionals, but this is restricted to five industries (Agriculture, Construction, Wholesale, Administrative Services, Public Administration). In all other industries, men and women are roughly equally represented as Professionals or men are overrepresented. Men are also underrepresented as Community and Personal Service Workers (in all industries – especially Hospitality – except for Public Administration where the gender difference is dramatically reversed) and as Sales Workers (in all industries – especially Retail Trade – except for Education and Healthcare).

Overall, Construction and Logistics stand out as industries with particularly large gender differences in occupational distribution.

Turning to ethnic differences in occupational distribution (Figures 23-25), at the aggregate level the ethnic breakdown of occupations is as follows: 16% of Europeans, 11% of Māori, 8% of Pacific peoples, and 12% of Asians are Managers; 26% of Europeans, 16% of Māori, 14% of Pacific, and 26% of Asians are Professionals; 12% of Europeans, 11% of Māori, 11% of Pacific, and 13% of Asians are Technicians and Trades Workers; 10% of Europeans, 12% of Māori, 12% of Pacific, and 11% of Asians are Community and Personal Service Workers; 13% of Europeans, 10% of Māori, 11% of Pacific, and 10% of Asians are Clerical and Administrative Workers; 10% of Europeans, 9% of Māori, 10% of Pacific, and 12% of Asians are Sales Workers; 5% of Europeans, 9% of Māori, 13% of Pacific, and 5% of Asians are Machinery Operators and

Drivers; and 9% of Europeans, 20% of Māori, 20% of Pacific, and 11% of Asians are Labourers. Thus, the largest ethnic differences are in Labouring and Machine Operation (relatively high concentrations of Māori and Pacific), Professional occupations (high concentration of Europeans and Asians), and Managerial occupations (high concentration of Europeans). These ethnic differences are likely to contribute to ethnic pay gaps given the occupational differences in earnings previously shown (Figure 21). Māori and Pacific peoples share fairly similar occupational distributions, while Europeans and Asians share similar distributions.

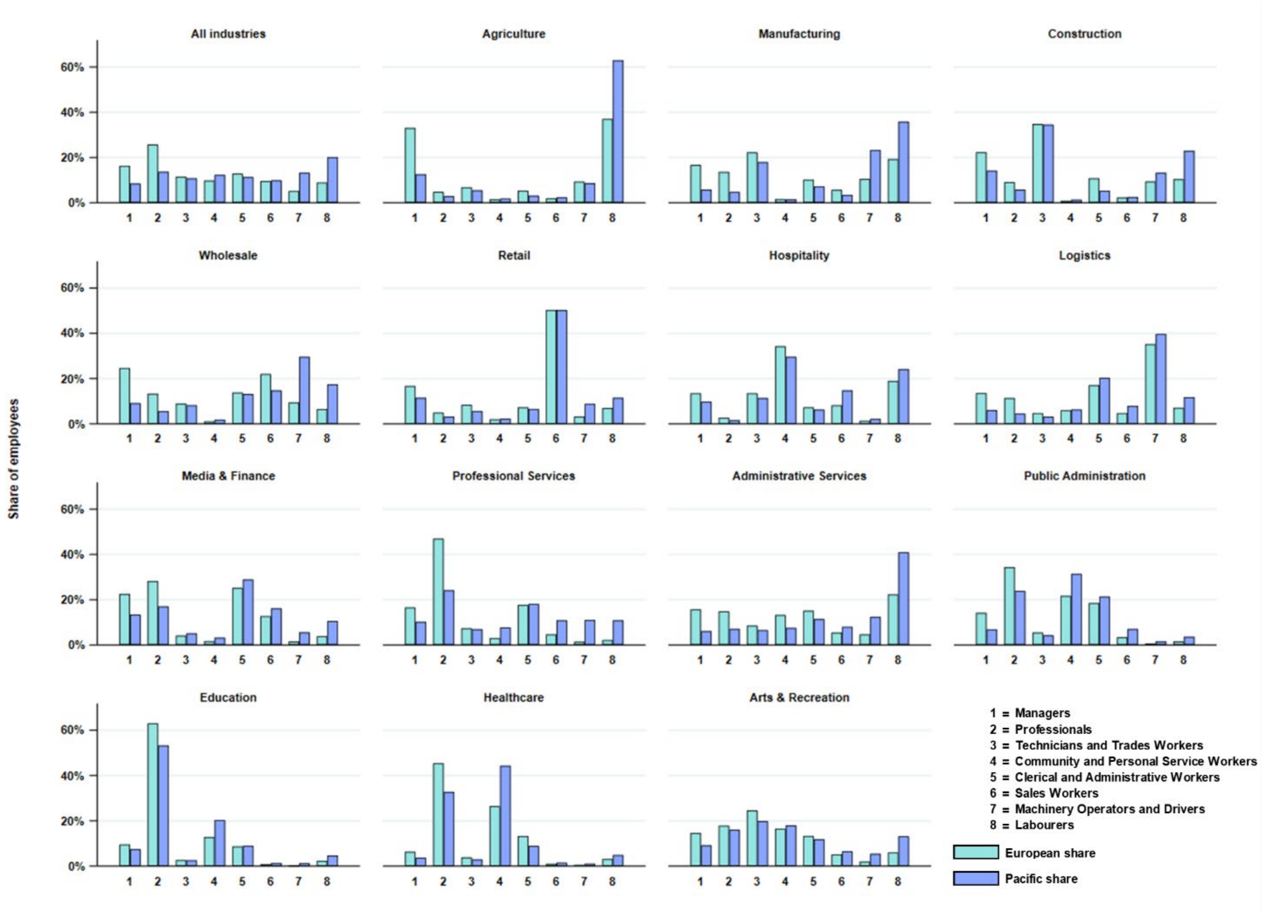
Figure 23. Distribution of Māori and Europeans across occupations as at March 2018, by industry



Source: Authors' calculations using 2018 Census data.

Figure 23 shows that, relative to Europeans, Māori are most underrepresented in Professional occupations. This is the case in every industry, but especially in the Professional Services industry, in Healthcare, and in Public Administration. Māori are also underrepresented as Managers in every industry, especially in Agriculture, Wholesale Trade, and Manufacturing. Māori are overrepresented as Labourers in every industry, especially Manufacturing, Administrative Services, and Agriculture.

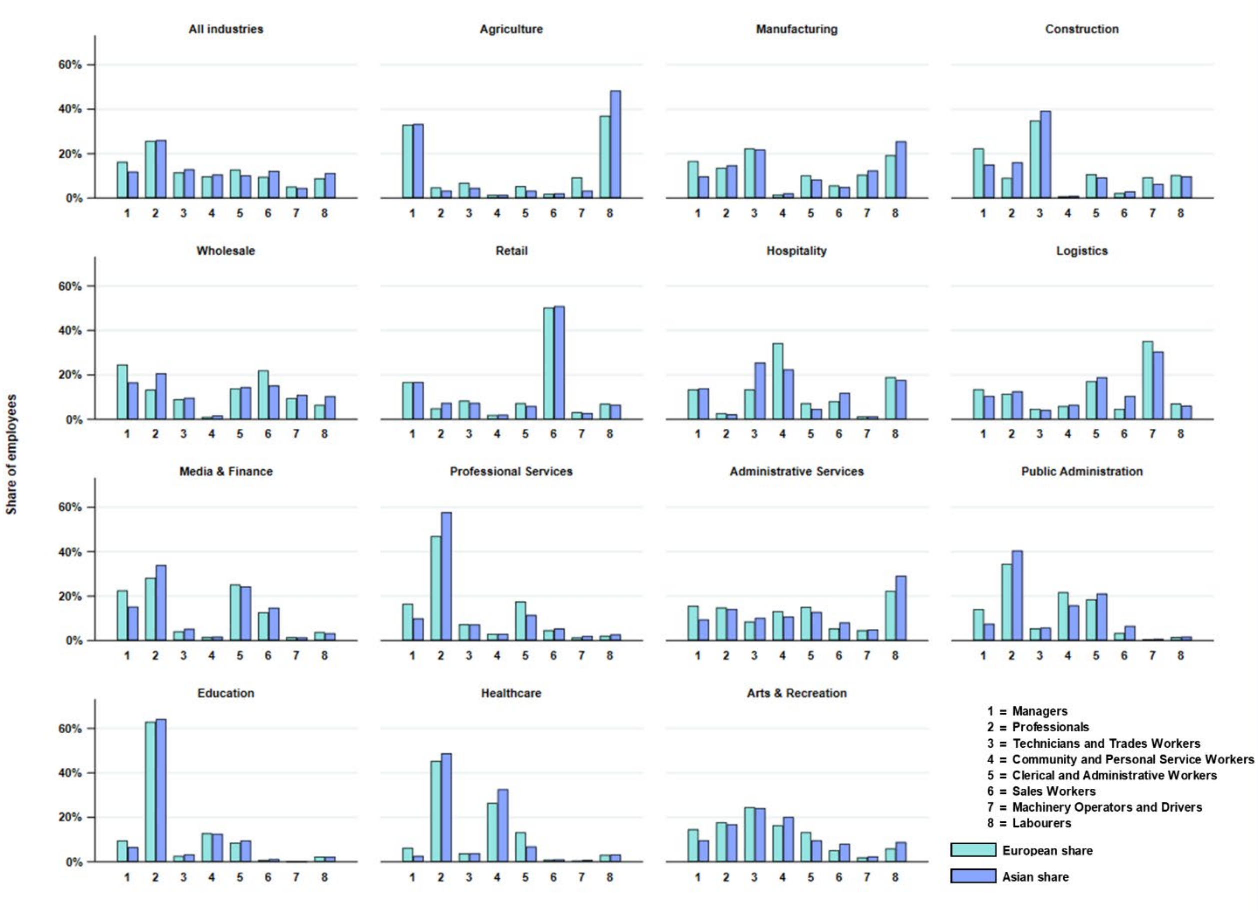
Figure 24. Distribution of Pacific peoples and Europeans across occupations as at March 2018, by industry



Source: Authors' calculations using 2018 Census data.

Figure 24 shows that, in general, these patterns also apply to Pacific peoples: they are most underrepresented as Professionals (in every industry, but especially Professional Services and Healthcare) and as Managers (in every industry, especially Agriculture, Wholesale Trade and Manufacturing), and most overrepresented as Labourers (in every industry, especially Agriculture, Administrative Services, and Manufacturing) and Machinery Operators and Drivers (in every industry, especially Wholesale and Manufacturing).

Figure 25. Distribution of Asians and Europeans across occupations as at March 2018, by industry



Source: Authors' calculations using 2018 Census data.

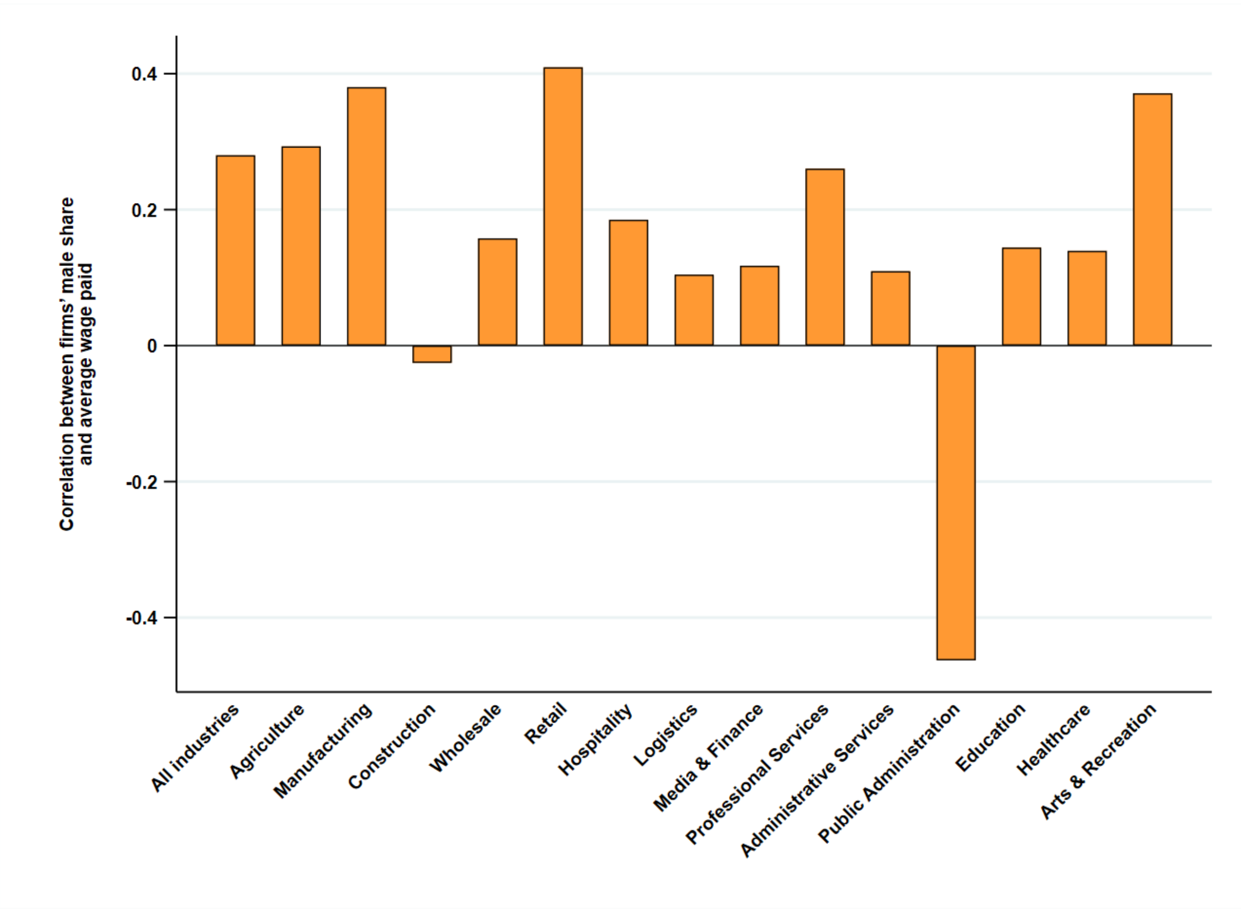
Figure 25 shows that Asians more closely resemble the occupational distribution of Europeans, but to the extent there are differences compared to Europeans, they tend to be underrepresented as Managers (in most industries; Agriculture, Retail, and Hospitality are the exceptions) and overrepresented as Professionals (in most industries) and as Labourers in specific industries only (Agriculture, Administrative Services, Manufacturing).

5.4 Firm distribution by industry

Do higher-pay firms within an industry have a higher share of male and/or European employees? Figure 26 presents the correlation between firms' share of male employees and average earnings within firms. A positive correlation indicates that higher-paying firms are positively associated with a greater share of male employees.

In most industries, there is a positive correlation between firms' share of male employees and the average annual earnings of firms' employees. That is, men are more likely to work at higher-paying firms in most industries. The main exception is Public Administration, which has a large negative correlation. Construction also has a small negative correlation, which accords with the near-zero gender pay gap in this industry. The largest positive correlation is in the Retail industry, followed closely by Manufacturing and Arts & Recreation.

Figure 26. Correlation between firms' share of male employees and average annual earnings paid to their employees, by industry

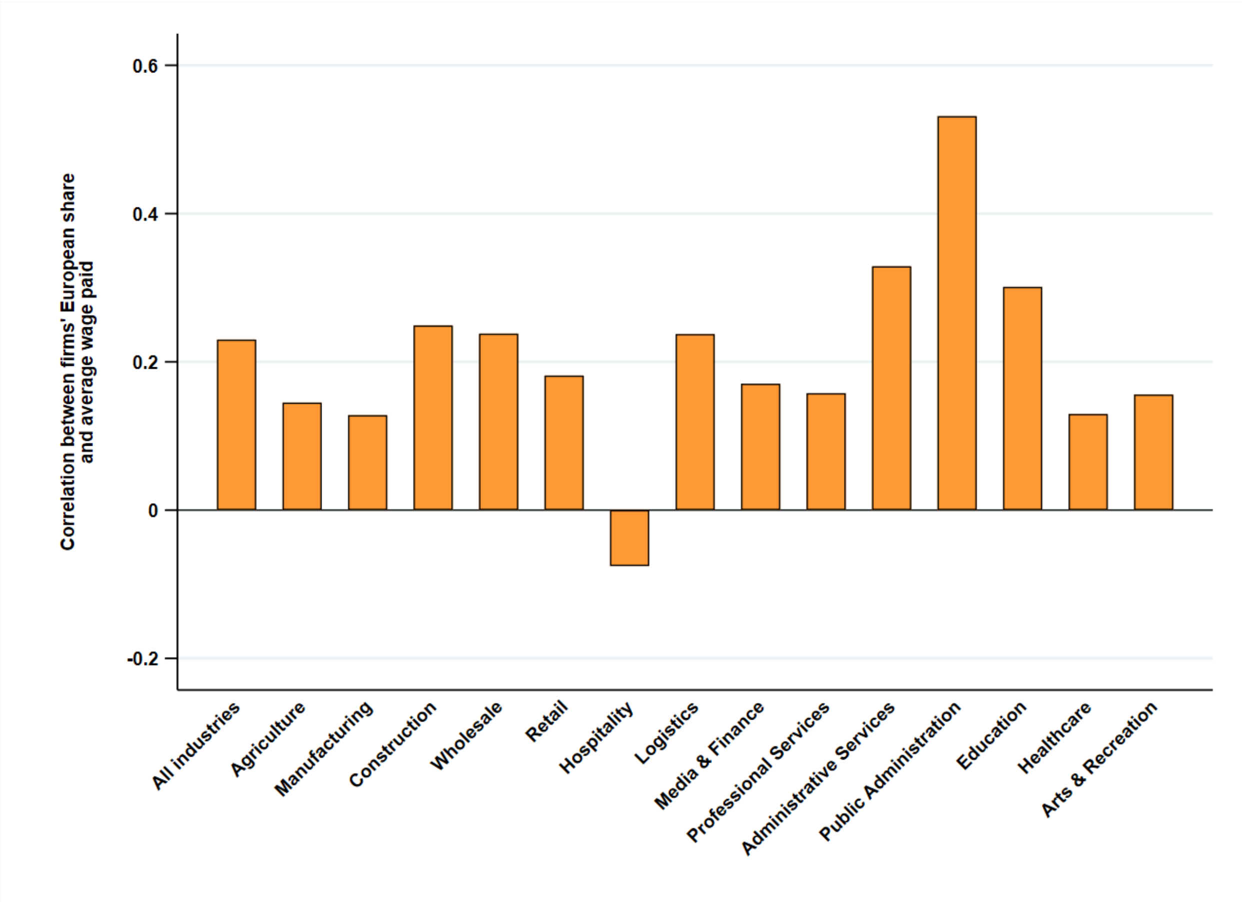


Source: Authors' calculations using IR LEED data, year ended June 2021

In all industries except Education and Public Administration, this correlation between a firm's share of male employees and average earnings has increased between 2016 and 2021 (not shown). It increased most strongly in Administrative Services from -0.07 in 2016 to 0.08 in 2021 and in Healthcare from 0.05 in 2016 to 0.13 in 2021.

The correlation between the share of European employees in a firm and the average earnings of the firm's employees is also positive in all but one industry (Hospitality) (Figure 27). The largest correlation is in the Public Administration industry. This contrasts with the results for male employees (above), where this industry had a negative correlation. Between 2016 and 2021, the correlation declined in all industries except Education, Public Administration, and Logistics (not shown).

Figure 27. Correlation between firms' share of European employees and average annual earnings paid to their employees, by industry



Source: Authors' calculations using IR LEED data, year ended June 2021

5.5 Decomposition of pay gaps

So far, this section has looked at structural reasons behind gender and ethnicity pay gaps in a descriptive way. We now investigate this in a more analytical way via Blinder-Oaxaca decompositions, which provide insights into why pay gaps. This subsection briefly explains the Blinder-Oaxaca decomposition method (a fuller explanation is provided in Section 3) and how to interpret the results. It then presents results for the industry gender pay gaps followed by the industry ethnic pay gaps.

The Blinder-Oaxaca decomposition method

The Blinder-Oaxaca decomposition method splits each pay gap into ‘explained’ and ‘unexplained’ components. The ‘explained component’ is the portion of the pay gap that can be statistically accounted for by differences in group characteristics such as differences in educational qualifications or occupation. In the analysis that follows, we break down the explained component into the contribution made by each of the different groupings of characteristics to the overall gap (these groupings are provided in Section 2, Table 2 and include individual, education, region and job-related characteristics). The ‘unexplained component’ is the portion of the pay gap that cannot be attributed to group differences in characteristics. As detailed earlier, the unexplained component is particularly problematic to interpret and can be driven by several causes: (i) unobserved group differences in characteristics not captured in the current data; (ii) group differences in the non-pecuniary elements of jobs; (iii) discriminatory behaviour; (iv) unconscious bias. However, it is important to note that it is possible for discrimination and unjust inequalities to exist in *both the explained and unexplained components*. For example, pay gaps may be partly explained by group differences in educational attainment (hence educational differences contribute to the explained component). Yet these educational differences may themselves be unfair disparities or arise in part from discrimination in the education system.

A known issue with the Blinder-Oaxaca decomposition is that the results it produces can be affected by sample selection bias, given that hourly earnings are only observed for employed individuals in our sample (the earnings of people who are not currently participating in the labour market are not observed). To correct our estimates for sample selection bias, we apply the Heckman correction procedure, which deducts the selection effects from the overall pay gap and then applies the decomposition equations to the adjusted pay gap (as detailed in Section 3).

The explained component of the decompositions can be less than 100%, equal to 100%, or more than 100%, and can be positive or negative. Box 1 provides details of how to interpret results from the Blinder-Oaxaca decomposition. Descriptive statistics of the HLFS sample used in the Blinder-Oaxaca decompositions are presented in Appendix D and full results of the decompositions are presented in Appendix E.

Box 1: Interpreting results from the Blinder-Oaxaca decomposition

The Blinder-Oaxaca decomposition is a statistical technique that takes the average difference between two groups (e.g., men and women) in some outcome like hourly earnings and apportions that difference into 'explained' and 'unexplained' components. The 'explained' component is the part of the difference in hourly earnings (the part of the pay gap) that is statistically accounted for by group differences in characteristics that influence earnings and are captured in a dataset as explanatory variables (such as educational qualifications and occupation). The 'unexplained' component is the residual part of the difference in hourly earnings that is not accounted for by differences in these variables (it captures differences in 'returns' in the labour market to the explanatory variables). In this report, the explained and unexplained components are expressed as percentages that together add up to 100 percent (e.g., 10% explained and 90% unexplained).

To estimate the explained component, the version of the decomposition technique used in this report asks the counterfactual question, "*What would the difference in average hourly earnings be if women had the same characteristics as the pooled sample of women and men?*". There are several possible answers to this question which determine the magnitude and sign (positive or negative) of the explained component. Below is a guide to interpreting these possibilities for the explained component.

The explained component is………	Interpretation
Less than 100 percent	The Pacific pay gap has an explained component of 19% (the unexplained component is 81%), so if Pacific peoples had the same characteristics as the pooled sample of Pacific peoples and Europeans, we would expect ***a smaller pay gap than the one actually observed***.
Equal to 100 percent	The Asian pay gap has an explained component of 100% (the unexplained component is zero), so if Asians had the same characteristics as the pooled sample of Asians and Europeans, we would expect them to have the same pay and therefore no pay gap.
Greater than 100 percent	The Māori pay gap has an explained component of 110% (by definition the unexplained component is -10%), so if Māori had the same characteristics as the pooled sample of Māori and Europeans, we would expect ***a larger pay gap than the one actually observed***.
Negative	The gender pay gap has an explained component of -9% (the unexplained component is 109%), so if women had the same characteristics as the pooled sample of men and women, we would expect ***a reversal of the observed pay gap*** (higher hourly earnings among women than men, hence a pay gap that favours women).

Decomposition results: How much of the pay gaps are 'explained'?

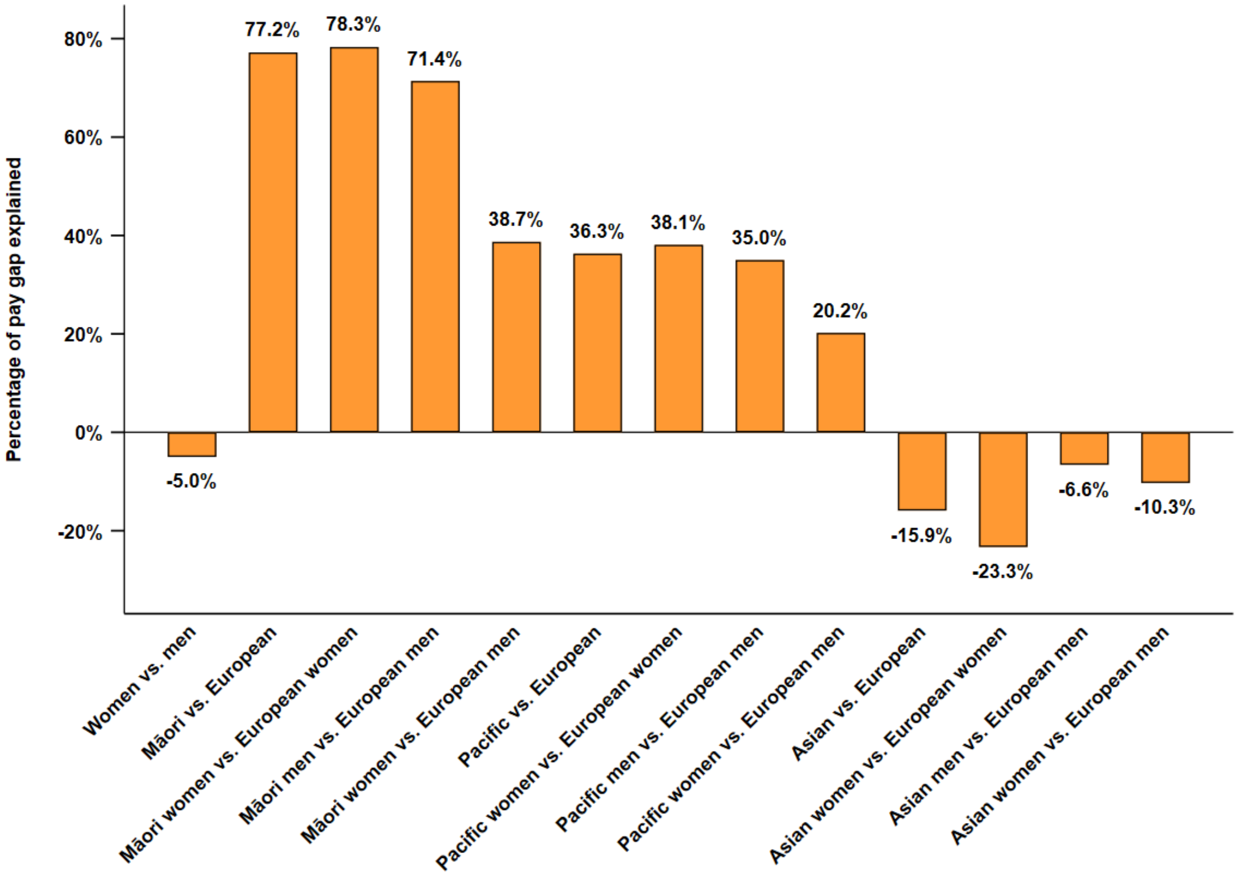
Figure 28 summarises how much of each of the 13 aggregate (all industries) pay gaps can be explained by the variables included in the decomposition. In aggregate (all industries), the total explained component of the gender pay gap is negative (-5%). This means that given their individual, education and job-related characteristics, as well as their region and industry, we would expect women to be paid *more* than men on average, rather than less. (See Table 2 for details of individual, household, region, education and job-related characteristics.)

In terms of ethnic pay gaps, on average, three-quarters of the ethnic and intersectional pay gaps among Māori can be statistically explained by the variables included in the decomposition. However, only about half this amount can be explained for the gender pay gap among Māori.

Just over one-third of the Pacific versus European, Pacific men versus European men and Pacific women versus European women pay gaps can be explained. However, the explained component drops to one-fifth for the Pacific women versus European men pay gap. Pay gaps among Asians – whether ethnic, gender, or intersectional – all have negative explained components, but a greater portion of the ethnic and intersectional pay gaps can be explained than the gender pay gaps. For specific findings with respect to particular industries of interest, refer to the results provided in Appendix E.

Next, we will delve more into the contributions of individual characteristics, education levels, job-related characteristics, region and industry of employment to the explained portion of the pay gaps (see Table 2 for a list of all explanatory variables used in the decompositions).

Figure 28. Proportion of 'all industries' pay gaps explained by group differences in observed characteristics from Blinder-Oaxaca decomposition



Source: Authors' calculations using June quarter HLFS data pooled over 2016 to 2022.

Decomposition results: Gender pay gaps

In aggregate (all industries), the total explained component of the gender pay gap is negative (-5%). Individual, region, educational and job-related characteristics components are all negative (Figure 29 and Table E.1 in Appendix E). For example, the educational characteristics explain -10% of the gender pay gap, meaning that women have lower average pay than men despite having higher average education levels than men. [6] The only component which is positive is industry, reflecting that women tend to work in lower-paid industries than men (thus, if the industry distribution for men and women were the same, then women would be paid more). This also highlights, however, that, as noted above, the explained

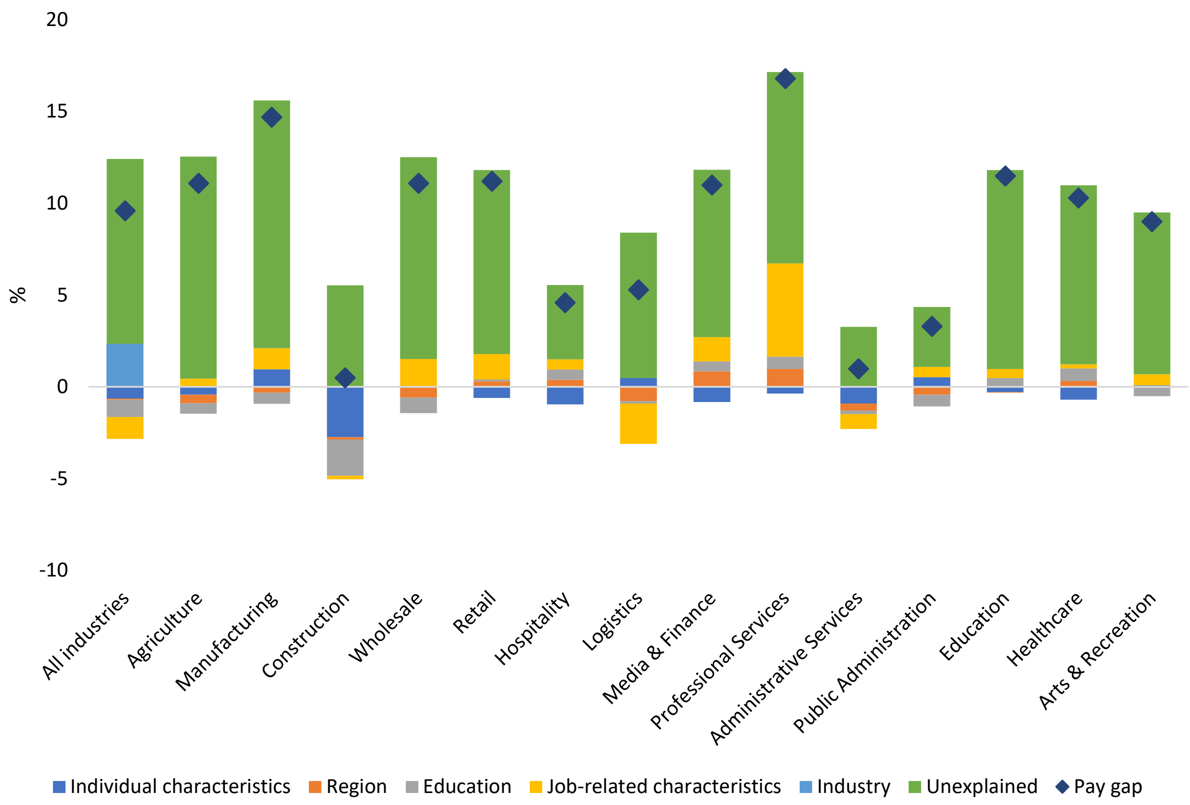
[6] We attempted to include in the decomposition a 'field of study' variable drawn from the Census – capturing the field of study of respondents' post-school qualifications, where they have one (e.g., Natural and physical sciences, Management and commerce, Creative arts, etc.). But including this variable was not feasible because 23 percent of the HLFS sample (pooled across all years) were not linked to the relevant census (the 2018 census for HLFS respondents interviewed between 2018 and 2022 and the 2013 census for respondents interviewed between 2016 and 2017) and, of the remainder who were linked to a census, 50 percent had no post-school qualification (hence no field of study information). Consequently, cell counts for the various field of study categories were too small (even after attempts at sensibly collapsing them).

component can still present issues in terms of gender equality as the fact that women work in lower-paid industries is itself an issue. This particular issue has received increasing policy attention, reflected, for example, in the passing of the Equal Pay Amendment Act 2020 to improve the process to raise and resolve claims of systematic pay undervaluation in female-dominated occupations.

Turning to the industry-level results, in most industries, very little of the gender pay gap is explained by the variables included in the decompositions. Nine industries have small, positive explained components (of between 1% and 17%), meaning that if women working in these industries had the same individual, regional, education and job-related characteristics as the pooled sample of men and women, the pay gap would still exist but it would be a little smaller. In four industries – Agriculture, Construction, Logistics, and Administrative Services – the explained component is negative, meaning the gender pay gap would be reversed (so women would be paid more than men on average) if women had the same characteristics as the pooled sample of men and women. Professional Services is the only industry with a reasonable-sized explained component of 38%. Most of this explained component stems from job-related characteristics, which includes factors such as occupation.

Generally speaking, as evident in Figure 29 and Table E.1 in Appendix E, within the small explained component apparent in many gender pay gaps across industries, job-related characteristics tend to make the largest contribution. Note however that this does not hold in three industries that have small pay gaps and negative explained components (Construction, Logistics, and Administrative Services). In these three industries, job-related characteristics make a negative contribution to the explained component, meaning that women get paid less in these industries despite having more favourable job-related characteristics, such as occupation. Individual, regional, and educational characteristics tend to make negative or small positive contributions to explaining the gender pay gap.

Figure 29. Proportion of gender pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition



Source: Authors' calculations using June quarter HLFS data pooled over 2016 to 2022.

Notes: Difference in log wages multiplied by 100 (approximately a percentage change) decomposed into components using Blinder-Oaxaca estimation from Equation (4).

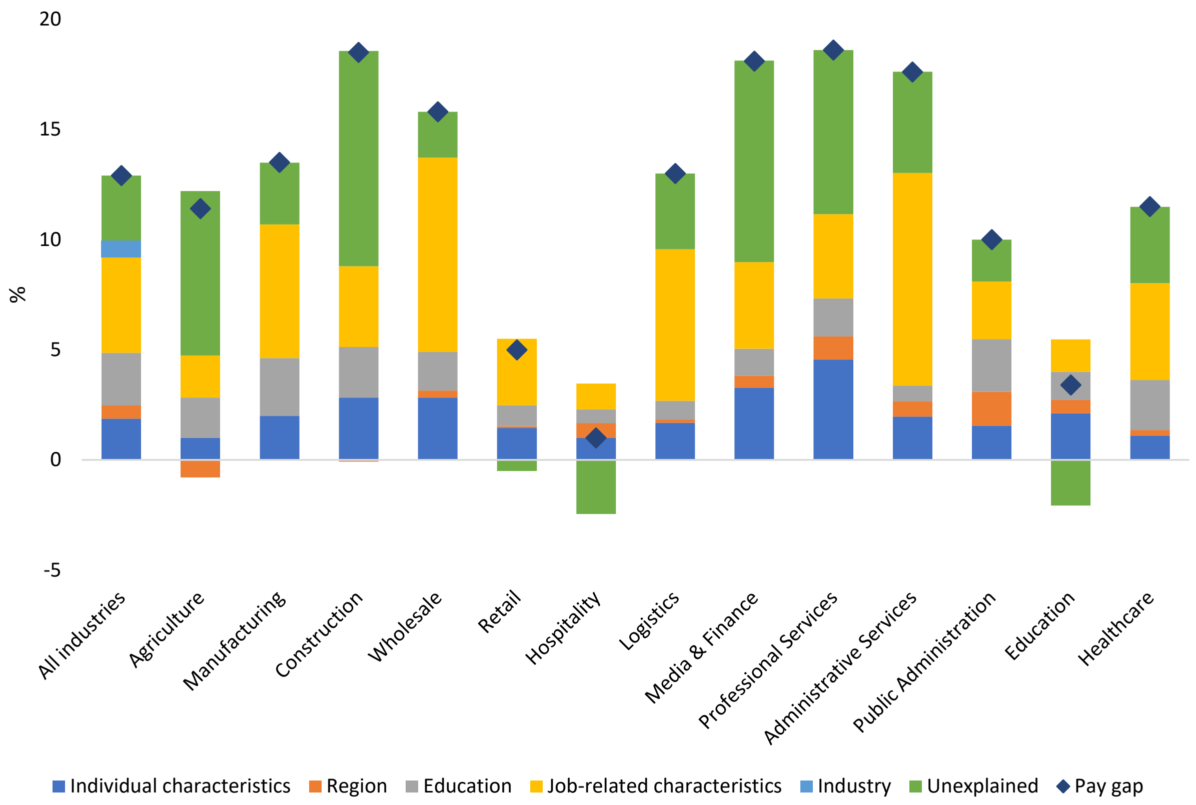
Decomposition results: Ethnic pay gaps

In comparison to the gender pay gaps, the Māori pay gaps have larger explained components that approximate or exceed 50% in nearly all industries (Figure 30 and Table E.1). Approximately half of the Māori pay gap is explained by the included covariates in the Construction (47%), Media & Finance (50%), and Arts & Recreation (56%) industries. The explained component exceeds 100% in the Retail, Hospitality, and Education industries, indicating that if Māori had the same characteristics as the pooled sample of Māori and Europeans (particularly the same individual- and job-related characteristics), the pay gap would be even larger. The explained component is notably lower in the Agriculture industry (35%), where approximately two-thirds of the Māori pay gap is unexplained (by the included variables) in this industry.

In general, for most Māori industry pay gaps, job-related characteristics make the largest contribution to the explained component, followed by educational characteristics, except for the Professional Services, Education, and Arts & Recreation industries, where individual characteristics explain more of the Māori pay gap than job-related characteristics.

It is important to reiterate, given the higher explained proportion in Māori pay gaps relative to gender pay gaps, that the explained component of pay gaps is not necessarily free from the effects of discrimination (New Zealand Treasury, 2018). Where discrimination exists, it can impact both the explained and unexplained components of the pay gap. For example, low expectations of teachers with regard to educational achievement for Māori may impact on their attainment in this space (Hynds et al., 2017). Such cases of structural discrimination where it exists may therefore come through in the explained component of the pay gap (New Zealand Treasury, 2018; NZ Human Rights Commission, 2022)

Figure 30. Proportion of Māori vs. European pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition

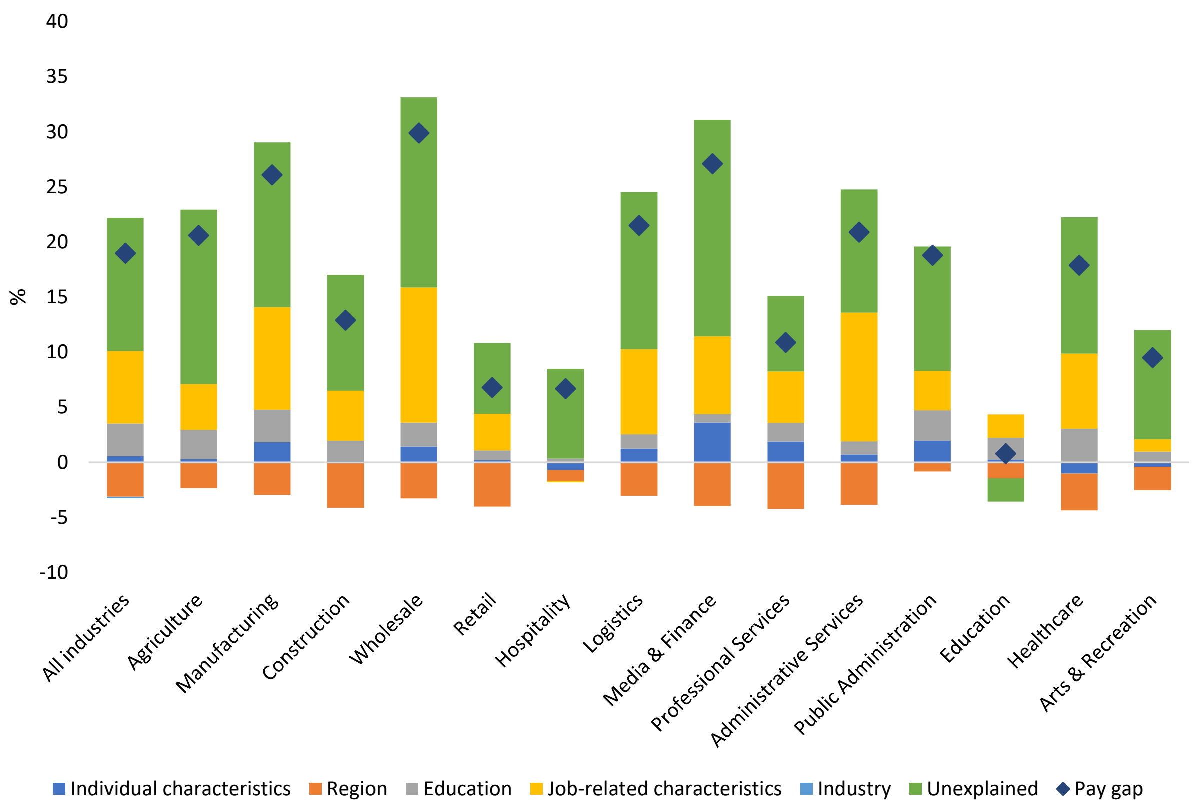


Source: Authors' calculations using June quarter HLFS data pooled over 2016 to 2022.

Notes: Difference in log wages multiplied by 100 (approximately a percentage change) decomposed into components using Blinder-Oaxaca estimation from Equation (4).

In terms of the Pacific pay gap, the unexplained is the dominant component in most industries (Figure 31). The explained component ranges between 19% and 47% in 10 industries, is 6% in the Retail industry, is negative in Hospitality and Arts & Recreation industries, and exceeds 100% in the Education industry. In most industries, job-related characteristics make the largest contribution to the explained component (except for Hospitality, where job-related characteristics make a negative contribution). Of note is that, in every industry, regional characteristics make a negative contribution to explaining the Pacific pay gap. This means the pay gap between Pacific peoples and Europeans would be larger if Pacific peoples had a more similar regional distribution to Europeans. This is because Pacific workers benefit from being geographically more concentrated in Auckland, where wages are higher (relative to most other regions of NZ), as explained in Cochrane & Pacheco (2022).

Figure 31. Proportion of Pacific vs. European pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition

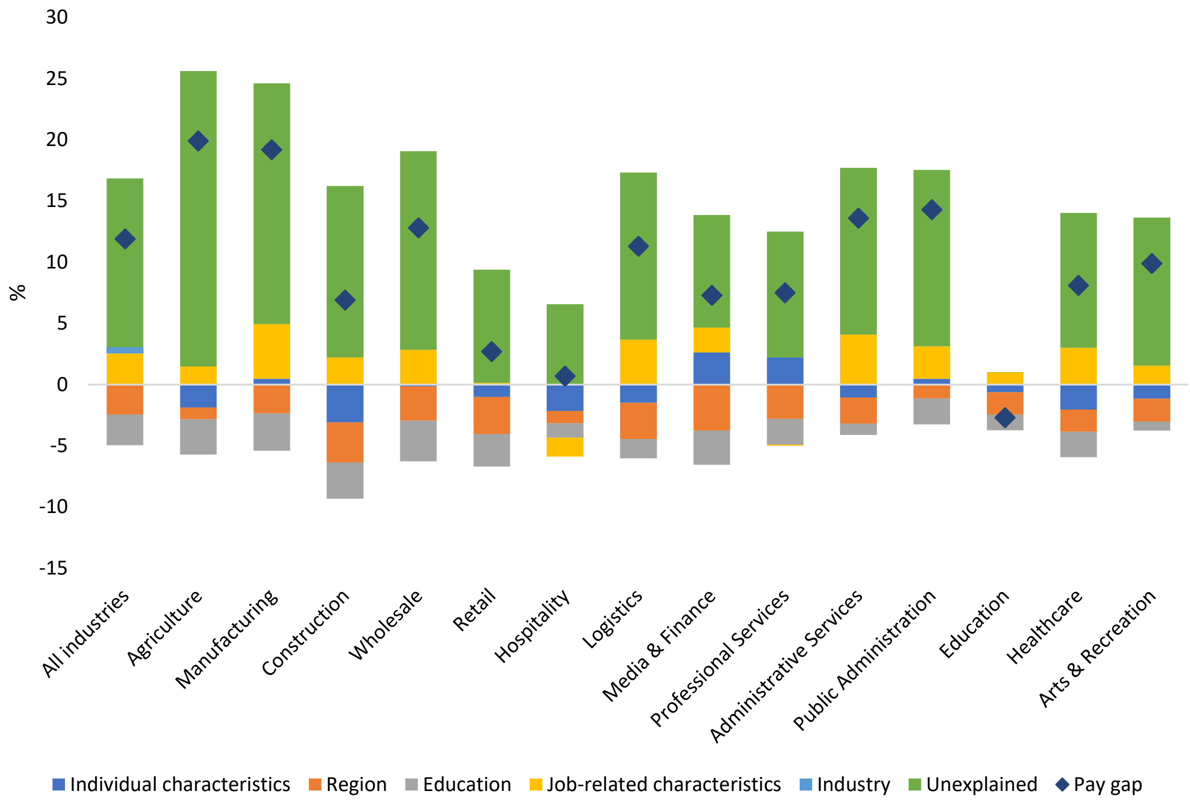


Source: Authors' calculations using June quarter HLFS data pooled over 2016 to 2022.

Notes: Difference in log wages multiplied by 100 (approximately a percentage change) decomposed into components using Blinder-Oaxaca estimation from Equation (4).

The Asian pay gap has negative explained components in every industry (except Education, which has a negative pay gap), meaning the pay gap would be negative (i.e. Asians would have higher average pay than Europeans) if they had the same characteristics as the pooled sample of Asians and Europeans (Figure 32). Similar to the Pacific results, regional characteristics make a negative contribution to explaining the Asian pay gap in all but one industry. Likewise educational characteristics make a negative contribution in all but one industry, reflecting that, all else equal, we would expect Asian workers to have higher wages given their high average education levels. In the Education industry, the pay gap is largely explained by Asian-European differences in regional, educational, and individual characteristics (but not differences in job-related characteristics, which make a negative contribution to explaining the gap). In most industries, job-related characteristics make the only positive contribution to the explained component, with all other characteristics making negative (or very small positive) contributions. In two industries – Media & Finance and Professional Services – individual characteristics make a larger contribution to explaining the pay gap than job-related, while in the Hospitality industry (where the Asian pay gap is near zero), all characteristics contribute negatively to explaining the pay gap.

Figure 32. Proportion of Asian vs. European pay gaps explained by differences in observed characteristics and unexplained from Blinder-Oaxaca decomposition



Source: Authors' calculations using June quarter HLFS data pooled over 2016 to 2022.

Notes: Difference in log wages multiplied by 100 (approximately a percentage change) decomposed into components using Blinder-Oaxaca estimation from Equation (4).

Finally, the decomposition results for the intersectional pay gaps (see Appendix E) present a mixed picture when compared to the relevant ethnic or gender pay gap. For example, compared to the decomposition of the Māori pay gap, the decomposition of the pay gap between Māori women and

European women produces explained components that increase in some industries (e.g., Agriculture, Logistics and Education), decrease in others (e.g., Manufacturing, Wholesale and Retail) and are about the same in others (e.g., Public Administration, Health and Arts & Recreation).

References

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *The Journal of Human Resources*, *8*(4). https://doi.org/10.2307/144855

Cochrane, B., & Pacheco, G. (2022). *Empirical analysis of Pacific, Māori and ethnic pay gaps in New Zealand*. NZ Work Research Institute. https://workresearch.aut.ac.nz/research/the-pacific-pay-gap-inquiry

Dee, T. S. (2005). A teacher like me: Does race, ethnicity, or gender matter? *The American Economic Review*, *95*(2), 158–165.

Fabling, R., Maré, D., & Grimes, A. (2012). *Performance pay systems and the gender wage gap* (Motu Working Paper No. 12–13; Motu Working Paper). Motu Working Paper. https://www.motu.nz/our-research/population-and-labour/individual-and-group-outcomes/performance-pay-systems-and-the-gender-wage-gap/

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*(1), 153–161. https://doi.org/10.2307/1912352

Hynds, A., Averill, R., Hindle, R., & Meyer, L. (2017). School expectations and student aspirations: The influence of schools and teachers on Indigenous secondary students. *Ethnicities*, *17*(4), 546–573.

Lustig, N. *The 'missing rich' in household surveys: Causes and correction approaches* (CEQ Working Paper No. 75). CEQ Institute. https://repec.tulane.edu/RePEc/ceq/ceq75.pdf

Najam, Z., & Allan, C. (forthcoming). *A first look at administrative hours data*. Ministry of Business, Innovation and employment.

New Zealand Treasury. (2018). *Statistical analysis of ethnic wage gaps in New Zealand* (No. 18/03; Analytical Paper). New Zealand Treasury. https://www.treasury.govt.nz/publications/ap/ap-18-03-html

NZ Human Rights Commission. (2022). *Voices of Pacific Peoples: Eliminating pay gaps*. NZ Human Rights Commission. https://pacificpaygap.hrc.co.nz/about-the-inquiry/pacific-pay-gap-inquiry-reports/

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, *14*(3). https://doi.org/10.2307/2525981

Pacheco, G., Li, C., & Cochrane, B. (2017). *Empirical evidence of the gender pay gap in New Zealand*. Ministry for Women. https://women.govt.nz/documents/empirical-evidence-gender-pay-gap-new-zealand

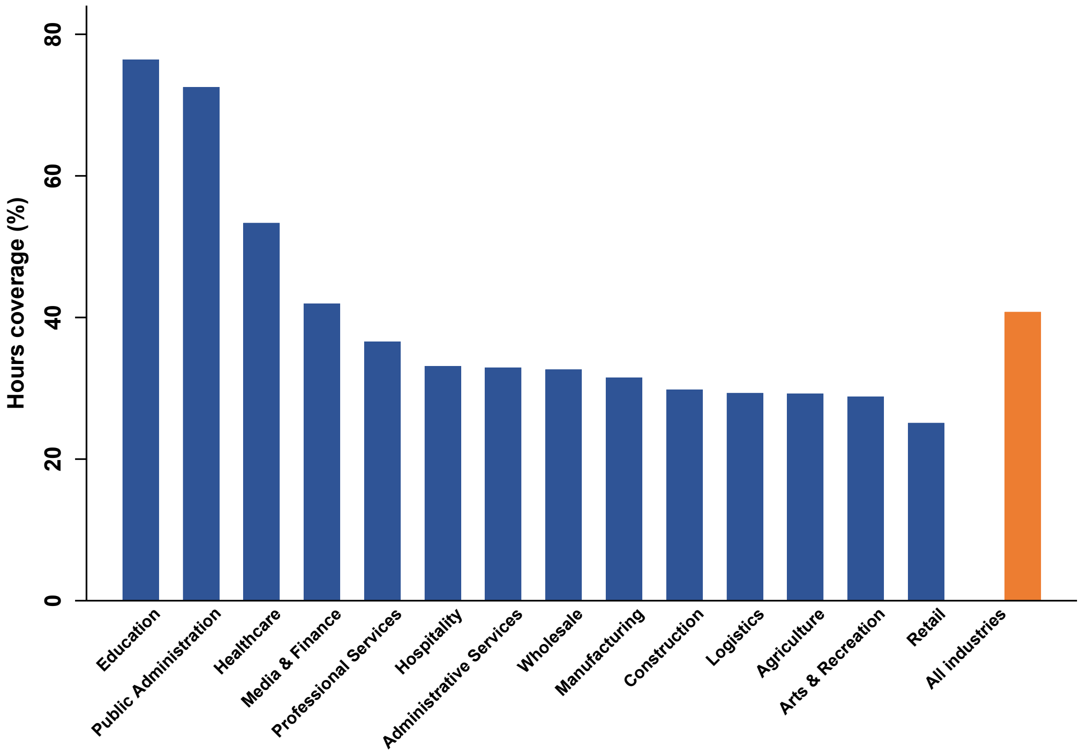
Redding, C. (2019). A teacher like me: A review of the effect of student–teacher racial/ethnic matching on teacher perceptions of students and student academic and behavioral outcomes. *Review of Educational Research*, *89*(4), 499–535. https://doi.org/10.3102/0034654319853545

Rubie-Davies, C., Hattie, J., & Hamilton, R. (2006). Expecting the best for students: Teacher expectations and academic outcomes. *The British Journal of Educational Psychology*, *76*(Pt 3), 429–444.

Rubie-Davies, C., & Peterson, E. R. (2016). Relations between teachers' achievement, over- and underestimation, and students' beliefs for Māori and Pākehā students. *Contemporary Educational Psychology*, *47*, 72–83.

Appendix A: IR hours data coverage

Figure A.1. IR data - Share of employees with hours information by industry, June 2021

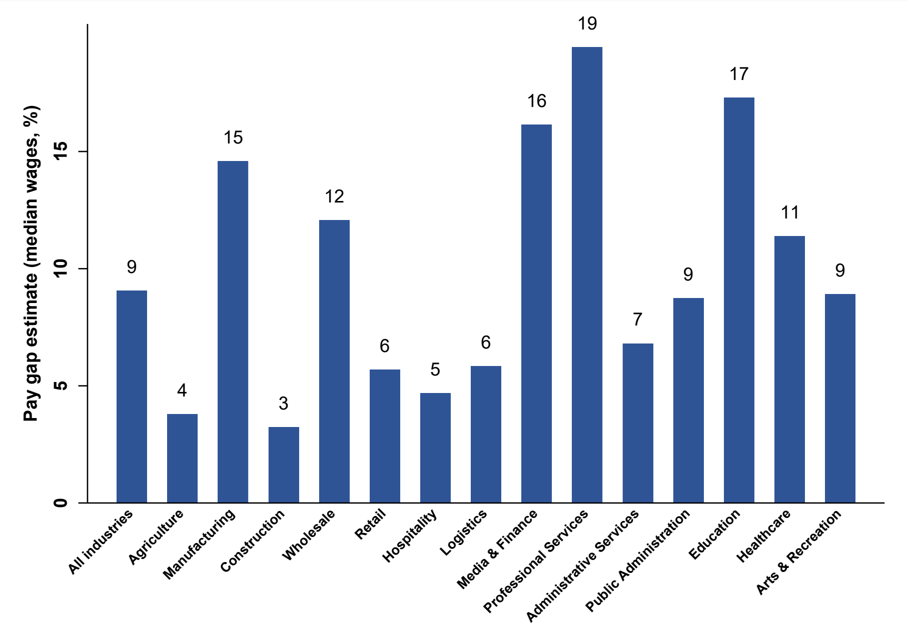


Source: Authors' calculations using June 2021 IR data

The following adjustment was made to the hours data in the Education industry. Hours in the education sector are often recorded in days rather than hours. If unadjusted, this results in this industry having unrealistically high average hourly earnings. Because the Education industry is large and female-dominated, it also leads to an overestimation of aggregate average female hourly pay, and an underestimation of the size of the aggregate gender pay gap. A full-time, 40-hour a week role is recorded as 7 days. Part-time work is recorded as a fraction of 7 days. Therefore, an adjustment was made to recorded hours so that hours = (recorded "hours"/7)*40. For example, 0.8FTE would be calculated as (5.6/7)*40 = 32 hours a week. However, some employees' hours are actual hours (not days). This is because while teachers' hours are recorded as days, other education industry staff such as caretakers' hours are actually recorded as hours. Therefore, if an employee works for 7 "hours" or less a week, the above conversion into actual hours is calculated. However, if this results in the employee getting paid less than the minimum wage, it is assumed that that employee's information was recorded in hours, not days.

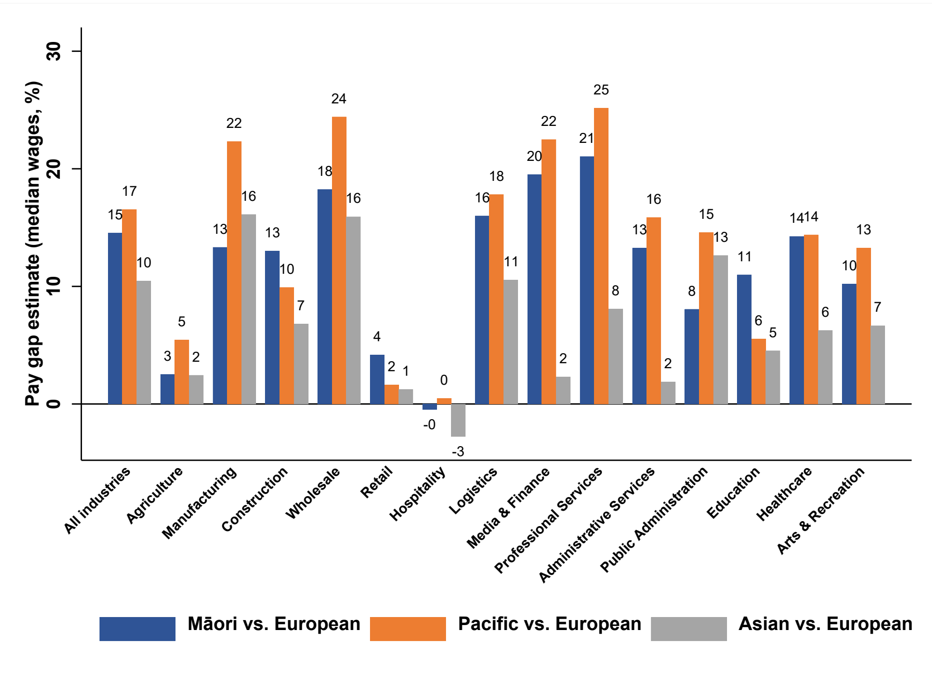
Appendix B: Median wage pay gaps

Figure B.1. Gender pay gaps by industry, median wages, 2022



Source: Authors' calculations using pooled June 2021 and 2022 HLFS data

Figure B.2. Ethnicity pay gaps by industry, median wages, 2022



Source: Authors' calculations using pooled June 2021 and 2022 HLFS data

Appendix C: Industry pay gaps over time

Description of the data are in Section 2. Here we provide the pay gaps estimated for each industry.

Figure C.1. Agriculture

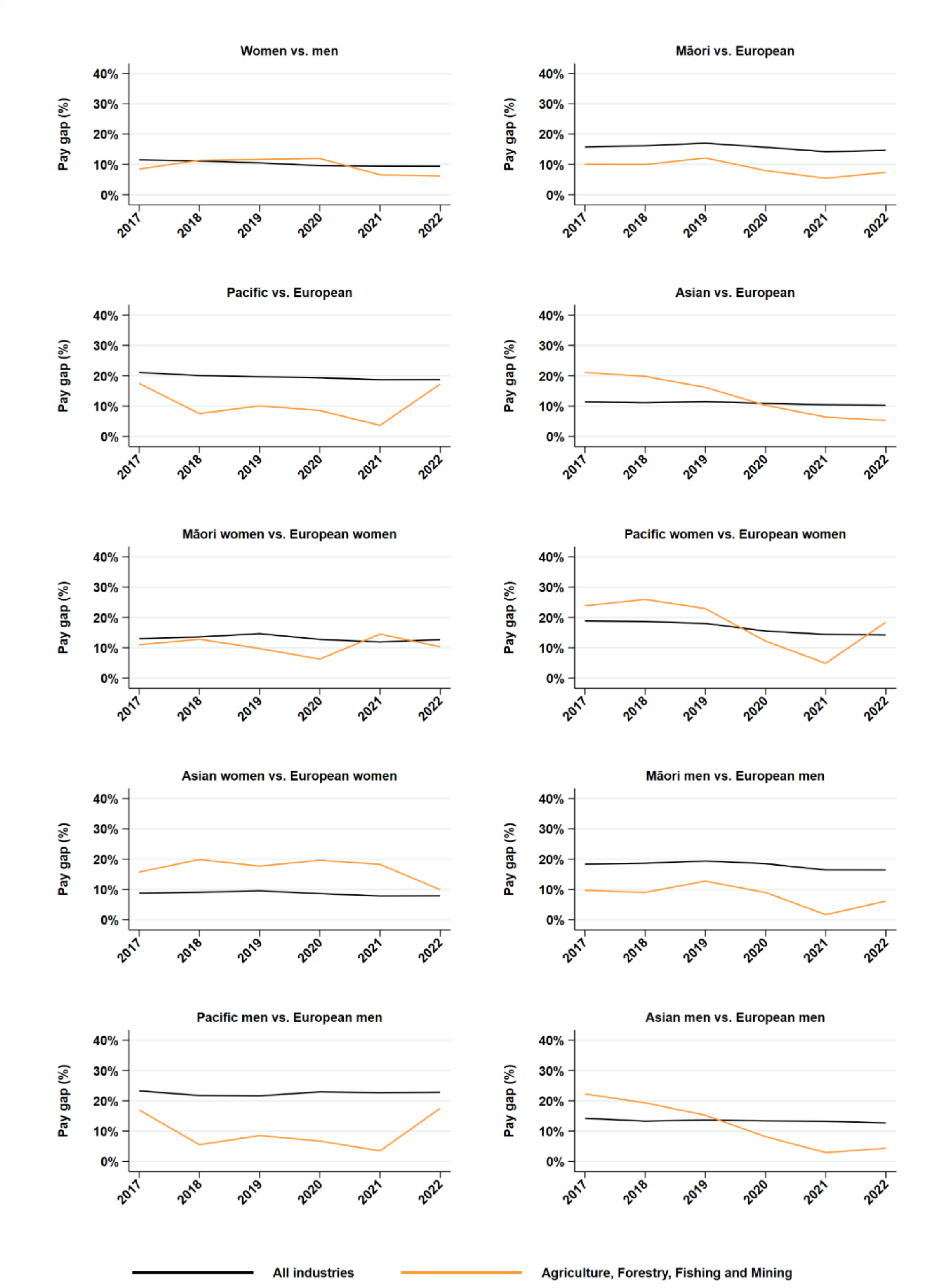


Figure C.2. Manufacturing

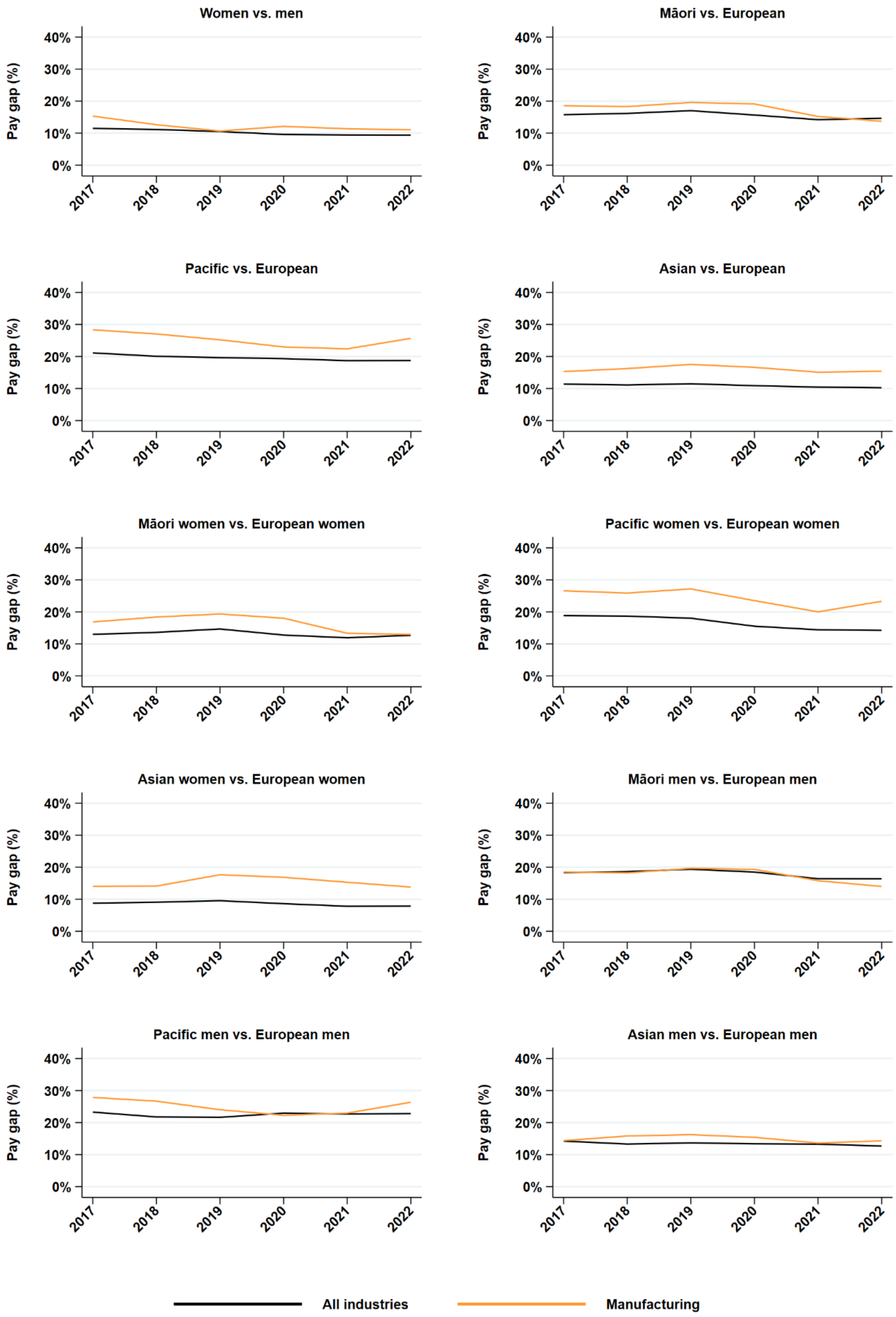


Figure C.3. Construction

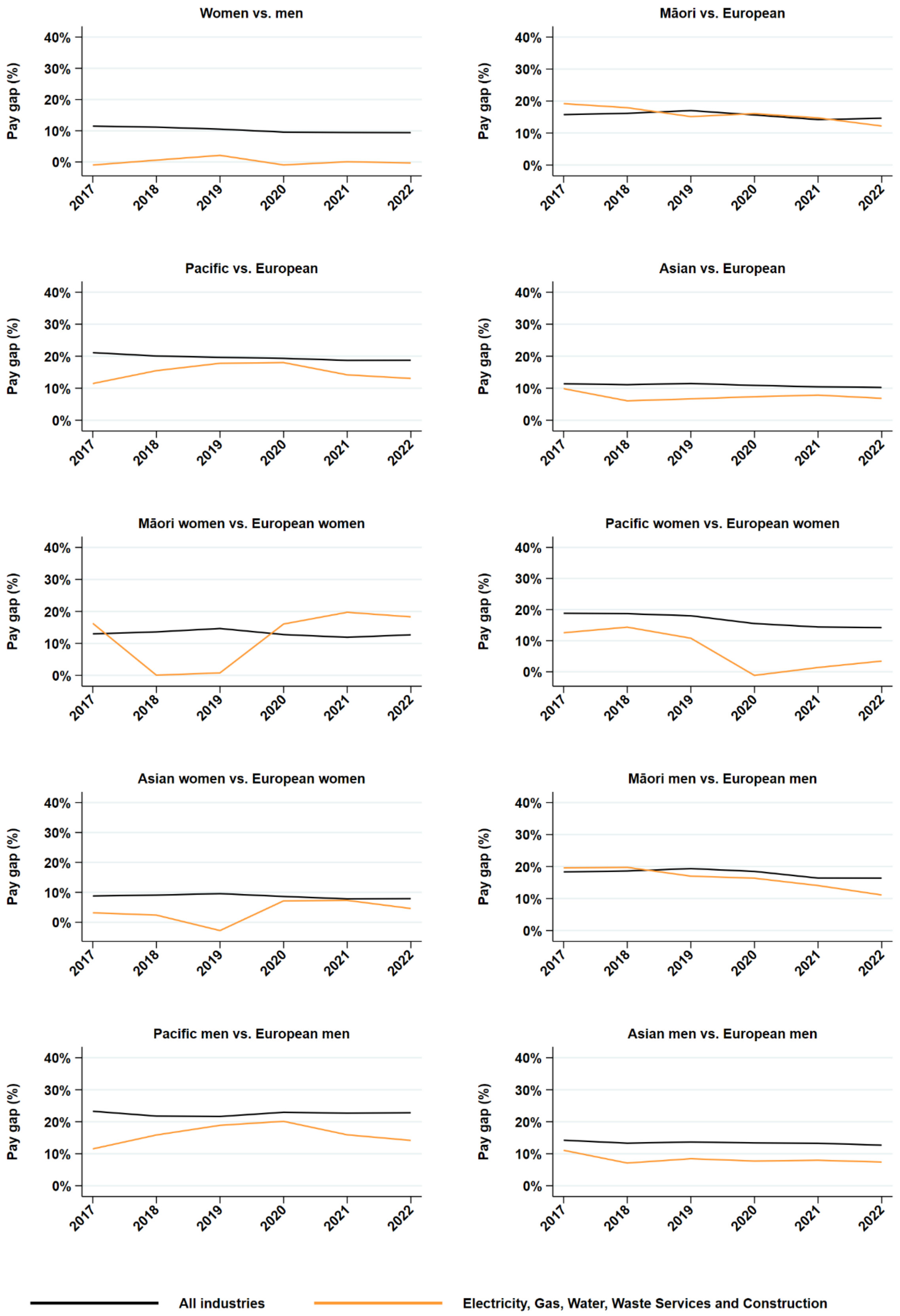


Figure C.4. Wholesale

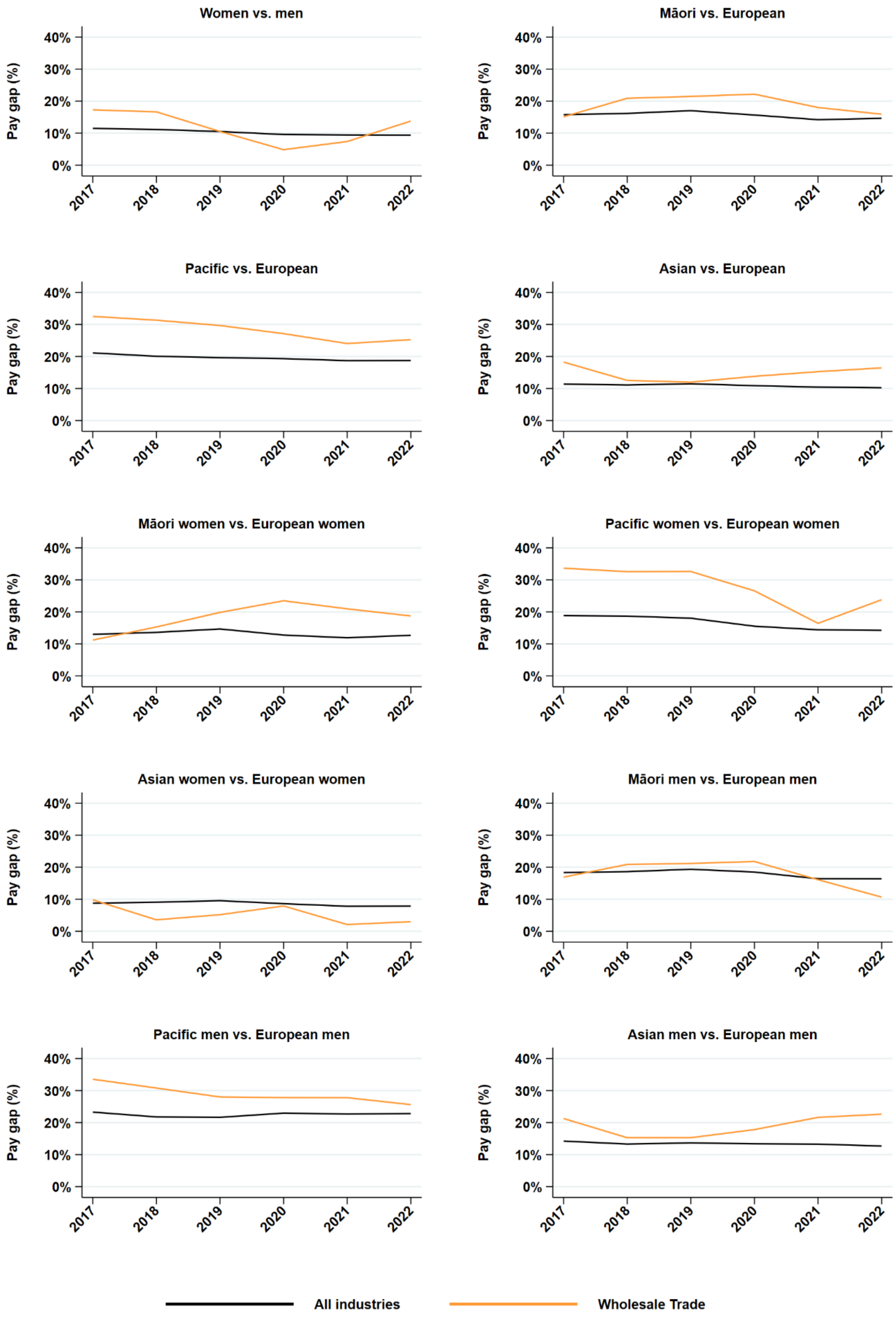


Figure C.5. Retail

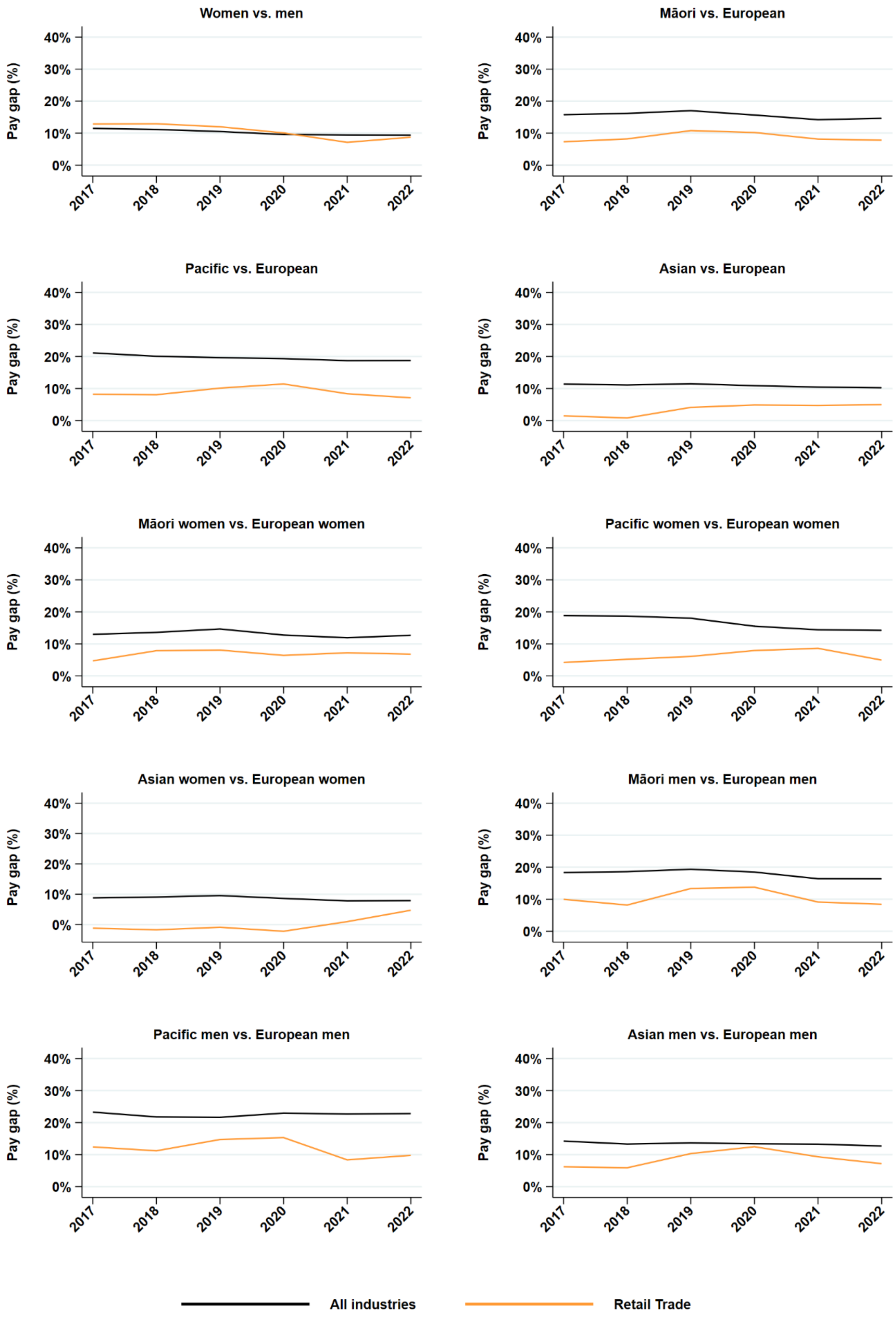


Figure C.6. Hospitality

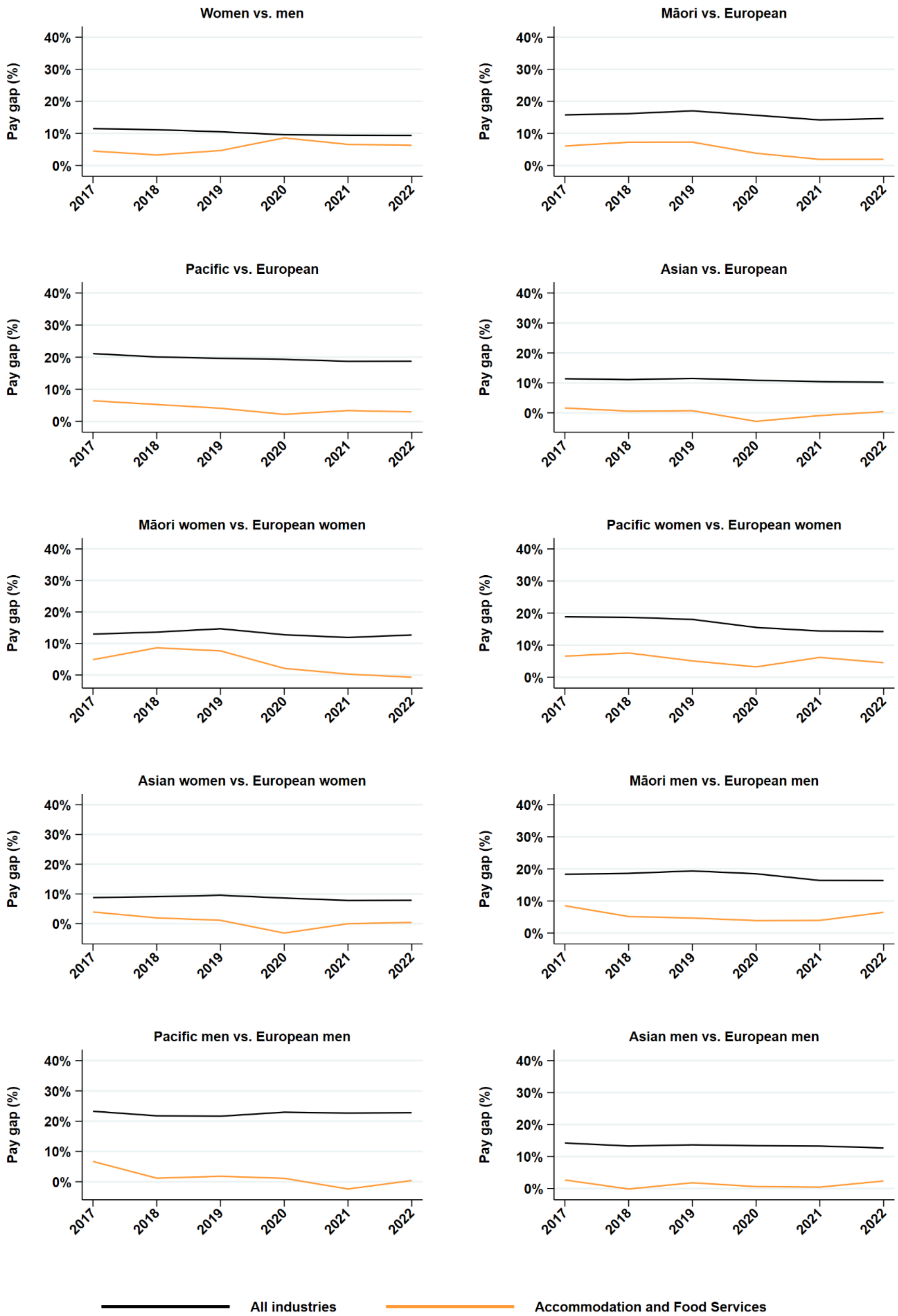


Figure C.7. Logistics

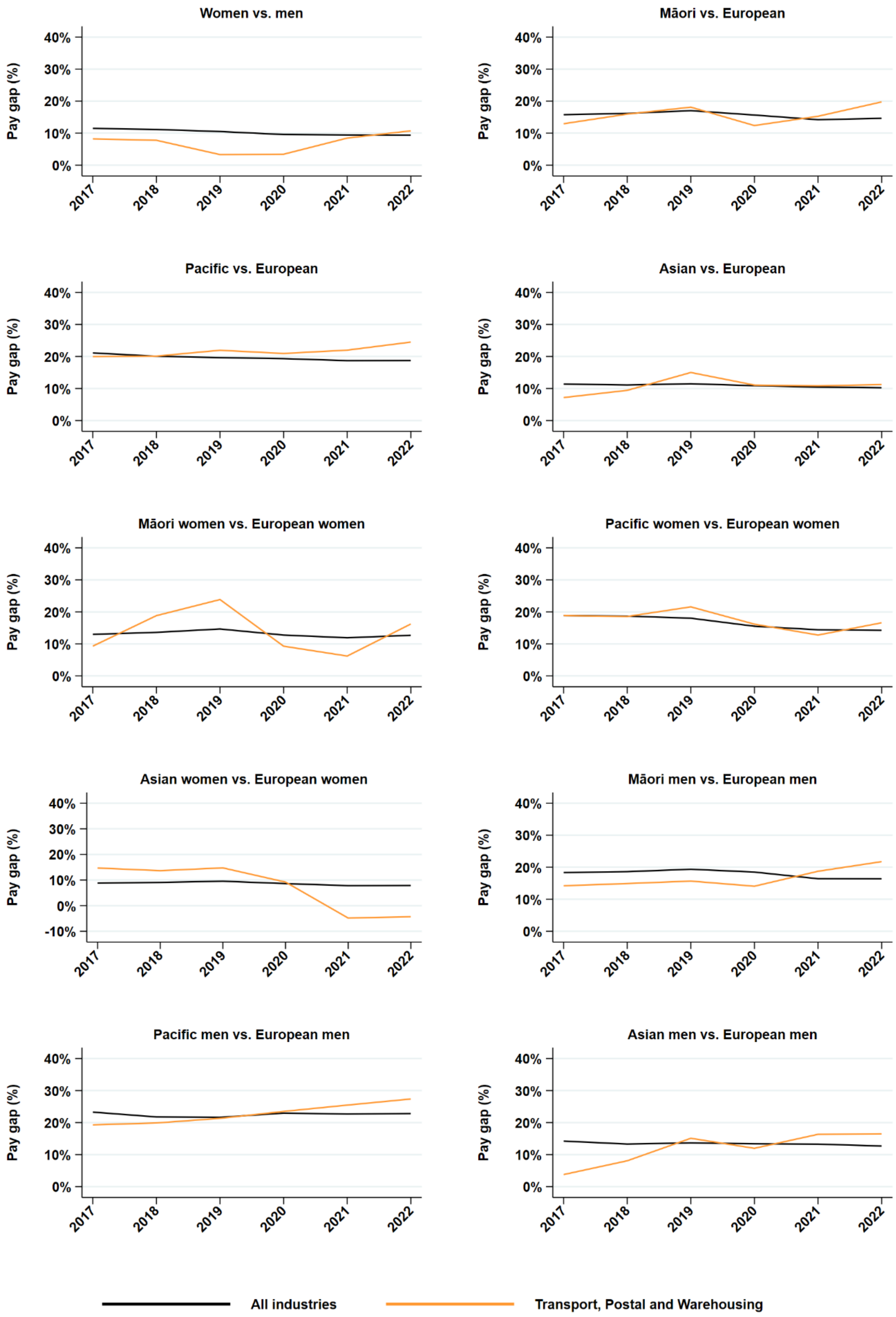


Figure C.8. Media & Finance

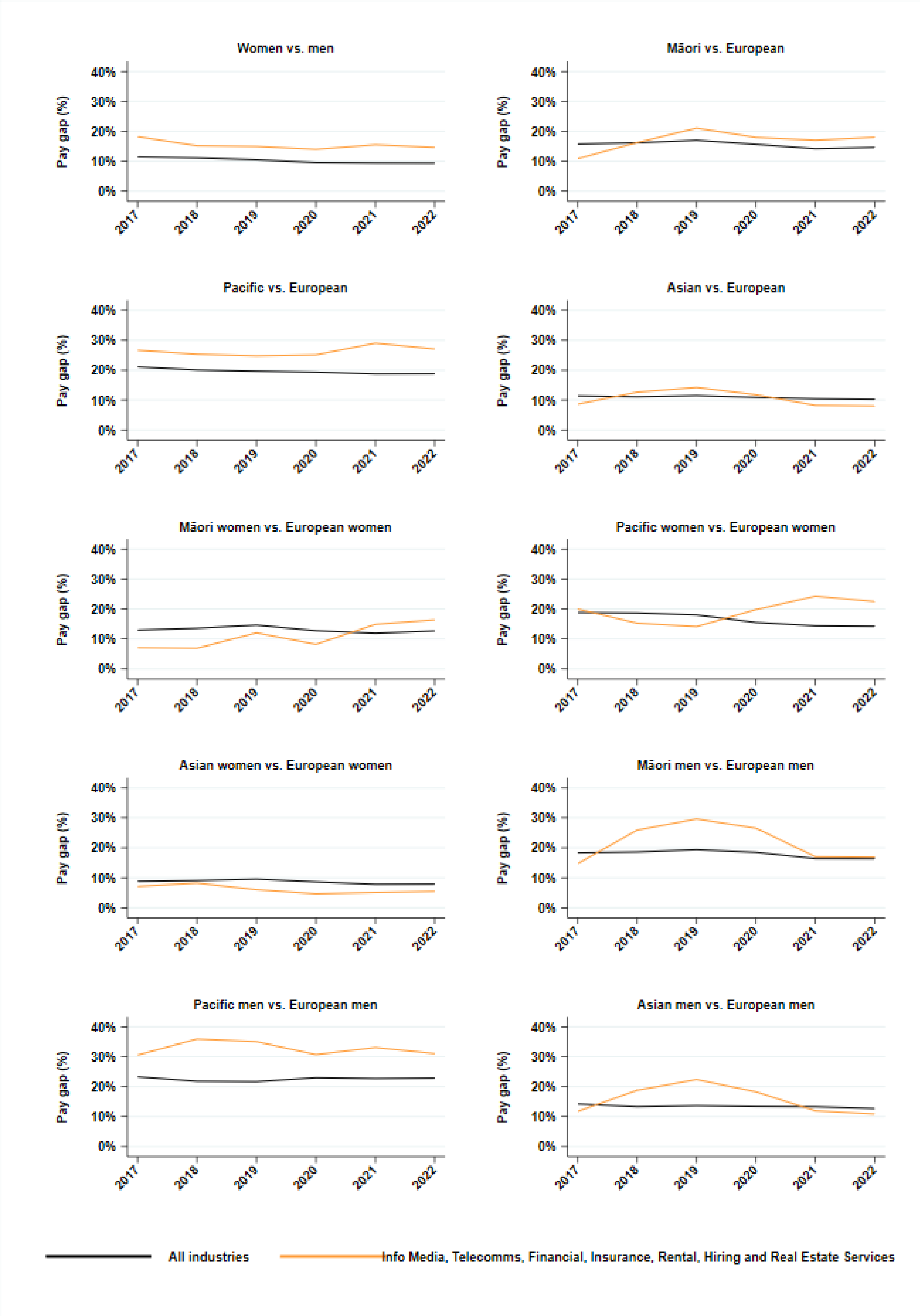


Figure C.9. Professional Services

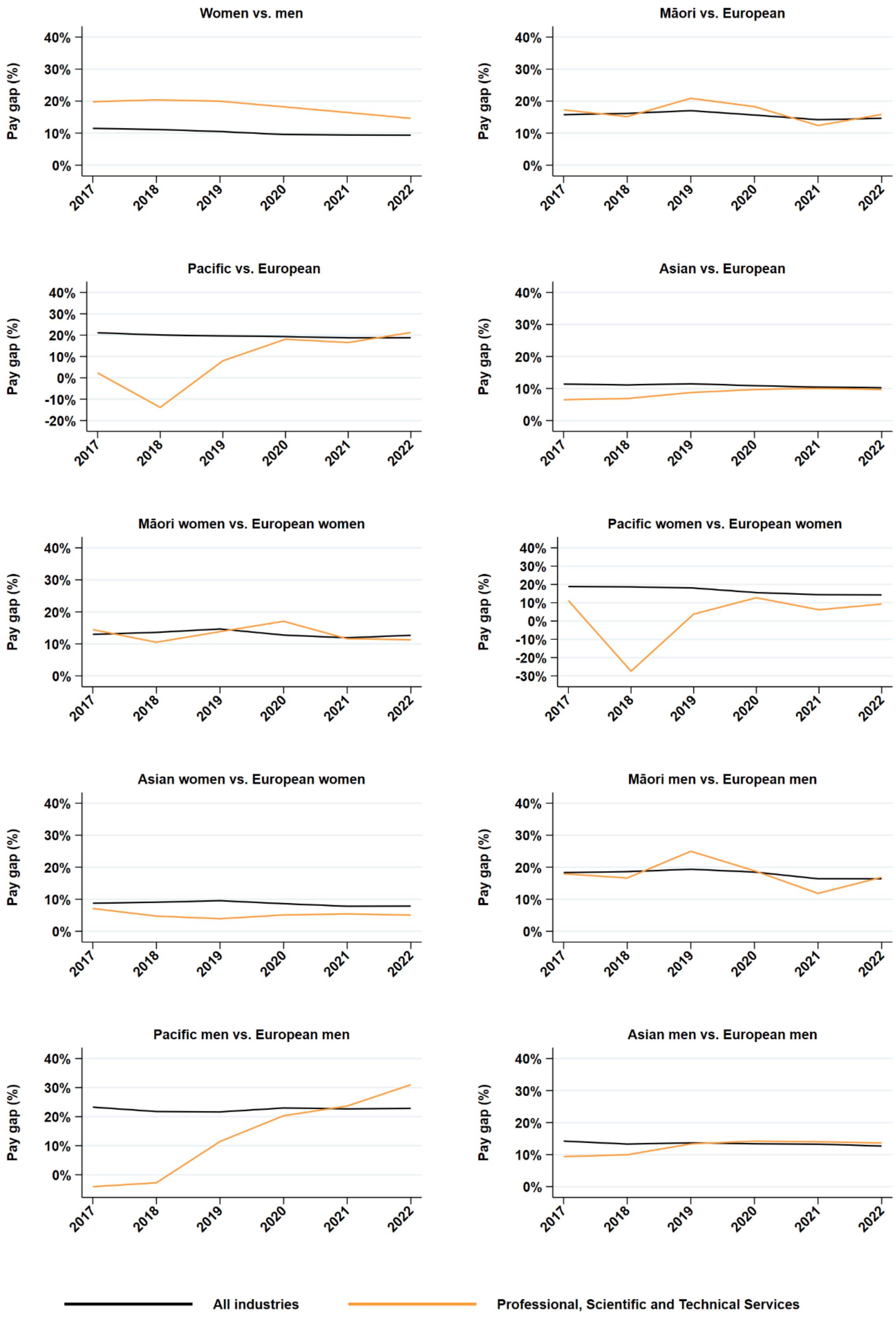


Figure C.10. Administrative Services

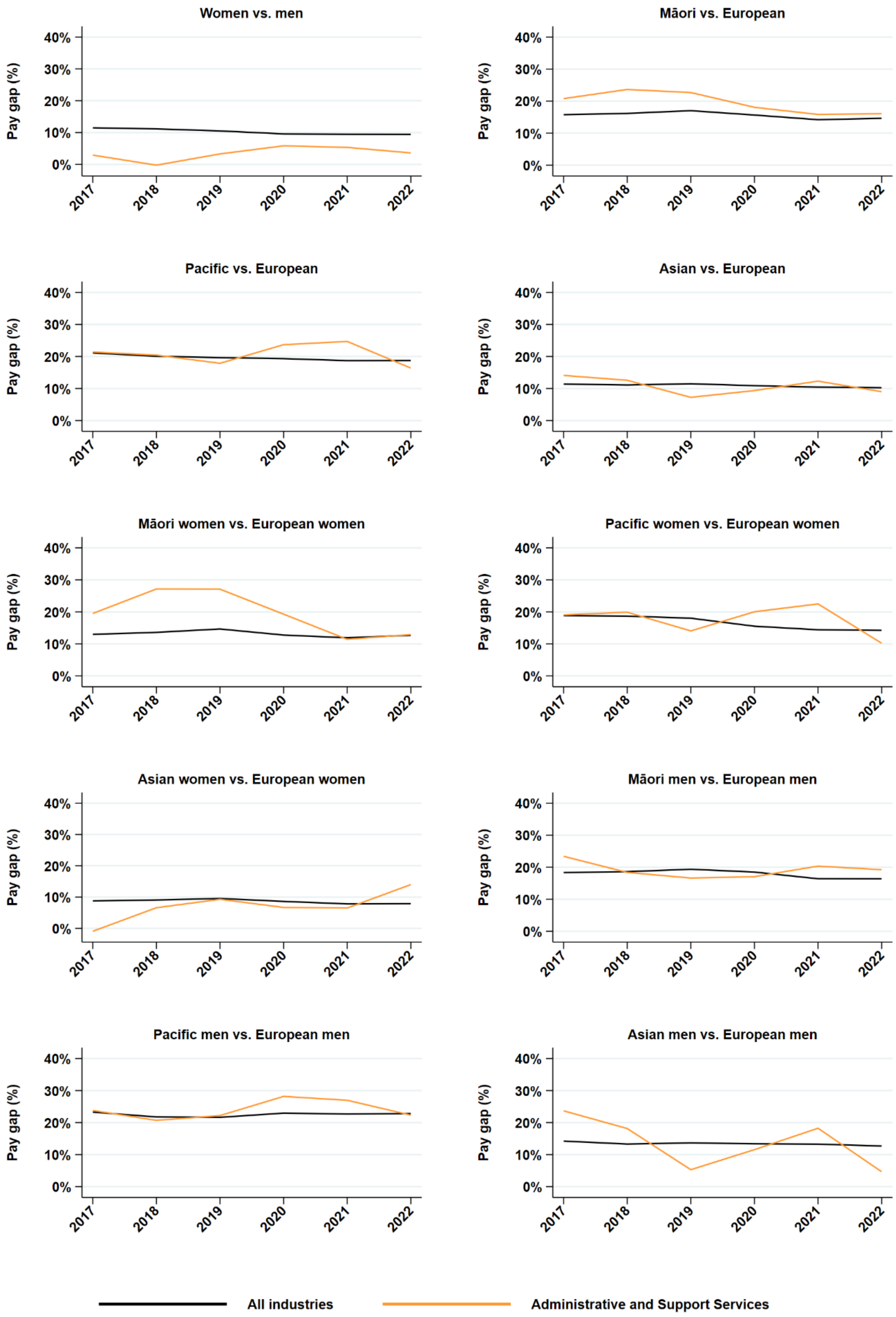


Figure C.11. Public Administration

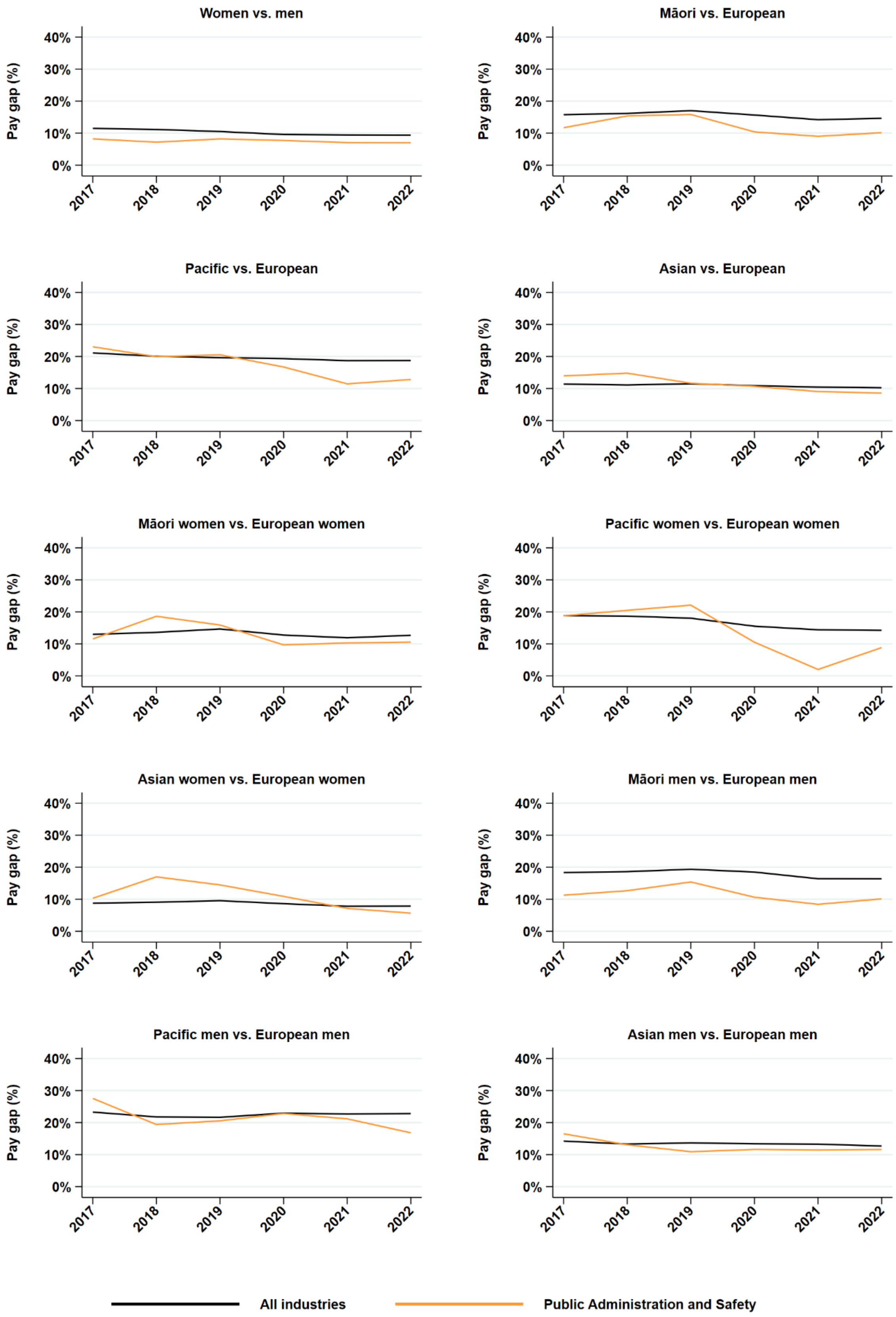


Figure C.12. Education

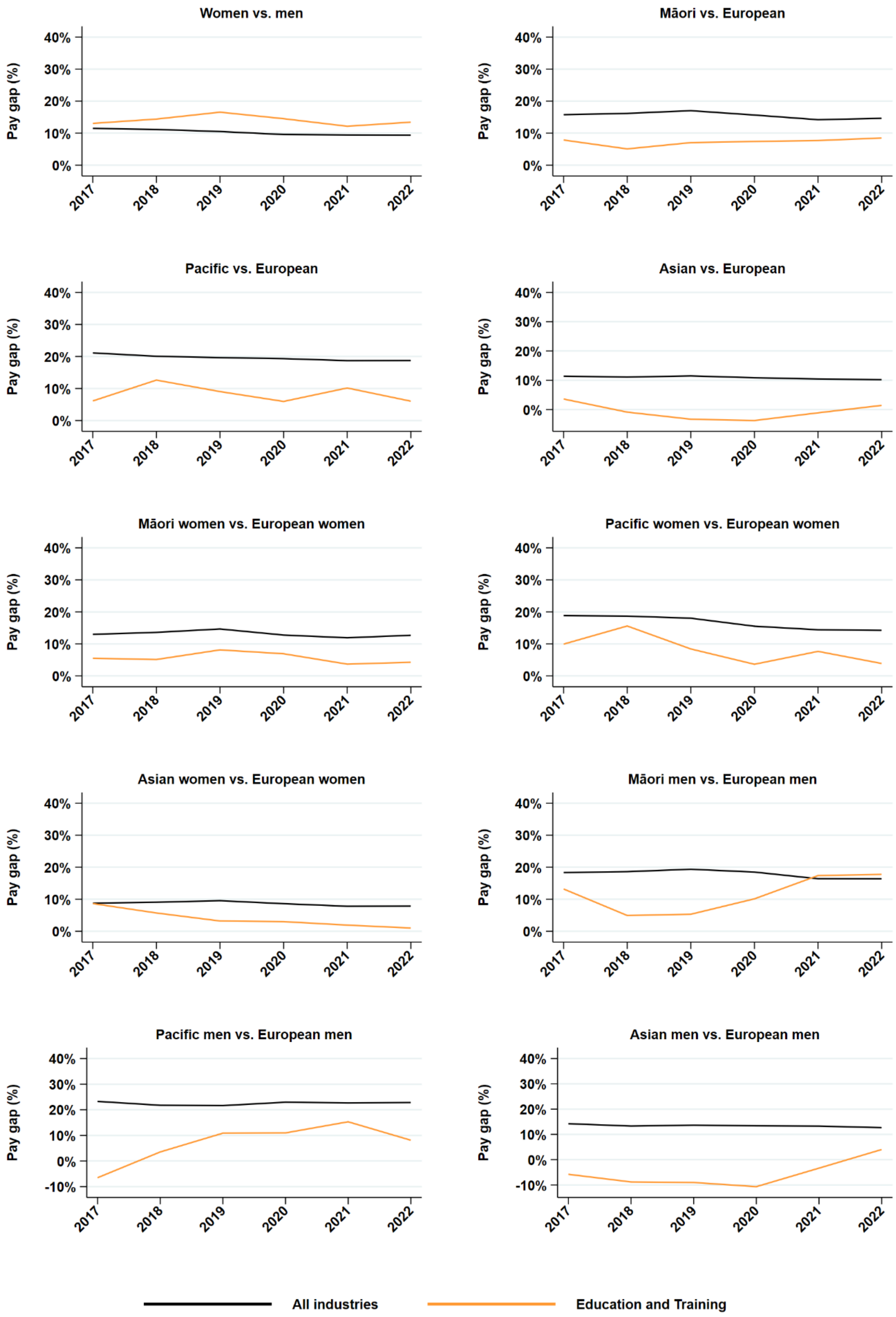


Figure C.13. Healthcare

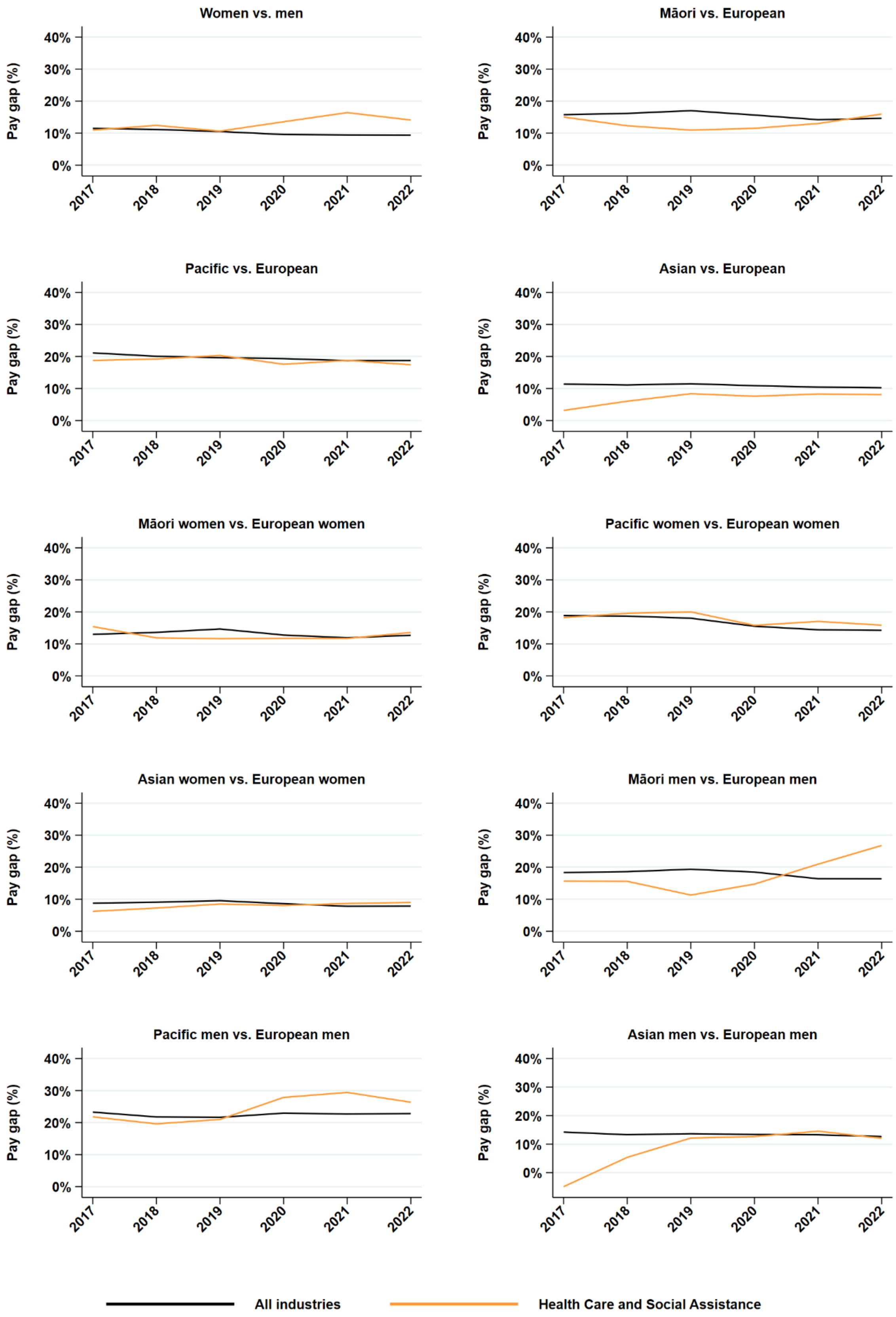
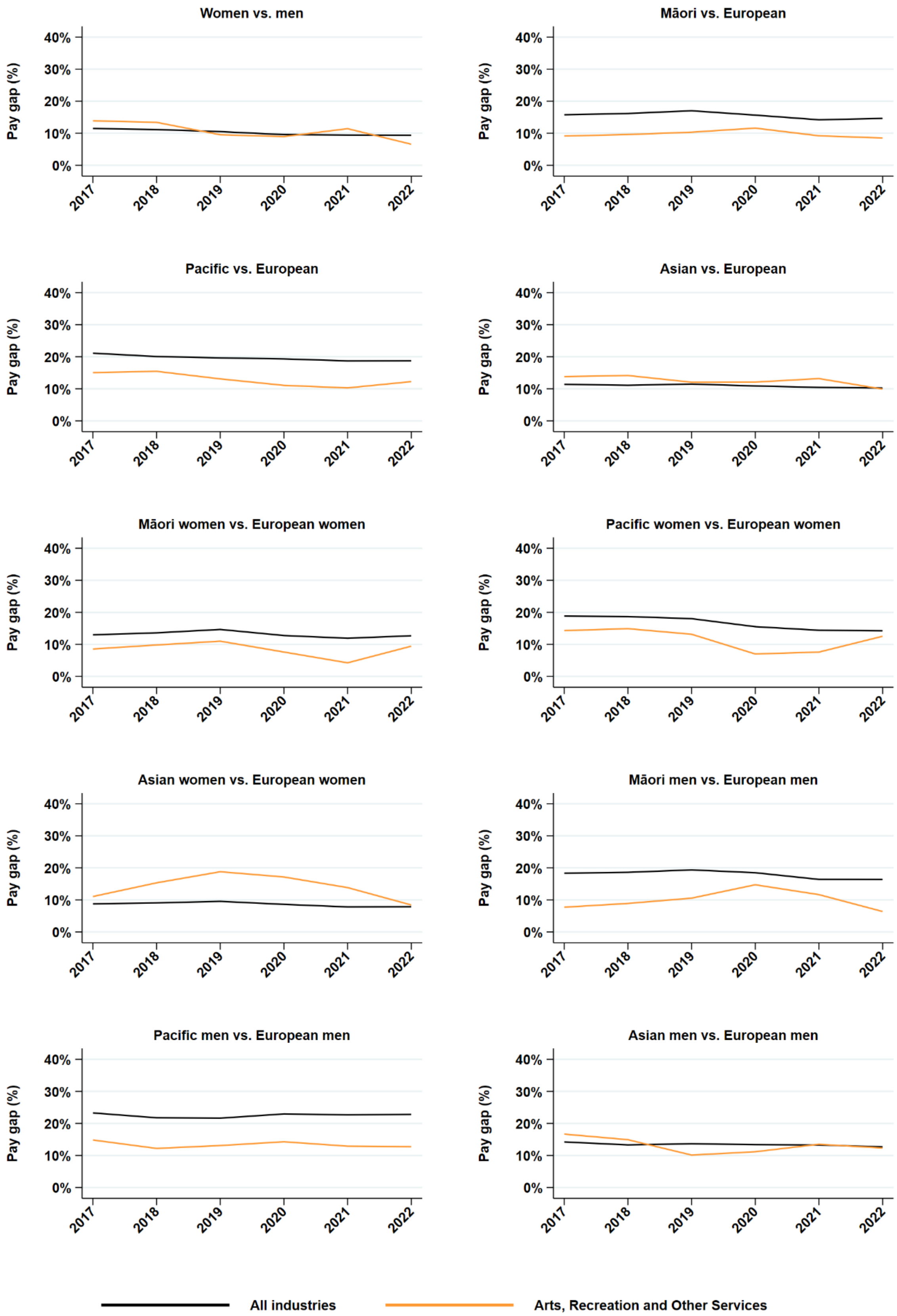


Figure C.14. Arts & Recreation



Appendix D: Sample descriptives table

Table D.1. Descriptive statistics of HLFS sample used in Blinder-Oaxaca decompositions

	Male (%)	Female (%)	*p*-value from χ^2 test	European (%)	Māori (%)	Pacific peoples (%)	Asian (%)	MELAA or other (%)	*p*-value from χ^2 test
Sex									<0.001
Male				50	51.3	53	53.5	53.5	
Female				50	48.7	47	46.5	46.6	
Ethnic group[1]			<0.001						
European	59.8	62.3							
Māori	14.8	14.6							
Pacific peoples	6.4	5.9							
Asian	16.5	14.9							
MELAA[2] or other ethnicity	2.6	2.3							
Years lived in New Zealand			<0.001						<0.001
Born in New Zealand	66.9	68.9		78.8	97.7	46.4	8.8	48.8	
0 to 5 years	8.2	6.7		4.1	0.1	6.9	26.4	17.9	
6 to 11 years	7.5	6.5		3.9	0.2	8.8	24	11.4	
12 to 19 years	8.3	8.2		5.7	0.4	12.5	23.2	12.4	
20 years or more	8.4	9.3		7.3	1.3	23.1	16.3	9.2	
Missing	0.7	0.5		0.3	0.1	2.3	1.4	0.3	
Household type			<0.001						<0.001
Couple only	19.9	22.9		25	15.8	8.2	16.7	27	
Couple with dependent child(ren)[3]	36.8	33		33.9	35.1	40.2	37	34.2	
One parent with dependent child(ren)[3]	2.8	7.2		4.1	10.4	6.5	2.5	4.7	
One-person household	7.6	6.3		8.2	6.5	2.7	3.9	8.9	
All other household types	32.7	30.5		28.6	32.1	42.3	39.9	25.1	
Missing	0.1	0.1		0.1	0.1	0.2	0.1	S	
Partnership status			<0.001						<0.001
Not partnered	35.1	35.4		33.3	42.3	40.2	34.5	33.4	
Partnered	64.9	64.6		66.7	57.7	59.7	65.5	66.6	
Missing	S	S		S	S	S	S	S	
Region			<0.001						<0.001
Northland	2.9	3.1		2.8	7.1	1	1	1.5	
Auckland	34.1	34.5		27.4	21.8	66.9	60.8	28.6	
Waikato	9.3	9.2		9.4	12.9	4.4	7.6	8.9	
Bay of Plenty	6.1	6.2		6.1	10.7	2.6	3.3	5.5	
Gisborne/Hawke's Bay	4.1	4.3		3.9	9.6	1.5	1.4	5.8	
Taranaki	2.3	2.3		2.4	3.2	0.4	0.7	10.1	
Manawatu-Wanganui	5.1	4.8		5.1	8.5	2.4	2.1	4.6	
Wellington	11.7	12.3		13.1	10.2	12	9.5	10.1	

Table D.1. Descriptive statistics of HLFS sample used in Blinder-Oaxaca decompositions continued

	Male (%)	Female (%)	p-value from χ^2 test	European (%)	Māori (%)	Pacific peoples (%)	Asian (%)	MELAA or other (%)	p-value from χ^2 test
Region									
Nelson/Tasman/Marlborough/ West Coast	3.8	3.6		4.7	3.2	1.4	1.3	3.5	
Canterbury	13.5	12.8		16.3	8.2	5	8.7	14.6	
Otago	4.9	4.9		6.4	2.4	1.7	2.5	5.6	
Southland	2.2	2		2.5	2.3	0.7	1.1	1.3	
Occupation in main job[4]			<0.001						<0.001
Managers	17.5	12.1		17.1	11.7	8	12.3	13.1	
Professionals	21.1	30.8		28.1	18.3	14	28.9	26.8	
Technicians and Trades Workers	18.9	4.7		11.9	11.1	11.8	12.8	13.7	
Community and Personal Service Workers	5.9	13.2		8.7	11.7	12	9.3	9.9	
Clerical and Administrative Workers	5.9	18.1		12.6	10.3	11.5	10.8	11.3	
Sales Workers	6.9	11.2		8.9	8	8.6	10.9	7.7	
Machinery Operators and Drivers	10.5	1.6		4.9	10.1	13.4	4.9	5.7	
Labourers	12.4	7.5		7.4	17.9	19.1	9.1	10.8	
Missing	0.8	0.7		0.6	1	1.5	1	0.9	
Type of employment relationship in main job			<0.001						<0.001
Permanent employee	93.2	90.8		93.3	89.2	89.8	90.6	90.3	
Casual employee	3.1	4.2		2.9	4.8	5.2	4.9	4.5	
Fixed term employee	1.6	3.2		2.4	2.5	1.8	2.3	3	
Seasonal employee	1.1	0.7		0.7	2.3	1.4	0.5	0.7	
Temporary employee	0.5	0.6		0.5	0.5	0.7	0.8	0.8	
Missing	0.6	0.5		0.3	0.7	1.2	0.9	0.8	
Full-time/part-time status			<0.001						<0.001
Full-time	92.1	74.5		82.8	83.2	88.2	84.7	81.5	
Part-time	7.9	25.5		17.2	16.8	11.8	15.3	18.5	
Member of union in main job			<0.001						<0.001
Union member	15.7	22.8		18.8	23.1	24.7	14.8	19.3	
Not a union member	81	74.7		79	72.7	68.6	82.2	78.3	
Missing	3.3	2.5		2.2	4.2	6.7	3	2.4	
Industry of main job[6]			<0.001						<0.001
Agriculture	5.8	2.2		4	6	2.5	3.1	4.5	
Manufacturing	14.6	6.2		9.5	12.8	16.7	9.4	10.9	
Construction	15.5	2.9		9.5	11	10.1	6.7	9.4	
Wholesale Trade	5.7	3.3		4.8	3.7	4.9	4.1	4.3	
Retail Trade	8.7	11.1		9.6	9.2	9.4	12.4	7.5	
Hospitality	4.3	7		4.4	5.6	5.3	10.4	6.6	

Table D.1. Descriptive statistics of HLFS sample used in Blinder-Oaxaca decompositions continued

	Male (%)	Female (%)	p-value from χ^2 test	European (%)	Māori (%)	Pacific peoples (%)	Asian (%)	MELAA or other (%)	p-value from χ^2 test
Industry of main job[6]									
Logistics	5.8	2.6		3.8	5.2	7.7	3.9	4.4	
Media & Finance	6	6.8		6.8	4.2	5	7.8	4.6	
Professional Services	8.5	7.7		9.1	3.6	3.1	10	8.8	
Administrative Services	2.7	3.1		2.5	3.4	3.9	3.3	3.1	
Public Administration	7.2	7.6		7.9	8	7.5	5	6.4	
Education	5	14.1		10.5	9.9	6.1	6	10	
Healthcare	3.8	19.1		11.1	10.3	11.2	12.6	11.9	
Arts & Recreation	5.3	5.3		5.6	5.5	4.2	4.1	6.5	
Missing	1.3	1		0.8	1.5	2.3	1.4	1.1	
Continuous variables:	Mean (SD)	Mean (SD)	p-value	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	p-value
Age (in years)	38.7 (13.0)	39.8 (13.3)	<0.001	40.5 (13.5)	37.4 (13.4)	37.4 (12.6)	36.5 (11.0)	40.7 (12.7)	<0.001
No. dependent children in family	0.7 (1.1)	0.7 (1.0)	<0.001	0.7 (1.0)	0.9 (1.2)	1.1 (1.3)	0.6 (0.9)	0.7 (1.0)	<0.001
Weekly hours worked in main job[5]	40.9 (11.0)	33.8 (12.5)	<0.001	37.5 (12.5)	37.6 (13.0)	38.2 (10.7)	36.7 (10.9)	36.9 (12.6)	<0.001
Usual hours worked last week in main job	41.2 (10.5)	34.0 (12.2)	<0.001	37.7 (12.2)	38.0 (12.7)	38.5 (10.1)	36.8 (10.5)	37.2 (12.8)	<0.001
Actual hours worked last week in main job	38.4 (13.8)	31.4 (14.4)	<0.001	34.9 (14.8)	35.0 (15.5)	36.3 (13.0)	34.8 (12.8)	34.7 (15.4)	<0.001
Job tenure in main job (in weeks)	309.2 (379.2)	285.0 (341.2)	<0.001	326.4 (386.5)	283.1 (352.3)	282.2 (323.7)	204.4 (244.5)	290.5 (369.5)	<0.001
No. months employed over past 12 months	11.4 (1.9)	11.2 (2.1)	<0.001	11.4 (1.8)	11.1 (2.2)	11.1 (2.2)	11.1 (2.1)	11.1 (2.2)	<0.001
Total weekly household income ($)	2,555 (1,439)	2,542 (1,537)	<0.001	2,622 (1,536)	2,355 (1,384)	2,576 (1,483)	2,462 (1,386)	2,362 (1,351)	<0.001
Total no. of observations	6,900,100	6,630,300		8,255,200	1,990,900	829,200	2,124,800	330,200	

Symbols:

S suppressed

Notes:

[1] Ethnic group has been administratively prioritised (assignment to one ethnic group based on a predetermined hierarchy).

[2] Middle Eastern, Latin American, African.

[3] This category includes both those with and those without adult children or others in the household.

[4] Coded to level 1 (major group) of the Australian and New Zealand Standard Classification of Occupations.

[5] Includes hours on paid leave.

[6] Coded at level 1 of the Australian and New Zealand Standard Industrial Classification 2006 and then collapsed to 14 categories.

Appendix E: Blinder-Oaxaca decomposition results

Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction)

	All industries	Agri.	Manufact.	Construct.	Wholesale	Retail	Hospitality	Logistics	Media & Finance	Profess. Services	Admin. Services	Public Admin.	Education	Health.	Arts & Rec.
Women vs. men															
Individual characteristics (%)	-6.6	-3.8	6.6	-546.2	0.3	-5.3	-20.6	9.0	-7.5	-2.1	-90.4	16.1	-2.5	-6.8	0.9
Region (%)	-0.7	-4.2	-2.1	-26.3	-5.3	2.7	8.5	-14.5	7.8	5.8	-38.7	-12.8	-0.2	3.1	-0.5
Education characteristics (%)	-9.7	-5.1	-4.1	-395.4	-7.5	0.9	12.0	-2.4	4.8	4.0	-18.5	-19.4	4.2	6.7	-5.1
Job-related characteristics (%)	-12.4	4.1	7.8	-38.7	13.4	12.4	12.1	-41.7	12.1	30.3	-80.4	17.1	4.3	2.1	6.7
Industry (%)	24.4														
Total explained (%)	-5.0	-8.9	8.2	-1006.5	0.9	10.6	12.1	-49.6	17.2	38.0	-228.0	1.1	5.8	5.2	2.0
Unexplained (%)	105.0	108.9	91.8	1106.5	99.1	89.4	87.9	149.6	82.8	62.0	328.0	98.9	94.2	94.8	98.0
Pay gap (%)	9.6	11.1	14.7	0.5	11.1	11.2	4.6	5.3	11.0	16.8	1.0	3.3	11.5	10.3	9.0
Māori vs. European															
Individual characteristics (%)	14.5	8.7	14.8	15.3	17.9	29.0	99.7	13.0	18.1	24.5	11.2	15.6	62.1	9.6	30.3
Region (%)	4.7	-7.0	0.0	-0.4	2.0	1.5	67.1	1.1	3.0	5.6	4.0	15.3	18.0	2.2	2.3
Education characteristics (%)	18.5	16.1	19.4	12.4	11.1	19.1	62.5	6.5	6.8	9.3	4.0	24.0	37.5	19.7	5.8
Job-related characteristics (%)	33.6	16.8	45.0	19.8	55.8	60.4	116.8	52.9	21.7	20.6	54.8	26.1	43.4	38.2	17.4
Industry (%)	5.9														
Total explained (%)	77.2	34.6	79.3	47.2	86.8	110.0	346.0	73.5	49.5	60.0	73.9	81.0	161.0	69.8	55.8
Unexplained (%)	22.8	65.4	20.7	52.8	13.2	-10.0	-246.0	26.5	50.5	40.0	26.1	19.0	-61.0	30.2	44.2
Pay gap (%)	12.9	11.4	13.5	18.5	15.8	5.0	1.0	13.0	18.1	18.6	17.6	10.0	3.4	11.5	6.8

Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction) continued

	All industries	Agri.	Manufact.	Construct.	Wholesale	Retail	Hospitality	Logistics	Media & Finance	Profess. Services	Admin. Services	Public Admin.	Education	Health.	Arts & Rec.
Pacific vs. European															
Individual characteristics (%)	2.9	1.4	7.0	0.9	4.8	3.1	-10.2	5.8	13.3	17.4	3.5	10.4	31.3	-5.6	-4.2
Region (%)	-16.4	-11.3	-11.3	-31.9	-10.9	-59.1	-14.8	-14.1	-14.6	-38.8	-18.4	-4.3	-180.3	-18.7	-22.2
Education characteristics (%)	15.7	12.9	11.3	14.4	7.3	13.0	5.2	6.1	2.9	15.6	5.7	14.7	248.6	17.1	10.5
Job-related characteristics (%)	34.6	20.2	35.7	35.2	41.0	48.9	-1.9	35.9	26.0	42.7	55.8	19.1	265.9	38.1	11.5
Industry (%)	-0.6														
Total explained (%)	36.3	23.1	42.7	18.6	42.3	5.8	-21.7	33.7	27.5	37.0	46.5	40.0	365.5	30.9	-4.3
Unexplained (%)	63.7	76.9	57.3	81.4	57.7	94.2	121.7	66.3	72.5	63.0	53.5	60.0	-265.5	69.1	104.3
Pay gap (%)	19.0	20.6	26.1	12.9	29.9	6.8	6.7	21.5	27.1	10.9	20.9	18.8	0.8	17.9	9.5
Asian vs. European															
Individual characteristics (%)	-0.6	-9.4	2.5	-44.6	-1.2	-37.5	-308.2	-13.0	36.1	29.5	-7.8	3.4	23.1	-25.2	-11.6
Region (%)	-19.9	-4.8	-12.2	-47.6	-21.8	-111.8	-140.7	-26.3	-51.3	-37.3	-15.6	-7.9	67.5	-22.4	-18.7
Education characteristics (%)	-21.1	-14.5	-15.9	-42.8	-25.9	-98.8	-167.3	-14.0	-38.5	-28.1	-6.8	-14.9	47.8	-25.7	-7.6
Job-related characteristics (%)	21.3	7.5	23.3	32.2	22.3	5.6	-222.8	32.6	27.9	-1.1	30.0	18.5	-37.6	37.3	15.8
Industry (%)	4.4														
Total explained (%)	-15.9	-21.2	-2.4	-102.9	-26.6	-242.5	-839.1	-20.7	-25.8	-37.0	-0.2	-0.7	100.9	-36.0	-22.0
Unexplained (%)	115.9	121.2	102.4	202.9	126.6	342.5	939.1	120.7	125.8	137.0	100.2	100.7	-0.9	136.0	122.0
Pay gap (%)	11.9	19.9	19.2	6.9	12.8	2.7	0.7	11.3	7.3	7.5	13.6	14.3	-2.7	8.1	9.9

Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction) continued

	All industries	Agri.	Manufact.	Construct.	Wholesale	Retail	Hospitality	Logistics	Media & Finance	Profess. Services	Admin. Services	Public Admin.	Education	Health.	Arts & Rec.
Māori women vs. European women															
Individual characteristics (%)	10.7	2.7	6.5	5.0	10.7	20.2	-29.0	20.5	16.1	16.6	3.3	11.0	357.9	10.7	28.7
Region (%)	5.5	-33.9	4.8	-1.7	3.3	-6.3	-30.6	-4.5	3.7	10.5	4.2	18.1	112.3	1.1	5.4
Education characteristics (%)	22.7	48.1	25.8	12.0	12.3	22.9	-38.5	3.2	6.7	15.9	2.6	28.5	232.3	18.9	12.9
Job-related characteristics (%)	30.9	54.3	30.9	10.9	30.2	52.6	-59.1	90.3	19.3	21.2	37.6	23.6	234.0	38.5	8.6
Industry (%)	8.5														
Total explained (%)	78.3	71.2	67.9	26.2	56.5	89.4	-157.2	109.5	45.8	64.3	47.7	81.2	936.5	69.2	55.6
Unexplained (%)	21.7	28.8	32.1	73.8	43.5	10.6	257.2	-9.5	54.2	35.7	52.3	18.8	-836.5	30.8	44.4
Pay gap (%)	10.4	4.1	15.7	22.4	15.8	3.9	-1.2	8.1	12.9	12.8	23.2	10.5	0.5	11.7	5.5
Pacific women vs. European women															
Individual characteristics (%)	5.7	18.9	2.7	5.1	14.7	6.0	-2.8	8.6	10.6	-590.8	1.3	23.9	12.4	-6.0	9.0
Region (%)	-22.6	-30.9	-14.6	-58.8	-21.1	-104.4	-17.4	-24.2	-21.1	1386.6	-17.7	-12.3	157.1	-19.2	-30.3
Education characteristics (%)	20.2	20.2	11.7	-3.4	6.9	13.5	8.5	5.9	2.3	-499.4	5.2	36.6	-230.4	19.9	19.9
Job-related characteristics (%)	35.3	52.8	32.1	15.7	34.0	40.2	-20.1	43.9	19.0	-632.4	48.1	38.8	-171.8	38.6	16.4
Industry (%)	-0.6														
Total explained (%)	38.1	60.9	31.9	-41.3	34.5	-44.6	-31.8	34.2	10.8	-336.0	36.9	87.0	-232.7	33.2	15.0
Unexplained (%)	61.9	39.1	68.1	141.3	65.5	144.6	131.8	65.8	89.2	436.0	63.1	13.0	332.7	66.8	85.0
Pay gap (%)	14.3	14.8	28.0	8.4	25.0	4.4	4.0	17.8	21.2	-0.4	21.8	7.4	-1.0	16.5	4.9

Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction) continued

	All industries	Agri.	Manufact.	Construct.	Wholesale	Retail	Hospitality	Logistics	Media & Finance	Profess. Services	Admin. Services	Public Admin.	Education	Health.	Arts & Rec.
Asian women vs. European women															
Individual characteristics (%)	7.1	5.3	-0.5	-6.7	69.8	412.1	-132.6	-18.3	132.9	104.6	20.9	1.3	25.4	-14.0	4.0
Region (%)	-33.0	-6.5	-16.5	90.3	-98.3	2392.6	-346.3	49.9	-223.4	-123.6	-76.4	-15.1	-165.6	-20.7	-16.7
Education characteristics (%)	-34.9	-15.2	-16.9	119.4	-100.9	2207.2	-415.3	26.7	-189.3	-109.9	-12.9	-21.0	-121.7	-23.1	-7.9
Job-related characteristics (%)	38.0	26.5	40.2	61.2	1.0	-158.6	-239.2	-24.0	67.5	-53.6	84.3	24.1	141.0	39.6	24.0
Industry (%)	-0.5														
Total explained (%)	-23.3	10.2	6.3	264.3	-128.3	4853.3	-1133.5	34.3	-212.3	-182.6	15.8	-10.7	-120.9	-18.2	3.3
Unexplained (%)	123.3	89.8	93.7	-164.3	228.3	-4753.3	1233.5	65.7	312.3	282.6	84.2	110.7	220.9	118.2	96.7
Pay gap (%)	7.5	15.4	15.9	-4.7	3.7	-0.1	0.3	-8.0	2.0	2.7	3.1	9.4	1.2	8.8	10.2
Māori men vs. European men															
Individual characteristics (%)	17.0	10.8	19.0	16.4	23.6	29.1	30.9	9.4	18.4	26.8	26.6	17.8	17.6	14.9	32.0
Region (%)	3.4	-5.1	-2.4	0.0	2.4	6.4	17.1	1.6	1.2	3.3	0.1	11.1	9.7	4.2	-0.4
Education characteristics (%)	13.2	11.5	17.8	11.1	12.7	13.5	10.4	6.7	7.5	3.0	2.6	15.1	13.2	16.7	3.5
Job-related characteristics (%)	32.3	9.2	52.1	21.4	90.2	59.2	37.6	43.6	21.2	19.3	88.1	24.9	18.2	23.8	27.0
Industry (%)	5.5														
Total explained (%)	71.4	26.4	86.5	48.9	128.8	108.2	96.0	61.4	48.3	52.4	117.4	69.0	58.7	59.6	62.1
Unexplained (%)	28.6	73.6	13.5	51.1	-28.8	-8.2	4.0	38.6	51.7	47.6	-17.4	31.0	41.3	40.4	37.9
Pay gap (%)	16.1	13.7	12.1	18.5	12.3	6.6	6.0	16.2	22.9	21.7	11.7	11.1	11.1	13.3	5.3

Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction) continued

	All industries	Agri.	Manufact.	Construct.	Wholesale	Retail	Hospitality	Logistics	Media & Finance	Profess. Services	Admin. Services	Public Admin.	Education	Health.	Arts & Rec.
Pacific men vs. European men															
Individual characteristics (%)	2.5	-2.2	7.2	-0.7	0.2	0.3	-23.1	-0.2	13.7	8.4	5.3	6.9	34.7	-0.2	-8.0
Region (%)	-13.1	-8.5	-11.0	-25.4	-7.1	-32.6	-14.6	-10.8	-10.1	-21.6	-14.5	-2.8	-20.4	-15.6	-24.5
Education characteristics (%)	11.4	9.3	11.2	12.2	7.8	6.1	2.0	5.5	2.3	8.3	6.3	9.4	35.8	4.4	6.9
Job-related characteristics (%)	32.9	13.0	38.2	31.4	42.2	51.0	16.0	39.7	29.3	40.3	58.2	17.4	45.2	26.9	11.1
Industry (%)	1.3														
Total explained (%)	35.0	11.6	45.6	17.5	43.1	24.7	-19.7	34.2	35.3	35.4	55.5	31.0	95.3	15.5	-14.5
Unexplained (%)	65.0	88.4	54.4	82.5	56.9	75.3	119.7	65.8	64.7	64.6	44.5	69.0	4.7	84.5	114.5
Pay gap (%)	23.4	24.8	23.8	15.5	32.1	10.2	9.8	22.8	36.1	14.9	22.8	28.0	6.1	28.1	11.6
Asian men vs. European men															
Individual characteristics (%)	-0.2	-13.2	-2.6	-43.4	-9.2	7.7	-126.5	-15.0	35.3	32.2	-15.9	4.6	7.0	-18.0	-20.4
Region (%)	-14.3	-4.5	-12.9	-32.0	-11.9	-30.0	-35.3	-18.5	-32.4	-23.1	-9.5	-5.2	14.7	-19.1	-19.4
Education characteristics (%)	-13.2	-12.3	-17.1	-22.3	-15.7	-21.0	-50.2	-9.3	-15.3	-13.5	-7.8	-10.7	7.2	-9.6	-6.0
Job-related characteristics (%)	13.6	3.4	19.0	29.7	22.2	5.6	-90.5	28.0	28.8	11.9	28.3	19.0	5.2	13.4	12.3
Industry (%)	7.5														
Total explained (%)	-6.6	-26.5	-13.7	-68.0	-14.6	-37.7	-302.5	-14.8	16.5	7.5	-4.9	7.7	34.0	-33.2	-33.5
Unexplained (%)	106.6	126.5	113.7	168.0	114.6	137.7	402.5	114.8	83.5	92.5	104.9	92.3	66.0	133.2	133.5
Pay gap (%)	16.2	24.0	17.2	9.8	18.7	8.5	2.4	15.0	9.7	9.9	18.4	17.6	-12.7	9.8	9.8

Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction) continued

	All industries	Agri.	Manufact.	Construct.	Wholesale	Retail	Hospitality	Logistics	Media & Finance	Profess. Services	Admin. Services	Public Admin.	Education	Health.	Arts & Rec.
Māori women vs. European men															
Individual characteristics (%)	6.9	3.9	6.1	-5.2	8.6	9.3	6.8	6.4	9.8	12.9	5.7	15.3	16.9	7.0	12.1
Region (%)	2.1	-7.2	-0.7	-1.6	0.1	2.6	42.2	-3.2	3.6	6.5	4.9	5.0	6.6	2.2	-1.8
Education characteristics (%)	3.7	6.4	6.8	3.8	5.2	3.5	24.8	1.9	4.9	5.2	3.3	8.4	9.3	7.1	0.3
Job-related characteristics (%)	10.1	9.3	20.8	10.2	26.4	21.6	12.2	25.4	15.3	19.0	32.5	21.8	8.4	18.1	10.1
Industry (%)	15.9														
Total explained (%)	38.7	12.4	33.1	7.2	40.3	36.9	86.1	30.5	33.5	43.6	46.4	50.5	41.3	34.4	20.7
Unexplained (%)	61.3	87.6	66.9	92.8	59.7	63.1	13.9	69.5	66.5	56.4	53.6	49.5	58.7	65.6	79.3
Pay gap (%)	24.1	20.3	29.7	24.8	29.0	17.5	4.7	18.1	31.4	35.0	26.7	17.6	14.7	25.4	16.8
Pacific women vs. European men															
Individual characteristics (%)	1.9	-26.3	4.8	-19.7	5.3	7.7	-16.1	5.1	5.9	17.2	-3.6	20.8	-8.9	-2.3	1.9
Region (%)	-11.7	-43.4	-8.5	-41.2	-9.0	-19.8	-10.6	-12.6	-8.1	-16.7	-14.6	-10.4	-13.5	-10.3	-10.7
Education characteristics (%)	5.1	36.3	5.8	-12.4	3.9	2.3	8.1	4.4	2.3	6.6	2.3	9.1	16.4	5.6	2.9
Job-related characteristics (%)	15.0	45.2	23.2	12.5	32.0	24.8	-9.8	16.8	15.3	34.1	34.1	24.6	14.9	23.3	13.1
Industry (%)	9.9														
Total explained (%)	20.2	11.8	25.3	-60.8	32.2	15.0	-28.4	13.6	15.4	41.2	18.2	44.0	9.0	16.3	7.3
Unexplained (%)	79.8	88.2	74.7	160.8	67.8	85.0	128.4	86.4	84.6	58.8	81.8	56.0	91.0	83.7	92.7
Pay gap (%)	28.2	6.5	42.0	10.7	37.0	18.9	9.5	24.4	38.2	22.2	26.5	15.2	15.0	32.1	16.3

Table E.1 Blinder-Oaxaca decomposition of pay gaps (with Heckman correction) continued

	All industries	Agri.	Manufact.	Construct.	Wholesale	Retail	Hospitality	Logistics	Media & Finance	Profess. Services	Admin. Services	Public Admin.	Education	Health.	Arts & Rec.
Asian women vs. European men															
Individual characteristics (%)	-2.4	-14.4	3.0	151.2	-7.5	-3.2	-59.5	75.0	6.4	11.0	-60.1	-0.4	-7.5	-3.5	-3.3
Region (%)	-13.0	-3.9	-8.9	422.6	-15.1	-19.9	-18.2	-244.4	-15.6	-10.5	-61.1	-14.1	-21.6	-5.5	-10.0
Education characteristics (%)	-15.0	-12.7	-12.5	733.6	-30.8	-22.6	-15.1	-190.3	-11.3	-5.2	-23.8	-17.0	-2.1	-3.2	-4.8
Job-related characteristics (%)	9.0	6.0	20.6	101.8	15.4	14.1	-9.6	231.7	15.2	17.5	53.4	21.2	11.6	15.2	14.8
Industry (%)	11.1														
Total explained (%)	-10.3	-25.1	2.1	1409.1	-38.0	-31.6	-102.4	-128.0	-5.4	12.8	-91.7	-10.3	-19.7	3.0	-3.3
Unexplained (%)	110.3	125.1	97.9	-1309.1	138.0	131.6	202.4	228.0	105.4	87.2	191.7	110.3	119.7	97.0	103.3
Pay gap (%)	20.6	30.4	30.5	-1.0	17.7	13.5	5.6	1.2	19.5	22.9	5.4	12.8	14.7	23.7	21.2

NEW ZEALAND POLICY RESEARCH INSTITUTE
TE KĀHUI RANGAHAU MANA TAURITE

Auckland University of Technology, Auckland, New Zealand

policy.research@aut.ac.nz | **www.nzpri.aut.ac.nz**

AUT UNIVERSITY NEW ZEALAND