Gender, Ethnicity, and Wages in New Zealand

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Abstract

Significant gender and ethnic wage gaps have been observed in New Zealand in the last two decades. This paper analyses the wage gaps by estimating selectivity-corrected earnings equations and performing wage decomposition using data from the Statistics New Zealand's 2003 CURF (Confidentialised Unit Record File) data set. It is found that hardly any amount of the gender wage gap can be explained by differences in the endowments of males and females. Women seem to earn less simply because of their gender. It is also found that the level of discrimination against women is the same amongst Pakeha and Maori, but about 30% less amongst Pacific Islanders.

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1 Introduction

Wage differentials between men and women, and between individuals belonging to different racial and/or ethnic groups, is one of the most studied issues in labour economics. Such differentials are observed in every country, and the research typically tries to identify the sources of the observed wage gaps. A common approach relies on the human capital model where skills people have developed through education, training and experience form, together with their cognitive skills, form the basis for the wages earned. Wage gaps due to differences in these factors are considered normal, and the portion of the gap that is not due to these differences is seen as evidence of discrimination in the labour market. Consequently, there is much empirical research that *decomposes* the observed wage gaps into two components to determine what proportion of the differential is due to labour market discrimination.

Wage differentials, particularly gender wage gaps, have received a lot of attention in New Zealand. However, the use of wage decompositions to identify the sources of the gaps does not appear to be used as widely as one would expect, particularly with post-2000 data. This is the contribution this paper aims to make. It uses 2003 data from Statistics New Zealand to estimate a wage equation and performs wage decompositions to determine the magnitude of discrimination in the New Zealand labour market. It analyses both gender and ethnic differentials.

The paper is organised as follows. Section 2 provides a background to the wage gap literature in New Zealand and the wage decompositions. Section 3 describes the data set used in the analysis. The empirical specification and the estimation results are presented in Section 4. The results are discussed in Section 5. Section 6 presents my concluding remarks.

2 Background

2.1 Decomposition of wage gaps

The decomposition of observed wage gaps across gender or ethnicity has been the traditional way of analysing wage gaps in labour economics for a long time. The human capital models of Mincer and Polachek (Mincer and Polachek, 1974) and Polachek (Polachek, 1981) provide an economic reason for observing wage gaps: different levels of acquired skills lead to differences in productivity and hence in wages. Based on this, a number of regression-based wage decomposition methods are developed. These methods start with estimating a Mincerian earnings equation and disentangle the observed total wage gap into a component that is due to differences in explanatory factors and an unexplained remainder, which is typically interpreted as discrimination. The decomposition method suggested by (Blinder, 1973) and (Oaxaca, 1973) has become the standard tool to analyse wage gaps in this way.

Consider the econometric specification of an earnings equation

$$y_i = \mathbf{x}_i'\beta_i + \varepsilon_i, \qquad E(\varepsilon_i) = 0 \qquad i \in (A, B) \tag{1}$$

where y_i is the natural logarithm of wages earned by individual i, $\mathbf{x}_i$ is a vector containing the human capital characteristics of individual i and a constant, and A and B represent two different groups (such as male and female). The Blinder-Oaxaca decomposition is based on the mean outcome difference

$$\hat{\Delta} = \bar{y}^A - \bar{y}^B = \hat{y}^A - \hat{y}^B = \bar{\mathbf{x}'}^A \hat{\beta}^A - \bar{\mathbf{x}'}^B \hat{\beta}^B \tag{2}$$

where $\hat{\beta}^A$ and $\hat{\beta}^B$ are the estimated regression coefficients for the two groups, and $\bar{\mathbf{x}'}^A$ and $\bar{\mathbf{x}'}^B$ are the vectors of the means of the explanatory variables in the two groups. This can be rewritten as (see (Jann, 2008))

$$\hat{\Delta} = \underbrace{(\bar{\mathbf{x}'}^A - \bar{\mathbf{x}'}^B)\hat{\beta}^B}_{\text{explained part}} + \underbrace{\bar{\mathbf{x}'}^B(\hat{\beta}^A - \hat{\beta}^B) + (\bar{\mathbf{x}'}^A - \bar{\mathbf{x}'}^B)(\hat{\beta}^A - \hat{\beta}^B)}_{\text{unexplained part}}. \tag{3}$$

The first component of this threefold aggregate decomposition represents the part of the difference that is due to group differences in the endowments of the individuals in the two groups. It is considered normal that the mean wage in group B would be different if group B had group A's endowments. The fist component is therefore called the explained part. The second component measures the share attributable to differences in the returns the endowments receive, and is called the "coefficients effect". It measures the expected change in group B's mean wage if group B had group A's coefficients. The third component is an interaction term that reflects the fact both endowments and coefficients differ between the two groups.[1] The sum of the second and third components is the "unexplained part" which is attributed to discrimination. This sum measures how much of the mean difference in wages cannot be accounted by differences in endowments.

The decomposition in (3) is based on the assumption that in the absence of discrimination the group B wage structure would prevail, since the endowment differences are weighted by group B coefficients. A more general twofold decomposition can be obtained if a nondiscriminatory coefficient vector, $\hat{\beta}^*$, is used to determine the contribution of the differences in endowments (see (Neumark, 1988) or (Jann, 2008)):

$$\hat{\Delta} = \underbrace{(\bar{\mathbf{x}'}^A - \bar{\mathbf{x}'}^B)\hat{\beta}^*}_{\text{explained part}} + \underbrace{\left[\bar{\mathbf{x}'}^A(\hat{\beta}^A - \hat{\beta}^*) + \bar{\mathbf{x}'}^B(\hat{\beta}^* - \hat{\beta}^B)\right]}_{\text{unexplained part}}. \tag{4}$$

The unexplained part represents the differences in coefficients, with no assumptions about what the "true" wages would be in the absence of discrimination. It is the sum of two terms, with the first term representing the group A (dis)advantage and the second representing the group B (dis)advantage ((Goraus et al., 2015)). If it is assumed that group A wages would prevail in the absence of discrimination, $\hat{\beta}^* = \hat{\beta}^A$ gives

$$\hat{\Delta} = (\bar{\mathbf{x}'}^A - \bar{\mathbf{x}'}^B)\hat{\beta}^A + \bar{\mathbf{x}'}^B(\hat{\beta}^A - \hat{\beta}^B). \tag{5}$$

If, on the other hand, it is assumed that group B wages would prevail in the absence of discrimination, $\hat{\beta}^* = \hat{\beta}^B$ gives

$$\hat{\Delta} = (\bar{\mathbf{x}'}^A - \bar{\mathbf{x}'}^B)\hat{\beta}^B + \bar{\mathbf{x}'}^A(\hat{\beta}^A - \hat{\beta}^B). \tag{6}$$

Equations (5) and (6) are the original decompositions suggested by (Blinder, 1973) and (Oaxaca, 1973). However, neither choice for $\hat{\beta}^*$ is obvious, and there have been various suggestions as to what should be used. (Reimers, 1983), for example, suggests using the average of the coefficients from the two groups. (Neumark, 1988), on the other hand, advocates the use of the coefficients from a pooled regression over both groups.

[1] Note that the decomposition in equation (3) is from the viewpoint of group B, since the group differences in endowments are weighted by the coefficients in group B. Similarly, the coefficients effect weights the differences in coefficients by group B's endowments. It is possible to express the decomposition from the viewpoint of group A by replacing $\hat{\beta}^B$ in the first component with $\hat{\beta}^A$, and $\bar{\mathbf{x}'}^B$ with $\bar{\mathbf{x}'}^A$ in the second component. (See (Jann, 2008) for more on this reverse decomposition.)

2.1.1 Selectivity bias adjustment

A typical problem in estimating Mincerian wage equations is that no market wage is observed for individuals who do not work. Including only those individuals who work in the estimation could cause *sample selection* bias, since the decision to work may be systematically correlated to potential wages ((Heckman, 1979)). The most common method to solve this problem is to estimate a Heckman sample selection model by using a two-step procedure or full maximum likelihood estimation. Then the most straightforward approach to account for selection bias in the decomposition is to deduct the selection effects from the overall differential and then apply the standard decomposition formulas to this adjusted differential ((Jann, 2008)).[2]

2.2 Wage Decompositions in New Zealand

The gender wage gap, as measured by Statistics New Zealand, has ranged between 9.9% to 16.3% between 1998 and 2015 ((Statistics NZ, 2014)). Inequalities in labour market outcomes in New Zealand have therefore been the subject of several studies. Some of these focus on labour force status, but the majority have investigated inequalities in earnings. My focus is the studies that use wage decompositions using hourly wages of wage and salary earners. (Dixon, 1997) is the first one of the very few of these studies. Using data for years between 1984 and 1995, (Dixon, 1997) finds that there was a substantial reduction in the gender wage gap between 1984 and 1995, and that at least half of the reduction was due to the human capital characteristics of the males and females were getting closer to each other. The decompositions are based on the variance of the logarithm of hourly earnings. (Dixon, 1998) extends this study by using data for two more years and a decomposition method developed by (Juhn et al., 1993). (Dixon, 2000) and (Dixon, 2001) provide a further extension by using data for one more year and using a Blinder-Oaxaca wage decomposition. (Dixon, 2001) focuses on 1997-1998, and finds that human capital factors were able to account for one-quarter to two-thirds of the gender wage gaps. The wage regressions on which the decompositions are based in all of these studies are estimated by using the wages of employed individuals, ignoring the sample selection bias.

[2] An in-depth treatment of this issue can be found in (Neuman and Oaxaca, 2004).

(Dixon, 2004) is the first study that applies wage decompositions using post-2000 data. She finds that about 25 percent of the reduction in gender wage gaps between 1997 and 2003 could be explained by changes in demographic or educational profiles of the employees. (Gosse and Ganesh, 2004) apply the Oaxaca-Blinder decomposition method to examine the gender wage gap in the New Zealand public service in 2002. They find that including job size in the model reduces the unexplained wage gap to an almost negligible amount of 1.1 percent. (Gibb et al., 2009) also use the Oaxaca-Blinder decomposition method, but they focus 30 year-olds. They find that although the observed gender wage gap is about 38 percent, 66.4 percent of it could be explained by differences in human capital, job characteristics and family factors.

3 The Data Set

The data set used in this study is Statistics New Zealand's CURF (Confidentialised Unit Record File) for 2003. The CURF contains unit record level data from the June 2003 quarter Household Labour Force Survey (HLFS) and its supplement the New Zealand Income Survey (IS). It contains 28,982 observations. The information in the CURF has been confidentialised to protect the identity of respondents. In the first place, all household linkages have been removed, although there is the potential still for some household level analysis since variables have been added which identify household types, including variables representing numbers of children, numbers of adults, and weekly household (as well as individual) income. It is, however, impossible to identify, for example, married couples, so that joint estimation of household labour supply is not possible.

Other methods used to ensure the confidentiality of the data include the collapsing of categories for some variables into a smaller number of categories (for example, country of birth has been collapsed to a simple indicator as to whether an individual was born in New Zealand or not), the top-coding of some variables (for example, income has been top-coded to mask outliers amongst high income earners) and some minor degree of data swapping in the case of "unique" individuals whose combination of responses could potentially identify them.

There are many variables provided in the CURF for each individual, including actual and total earnings from the primary and any other wage and salary jobs, income from other sources broken down by source, indicators of receipt of various transfer payments, age, country of birth (and years in New Zealand), ethnicity, employment and labour force status, occupation and industry group (for the employed), local government region, marital status, qualifications, sex, household type, and numbers of dependent children in various age groups. My analysis is limited to individuals who are in the labour force and who are aged between 15 and 64 years. The resulting sample data set contains 14,360 observations.

Following a similar classification used by Statistics NZ, we categorize the individuals into five ethnic groups: Pakeha/European, Maori, Mixed Maori, Pacific Islanders, and Other.[3] The Mixed Maori represent the survey respondents who ticked both Maori and at least one other ethnic group, which is an option offered in the survey. Thus, Maori represent the individuals who identify themselves solely as Maori. The Pacific Islanders are made up of Samoan, Cook Islanders, Tongan, Niuean, Tokelauan, and Fijians. The ethnic group Other refers to all those not identifying themselves as European, Maori or Pacific Islander. This classification is dominated by Asian people.

The sample means of the variables used in my analysis are given in Table 1. The mean hourly wage of female employees is 86% of the mean hourly wage of male employees. Maori employees earn about 15% less than Pakeha. The difference in mean wages is 22.6% in comparing the Pacific Islanders with the Pakeha.

4 Empirical Analysis

I estimate a standard Heckman selection model where the earnings equation has the logarithm of wages, y_i, specified as

$$y_i = \mathbf{x}'_{1i}\beta_1 + \varepsilon_{1i}, \tag{7}$$

together with the selection equation

$$s_i^* = \mathbf{x}'_{2i}\beta_2 + \varepsilon_{2i}. \tag{8}$$

The selection equation describes whether an individual is employed and not, and the

[3]Maori are the indigenous people of New Zealand. Pakeha is the term used for European people.

wage is observed only if $s_i^* > 0$. It is assumed that

$$\begin{aligned} \varepsilon_1 &\sim N(0,\sigma) \\ \varepsilon_2 &\sim N(0,1) \\ corr(\varepsilon_1, \varepsilon_2) &= \rho \end{aligned}$$

The model can be estimated by using either Heckman's two-step procedure or full maximum likelihood method (MLE) under the distributional assumptions stated above. I use the full MLE method whenever possible (that is, so long as convergence is achieved).

The vectors of covariates, $\mathbf{x}_1$ and $\mathbf{x}_2$, include variables related to individual demographics such as age, education, and marital status. The full list of the variables and their definitions are presented in Table 2. Age acts as a proxy for experience. Although this is not perfect, we do not have information on detailed labour market profiles of the individuals in the sample. Numbers of school-age and under-five children, marital status dummies are included to capture the differing opportunities and incentives the individuals face in finding employment. These variables enter only the selection equation. The regional dummy variable, taking the value of 1 for individuals who reside in one of the three main urban cities reflects the different employment opportunities and wages in main centres and provincial areas, and is included in both the selection and wage equations. The set of education dummy variables captures differences in qualification, and is also used in both equations.

Table 3 presents the estimated selectivity-corrected earnings equations for the full sample, males, and females. The models are estimated by full maximum likelihood method. The hypothesis that $\rho = 0$ is rejected strongly in each case, justifying the use of the sample selection model. Note that the estimated coefficients of *gender*, *maori*, *paci*, and *other* in the full sample are statistically highly significant, implying that individuals belonging to these groups are discriminated against.

Table 4 presents the gender wage decompositions. These are obtained by estimating the sample selection model separately for males and females, and then obtaining the threefold decomposition in euqation (3) using Jann's *oaxaca* Stata command described in (Jann, 2008). Column 1 performs the decomposition for the full sample, whereas the remaining columns perform the decomposition separately for Pakeha, Maori, Pacific Islanders, and Mixed maori. The decompositions for the full sample and Pakeha are based on full maximum likelihood estimation of the sample selection model. However, the decompositions for Pacific Islanders and Mixed Maori are based on the two-step estimation of the model, since full MLE does not convergence for these two groups.

5 Discussion

The signs of the estimated coefficients in Table 3 are as expected.[4] The age variable enters the log wage regressions in a quadratic form that permits calculation of a turning point, representing the age at which the effect of an extra year becomes negative. The turning point can be computed as the negative of the coefficient on age divided by twice the coefficient on age-squared. The results suggest that the turning point is approximately 46.7 years of age for the full sample. The turning point is 47.6 years of age for males, and 45.7 for females.

Any form of qualification is found to have a significant positive effect on the wages earned. Even the lowest form of qualification in the form of school level qualification is found to increase the wages earned by 9.1% for the full sample, with this effect being as high as 39.1% for university level qualification. However, the impact of school-level qualification is lower for males, and higher for females.

The coefficients of the ethnicity dummy variables in the wage equation are negative and statistically significant Maori, Pacific Islanders, and other ethnicities. All else being equal, the Pacific Islanders earn about 12.1%, and Maori 3.3% less than Pakeha. Mixed Maori do not seem to be disadvantaged. However, females seem to suffer most, earning 14.8% less than males.

This considerable gender effect is analysed further by the gender wage decompositions presented in Table 4. The decompositions are performed first for the full sample, and then separately for Pakeha, Maori, Pacific Islanders, and Mixed Maori to see if there are any difference across different ethnic groups. The first two rows report the mean predicted

[4]The coefficients for the selection equation are available on request. The estimated coefficients of the selection equation imply that age, number of pre-school children, marital status, education, and ethnicity are important factors in the job participation decision. Existence of pre-school children lowers the probability of employment, while married and divorced people are more likely to be employed. Any level of education has a positive effect on the probability of being employed. Main city residents are more likely to be employed. Females are found to be less likely to be employed. Maori, Mixed Maori, and Pacific Islanders are less likely to be employed compared with Pakeha.

wages for males and females. The mean gender wage gap is reported along the third row of the table. The predicted gap is 14% for the full sample, 16% for Pakeha, 12% for Maori, and 10% for Pacific Islanders.[5] The gender wage gap is found to be not statistically significant for other ethnic groups combined. Note that the gender wage gap is highest for Pakeha. The lower panel of the table presents the breakdown of the gap into three parts. The first part reflects the proportion of the wage gap that can be attributed to differences in endowments of males and females. The results indicate that women would earn 96 to 98% of men's wages if they had the same characteristics as men. The second part quantifies the change in women's wages when the men's coefficients are applied to calculate the returns to women's characteristics. The results indicate that almost all of the gap is due to women receiving less return to their characteristics compared to men. If, for example, women in the full sample had the same coefficients as men, their mean wage would be 16% higher with their observed levels of endowments. The degree of discrimination is higher, 18%, for Pakeha, and lower, 11%, for Pacific Islanders.

6 Concluding Remarks

This paper explores the observed gender and ethnic wage gaps by estimating earnings equations using data from 2003. The raw data reveal that the average wage for males is 16.69% higher than the average female wage, and the average wage for Pakeha is 17.31% higher than the average wage for Pakeha. The regression results indicate that, all else being the same, Maori earn only 3.3% less than Pakeha. However, the gender wage gap remains to be quite significant, almost 15%, when other factors are controlled for. This gap is analysed further by performing wage decompositions based on the estimated selectivity-corrected earnings equation. It is found that hardly any amount of the gender wage gap can be explained by differences in the endowments of males and females. Women seem to earn less simply because of their gender. It is also found that the level of discrimination against women is the same amongst Pakeha and Maori, but about 30% less amongst Pacific Islanders.

[5] The reported numbers along the third row are the ratios of the mean male wages to mean female wages. So, for example, males earn, on average, 14% more than the females in the full sample.

References

Blinder, A. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human Resources 8*, 436–455.

Dixon, S. (1997). The distribution of earnings in New Zealand 1984-1995. In *Proceedings of the Seventh Labour, Employment and Work Conference, 28-29 November 1996, Wellington*, pp. 31–42. Victoria University of Wellington.

Dixon, S. (1998). Growth in the dispersion of earnings: 1984-97. *Labour Market Bulletin 1&2*, 71–107.

Dixon, S. (2000). Pay inequality between men and women in New Zealand. Occasional Paper 2000/1, Department of Labour, Labour Market Policy Group, Wellington.

Dixon, S. (2001). Work experience and the gender earnings gap. *New Zealand Economic Papers 35*(2), 152–174.

Dixon, S. (2004). Understanding reductions in the gender wage differential 1997-2003. Report, Department of Labour, Wellington, New Zealand.

Gibb, S. J., D. M. Fergusson, and L. J. Horwood (2009). Sources of the gender wage gap in a New Zealand birth cohort. *Australian Journal of Labour Economics 12*(3), 281–298.

Goraus, K., J. Tyrowicz, and L. van der Velde (2015). Which gender wage estimates to trust? a comparative analysis. *Review of Income and Wealth*. doi: 10.1111/roiw.12209.

Gosse, M. and S. Ganesh (2004). The gender pay gap and the importance of job size: Evidence from the New Zealand public service. *New Zealand Economic Papers 38*(1), 101–118.

Heckman, J. J. (1979). Sample selection as a specification error. *Econometrica 47*, 153–161.

Jann, B. (2008). The blinder-oaxaca decomposition for linear regression models. *The Stata Journal 8*(4), 453–479.

Juhn, C., K. M. Murphy, and B. Pierce (1993). Wage inequality and the rise in returns to skill. *Journal of Political Economy 101*(3), 410–442.

Mincer, J. and S. W. Polachek (1974). Family investments in human capital: earnings of women. *Journal of Political Economy 82*, S76–S108.

Neuman, S. and R. L. Oaxaca (2004). Wage decompositions with selectivity-corrected wage equations: a methodological note. *Journal of Economic Inequality 2*, 3–10.

Neumark, D. (1988). Employer's discriminatory behavior and the estimation of wage discriminitaion. *The Journal of Human Resources 23*(3), 279–295.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic review 14*, 693–709.

Polachek, S. W. (1981). Occupational self-selection: a human capital approach to sex differences in occupational structure. *Review of Economics and Statistics 63*, 60–69.

Reimers, C. W. (1983). Labor market discrimination against hispanic and black men. *Review of Economics and Statistics 65*, 570–579.

Statistics NZ, . (2014). *Measuring the gender wage gap.*

Table 1: Sample Statistics

	Employed (n=13438)	Unemployed (n=920)
Mean hourly wage in dollars (overall)	17.13	
Mean hourly wage in dollars (Pakeha)	17.69	
Mean hourly wage in dollars (Maori)	15.08	
Mean hourly wage in dollars (mixed)	15.59	
Mean hourly wage in dollars (Pacific islander)	13.69	
Mean hourly wage in dollars (other ethnicity)	16.83	
Mean hourly wage in dollars (male)	18.46	
Mean hourly wage in dollars (female)	15.82	
Mean age	38.32	33.33
Percentage females	50.54	50.98
Percentage married	63.15	37.93
Percentage separated	9.01	11.52
Percentage with university degree	14.03	9.02
% with post-school qualification	7.02	9.46
% with school qualification	24.77	25.00
% with vocational qualification	34.67	24.67
Mean no. of school-age children	0.42	0.41
Mean no. of children under 5 years	0.19	0.21
Percentage in top two occupational groups	35.08	
Percentage in middle five occupational groups	56.59	
Percentage Maori	8.98	18.48
Percentage mixed Maori	3.45	7.61
Percentage Pacific islander	4.95	6.96
Percentage other ethnic groups	7.05	12.17
Percentage Pakeha	75.57	54.78
Percentage main city resident	52.87	56.20

Table 2: Explanatory Variables

Variable	Definition
Individual Demographics	
age	Age in years
agesq	Square of age /100
gender	1 if female, 0 otherwise
mcnt	1 if main city resident, 0 otherwise
occupation1	1 if in top two occupational groups, 0 otherwise
occupation2	1 if in middle five occupational groups, 0 otherwise
Education (ref: no qualification)	
uni	1 if highest qualification is a university degree
pschool	1 if highest qualification is a post-school qualification
school	1 if highest qualification is school qualification
voca	1 if highest qualification is a vocational qualification
Ethnicity (ref: Pakeha/European)	
maori	1 if Maori, 0 otherwise
mixed	1 if Maori and other ethnic group, 0 otherwise
paci	1 if Pacific Islander
other	1 if other ethnic group, 0 otherwise

Table 3: Selectivity Corrected Earnings Equations

	(1) Full Sample	(2) Male	(3) Female
age	0.0437***	0.0495***	0.0382***
	(0.00148)	(0.00218)	(0.00199)
agesq	-0.0468***	-0.0520***	-0.0418***
	(0.00188)	(0.00276)	(0.00254)
gender	-0.160***		
	(0.00586)		
mcnt	0.0870***	0.0772***	0.0982***
	(0.00611)	(0.00903)	(0.00821)
occupation1	0.304***	0.289***	0.313***
	(0.0121)	(0.0168)	(0.0177)
occupation2	0.0921***	0.0788***	0.0936***
	(0.0110)	(0.0149)	(0.0164)
school	0.0868***	0.0628***	0.106***
	(0.00916)	(0.0136)	(0.0123)
voca	0.151***	0.144***	0.150***
	(0.00870)	(0.0124)	(0.0122)
uni	0.330***	0.319***	0.330***
	(0.0117)	(0.0174)	(0.0157)
pschool	0.112***	0.103***	0.113***
	(0.0130)	(0.0184)	(0.0183)
maori	-0.0335**	-0.0186	-0.0475***
	(0.0105)	(0.0154)	(0.0142)
paci	-0.129***	-0.169***	-0.0903***
	(0.0140)	(0.0200)	(0.0194)
other	-0.0857***	-0.115***	-0.0575***
	(0.0118)	(0.0174)	(0.0158)
mixed	-0.0118	-0.0208	-0.00492
	(0.0162)	(0.0231)	(0.0225)
constant	1.601***	1.498***	1.552***
	(0.0291)	(0.0422)	(0.0402)
Observations	14358	7098	7260

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Selectivity Corrected Gender Wage Gaps

	(1) full sample	(2) Pakeha	(3) Maori	(4) Pacific Islanders	(5) Mixed
Predicted average wage (male)	16.57***	17.17***	15.02***	13.31***	14.91***
	(0.088)	(0.108)	(0.226)	(0.196)	(0.405)
Predicted average wage (female)	14.54***	14.86***	13.39***	12.12***	13.67***
	(0.077)	(0.088)	(0.221)	(0.496)	(0.954)
Difference	1.14***	1.16***	1.12***	1.10*	1.09
	(0.009)	(0.010)	(0.025)	(0.047)	(0.081)
Decomposition					
Endowments	0.98***	0.98***	0.96***	0.96*	0.98
	(0.004)	(0.004)	(0.010)	(0.017)	(0.022)
Coefficients	1.16***	1.18***	1.16***	1.11*	1.12
	(0.007)	(0.008)	(0.024)	(0.047)	(0.080)
Interaction	1.00	1.00	1.00	1.03	0.99
	(0.002)	(0.002)	(0.008)	(0.016)	(0.015)
Observations	13438	10155	1207	665	463

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$