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Glass Ceiling or Sticky Floor? Exploring the Australian Gender Pay Gap using Quantile Regression and Counterfactual Decomposition Methods

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*The data used in this study are from the first wave of the Household, Income and Labour Dynamics in Australia (HILDA) survey. A data appendix with additional results, and copies of the computer programs used to generate the results presented in the paper, are available from the author upon request. E-mail: hiau.kee@anu.edu.au.

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ABSTRACT

Using the HILDA survey, this paper analyses Australian gender wage gaps in both public and private sectors across the wage distribution. Quantile Regression (QR) techniques are used to control for various characteristics at different points of the wage distributions. Counterfactual decomposition analysis, adjusted for the QR framework, is utilised to examine if the gap is attributed to differences in gender characteristic, or differing returns between genders. The main finding is that a strong glass ceiling effect is detected only in the private sector. Secondly, the acceleration in the gender gap across the distribution does not vanish even after extensive controls. This suggests that the observed wage gap is a result of differences in returns to genders. By focussing only on the mean gender wage gap, substantial variations of the gap will be hidden.

Keywords: glass ceiling, sticky floor, quantile regression, public sector

JEL Classifications: J16, J31, J7

1. Introduction

The latest Australian Bureau of Statistics (ABS, Cat 6302.0) data suggest that on average, hourly earnings of full time males and females are $28.83 and $23.4 respectively. This is an earning ratio of 81 percent, which has narrowed by around 4 percentage points over the last decade. Furthermore, in Australia there are more women undertaking tertiary education compared to men. It is reported that 50.6 percent of professionals with bachelor's degrees are women in 2003 (ABS, Cat 6227.0). Despite the remarkable changes of recent labour market structure, women held just 1.3 percent of the top management positions in the largest Australian companies[1] (Wirth, 2001). According to the 2004 annual survey conducted by the *Government's Equal Opportunity for Women in the Workplace Agency*, only two of the top 200 companies are chaired by women, and just four have women chief executives.

The situation where gender pay gaps are typically wider at the top of the wage distribution is known as the '*glass ceiling*'. It is one of the most compelling metaphors recently used for analysing inequality between men and women in the workplace, to describe a barrier to further advancement once women have attained a certain level. They can see their male counterparts promoted while they are not. Whilst many wonder what it is that keeps women from reaching the top, the answer is likely to be complex and involve the interplay of several factors.

In contrast, the '*sticky floor*' can be viewed as the opposite scenario of the 'glass ceiling', when the gaps widen at the bottom of the wage distribution. Booth et al. (2003) defined it as a situation arising where otherwise identical men and women might be appointed to the same pay scale or rank, but the women are appointed at the bottom and men further up the scale.[2]

In Australia, the *Sex Discrimination Act 1984* was adopted to promote equality between men and women, as well as to eliminate discrimination on the basis of sex and marital status in the labour force. However, there is a general consensus that the public sector is more isolated from rigorous market competition. Consequently, females are more

[1] Some might argue this is a cohort effect. In 2001, the ABS reported a mean age of 40 years old for professionals. If the claim of cohort effect is true, males' higher education participation rate should be much higher than females 20 years ago. However in 1980, female higher education participation rate of 9.2 percent is already higher than males of 7.8 percent (DEETYA, 1997). Hence fewer female representatives in top management positions should not be attributed to the lag of time effect.

[2] Note that the focus of this analysis is to compare conditional and unconditional wage distribution of males and females, for promotional or rank issues of the working environment see Booth et al. (2003).

likely to be sheltered from possible discrimination. As an extension, the analysis will be stratified by public and private sectors.

The prime purpose of this study is to investigate whether a glass ceiling exists, or if instead a sticky floor is more prevalent in the Australian labour market. If a glass ceiling does exist, does it differ across the public and private sector? To address this question, conditional quantile regression (QR) will be utilised to estimate the gender pay gap across the entire wage distribution. Averaging the wage gaps is informative, but cannot address the question of whether or not a glass ceiling exists. Secondly, how much of the gender pay gaps can be attributed to the differences in gender characteristics, and the differences to the returns to those characteristics? To answer this, a counterfactual decomposition analysis adjusted for QR framework will be introduced.

2. <u>Literature Review</u>

The gender pay gap has traditionally been a central focus of the empirical labour literature (see for example Blau and Kahn, 2004). A persistent average gender wage gap is widely observed and has been identified based on the past empirical results (for Australia see inter alia Chapman and Mulvey, 1986; Wooden, 1998; Langford, 1995; Chang and Miller, 1996; Preston, 2000). Depending on which types of workers are compared and what is included in the control variables, the wage gap ranges between 10 to 35 percent.

Many researchers have attempted to investigate the gender pay gaps based on the average wage. This methodology focuses on the conditional mean, which might lead to the conclusion that the size of the wage gap and its possible causes are constant along the whole wage distribution. Little attention has been paid to either the glass ceiling effect, or to the unequal size of gaps experienced by the female high and low income earners, even though interesting insights might be gained by looking at the differences between different points in the wage distribution (some exceptions are mentioned below). An exclusive focus on the average may provide misleading insights into the gender pay gap. Is the female high-income earner more likely to be discriminated against? Does a glass ceiling exist? Are the factors that contribute to the existence of the gap the same for female low-income earners as they are for high-income earners?

By measuring the mean of the pay gap, OLS is unable to provide any answers; hence, in attempting to answer these questions, the methodology of quantile regression is preferred. The focus is the different size of the gap at different points of the conditional wages distributions. This study attempts to examine what factors are associated with greater wage dispersion, as well as how these factors vary across different levels of income for female Australian workers.

The quantile regression technique was proposed by Koenker and Bassett (1978). Earlier Kuhn (1987) pointed out that conventional mean regression has its limitations in measuring discrimination. He showed empirically that U.S. women at higher wage levels are more likely to report being discriminated against.

Buchinsky (1994, 1996, and 1998) further advanced the application of quantile regression in the U.S. labour market in the context of wage estimation and the return to education. He examined the gender wage gap at different points of the conditional wage distributions. In order to address female sample selection bias problem, he approximates the inverse Mill's ratio from a nonparametric single-index selection model, into a power series expansions. The results show that in the U.S., wage inequality decreased for the high-school graduates and increased for the younger college graduates. Furthermore, highly qualified women have experienced a significant improvement in terms of wages, regardless of their position in the wage distribution.

Usage of the quantile regression method can be said to have been popularised by Buchinsky (1998). Following Buchinsky, a small but growing literature has adopted this methodology. García et al (2001) investigated the Spanish labour market and concluded that the size of the absolute gender wage gap increases over the wage distribution. Albrecht et al (2003) showed that a strong glass ceiling effect exists in the Swedish labour market. Machado and Mata (2001) found that Portuguese gender wage gap is wider for high paid jobs and the biggest earning differential is located in the middle of the distribution. Dolado et al (2004) analysed Spanish labour market and concluded that highly educated females encountered a glass ceiling but the group with primary and secondary education encountered a sticky floor. Arulampalam et al (2004) investigated gender pay gaps by sectors of ten European countries and concluded that the observed glass ceilings are more prevalent than sticky floors in most countries.

This study seeks to investigate the extent to which gender affects the location and shape of the conditional wage distribution, and how these patterns differ across public and private sectors. To begin, the unconditional raw gap is estimated. It can be seen as a *preliminary indicator* of glass ceiling or sticky floor. However, the unconditional raw gap does not provide sufficient evidence to indicate whether or not glass ceiling or sticky floor exists. In addition, the next step is to estimate the conditional wage gap. Controls of interest in the current analysis include demographic, education, geographic, employer, occupation and industry variables. Once various controls are formed, if gender pay gaps are still observed across the entire conditional wage distributions, this gap may be caused by some unobserved heterogeneity that the models cannot capture. Numerous studies have suggested that this may reflex sex discrimination that females face at work.[3] In this study, *discrimination* is defined as the differences in return to the same characteristics between men and women. It is important to emphasis that any remaining gap after extensive control could be a form of discrimination, moreover, it could also be something else. A more detailed discussion will be presented in the later part of this analysis.

3. Methodology

To my knowledge, there is no published literature of gender wage gap in the Australian labour market focussing on other points of the wage distributions. The current analysis follows an approach similar to that of Albrecht et al (2003), in order to investigate how the gender gap evolves throughout the wage distribution, and to test whether wage discrimination is greater for female high income earners or among low income earners. As an extension, the analysis will be stratified by sectors, to examine if the wage gap differs across private and public sectors.

3.1 Data Description: Household, Income and Labour Dynamics in Australia (HILDA) Survey

Wave 1 of Hilda will be used for the analysis. HILDA is the first nationally based random panel dataset of Australian households. The initial wave of the survey was collected in the second half of 2001, and comprised 12,252 households selected from 488 different neighbourhood regions across Australia. The household response rate from the survey was 66 percent. It contains a wide range of information, including information on labour status, hours of work, earnings, fertility and relationship histories, actual labour market experience and detailed information on children. The broad diversity of variables constitutes an important part of the current analysis. It enables the examination of glass ceiling phenomenon, by allowing the researcher to control for observable heterogeneity in the analysis.

[3] For example see Albrecht et al. (2003), Kuhn (1987), Wooden (1999).

This dataset contains a total of 5,867 observations. Public sector sub-sample comprises 655 males and 913 females; while in the private sector there are 2,191 males and 1,726 females. The dependent variable is the log hourly wage, which is derived by using the respondent's main job, at 2001 prices. Appendix A contains a detailed descriptions of the variables used in the regressions.

3.2 Quantile Regression (QR)

The quantile regression model, first introduced by Koenker and Bassett (1978), can be viewed as a location model. The description is based on Buchinsky (1998). Let (y_i, x_i), i =1, 2, …, n; be the sample of a population, where y_i is the dependent variable of interest, x_i is a $k \times 1$ vector of regressors, for the θ th quantile of y_i conditional on the regressor vector x_i. The relation is given by

$$y_i = x_i' \beta_\theta + u_{\theta i} \quad \text{with} \qquad Quant_\theta (y_i \mid x_i) = x_i' \beta_\theta ,$$

where $u_{\theta i}$ is an unknown independent and identical distributed (i.i.d) error term. In the classical linear regression model, the normal distribution of the unknown error is specified. In this case however, the error term $u_{\theta i}$ for the θ th quantile is left unspecified and is only required to satisfy the constraint of

$$Quant_\theta (u_{\theta i} \mid x_i) = 0 ,$$

with no other distributional assumptions being made. The estimator for β_θ of the θth quantile regression, is obtained by solving

$$\hat{\beta}_\theta = \underset{\beta_\theta}{\arg\min} \left(\sum_{i:yi>xi'\beta\theta} \theta \mid y - x_i' \beta_\theta \mid + \sum_{i:yi<xi'\beta\theta} (1-\theta) \mid y_i - x_i' \beta_\theta \mid \right),$$

where 0< θ< 1. β_θ that minimises the sum of the weighted residuals is chosen to obtain the estimator for the θth quantile. For a negative residual, the weight is (1-θ); for a positive residual the weight is θ. Hence one of the advantages of QR is that, it allows one to estimate the marginal effect of a covariate on log wage at various points in the distribution, instead of just at the mean. In other words, by using QR technique, it is possible to estimate the effect of gender, education, occupations, industry and all other controls on log wage at the top (e.g. the 90th percentile), the median and the bottom (e.g. the 10th percentile) of the wage distribution. As for the coefficient β_θ , it can be interpreted as the estimated returns to individual characteristics at the θth quantile of the log wage distribution.

3.3 Counterfactual Wage Decomposition

Estimation by quantile regression provides us with an indication of whether or not the returns to observable characteristics differ by gender, and how these differences change as we move across the wage distributions. In addition, we also want to know how important is the unobserved heterogeneity in explaining the gender wage gap.

Hence the following step will be to construct an Oaxaca-Blinder type wage decomposition method adjusted for QR regression as in Machado and Mata (2000). However, rather than identifying the sources of the differences between the means of two distributions, quantile regression technique decomposes the differences between the male and female log wage distributions into a component that is due to differences in labour market characteristics between the genders, and a component that is due to differences in the rewards that the two genders receive for their labour market characteristics by various quantiles.

Denote women's and men's returns by β^f and β^m, and their characteristics by x^f and x^m respectively. The idea is to generate a counterfactual density, in particular, the female log wage density that would arise if women were given *men's* labour market characteristics but continued to be '*paid like women*'.[4] Hence in the situation where identical men and women possess same productive characteristics ($\beta^f = \beta^m$), men's wages would be equal to the women's wages, and no pay gap will be observed. Therefore, observed wage differences can be attributed to unequal treatment by gender, or other unobserved heterogeneity that the model fails to capture. A positive (negative) sign implies that market returns to men's characteristics are higher (lower) than the returns to women's characteristics.

This study follows Albrecht et al.'s (2003) application of Machado and Mata's (2000) bootstrap method to implement the decomposition directly at each quantile. This involves estimating marginal density of wages that are consistent with the estimated conditional densities. These procedures are summarised as follows:

1. Using a standard uniform distribution, sample the θ^{th} quantile of interest.

[4] Alternatively, one can also generate the density that would arise if women retained their own labour market characteristics but were 'paid like men'.

2. For men, at each percentile (1st to 99th), estimate a QR to predict men's wages which rewarded from their retained characteristics. In other words, this is an estimate form by using β_θ^m and x^m.
3. For women, take a draw from men's data, and construct a predicted wage by multiplying the chosen x^m by the estimate of β_θ^f.[5] This will be used to simulate the counterfactual distribution, namely what women would earn if they had men's characteristics but were 'paid like women'.[6]
4. Set the number of random draw *m*=5000. Use the men's predicted wage data from step (1), load the appropriate data set and randomly sample (with replacement) a number of individuals equal to the number of times that percentiles was selected.[7] Prediction obtained from this step is the simulated men's wage distribution.
5. Repeat step (4) for women using data sets from step (2) to simulate the counterfactual distribution.
6. To generate gender wage gaps, take the difference of each distribution from step (4) and (5) at various quantiles.

This whole procedure is then replicated by n=200 times in order to obtain standard deviations of the gender wage gaps over the n iterations.[8]

4. Results

In this section, sets of result estimated by different approaches will be presented. The observations included are full time and part time employees in the labour force, between the age of 18-60 years old, and who are not in employed agricultural sector. The

[5] The calculated marginal distribution of wages of men and the counterfactual marginal distribution for women are consistent with the estimated conditional distributions.

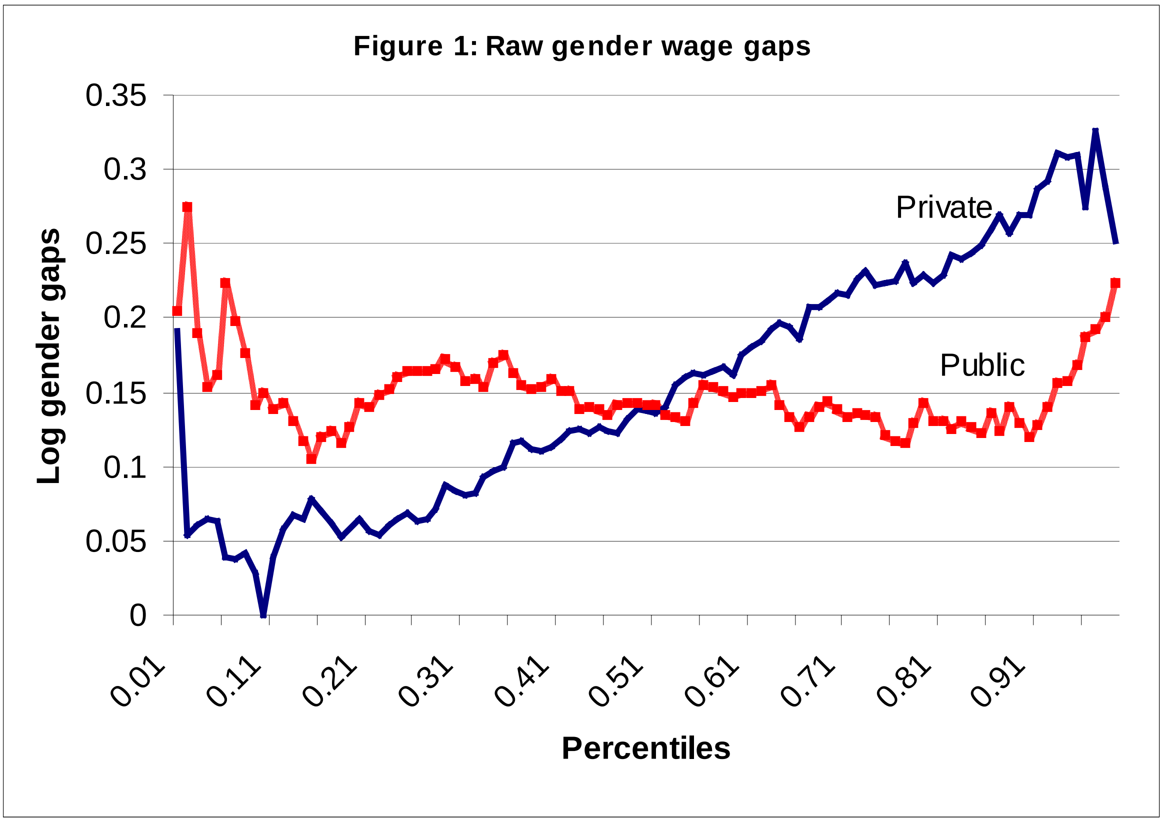
[6] To generate the density that would arise if women retained their own labour market characteristics but were paid like men, simply reverse the role of male and female in step (2) and (3). The results of this alternative decomposition are not presented as the qualitative findings about the unexplained gaps remains the same.

[7] In other words, if the 35th percentile was selected 50 times, randomly draw 50 men from the 35th percentile data set.

[8] So far this analysis has not considered the endogenous sample selection problem. Buchinsky (1998) demonstrated that QR is not immune from selectivity problem either. For the purpose of this study, a multinomial logit selection model is estimated, since individuals not only choose whether or not they want to participate in labour force, as well as which sectors to participate in. The obtained inverse Mill's ratios are insignificant in OLS regression of both sectors. In terms of QR, by truncated the inverse Mill's ratio at the third term, it is found that the corrected and uncorrected wage gap is remarkably similar in both private and public sector. Hence obtained results are not presented but will be available from the author upon request.

dependent variable is the log of the average hourly wage in respondent's main job. The results will be stratified by public and private sector.[9]

4.1 Raw Gender Wage Gap



The raw gender wage gap is presented in Figure 1. In the private sector, the raw gap exhibits a monotonic upward trend as we move towards the upper tail of the wage distributions, although declining at lower tail. The acceleration is also detected in the public sector, however it only starts around the 90th percentile. In contrast, the wage gap is found to be wider at the bottom end. This is especially obvious in the public sector.

The tendency of upward acceleration can be seen as an indicator of glass ceiling; whereas the wider bottom end can be seen an indicator of sticky floor. Note that in the private sector, the glass ceiling phenomenon seems to dominate; whereas in the public sector, the sticky floor phenomenon seems to be more noticeable.

However these are only the unconditional wage gaps. In the next section, estimations using the quantile regression will be presented to see how much of the

[9] To test if the estimation should be stratified by sectors, a Wald test is conducted by interacting all the explanatory variables with the private sector dummy. The result of F=3.72 is statistically significant at 5 percent level, and the conclusion is that stratification by sector is appropriate.

observed raw gender wage gap can be attributed to differences in the returns to those characteristics.

4.2 Pooled Quantile Regressions with Gender Dummy

To investigate the effects of differences in characteristics on the gender gap at different points of the wage distribution, a series of quantile regressions on the pooled data set with gender dummy is constructed. Pooled quantile regression imposes the restriction that returns to the included labour market characteristics are the same for males and females. In other words, the variable of interest, the gender dummy, indicates the extent to which gender gap remains unexplained at different quantiles after controlling for individual differences and characteristics.

To test if differences between various quantiles are statistically significant, joint interquantile tests are conducted at the 5 percent level. Significant statistical differences were found between the 10th and the 25th, the 25th and the 50th, as well as all other adjacent quantiles.[10] The hypothesis of equality is overwhelmingly rejected in all cases. This finding justifies the usage of quantile regression, leading to the conclusion that the quantile regression method has value over and above the OLS, and that the mean results obtained by the OLS might be misleading.

Table 2 presents the estimated gender dummy coefficients at the 10th, 25th, 50th, 75th and 90th percentiles in the pooled quantile regression. As a comparison, the OLS gender dummy coefficient is also presented. Panels in Table 2 are a result of stepwise regressions due to the potential endogeneity of the explanatory variables especially of occupation and industry dummies. A list of all controls for each stepwise regression is found in the Appendix A.

From panels 2-4 in Table 2, in the private sector, a large reduction of the gap is found at the top of the wage distribution. Controlling for covariates does not account for much of the gaps at lower income levels. This implies that gender characteristics differences explain a large part of the glass ceiling effect, in other words males get more pay than their females counterpart because they are more experienced or more educated. The existence of the private sector wage gap cannot be attributed to the differences in return to those characteristics. On the other hand in the public sector, this reduction is found at the bottom instead of the top of the wage distribution after we put in additional

[10] Test statistics see Table 5 in Appendix A.

controls. In other words, individuals' characteristics account for a large proportion of the gap for lower income earners and the sticky floor effect has faded. The widest distance is still found at the top of the wage distribution, indicating that the public sector also has a glass ceiling.

Table 2: Pooled Quantile Regression by sectors

Pooled Private						
	OLS	10th	25th	50th	75th	90th
Raw gap	0.153***	0.000	0.068***	0.137***	0.223***	0.269***
	(0.015)	(0.018)	(0.016)	(0.017)	(0.022)	(0.032)
Basic and educational variables	0.121***	0.008	0.061***	0.115***	0.176***	0.204***
	(0.015)	(0.023)	(0.015)	(0.016)	(0.019)	(0.028)
Basic, education and geographic variables	0.124***	0.013	0.057***	0.115***	0.180***	0.226***
	(0.015)	(0.021)	(0.016)	(0.016)	(0.017)	(0.031)
Basic, education, geographic and employer variables	0.115***	0.013	0.055***	0.105***	0.157***	0.199***
	(0.015)	(0.022)	(0.015)	(0.015)	(0.018)	(0.027)
Basic, education, geographic, employer, occupations & industries variables	0.129***	0.058**	0.081***	0.101***	0.180***	0.190***
	(0.015)	(0.024)	(0.018)	(0.016)	(0.021)	(0.026)
Pooled public						
	OLS	10th	25th	50th	75th	90th
Raw gap	0.152***	0.149***	0.164***	0.141***	0.121***	0.120***
	(0.020)	(0.042)	(0.024)	(0.023)	(0.027)	(0.027)
Basic and educational variables	0.138***	0.103**	0.085***	0.140***	0.144***	0.169***
	(0.020)	(0.043)	(0.021)	(0.023)	(0.020)	(0.029)
Basic, education and geographic variables	0.134***	0.118***	0.099***	0.121***	0.119***	0.140***
	(0.020)	(0.043)	(0.023)	(0.024)	(0.019)	(0.026)
Basic, education, geographic and employer variables	0.122***	0.089**	0.105***	0.102***	0.110***	0.144***
	(0.020)	(0.038)	(0.026)	(0.020)	(0.020)	(0.030)
Basic, education, geographic, employer, occupations & industries variables	0.109***	0.065*	0.093***	0.102***	0.107***	0.159***
	(0.021)	(0.039)	(0.027)	(0.021)	(0.021)	(0.033)

Source: The data are from the Household, Income and Labour Dynamics in Australia (HILDA) survey. *Note*s: [a] OLS indicates ordinary least square. [b] Reported figures are the estimated coefficients following by its standard errors. [c] Statistics were computed using 1,000 bootstrap samples to obtain appropriate standard errors. [d] * statistically significant at the .10 level; ** at the .05 level; *** at the 0.1 level. [e] Refer to Data Appendix for the list of all variables. [f] For private sector, n=3917; public sector, n=1568

Throughout this section, we assume that the returns to labour market characteristics are the same for men and women. To test if pooling estimation is appropriate, a Wald test is conducted by interacting all explanatory variables with the gender dummy. The results is statistically different at the 5 percent level, hence the estimation should be stratified by gender. However, the pooling results are still presented in this section for the ease of interpretation, and simplicity of understanding. In the following section, results from stratification by gender will be presented.

4.3 Quantile Regression by Gender

QR by gender relaxes the assumption of equal returns to males and females. Results are reported in Table 3. To save space, included controls are basic and education variables,[11] as they are often of primary interest. The results shows the extent to which returns to basic control variables differ between men and women at the various points in their respective distributions.

In the private sector, age variables constantly have larger effect for females than males. Interestingly in the public sector, age coefficients are larger for males than females except for the top part of the wage distribution. If we use age variables as a proxy for experience, this implies that women will tend to be more disadvantaged in the private sector than the public sector, if women's labour force participation is interrupted by family commitments.[12] Note also women's earning and age relationship tend to be flatter compared to men's in both sectors, which means the effect of diminishing return comes in earlier for women than men.

A male bachelor degree holder enjoys a higher return than a female in the public sector. This situation no longer holds in private sector. Higher education variables are found to have larger effect for high income females. This means that in the private sector, higher qualification is an important factor in explaining levels of income. Note that for both sectors, females obtain higher returns from lower qualifications in general. Another interesting finding is that coefficients of education variables are usually larger in the private sector than the public sector. This suggests that educational qualifications are rewarded more in the private sector.

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[11] For list of basic and education variables, see Appendix A.
[12] A more appropriate proxy for experience is a persons' tenure (and its' squared term), which are also included as the additional controls later on.

Table 3: Quantile regressions stratified by gender

	Private											
	Women n=1,726						Men n=2,191					
	OLS	10th	25th	50th	75th	90th	OLS	10th	25th	50th	75th	90th
age	0.053***	0.059***	0.056***	0.044***	0.045***	0.061***	0.048***	0.055***	0.047***	0.040***	0.044***	0.057***
	(0.006)	(0.010)	(0.006)	(0.007)	(0.008)	(0.011)	(0.006)	(0.014)	(0.007)	(0.007)	(0.009)	(0.013)
age2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	0.000***	-0.001***	-0.001***	0.000***	0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
postgrad	0.328***	0.004	0.305	0.314**	0.396**	0.561**	0.330***	0.235	0.347**	0.521***	0.456***	0.320***
	(0.104)	(0.239)	(0.222)	(0.137)	(0.158)	(0.274)	(0.071)	(0.330)	(0.142)	(0.094)	(0.097)	(0.107)
bachelor	0.215***	0.146**	0.139***	0.221***	0.386***	0.382***	0.295***	0.180***	0.270***	0.323***	0.377***	0.367**
	(0.035)	(0.055)	(0.042)	(0.044)	(0.052)	(0.063)	(0.037)	(0.050)	(0.045)	(0.040)	(0.057)	(0.071)
diploma	0.152***	0.133**	0.084**	0.131***	0.173***	0.316***	0.170***	0.070	0.145***	0.198***	0.267***	0.224***
	(0.035)	(0.056)	(0.038)	(0.034)	(0.062)	(0.074)	(0.040)	(0.064)	(0.047)	(0.045)	(0.068)	(0.088)
cert	-0.024	0.046	0.004	0.010	-0.032	-0.025	-0.059*	-0.029	0.003	-0.026	-0.061	-0.163***
	(0.029)	(0.047)	(0.029)	(0.025)	(0.031)	(0.052)	(0.030)	(0.047)	(0.031)	(0.030)	(0.040)	(0.056)
yr11_less	-0.112***	-0.060	-0.083***	-0.071**	-0.114***	-0.095*	-0.156***	-0.082	-0.081**	-0.133***	-0.203***	-0.272***
	(0.030)	(0.056)	(0.028)	(0.024)	(0.032)	(0.055)	(0.033)	(0.050)	(0.032)	(0.031)	(0.043)	(0.055)
miss_edu	-0.015	0.011	0.003	0.000	0.055	0.029	-0.105	-0.054	0.032	-0.010	-0.146*	-0.206
	(0.055)	(0.123)	(0.053)	(0.044)	(0.077)	(0.127)	(0.077)	(0.282)	(0.109)	(0.072)	(0.086)	(0.276)
kids0_4	0.012	-0.054	-0.019	0.041*	0.041	0.052	0.059**	0.071*	0.061**	0.016	0.035	0.064
	(0.029)	(0.059)	(0.038)	(0.024)	(0.037)	(0.065)	(0.025)	(0.040)	(0.025)	(0.025)	(0.033)	(0.054)
kids5_14	-0.021	-0.111	-0.089**	-0.028	0.020	0.112	0.044	-0.064	-0.003	0.097***	0.097*	0.107*
	(0.038)	(0.089)	(0.039)	(0.033)	(0.064)	(0.108)	(0.036)	(0.064)	(0.057)	(0.036)	(0.055)	(0.055)
married	0.063***	0.075**	0.045*	0.033*	0.053*	0.009	0.071***	0.080*	0.061**	0.080***	0.050	0.039
	(0.022)	(0.037)	(0.022)	(0.019)	(0.026)	(0.046)	(0.024)	(0.042)	(0.025)	(0.024)	(0.036)	(0.048)
parttime	-0.029	-0.110***	-0.045**	-0.024	-0.003	0.071*	-0.109***	-0.264***	-0.162***	-0.106***	-0.075*	0.008
	(0.020)	(0.030)	(0.019)	(0.020)	(0.025)	(0.039)	(0.029)	(0.062)	(0.037)	(0.033)	(0.044)	(0.059)
_cons	1.692***	1.222***	1.481***	1.844***	1.987***	1.903***	1.80***3	1.276***	1.581***	1.928	2.089***	2.130***
	(0.107)	(0.168)	(0.110)	(0.122)	(0.130)	(0.188)	(0.108)	(0.234)	(0.128)	(0.132)	(0.156)	(0.227)
	Public											
	Women n=913						Men n=655					
	OLS	10th	25th	50th	75th	90th	OLS	10th	25th	50th	75th	90th
age	0.037***	0.028	0.036***	0.035***	0.042***	0.037**	0.056***	0.073***	0.063***	0.042**	0.023	0.025
	(0.010)	(0.021)	(0.014)	(0.010)	(0.012)	(0.015)	(0.011)	(0.018)	(0.022)	(0.018)	(0.014)	(0.019)
age2	0.000***	0.000	0.000**	0.000***	0.000***	0.000**	-0.001***	-0.001***	-0.001***	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
postgrad	0.315***	0.295*	0.353***	0.336***	0.275***	0.327***	0.267***	0.130	0.241***	0.264***	0.238***	0.358***
	(0.069)	(0.171)	(0.081)	(0.077)	(0.079)	(0.0910)	(0.067)	(0.188)	(0.092)	(0.067)	(0.081)	(0.092)
bachelor	0.244***	0.304**	0.260***	0.270***	0.136**	0.140***	0.182***	0.127	0.152**	0.181***	0.145**	0.221***
	(0.054)	(0.113)	(0.069)	(0.058)	(0.069)	(0.054)	(0.057)	(0.102)	(0.071)	(0.063)	(0.057)	(0.052)
diploma	0.194***	0.211*	0.194***	0.197***	0.135**	0.114**	0.142***	0.095	0.109	0.105**	0.090*	0.096
	(0.054)	(0.111)	(0.070)	(0.055)	(0.068)	(0.050)	(0.0550	(0.096)	(0.068)	(0.047)	(0.051)	(0.059)
cert	-0.069	-0.040	-0.067	-0.041	-0.132**	-0.116*	-0.069	-0.107	-0.113	-0.082	-0.095*	-0.021
	(0.057)	(0.128)	(0.066)	(0.061)	(0.072)	(0.062)	(0.055)	(0.095)	(0.071)	(0.050)	(0.053)	(0.058)
yr11_less	-0.135**	-0.023	-0.067	-0.108*	-0.209*	-0.175**	-0.135**	-0.174	-0.189**	-0.148*	-0.155**	-0.073
	(0.061)	(0.124)	(0.067)	(0.059)	(0.078)	(0.070)	(0.064)	(0.111)	(0.084)	(0.075)	(0.060)	(0.086)
miss_edu	0.155**	0.146	0.147	0.109	0.064	0.240*	-0.052	-0.271	0.003	-0.181	-0.069	0.039
	(0.073)	(0.129)	(0.092)	(0.071)	(0.119)	(0.128)	(0.150)	(0.300)	(0.282)	(0.190)	(0.190)	(0.183)
kids0_4	0.045	0.124*	0.051	0.035	0.027	-0.032	-0.033	0.170***	0.058	-0.030	-0.060	-0.124**
	(0.041)	(0.072)	(0.058)	(0.040)	(0.057)	(0.055)	(0.040)	(0.060)	(0.041)	(0.036)	(0.036)	(0.047)
kids5_14	-0.043	-0.028	-0.109*	-0.022	-0.051	-0.105	-0.012	0.133*	0.025	-0.014	0.022	-0.057
	(0.047)	(0.087)	(0.064)	(0.059)	(0.042)	(0.062)	(0.048)	(0.073)	(0.056)	(0.044)	(0.050)	(0.043)
married	0.049*	0.065	0.052*	0.034	0.027	0.020	0.039	-0.033	0.041	0.053	0.060*	0.121**
	(0.027)	(0.061)	(0.029)	(0.030)	(0.027)	(0.036)	(0.046)	(0.045)	(0.039)	(0.036)	(0.031)	(0.047)
parttime	-0.020	-0.141**	-0.053	-0.058*	0.019	0.128***	-0.178	-0.411*	-0.232***	-0.129*	-0.009	-0.033
	(0.027)	(0.070)	(0.034)	(0.032)	(0.037)	(0.039)	(0.224)	(0.214)	(0.069)	(0.077)	(0.053)	(0.070)
_cons	1.986***	1.626***	1.788***	2.056***	2.174***	2.440***	1.816***	1.107***	1.484***	2.090***	2.607***	2.667***
	(0.188)	(0.372)	(0.280)	(0.168)	(0.229)	(0.296)	(0.033)	(0.314)	(0.439)	(0.349)	(0.298)	(0.388)

Source: The data are from the Household, Income and Labour Dynamics in Australia (HILDA) survey.
Note: [a] OLS indicates ordinary least square. [b] Reported figures are the estimated coefficients following by its standard errors. [c] Statistics were computed using 1,000 bootstrap samples to obtain appropriate standard errors. [d] * statistically significant at the .10 level; ** at the .05 level; *** at the 0.1 level. [e] Refer to Data Appendix for the list of all variables.

In terms of demographic variables, in general marital status and children variables have larger effect for women in both sectors, however they are always insignificant. The magnitude of part time status dummy is more often larger for males, implying that male part time workers are more likely to earn less compared to females. A possible explanation is that female part time workers are more common and more acceptable in the society, whereas males are always expected to work full time.

Presented results from Table 3 indicate that the returns to labour market characteristics are different for men and women. The assumption of equal returns to males and females in the previous section could be misleading. In the following section, the results obtained from decomposition method will be presented. Decomposing gender wage gap by quantiles allow us to examine if the existence of the gap is attributed to the differences in gender characteristics, or differences in the returns to those characteristics.

4.4 Decompositions

Results from the counterfactual decompositions are presented in Table 4. The estimated OLS and unconditional raw gender gap are also listed for comparison. As in Figure 2 and 4, estimated gender wage gap are presented for each quantile of the log wage distribution along the 95 percent confidence intervals in both sectors.

The first striking finding from Table 4 is that, estimated pay gaps across the entire wage distributions are positive, even after we put in additional control variables. Also almost all the estimates are all significantly different from zero at 5 percent level. As outlined in the previous section, a positive gap implies that market returns to men are higher than women's. In other words, holding gender characteristics differences constant, men and women receive different returns to their identical characteristics. This is similar to the findings of Arulampalam et al (2004) for European countries.

Table 4: Estimated Wage Gap

Private				
OLS	Percentile	Raw	Decomposition	Decomp with occ & ind
0.153*** (0.015)	10th	0.000 (0.018)	0.008 (.014)	0.065*** (0.014)
	25th	0.068*** (0.016)	0.060*** (0.009)	0.120*** (0.008)
	50th	0.137*** (0.017)	0.128*** (0.009)	0.177*** (0.009)
	75th	0.223*** (0.022)	0.202*** (0.011)	0.229*** (0.012)
	90th	0.269*** (0.032)	0.262*** (0.018)	0.258*** (0.018)
Public				
OLS	Percentile	Raw	Decomposition	Decomp with occ & ind
0.152*** (0.020)	10th	0.149*** (0.042)	0.110*** (0.013)	0.109*** (0.015)
	25th	0.164*** (0.024)	0.123** (0.009)	0.114*** (0.009)
	50th	0.141*** (0.023)	0.133*** (0.007)	0.124*** (0.008)
	75th	0.121*** (0.027)	0.136*** (0.007)	0.138*** (0.007)
	90th	0.120*** (0.027)	0.158*** (0.010)	0.157*** (0.010)

Source: The data are from the Household, Income and Labour Dynamics in Australia (HILDA) survey.
Note: [a] OLS indicates ordinary least square; Raw indicates unconditional raw gender gap; Decomposition indicates estimated wage gap by counterfactual decomposition method; and Decomp with occ & ind indicates decomposition with occupation and industry dummies. [b] Reported figures are the estimated wage gap following by its standard errors. [c] * statistically significant at the .10 level; ** at the .05 level; *** at the 0.1 level.[d] Controls for Decomposition are age, age squared, postgrad, diploma, bachelor, cert, yr11_less, miss_edu, kids0_4, kids5_14, bornoz, married, defacto, divorced, contract, casual and parttime. [e] Refer to Data Appendix for the list of all variables. [f] For private sector, n=3917; public sector, n=1568.

Figure 2: Gender Pay Gap in Private sector

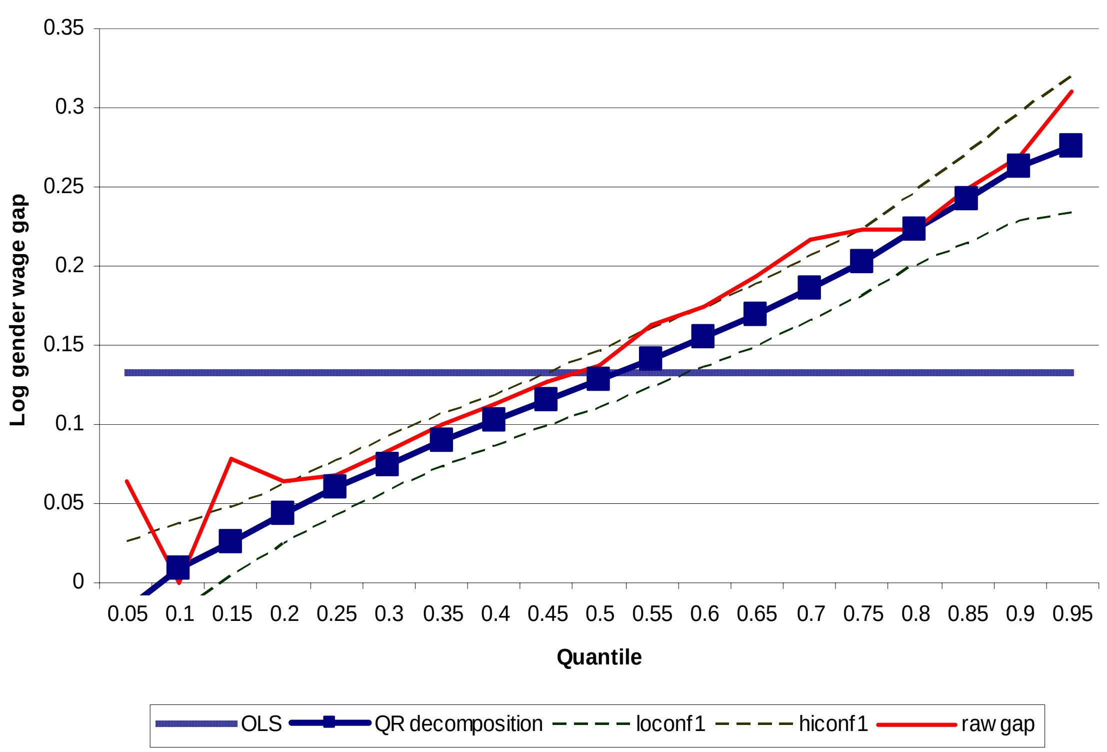


Figure 3: Private sector with occupations and industries

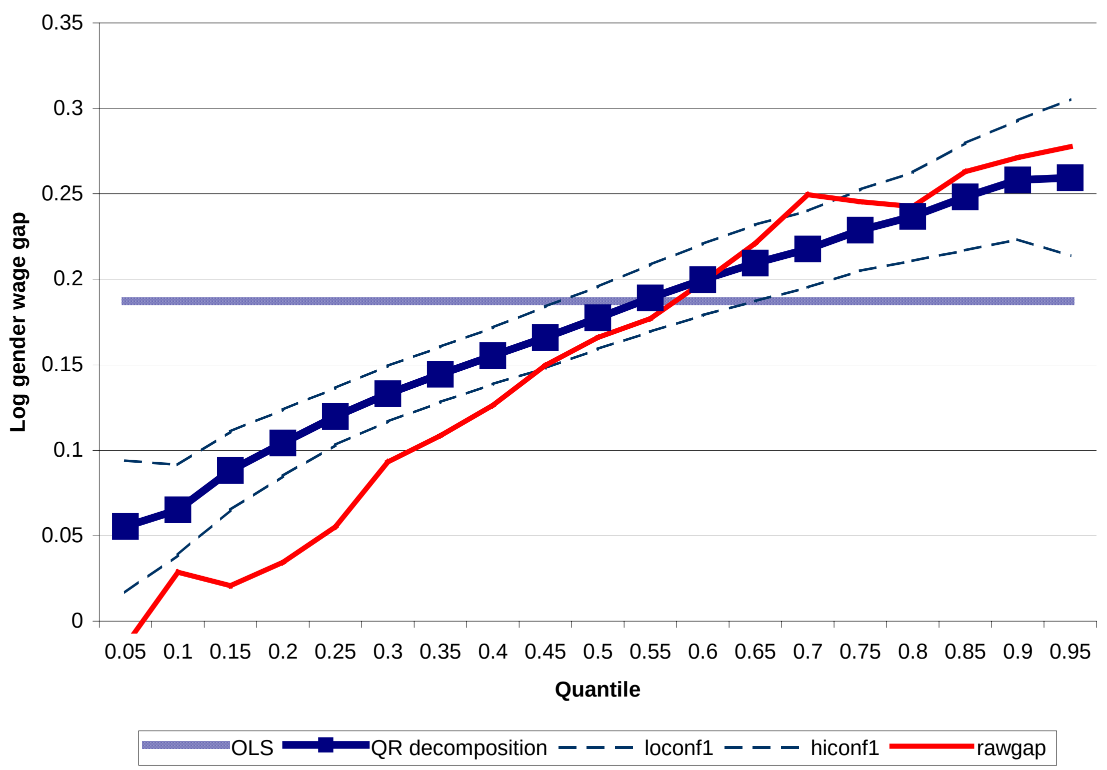


Figure 4: Gender Pay Gap in Public sector

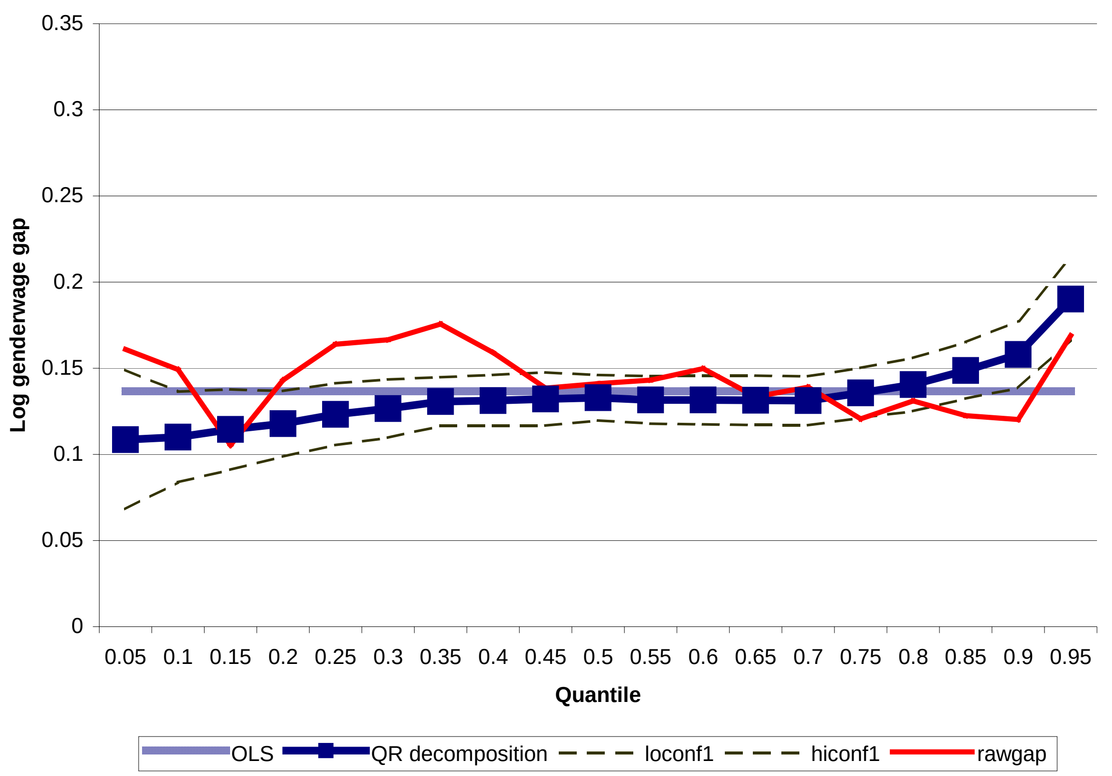
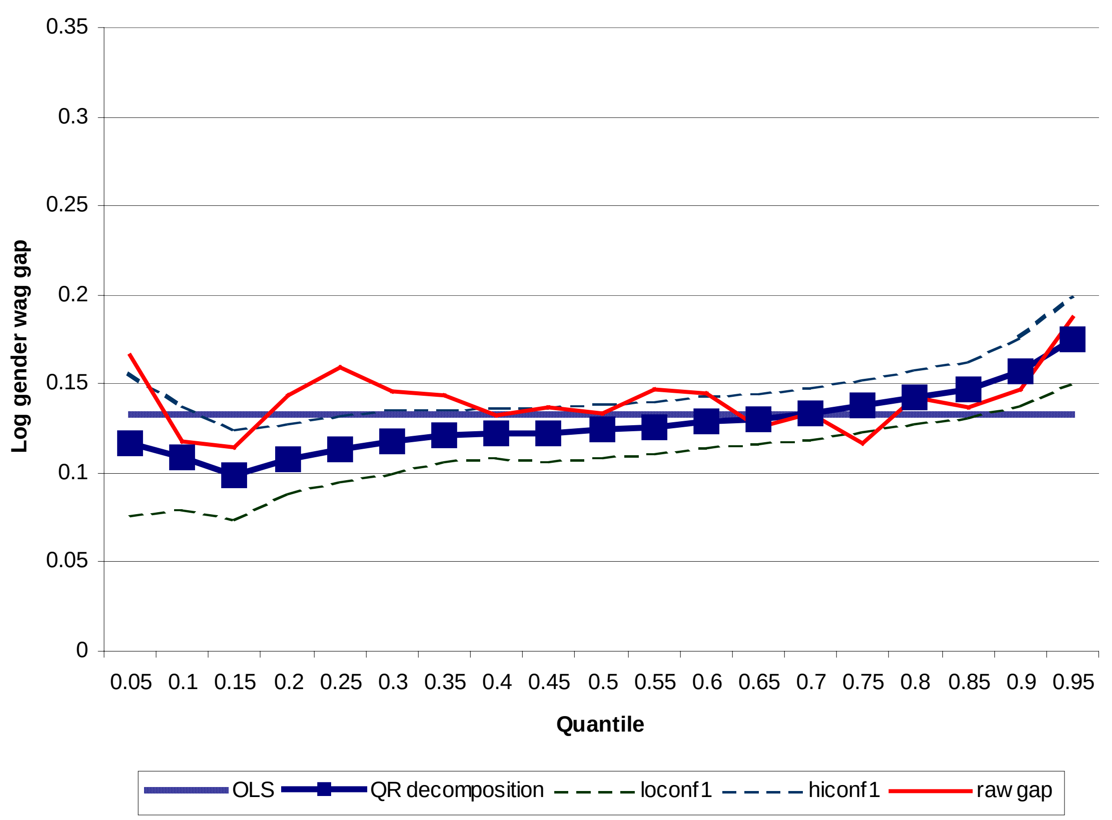


Figure 5: Public sector, with occupations and industries



Consider the private sector estimates. Figure 2 gives the results of observed gender wage gaps with demographic and education control variables; Figure 3 indicates the results after adding occupation and industry dummie.[13] The striking result is the sharp acceleration of the gap as we move towards the upper tail of the conditional wage distribution. This finding suggests that there is a glass ceiling in the private sector. High income females are more likely to be disadvantaged, due to the unobserved heterogeneity that the model does not control for. Summarising this gap using the OLS estimator could be misleading as a lot of information is hidden by solely focusing on examination of the mean.

Next, consider public sector estimates. Figure 4 and Figure 5 gives the estimates of the gender wage gaps with and without occupation and industry dummies based on similar reasons to those outlined previously. From Figure 4, the wider gaps are found from around the 75th to the top percentiles. However, note that the change of the estimated differences is only around 10 percentage point. This finding relates to the conclusion that high and low income females are equally disadvantaged in the public sector, and the gap is distributed rather constantly across the entire wage percentile.

Furthermore, the obtained result with and without occupation and industry controls are remarkably similar in both private and public sector. This can be seen by comparing Figure 2 to Figure 3 and Figure 4 to Figure 5. This suggests that our model is robust to the potential endogeneity from occupation and industry, and also segregation of women into certain occupations and industries is not the major drive of the gender wage gap.

A prominent difference is found by comparing the results from Table 4 and Table 2. Table 2 shows the gender gaps controlling for differences in labour market characteristics but assumes that men and women receive similar rewards for these characteristics. The result is that a substantial amount of the public sector sticky floor and private sector glass ceiling effect is an outcome of the differences in gender characteristics. However Table 4 indicates otherwise. From Table 4, even after we control for demographic and education variables, the gender gap rises throughout the distribution. This indicates that it is not gender demographic and education differences that account for the gap at the top of the

[13] The results with and without occupation and industry dummies are presented separately due to the potential endogeneity of the variables. It is possible that one might choose their jobs and industries base on the earning prospects. Controls included for the decomposition are age, age squared, postgrad, diploma, bachelor, cert, yr11_less, miss_edu, kids0_4, kids5_14, bornoz, married, defacto, divorced, contract, casual and parttime. Refer to Appendix for the list of all occupations and industries.

distribution. Rather, it is a result of the differential rewards, in other words the glass ceiling is due to the differences in returns between genders.

5. Conclusion

By utilising QR framework and counterfactual decomposition method, the current study has analysed the movements of gender pay gaps along the wage distribution. In addressing the prime hypothesis that is posted initially, the major finding reveals the existence of glass ceiling in the Australia private sector; whereas the gender wage gap seems to be relatively constant over all percentiles in the public sector.

In this paper estimation took the following steps. First the results from the unconditional raw gender gap identified the existence of the gender pay gap in both sectors. The second step was obtaining the conditional QR estimates. By imposing the restriction of equal returns to labour market characteristics between genders, it was found that gender differences accounted for substantial amount of the public sector sticky floor and private sector glass ceiling.

Estimates stratified by genders as well as sectors were also undertaken. The results indicated that the pooled QR results are misleading. Accordingly, a counterfactual decomposition analysis was undertaken to determine if the gender wage gap is a result of gender characteristic differences, or the differences in returns to those characteristics. The finding is that in the public sector, the gender gap exists but is distributed more evenly. Whereas in the private sector, even after the control of various occupations and industries, the gender gap continued to accelerate at the upper tail of the conditional wage distribution, hence there is a glass ceiling. Clearly, the observed gender pay gap in both sectors is a result of the *differences in returns* to gender characteristics.

A glass ceiling effect was identified in the Australian private but not public sector. One possible explanation is the adoption of different pay schemes between two sectors. In the public sector, the wage is classified by various Australian Public Service (APS) classifications, which implicitly implies that public servants earnings are capped at certain upper limits. Competition in the private sector is more rigorous and there is no standardised pay scheme available across companies or firms. As a result of this, potential earnings could be extremely diverse.

Since the observed wage gap is attributed to the differences in returns to gender characteristics, this result relates to the explanation regarding the environment faced by women in the labour force. This is in accordance with the finding of Albrecht et al (2003) in Sweden labour market. Their conjecture is that Swedish parental leave policy and the day care system provides strong incentives for females to participate but not commit strongly to a career. According to the OECD employer survey (2001), family-friendly arrangements are more commonly provided in the Australian public sector. The absence of the glass ceiling effect in the public sector could possibly be credited to the more complete family-friendly arrangements, which allows females to participate as well as to commit to their career. Consequently a greater flexibility in parental leaves and a higher accessibility to childcare system could provide the scope to potentially improve the working conditions faced by private sector females. If the working conditions are improved, the situation which females are more commonly found in less demanding jobs and thus fall substantially behind men towards the top might be altered.

The differences in returns to gender characteristics could be a form of discrimination, or it could be some unobserved heterogeneity that the model does not capture. If discrimination is the main factor that is driving the pay gap after extensive controls, then female workers are still more likely to be disadvantaged, subject to the unobservable family commitments or conventional social norms, even under the existence of equal opportunity legislation in Australia.

In conclusion, previous literature decomposing the mean wage gap, analysis by QR framework is largely descriptive, as also in this analysis. However, QR has the advantage over mean regression of revealing more insights about where the widest gaps are. Even so, in terms of policy implications, this technique does not point out any potential causes. It simply provides more information on the extent and distribution of differing returns between genders. This highlights important gender issues that need further investigation, and future studies can be considered to investigate the possible causes of glass ceilings. Reasonable speculation might relate to both labour market demand and supply side factors. A possible cause on the demand side could be that wage setting procedures for high fliers might favour men either overtly or covertly. This might arise if, for example, firms are willing to pay more to get one of their own type,[14] while on the supply side, high-flying women might be prepared to accept relatively lower salaries than men. This maybe due to a reluctance to bargain aggressively, hence gratitude at getting a job in a male-dominated world of high-fliers; or simply because of the lack of information about what male counterparts are being paid. This situation might

[14] The situation where employers may prefer to incur higher costs rather than contract with members of certain groups are known as a form of economic discrimination (Becker, 1971).

be more likely to occur at the top of the wage distribution, where there are relatively fewer women.

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APPENDIX A

List of all Control Variables

1. *Basic and educational variables:* age, age2, kids0_4, kids5_14, bornoz, married, defacto, divorced, contract, casual and part time. Educational variables are postgrad, bachelor, diploma, cert, yr11_less and miss_edu. Base of all education variables is year_12.

2. *Geographic variables:* NSW, VIC, QLD, SA, WA, TAS and NT. The base is ACT. Also included are regional variables urban, in_region and out_region, with the base of ‘remote’.

3. *Employer variables:* size20_99, size100_499, size500, size20_up, tenure of employment, ten_emp2 and union.

4. *Occupation dummies:* manager, professional, associate professional, tradesperson, advanced clerk, intermediate clerk, inter production and elementary clerk. Labourer is used as the based.

5. *Industry dummies:* Dummies are mining, manufacturing, energy, construction, retail and service, transport, finance and government. Base of all variables is cultural.

Variable Names and Definitions

age	Age of the respondent at the wave 1 interview date.
age2	Age squared.
sex	=0 for females; =1 for males.
kids0_4	=1 if respondent has own/non-resident children aged 0-4 years old; =0 otherwise.
kids5_14	=1 if respondent has own/non-resident children aged 5-14 years old; =0
bornoz	=1 if country of birth of respondent is Australia; =0 else where.
married	=1 if respondents' current marital status is married; =0 otherwise.
defacto	=1 if respondents' current marital status is defacto; =0 otherwise.
divorce	=1 if respondents' current marital status is divorced; =0 otherwise.
contract	=1 if respondent is employed on a fixed term contract; =0 otherwise.
casual	=1 if respondent is employed on a casual basis; =0 otherwise.
part time	=1 if respondent is employed on a part time basis; =0 otherwise.
postgrad	=1 if respondent's highest level of education is postgraduate; =0 otherwise.
bachelor	=1 if respondent's highest level of education is bachelor; =0 otherwise.
diploma	=1 if respondent's highest level of education is diploma; =0 otherwise.
cert	=1 if respondent's highest level of education is certificate; =0 otherwise.
year11_less	=1 if respondent's highest level of education is Year 11 or less; =0 otherwise.
miss_edu	=1 if respondent's highest level of education is undetermined; =0 otherwise.
year12	=1 if respondent's highest level of education is Year 12; =0 otherwise.
NSW	=1 if respondent's residential state is New South Wales; =0 otherwise.
VIC	=1 if respondent's residential state is Victoria; =0 otherwise.
QLD	=1 if respondent's residential state is Queensland; =0 otherwise.
SA	=1 if respondent's residential state is South Australia; =0 otherwise.
WA	=1 if respondent's residential state is Western Australia; =0 otherwise.
TAS	=1 if respondent's residential state is Tasmania; =0 otherwise.
NT	=1 if respondent's residential state is Northern Territory; =0 otherwise.
ACT	=1 if respondent's residential state is Australian Capital Territory; =0 otherwise.
urban	=1 if respondent reside in major cities of Australia; =0 otherwise.
in_region	=1 if respondent reside in inner regional of Australia; =0 otherwise.
outregion	=1 if respondent reside in outer regional of Australia; =0 otherwise.
remote	=1 if respondent reside in remote Australia; =0 otherwise.
size1_19	=1 if number of employees at work is between 1-19; =0 otherwise.
size20_99	=1 if number of employees at work is between 20-99; =0 otherwise.
size100_499	=1 if number of employees at work is between 100-499; =0 otherwise.
size500	=1 if number of employees at work is 500 or more; =0 otherwise.
size20_up	=1 if number of employees at work is not sure but 20 or more; =0 otherwise.
tenure	Tenure with current employer (in years).
ten_emp2	Tenure squared.
union	=1 if respondent belongs to trade union or employee association; =0 otherwise.
manager	=1 if respondent occupation is manager; =0 otherwise.
professional	=1 if respondent occupation is professional; =0 otherwise.
associate professional	=1 if respondent occupation is associate professional; =0 otherwise.
tradesperson	=1 if respondent occupation is tradesperson; =0 otherwise.
advanced clerk	=1 if respondent occupation is advanced clerk; =0 otherwise.
interproduction	=1 if respondent occupation is interproduction; =0 otherwise.
elementary clerk	=1 if respondent occupation is elementary clerk; =0 otherwise.
labourer	=1 if respondent occupation is labourer; =0 otherwise.
mining	=1 if respondent works in a mining industry; =0 otherwise.
manufacturing	=1 if respondent works in a manufacturing industry; =0 otherwise.
energy	=1 if respondent works in a energy industry; =0 otherwise.
construction	=1 if respondent works in a construction industry; =0 otherwise.
retail and service	=1 if respondent works in a retail and service industry; =0 otherwise.
transport	=1 if respondent works in a trasport industry; =0 otherwise.
finance	=1 if respondent works in a finance industry; =0 otherwise.
government	=1 if respondent works in a government industry; =0 otherwise.
cultural	=1 if respondent works in a cultural industry; =0 otherwise.

Table 5: Interquantile Test

	10th-25th	25th-50th	50th-75th	75th-90th	10th-50th	50th-90th
sex	**0.042*****	**0.045*****	**0.065*****	**0.069*****	**0.087*****	**0.133*****
	(0.017)	**(0.013)**	**(0.013)**	**(0.018)**	**(0.021)**	**(0.022)**
age	-0.013**	-0.009**	0.002	0.011*	-0.022***	0.013***
	(0.006)	(0.004)	(0.004)	(0.006)	(0.008)	(0.007)
age2	0.000**	0.000**	0.000	0.000*	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
postgrad	0.067	0.057	-0.037	-0.037	0.124	-0.073
	(0.075)	(0.048)	(0.039)	(0.046)	(0.082)	(0.058)
bachelor	0.083***	0.045**	-0.019	-0.002	0.128***	-0.021
	(0.027)	(0.024)	(0.022)	(0.029)	(0.032)	(0.033)
diploma	0.047**	0.043**	-0.009	-0.013	0.090**	-0.022
	(0.027)	(0.023)	(0.022)	(0.029)	(0.032)	(0.032)
cert	0.005	-0.005	-0.031*	-0.043*	0.000	-0.074***
	(0.025)	(0.021)	(0.018)	(0.026)	(0.029)	(0.030)
yr11_less	-0.022	-0.001	-0.060***	-0.034	-0.023	-0.093***
	(0.027)	(0.022)	(0.020)	(0.031)	(0.031)	(0.035)
miss_edu	0.010	-0.019	-0.031	0.050	-0.009	0.019
	(0.051)	(0.036)	(0.039)	(0.067)	(0.068)	(0.075)
kids0_4	0.008	-0.011	-0.008	0.005	-0.003	-0.003
	(0.022)	(0.016)	(0.017)	(0.024)	(0.029)	(0.026)
kids5_14	0.039	0.039**	0.006	-0.010	0.078*	-0.005
	(0.032)	(0.024)	(0.026)	(0.033)	(0.036)	(0.037)
bornoz	-0.001	-0.016	-0.026	-0.038*	-0.017	-0.064***
	(0.017)	(0.013)	(0.014)	(0.021)	(0.021)	(0.024)
married	-0.051**	0.013	0.003	0.010	-0.037	0.013
	(0.029)	(0.016)	(0.018)	(0.024)	(0.033)	(0.029)
defacto	-0.053**	0.014	-0.014	0.051	-0.040	0.037
	(0.027)	(0.020)	(0.019)	(0.031)	(0.030)	(0.034)
divorced	-0.071*	0.019	-0.015	0.023	-0.052	0.008
	(0.037)	(0.023)	(0.026)	(0.034)	(0.045)	(0.039)
contract	0.038**	0.012	0.048**	-0.003	0.050*	0.045
	(0.023)	(0.019)	(0.021)	(0.028)	(0.028)	(0.031)
casual	0.102***	0.053***	0.034**	-0.003	0.154***	0.031
	(0.029)	(0.016)	(0.017)	(0.024)	(0.035)	(0.027)
parttime	0.023	0.013	0.037*	0.063**	0.035	0.100***
	(0.022)	(0.014)	(0.016)	(0.021)	(0.028)	(0.026)
_cons	0.360***	0.352	0.163**	0.017	0.712***	0.180*
	(0.106)	(0.073)	(0.077)	(0.109)	(0.126)	(0.129)

Source: The data are from the Household, Income and Labour Dynamics in Australia (HILDA) survey.

Note: [a] Reported figures are the estimated coefficients following by its standard errors. [b] Statistics were computed using 1,000 bootstrap samples to obtain appropriate standard errors. [c] * statistically significant at the .10 level; ** at the .05 level; *** at the 0.1 level. [d] Note that sex variable is statistically significant across all adjacent quantiles. [e] n=5867.

APPENDIX B: Sample Selection Adjustment

Analysis neglecting sample selection bias could potentially underestimate the real effect of differences in returns. In this paper, it is assumed that a female worker makes among the following three decisions: to participate in the private sector; to participate in the public sector or not to participate in the labour force. A multinomial logit selection model is estimated to capture this selection decision. The reason is that it allows different returns to individual characteristics such as education and experience across sectors. Furthermore, a female worker is not only making the decision of whether or not she is participating in the labour force, but also of which sector to participate in. This raises the possibility of significant selection bias in the coefficients of the wage equations.

To test the sample selection problem, firstly an OLS wage equation, which includes the inverse Mill's ratio obtained from the first-stage multinomial selection equation is constructed. The finding concludes that the lambda coefficients are statistically insignificant in both public and private sectors. This result can be seen as a preliminary indicator that the model does not suffer severe selection bias problem.[15]

The selectivity correction for the women's wage equation has been carried out in a similar fashion as in Garcia et al (2001) and Dolado et al (2004). The conventional Heckman Lambda approach is used in conjunction with some simplifying and restrictive assumptions.[16] The steps are summarized as follows: Firstly the inverse Mill's ratio is estimated from a multinomial selection equation.[17] Secondly a wage decomposition model is estimated by adding inverse Mill's ratio to the list of regressors in the model.

The multinomial selection equation includes the additional instruments as follows: the first child in the family; born in a majority Muslim country; professional mum; self-declared as in good health conditions; regional variables or currently renting.[18] It is found that having children decreases the probability of labour force participation significantly in both sectors; whereas being the first born in the family makes a woman more likely to work. Females, whose mum is professional, have a higher likelihood of working. Interestingly, females born in a majority Muslim country are less likely to join the labour force.

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[15] Results see Table 6.

[16] A less restrictive and more precise estimation methodology is proposed by Buchinsky (1996). He generalised the estimation methodology of Newey et al (1990) and showed that consistent parameter estimates can be obtained by including a power series approximation in the context of quantile regression. Following Buchinsky, Albrecht et al (2004) constructed a single index selection model adjusted for QR wage decomposition.

[17] The inverse Mill's ratio with three power series expansion terms are used as suggested in Buchinsky(1998).

[18] For details see Table 7.

Figure 5 and 6 present the results of the QR wage decomposition incorporating the extra inverse Mill's ratios in the public and private sectors respectively. Consistent with our OLS Heckman model, it is found that the additional lambda terms in both sectors are statistically insignificant across most quantiles. The curve with sample selection correction and without sample selection correction is remarkably similar in both public and private sector. The evidences so far suggest that selectivity bias is not severe in this model.[19]

[19] Buchinsky (1998) tested for equality of the inverse Mill's ratio from the single index selection model and a standard probit model. A visual comparison showed they were of the same order of magnitude and had same signs. Additional sensitivity test showed that 23 out of 45 cases are significant different from each other.

Table 6: Multinomial Selection Model

Private		Public	
age	0.157***	age	0.321***
	(0.014)		(0.023)
age2	-0.003***	age2	-0.004***
	(0.000)		(0.000)
postgrad	-1.010***	postgrad	1.897***
	(0.324)		(0.257)
bachelor	-0.505***	bachelor	1.091***
	(0.123)		(0.165)
diploma	-0.289**	diploma	1.178***
	(0.122)		(0.165)
cert	-0.236**	cert	0.126
	(0.103)		(0.164)
yr11_less	-0.584***	yr11_less	-0.781***
	(0.098)		(0.171)
miss_edu	-0.391**	miss_edu	0.456**
	(0.172)		(0.222)
kids0_4	-1.276***	kids0_4	-1.267***
	(0.085)		(0.117)
kids5_14	-0.658***	kids5_14	-0.666***
	(0.110)		(0.142)
married	-0.305***	married	-0.166
	(0.079)		(0.101)
ghealth	0.513***	ghealth	0.791***
	(0.081)		(0.119)
move1	0.039	move1	-0.153
	(0.085)		(0.112)
move5	0.044	move5	-0.128
	(0.078)		(0.099)
mumprof	0.024	mumprof	0.084
	(0.074)		(0.094)
firstkid	0.153**	firstkid	0.065
	(0.065)		(0.085)
loneperson	0.095	loneperson	0.300**
	(0.118)		(0.143)
urban	0.747***	urban	-0.284
	(0.268)		(0.278)
in_region	0.495*	in_region	-0.165
	(0.271)		(0.282)
out_region	0.418	out_region	0.076
	(0.281)		(0.295)
rent	-0.307***	rent	-0.335***
	(0.078)		(0.109)
muslim	-0.465**	muslim	-1.212***
	(0.211)		(0.386)
_cons	-2.424***	_cons	-6.923***
	(0.377)		(0.550)

Source: The data are from the Household, Income and Labour Dynamics in Australia (HILDA) survey.

Note: [a] Reported figures are the estimated coefficients following by its standard errors. [b] * statistically significant at the .10 level; ** at the .05 level; *** at the 0.1 level. [d] n=7335. [e] The control group is “not to participate in the labour force”.

Table 7: OLS Wage Equation with Selectivity Correction

Private		Public	
age	0.051***	age	0.047***
	(0.005)		(0.008)
age2	-0.001***	age2	-0.001***
	(0.000)		(0.000)
postgrad	0.373***	postgrad	0.289***
	(0.058)		(0.049)
bachelor	0.284***	bachelor	0.194***
	(0.026)		(0.040)
diploma	0.171***	diploma	0.152***
	(0.027)		(0.040)
cert	-0.016	cert	-0.067*
	(0.021)		(0.040)
yr11_less	-0.131***	yr11_less	-0.160***
	(0.023)		(0.045)
miss_edu	-0.074	miss_edu	0.051
	(0.046)		(0.062)
kids0_4	0.054***	kids0_4	0.017
	(0.019)		(0.029)
kids5_14	0.016	kids5_14	-0.034
	(0.027)		(0.034)
married	0.079***	married	0.059**
	(0.016)		(0.021)
_cons	1.689***	_cons	1.830***
	(0.076)		(0.145)
Lambda	**0.003**	**Lambda**	**0.007**
	(0.004)		**(0.005)**

Source: The data are from the Household, Income and Labour Dynamics in Australia (HILDA) survey.

Note: [a] Reported figures are the estimated coefficients following by its standard errors. [b] * statistically significant at the .10 level; ** at the .05 level; *** at the 0.1 level. [c] For private sector, n=3917; public sector, n=1568.

Figure 5: Private sector

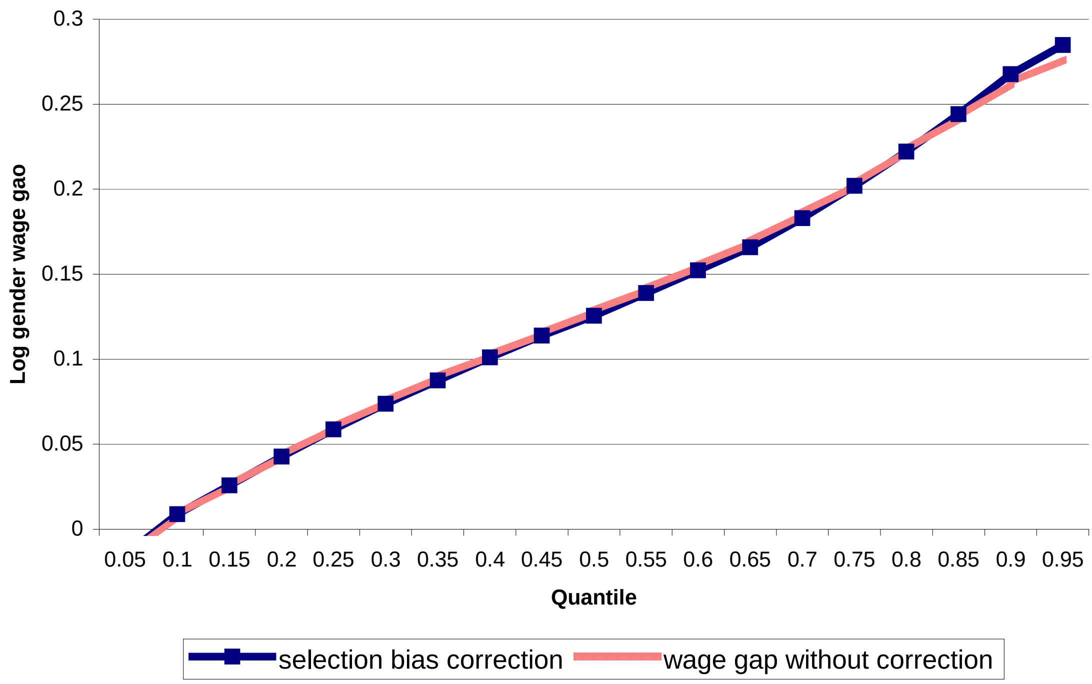

Figure 6: Public sector