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Peter M. Siminski
University of Wollongong, siminski@uow.edu.au

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Abstract

This paper estimates the average Australian public sector wage premium. It includes a detailed critical review of the methods available to address this issue. The chosen approach is a quasi-differenced panel data model, estimated by the Generalised Method of Moments, which has many advantages over other methods and has not been used before for this topic. I find a positive average public sector wage premium for both sexes. The best estimates are 6.7% for men and 10.5% for women. The estimate is statistically significant for men (p = 0.024) and for women (p < 0.001). No evidence is found to suggest that the public sector has an equalising effect on the wages of its workers.

JEL classification codes: J45, J31, J38

Keywords: public sector, wages, premium, panel data, GMM, Australia

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I Introduction

The public sector accounts for 16% of total employment in Australia (Australian Bureau of Statistics, 2007a). This is similar to many other OECD countries (OECD, 2001). Government thus has the potential for major distributional effects through wage setting policy. Much research has investigated the public sector wage 'premium', motivated primarily by concerns over efficiency as well as equity.[2] As discussed by Gregory & Borland (1999), wage setting in the public sector may not necessarily follow private sector principles. The public sector process may be insulated from market competition. To varying extents, all governments will seek to control employment costs in order to achieve efficiency goals. But wage policy may also be motivated by equity goals. Public sector practice may also be motivated by political incentives, and bureaucratic budget-maximising (or minimising) incentives, which may be at odds with social welfare goals.

The aim of this paper is to estimate the public sector wage premium. Specifically, it addresses the question: 'What would an average public sector employee be paid under private sector wage setting principles?' The evaluation problem is to overcome the missing counterfactual, which is the unobserved private sector wage for public sector employees at a point in time.

The econometric difficulties involved in addressing this question are substantial. The observed sectoral wage gap may include a constant effect across all employees. It may also stem from sectoral differences in returns to the characteristics of employees, which include education and experience as well as unobserved (by the econometrician) skills such as interpersonal skills, intelligence or work ethic. These effects need to be distinguished from the sectoral differences in the stock of such characteristics. Selection bias is hence an important issue. A given employee may select one sector over the other according to the potential returns to their given (observed and unobserved) characteristics. The employer may also select from the potential pool of employees according to such characteristics. These issues are described in Section II, whilst reviewing the most common and the most recent approaches that have been applied, or could be applied, to this topic.

The chosen model is discussed in Section III. It is a panel data model, similar to that used by Lemieux (1993; 1998) to analyse the effect of unionisation on wages. The parameters of interest are estimated using the Generalised Method of Moments (GMM) after quasi-differencing the wage equation. This approach has many advantages over the other methods reviewed. To the author's knowledge, it has not previously been applied to this topic.

[2] This literature is surveyed by Bender (1998) and Gregory & Borland (1999).

The data source is the Household Income and Labour Dynamics in Australia (HILDA) panel survey, which is described in Section IV. Section V presents results, including regression estimates and a decomposition of the average wage premium. Section VI offers conclusions. The results of alternate specifications are shown in an Appendix.

II Review of Previous Approaches and Their Limitations

There is a large literature on sectoral wage differences, surveyed by Bender (1998) and Gregory & Borland (1999). In the last 10-15 years the focus of such research has shifted from estimates of the average public sector effect on wages to the effect on the entire wage distribution. However, the econometric difficulties in such analyses make it difficult to confidently measure even the average effect, as will be argued below. In order to motivate the methods used in this paper, I first discuss the methods previously used and their limitations. I then note that these limitations also apply to the analogous quantile regression methods.

Models of the average wage premium

First consider the following model:

$$\ln(w_i) = a + bS_i + \beta X_i + \mu_i \qquad i = (1,\ldots,\mathrm{N}) \qquad (1)$$

Here, w_i is the observed hourly earnings of employee i and N is the number of observed employees. The left hand side is the natural log of w_i. The right hand side is linear in sector of employment (S = 1 if sector = public; S = 0 if sector = private) and other observable characteristics (X). In this model, b is the average public sector premium. The parameters (a, b, β) can be estimated by OLS. In estimating b, this method holds X constant and thus takes account of differences in observed characteristics between sectors. In this model, it is assumed that S is exogenous and hence uncorrelated with the residual. This implies that any sectoral differences in unobserved characteristics of workers do not affect wages. This model also assumes that returns to observed (and unobserved) characteristics are equal in the two sectors. It can be argued all of these assumptions may not hold, but these can be relaxed in other specifications, as will be shown.

The fixed effects (FE) model utilises repeated observations on individuals:

$$\ln(w_{it}) = a + bS_{it} + \beta X_{it} + \gamma_t D_t + \theta_i + \mu_{it} \qquad i = (1,\ldots,\mathrm{N}) \qquad t = (1,\ldots,\mathrm{T}) \qquad (2)$$

The subscript t denotes the time point of the observation and T is the number of time points, θ_i is a time-invariant individual effect, D_t is a vector of time dummy variables, γ_t is a vector of coefficients of D_t, with γ_0 = 0. In such a model, b is identified through the variation in wages within people who move between sectors: 'movers'. FE thus improves on OLS in two ways. It accounts for differences in unobserved characteristics of workers between sectors, assuming these do not vary over time. FE is also more robust to endogeneity of sector choice than OLS. FE allows sector choice to be made on observables (X) and time-invariant unobservables (θ). In other words, the expected value of the error term is zero conditional on X, θ and S at all time points: $E(\mu_{it}|X_{it},S_{it},\theta_i) = 0, \ \forall\, t$. In comparison, OLS is only consistent if sector choice occurs only on observables. A remaining limitation of FE is that it assumes that observable and unobservable characteristics are valued equally in the two sectors. In practice, a given individual may earn a higher wage in one sector over the other because of a constant sector effect (b) but also because of differences in returns to characteristics. As an estimator of the average wage premium, $\hat{b}$ will be biased if there are differences between sectors in the returns to observed or unobserved characteristics.

Perhaps the most common method for examining sectoral wage premium is a decomposition method such as that of Oaxaca (Oaxaca, 1973). The strength of such methods is that they do not assume common returns to observable between sectors. Separate wage equations are estimated for each sector. Let the P subscript denote the public sector and R denote the private sector:

$$\ln(w_{iP}) = \beta_P X_i + \mu_{iP} \tag{3a}$$

$$\ln(w_{iR}) = \beta_R X_i + \mu_{iR} \tag{3b}$$

Where β in this case includes the intercept. The mean sectoral (log) wage difference is decomposed as follows:

$$\overline{\ln(w_P)} - \overline{\ln(w_R)} = \hat{\beta}_P \overline{X_P} - \hat{\beta}_R \overline{X_R} \tag{4}$$

Where $\overline{X_P}$ and $\overline{X_R}$ represent the average (observed) characteristics of employees in the public and private sectors.

Let $\qquad \Delta\hat{\beta} = \hat{\beta}_P - \hat{\beta}_R$

and $\qquad \Delta\overline{X} = \overline{X}_P - \overline{X}_R$. Substitute into (4) to get

$$(\hat{\beta}_R + \Delta\hat{\beta})\overline{X_P} - \hat{\beta}_R \overline{X_R} = \hat{\beta}_R(\overline{X_P} - \overline{X_R}) + \Delta\hat{\beta}\overline{X_P} = \hat{\beta}_R \Delta\overline{X} + \Delta\hat{\beta}\overline{X_P} \tag{4a}$$

The first term represents the effect of differences in characteristics between sectors. Specifically it is the return in the private sector multiplied by the average difference in characteristics between sectors. The second term is the effect of differences in the returns to observable characteristics between sectors. In this version of the Oaxaca decomposition, returns to observable characteristics in the private sector are the 'benchmark' against which returns in the public sector are compared. The returns provided in the public sector are thus contrasted directly with those of the private market. This is the appropriate comparison for the research question under consideration in this paper. Other related decomposition approaches are proposed by Reimers (1983) and Neumark (1988), which are suited to analysing discrimination, but are less relevant here.

Whilst a simple Oaxaca decomposition allows for different returns to observables, the estimates ($\hat{\beta}_P$ and $\hat{\beta}_R$) will be biased if sector selection is made on unobservable characteristics that are correlated with wages (Heckman, 1979). Thus the results of decomposition will also be biased. This issue is analogous to the endogenteity of S, when estimated in a single wage equation. The Oaxaca decomposition can be extended with a Heckman-type sample selection correction. This is the approach used by Borland et al. (1998), which is the principal attempt to measure the Australian public sector wage premium, as well as many others internationally.

Whilst the selectivity corrected Oaxaca decomposition is a common approach, there are a number of issues which make it difficult to apply to the current investigation. The first difficulty is the existence of plausible exclusion restrictions for the selection model. For identification in a sample selection correction model to be convincing (i.e. to be identified beyond distributional assumptions arising from the nonlinearity of the probit selection model), it is necessary to choose variables which are assumed to be instrumental in the selection process, but do not directly affect the dependent variable in the substantive model. In Borland et al.'s (1998) model, this variable is age although no justification is given for this choice. Kanellopoulos (1997) also uses age, citing the expansion of public sector employment in the 1970s and 1980s. It can be argued that such an expansion of public employment represents an exogenous shock to labour demand, causing a disproportionate number of young people to make their careers in the public sector. However, age may also be correlated with unobserved characteristics which are valued differently in the two sectors (independently of experience, which is included in the wage equation). For example, Bellante and Link (1981) find that public sector workers are more risk averse than public sector workers. As noted by Gregory & Borland (1999) this may reflect a greater reward for risk aversion in the public sector, and hence greater rewards to risk taking in the private sector. Age is likely correlated with risk aversion (Halek and Eisenhauer, 2001; Pålsson, 1996). Other exclusion restrictions that have been used are attitudes towards unions (since union membership is correlated with public sector status (eg. Bender, 2003; Heitmeuller, 2006; Melly, 2006). This is a contentious choice since such attitudes are likely to be endogenous to working in a unionised environment (as acknowledged by Melly). Father's occupation has been frequently used (eg. Bender, 2003; Dustmann and van Soest, 1998; Hartog and Oosterbeek, 1993; Hou, 1993; Melly, 2006; Terrell, 1993). This assumes that one's father's employment in the public sector affects the selection decision but not wages. This may be contentious if one's father has contacts in their sector of employment which translate to higher pay (although Melly's results suggest this is not an important issue for Germany). The assumption is also violated if intergenerationally transmitted attitudes to the public sector employment are accompanied by intergenerationally transmitted (unobserved) skills. To put this in another way, if one lives with a public sector worker during childhood, they may acquire some skills or knowledge which are valued in public sector labour markets (and similarly for the private sector). Some studies (Hartog and Oosterbeek, 1993; Hou, 1993) use parent's education, which is also likely to be correlated with unobserved skills. If multiple instruments are available, overidentification tests can be used to support or reject the assumptions underlying exclusion restrictions. However, their results are contingent on statistical power.

Another limitation of the selectivity-corrected decomposition approach is that it cannot decompose the effect of differences in the stock of unobserved characteristics from the effect of differences in their returns. In the selectivity corrected decomposition, the equality shown in equations (4) and (4a) does not hold. The decomposition has additional terms, which are the effects of sample selection in the wage equations:

$$\overline{\ln(w_P)} - \overline{\ln(w_R)} = \hat{\beta}_R \Delta \overline{X} + \Delta\hat{\beta}\overline{X_P} + (\hat{\theta}_P \overline{\lambda}_P - \hat{\theta}_R \overline{\lambda}_R) \qquad (5)$$

where $\overline{\lambda}$ is the estimated mean Inverse Mills Ratio in the models for each sector, and $\hat{\theta}$ is the estimated coefficient of λ in the selectivity corrected wage equation in each sector. The selectivity correction terms capture both the effects of differences in unobserved skills and returns to those unobserved skills. In general, it is impossible to decompose these two effects. This is discussed in detail by Gyourku and Tracy (1988) and more recently by Neuman and Oaxaca (2004) in a different context. One approach is to take the selectivity correction terms to the left hand side of (5) and thereby decompose the selectivity corrected wage difference: $\overline{\ln(w_P)} - \overline{\ln(w_R)} - (\hat{\theta}_P \overline{\lambda}_P - \hat{\theta}_R \overline{\lambda}_R)$. The resulting decomposition recovers the 'unconditional' wage differential between sectors $(\Delta\hat{\beta}\overline{X_P})$. This approach corresponds to the following thought experiment. Take a person from the population of all employees who has the same *observed* characteristics as the average public sector worker. What is the expected difference between sectors in the wages that person could earn? In contrast, analysis of the 'conditional' wage differential addresses the following thought experiment. Take a person at random from the public sector and put them in the private sector. What is the expected change in their wage? This is the relevant thought experiment for the question in this paper. The selectivity corrected decomposition does not recover this estimate, unless one assumes that there are no differences in returns to unobservable characteristics between sectors.

A third complication for the selectivity corrected approach is that sector selection derives from both the supply and demand sides of the labour market. Workers who have the most to gain from public sector employment are most likely to prefer the public sector. However, public sector employers will choose the most appropriate workers from the pool of applicants. A single sample selection correction may not adequately account for the complexity. A more appropriate model is a two-stage nested selection model, where the employees choice of applying for public sector work is modelled first, and the employer's choice of choosing from applicants is modelled next (see Farber, 1983; and Lemieux, 1993 in relation to selection and unionisation). This could be implemented as part of a selection correction model. But it would require a further exclusion restriction which influences employers' selection of workers, but not the worker's productivity in that sector.

Models of the distribution of the public sector wage premium

All the methods discussed so far estimate the average sectoral wage premium. However, much of the recent literature is focussed on the effect at all points of the wage distribution, mainly through quantile regression approaches. All of the methods discussed above now have analogous methods in the quantile regression framework. Quantile regressions are able to estimate the effect of a covariate at any quantile of the conditional distribution of the dependent variable (Koenker and Bassett Jr, 1978). Briefly, the quantile regression method is to minimise the weighted sum of absolute differences (rather than the sum of squares) between the data points and the regression line. The choice of weight determines the quantile being considered. Thus one could estimate the effect of working in the public sector (*P*) on the entire distribution of wages using a series of quantile regressions. This section serves to briefly highlight that the limitations of the methods discussed above also apply to the quantile regression models. These methods are discussed in turn below.

The model in equation (1), which allows sector to enter as a constant term, can be estimated by quantile regression at any point of the conditional wage distribution.

Fixed Effects models are not possible in quantile regression. In a paper that is yet to be published, Abrevaya and Dahl (2006) propose a panel data quantile regression model, which is analogous to the correlated random effects model for least squares proposed by Chamberlain (1982). In this model, the fixed effect is modelled as a linear projection of observable characteristics in each period. This model can be interpreted in a similar way to FE models, in that the effect of sector on wages is identified by movers between sectors. It has the same major limitation as the FE model, as it assumes equal returns to observed and unobserved characteristics in the two sectors.

Decomposition approaches also have quantile regression equivalents, as proposed by Machado and Mata (2005). This was adapted by Melly (2005) and applied to estimate the public sector wage premium in Germany. This approach was also used by Cai and Liu (2007) to examine the Australian union wage premium. Melly (2006) has also made an attempt to incorporate sample selection correction into a quantile regression decomposition. However, the method is complex and is yet to be published.

III The Model

The approach adopted in this paper is based on that used by Lemieux (1993; 1998) to estimate the effect of unions on wages. This is a quasi-differenced panel data model, originally proposed by Chamberlain (1982)[3]. It combines the strengths of FE (allowing for differences in unobserved characteristics and allowing sector selection to be correlated with time-invariant unobservables) with that of Oaxaca decomposition (allowing for differences in returns between sectors). Unlike all the other approaches considered, it also identifies the effect of differences in returns to unobserved characteristics, distinguishing this from the effect of differences in their stock. The method is described below, drawing heavily on Lemieux (1998).

Assume that employees derive utility from consumption and leisure. Assume further that employees can choose their quantity of working hours in a given job. It follows from these assumptions that employees will choose a job with the highest hourly earnings of all available options. The set of available options depends on their skills. Their skills consist of the quantity and quality of experience and education as well as other factors such as intelligence, interpersonal skills and so on. A particular skill set may be more valuable in some jobs than in others.

Begin with expressions for the expected log wage for person *i* in each sector, denoted y_{it}^{R} and y_{it}^{P} in (6a) and (6b). Each equation includes observed skills (*X*) and sector specific returns (β) to those characteristics. Each equation contains two time invariant unobserved components: θ and ξ. The

[3] See also Gibbons et al. (2005) for an application of this approach in the context of industry wage models.

first of these (θ) represents comparative advantage, those unobserved skills which are valued differently between sectors, while ψ represents the extent to which those returns differ. The second (ξ) represents absolute advantage, or those unobserved skills which are equally valued in both sectors.[4] Observations are taken at more than one period (t):

$$y_{it}^{R} = \delta_t^{R} + \beta^{R} X_{it} + \theta_i + \xi_i \tag{6a}$$

$$y_{it}^{P} = \delta_t^{P} + \beta^{P} X_{it} + \psi\theta_i + \xi_i \tag{6b}$$

These two expressions can be combined into a single wage equation by substituting into the following:

$$\ln w_{it} = P_{it} y_{it}^{P} + (1 - P_{it}) y_{it}^{R} + \varepsilon'_{it}$$

where P = 1 if the employee is in the public sector and zero otherwise. ε' is an idiosyncratic error term. The resulting expression can be written as:

$$\ln w_{it} = \delta_t^{R} + P_{it}\overline{\delta} + X_{it}[\beta^{R} + P_{it}(\beta^{P} - \beta^{R})] + [1 + P_{it}(\psi - 1)]\theta_i + \varepsilon_{it} \tag{7}$$

where $\overline{\delta} = \delta_t^{P} - \delta_t^{R}$ and $\varepsilon_{it} = \xi_i + \varepsilon'_{it}$

Under the assumptions outlined above, there is no explicit role for job characteristics (other than sector) in the model. Since utility is not derived from the job itself, the characteristics of the job do not have an independent effect on wages. Recall that an employee chooses a job with the highest hourly earnings. For that individual, the set of jobs available is a function of their skill set. Thus job characteristics (including industry and occupation) are a consequence of a person's skills, rather a separate effect in the wage equation. This does not imply that returns to say, a university degree, are equal across occupations and industries. It merely states that a given person will choose the job which maximises the returns to their own particular skill set.

I also do not control for size of employer or union status. The public sector is a highly unionised workforce characterised by large employers. Both of these factors are associated with higher hourly earnings (Miller and Mulvey, 1996; Wooden, 2001). I treat these as inherent features of the public sector which I do not wish to abstract from. Wooden (2001) has shown that in the Australian labour market, characterised by enterprise bargaining, the effect of unions on wages operates at the level

[4] ξ is orthogonal to θ by construction and is inconsequential for much of what follows. See Lemieux (1998) for more detail on this specification of time invariant effects.

of the workplace rather than the individual. Thus workers in highly unionised workplaces enjoy a wage premium, regardless of their personal union membership. Since HILDA does not include such data on the workplace, any attempt to explicitly account for the effect of unionisation is likely to be misleading.

Decomposition of the Average Sectoral Wage Gap

If estimable, the parameters in (7) can be used in a decomposition which distinguishes between the effects of differences in observed and unobserved characteristics as well as the effects of differences in returns to both observed and unobserved characteristics. Consider the mean wage difference between sectors:

$$\overline{\ln(w_P)} - \overline{\ln(w_R)} = (\delta_t^P + \beta^P \overline{X}_P + \psi\overline{\theta}_P + \overline{\xi}_P) - (\delta_t^R + \beta^R \overline{X}_R + \overline{\theta}_R + \overline{\xi}_R)$$

$$= \overline{\delta} + \beta^P \overline{X}_P - \beta^R \overline{X}_R + \psi\overline{\theta}_P - \overline{\theta}_R$$

$$= [\overline{\delta} + \overline{X}_P(\beta^P - \beta^R) + (\psi - 1)\overline{\theta}_R] + [(\overline{X}_P - \overline{X}_R)\beta^R + (\overline{\theta}_P - \overline{\theta}_R)]$$

The contents of the first square brackets represent the effects of differences in wage setting policies, which includes a constant difference ($\overline{\delta}$) and differences in returns to characteristics. The second term represents the effects of differences in characteristics.

Estimation[5]

The first step to estimating (7) is to 'quasi-difference'. That is, to substitute θ for the expression obtained when θ is made the subject of the argument in a first lag as follows:

$$\theta_i = [\ln w_{it-1} - (\delta_{t-1}^R + P_{it-1}\overline{\delta} + X_{it-1}[\beta^R + P_{it-1}(\beta^P - \beta^R)] + \varepsilon_{it-1}]/[1 + P_{it-1}(\psi - 1)] \qquad (8)$$

Substituting into (7):

$$\ln w_{it} = F_t(X_{it}, P_{it}) + \frac{[1 + P_{it}(\psi - 1)]}{[1 + P_{it-1}(\psi - 1)]} \times [\ln w_{it-1} - F_{t-1}(X_{it-1}, P_{it-1})] + e_{it} \qquad (9)$$

where:

$$e_{it} = \varepsilon_{it} - \frac{[1 + P_{it}(\psi - 1)]}{[1 + P_{it-1}(\psi - 1)]}\varepsilon_{it-1}$$

[5] Analysis was conducted using SAS V9 and Stata V9.2

and

$$F_t(X_{it}, P_{it}) = \delta_t^R + P_{it}\overline{\delta} + X_{it}[\beta^R + P_{it}(\beta^P - \beta^R)]$$

Equation (9) is nonlinear and includes an endogenous regressor: $\ln w_{it-1}$, which is correlated with ε_{it-1} and hence with e_{it}. The endogenous $\ln w_{it-1}$ can be instrumented by $\ln w_{it-2}$, which is available for this study. I also use the interactions of $\ln w_{it-2}$ with X_{it-1}, X_{it}, P_{it-2}, P_{it-1} and P_{it} as well as the interactions of the sector history variables: P_{it}, P_{it-1} and $P_{it}P_{it-1}$ with X_{it-1} and X_{it} as further instruments. Equation (9) can be estimated consistently using the method of Nonlinear Instrumental Variables (NLIV) (Amemiya, 1974).[6] NLIV can be motivated by first-order moment conditions. Let Z_i denote the set of instrumental variables (including X and P). The first order population moment condition is $E(e_{it}Z_i) = 0$. Consistent estimates of the structural parameters (α) are obtained by choosing those α which minimise the following objective function:

$$e(\alpha)'Z(Z'Z)^{-1}Z'e(\alpha)$$

Where $e(\alpha) = (e_{it},...,e_{Mt})$, M is the number of people in the sample, and $Z = (Z_1':...: Z_M')'$.

Whilst NLIV is a consistent estimator, an efficient GMM estimator minimises the following objective function:

$$e(\alpha)'ZWZ'e(\alpha)$$

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[6] Note that whilst e is a function of P, the two are uncorrelated. To demonstrate this, consider:

$$E(P_{it}e_{it}) = E(P_{it}\varepsilon_{it}) - E\left(\frac{P_{it}[1+P_{it}(\psi-1)]}{[1+P_{it-1}(\psi-1)]}\varepsilon_{it-1}\right) = E\left(\frac{P_{it}[1+P_{it}(\psi-1)]}{[1+P_{it-1}(\psi-1)]}\varepsilon_{it-1}\right)$$

The expression $\frac{P_{it}[1+P_{it}(\psi-1)]}{[1+P_{it-1}(\psi-1)]}$ = 0, when $P_{it} = 0$

= 1, when $P_{it} = 1$ and $P_{it-1} = 1$

= ψ, when $P_{it} = 1$ and $P_{it-1} = 0$

In all cases, $E\left(\frac{P_{it}[1+P_{it}(\psi-1)]}{[1+P_{it-1}(\psi-1)]}\varepsilon_{it-1}\right) = 0$ and hence $E(P_{it}e_{it}) = 0$. Similarly for $E(P_{it-1}e_{it})$.

where the weighting matrix W is the inverse of the estimated variance matrix of the moment functions, estimated by NLIV (see Davidson and MacKinnon, 1993; Greene, 2003; Hansen, 1982).

In order to separately identify δ_t^R, δ_{t-1}^R and $\bar{\delta}$, it is necessary to impose a further restriction on the parameters. The expected value of θ across all people and both years is constrained to be zero:

$$\bar{\theta} = \left(\frac{1}{2N}\right)\sum_i (\hat{\theta}_{it} + \hat{\theta}_{it-1}) = 0$$

where *N* is the number of people and

$$\hat{\theta}_{is} = \{\ln w_{is} - (\delta_s^R + P_{is}\bar{\delta} + X_{is}[\beta^R + P_{is}(\beta^P - \beta^R)]\} / [1 + P_{is}(\psi - 1)] \text{ for } s \in (t, t-1) \quad (8b)$$

Note that whilst $\bar{\theta}$ is a consistent estimate of the mean value of θ, the distribution of $\hat{\theta}_{is}$ may be dissimilar to the distribution θ_{is} (see Lemieux, 1993). This is because $\hat{\theta}_{is}$ in (8b) is partly a function of ε_{is} as can be seen in (8) for *s* = *t*-1.

Identification

The estimates of $\bar{\delta}$ and ψ are identified only by movers between sectors. This can be seen by noting that both disappear from (9) when $P_{it} = P_{it-1}$. Thus reasonable estimates of $\bar{\delta}$ and ψ can only be obtained with a data set that has a sufficiently large number of movers.

Similarly, the coefficients of *X* in each sector (β^P and β^R) are only independently identified by people whose *X* changes between *t-1* and *t* ('changers'). The main observed characteristics of interest are the standard human capital variables: experience and education. To separately identify sectoral differences in returns to education, it is necessary for the data to contain individuals (in each sector) whose educational attainment changed between observations. In the case of experience, the main issue for identification is the ability to distinguish it's effect from that of pure wage inflation or other changes between observations that affect all workers (as measured by $\delta_t^R - \delta_{t-1}^R$). The returns to experience can thus identified by the set of people whose experience increased by less than the time elapsed between observations.

If the number of 'changers' is insufficient, an alternate identification strategy is available. Education can be treated as time invariant if changers are excluded from the analysis. Education can thus be incorporated as a component of θ, and differences in returns to education can be incorporated in ψ. This highlights the key difference between this model and standard panel data models. In a FE model, leaving education in θ implies an assumption of no sectoral differences in returns to education. This is not the case here. The disadvantage of this strategy is that sectoral differences in returns to education are not separately identified from differences in returns to other time invariant skills. This is not a major limitation, as all of the components of the decomposition are consistently identified. Thus differences in time invariant skills (including education) are identified by movers between sectors.

A similar strategy is available to incorporate the effects of experience. One can assume that experience increased by a constant amount between time *t-1* and *t*. Since the model relies on a three period balanced panel of employees, this constant is equal to the time elapsed between *t-1* and *t*. Experience at time *t* can be incorporated into θ, similarly to the treatment of education. The effect of a one period increase in experience is incorporated into $\delta_t^R - \delta_{t-1}^R$.

This alternate identification strategy is implicit in Lemieux (1998). Lemieux did not observe changes in experience or education. This is also the approach applied in this paper. As will be discussed below, HILDA does observe employees whose educational attainment changes between observations, but their numbers are insufficient.

An assumption shared by this approach and Lemieux's is that sector choice is uncorrelated with *e*, conditional on *X* and θ. This does not allow for the possibility that people change sectors due to shocks in person and sector specific productivity shocks (i.e. temporary comparative advantage). Lemieux argues that this possibility is reduced by considering only involuntary job changers. These were people who changed jobs due to 'plant closing, family responsibilities, illness, geographic moves, dismissal, or other forms of layoffs'. This does not seem to be a convincing argument for a number of reasons. Firstly, people may be dismissed or laid off precisely due to a fall in sector-specific productivity (especially if institutional constraints prevent a wage reduction). Secondly, even if an involuntary job loss is assumed to be exogenous, there is no reason to believe that subsequent sector choice in the next job is similarly exogenous. Rather than following Lemieux's approach, I accept as a limitation the assumption that sector choice is uncorrelated with *e*, conditional on *X* and θ. Furthermore, the number of sector changers who changed jobs involuntarily is too small in HILDA to adopt this approach. For example, such an approach would restrict the number of sector movers to 6 males and 13 females in the main model (estimated on Waves 4, 5 and 6).

Factors Not Accounted For in the Model

Some factors that may affect sectoral wage differences have not been incorporated in the model. In particular, earnings are an incomplete measure of the total return to labour. Employees may be willing to accept lower earnings in exchange for other benefits. Superannuation and paid maternity leave entitlements may be particularly important considerations.

Employer contributions to superannuation are a major component of total remuneration. Under the Superannuation Guarantee, employers have been required to contribute to each employee's superannuation at a rate equal to at least 9% of earnings since 2002. Historically, superannuation in the public sector has been generous. The Commonwealth Superannuation Scheme commenced in 1922, providing retirees with a defined benefit pension equal to up to 70% of their final salary, indexed to inflation (Department of Finance and Administration, 2001). Subsequent reforms have resulted in less generous pensions. If superannuation schemes remain more generous in the public sector, this may have a downward effect on public sector earnings through a compensating wage differential. However, sectoral comparisons of employer contributions are hampered by differences in the benefit structures of superannuation schemes. Schemes fall into three main structures: accumulation, defined benefits and a hybrid of the two. In accumulation funds, employers contribute superannuation continuously, in proportion to earnings. In defined benefit funds, the value of employer contributions is sometimes unknown until retirement because the benefits are often defined in relation to employees' final salary. For this reason, the major recent survey of superannuation in Australia, the Survey of Employment Arrangements and Superannuation (SEAS), only provides a measure of employer contributions for those who have active accumulation funds (and no defined benefit or hybrid accounts) (Australian Bureau of Statistics, 2001). This excludes 63% of public sector employee respondents and 15% of those in the private sector. For the remaining sample, average employer contributions are similar in the two sectors (6.6% in the public sector and 6.8% in the private sector).[7] This is unlikely to be a good indication of the overall generosity of employer contributions in the public sector. It does suggest, however, that few private sector employees receive more than the minimum legislated contribution from their employer.

In Australia, paid maternity leave is not mandatory. Public sector employers are much more likely to provide paid maternity leave than private sector employers. In 2005, the Australian Bureau of

[7] Author's calculations from the SEAS Expanded Confidentialised Unit Record File. The percentage contribution was calculated by the author for each employee as total employer contributions divided by usual weekly income from main job. The sample was restricted to employees. Employees of own business were excluded. People with more than one job were excluded as the employer contribution variable does not differentiate between jobs. At the time of the survey, the minimum legislated employer contribution was 8%. Employees with monthly income below $450 per month are exempt, as are those under 18 years of age working less than 30 hours per week. Thus it is reasonable for the average contribution to be less than 8%.

Statistics surveyed women who had a child under two years of age. Of those who were public sector employees whilst pregnant, 76% accessed paid maternity leave, compared to 27% in the private sector (Australian Bureau of Statistics, 2007b: 135). Paid maternity leave may have a downward effect on public sector wages for females to the extent that they are willing to sacrifice some earnings in order to access this benefit.

Other sectoral differences that have not been accounted may include job security and flexibility and possible differences in the utility derived from the work itself.

IV Data

The data used for this study are from the Household Income and Labour Dynamics in Australia (HILDA) Survey. HILDA is a nationally representative household-based panel survey, with annual observations taken since 2001. At the time of writing, the first six waves are available for analysis (2001-2006) and government funding has been committed for at least a further six waves.

The model described in the previous section requires a balanced panel with three observations per person and is identified by changes in *X* and *P* between the last two observations. One approach is to use Waves 4, 5 and 6 (W456), the most recent waves. Recall the notation in the previous sections referring to time periods *t*, *t-1* and *t-2*. Time period *t* thus refers to Wave 6 of HIDLA, *t-1* refers to Wave 5 and *t-2* refers to Wave 4. The main parameters of this model are identified by sector movers between Waves 5 and 6.

In order to improve the precision of the estimates, I supplement this approach with three pairs of corresponding models for Waves 3, 4 and 5 (W345), for Waves 2, 3 and 4 (W234), and for Waves 1, 2 and 3 (W123), respectively, which are identified by a different set of movements between sectors. The results of the W456 model are shown in detail in this section. The key results of the other models are also discussed in this section and are shown in detail in the Appendix. The four sets of estimates are treated as equally valid, and are combined to form one overall estimate for each sex, discussed at the end of the results section.

The dependent variable is the log of hourly earnings. Hourly earnings are derived as ‘current weekly gross wage and salary in main job’ divided by ‘hours per week usually worked in main job’. Sector of main job was self-reported and includes ‘Government business enterprise or commercial statutory authority’ and ‘Other governmental organisation’.

The only other observed characteristic included in the model (*X*) is a dummy variable for casual employment contracts. This is included because the wages of 'casual' employees usually include a loading that compensates for a lack of entitlements received under other contracts. The size of such loadings, however, varies considerably, depending on the Award or enterprise agreement under which an employee is covered. Watson (2005) notes a variation of 15% to 33.3% amongst enterprise bargaining agreement in the ACIRRT ADAM database between 1994-2002. The loading is also between 15% and 33% in most Awards, but is sometimes less than this and can be as high as 50% (Owens, 2001). Furthermore, many self-identified casuals do not receive any loading at all (Wooden and Warren, 2003). A manual adjustment to the wages of casual workers is considered infeasible, since it is unclear how large such an adjustment would need to be. Thus the size of the loading is estimated by the model. Secondly, it is possible that average casual loadings are different between the two sectors. In the main set of estimates, however, the loading is constrained to be equal in the two sectors, because of a small number of observations which would identify this parameter for the public sector. The main results are not sensitive to the relaxation of this assumption, as will be shown.

Observations are weighted by the cross sectional probability weight provided on the Wave 6 responding persons file.

The sample is defined as the set of responding persons who were employees (excluding those employed by their own business) at all three observations, who changed employers between the last two observations and who had non-missing values for the variables included in the model.[8] Separate models are estimated for men and for women. The final sample for the W456 model consists of 346 men and 282 women. Table 1 details the exclusions from the final sample. The requirement for a balanced panel of job changers accounts for the majority of exclusions. The sample size is similar for the W345, W234 and W123 models.

[8] Sector of employment is self reported in HILDA. It is possible that some apparent sector movers actually result from reporting errors in this variable. To address this issue, the sample is limited to those who reported a change in employer between the last two observations, which follows Lemiuex's (1998) approach in principle. In preliminary analysis, it was found that more than half of apparent sector movers did not report a change in employer in this same period. This suggests that a large proportion of sector movers may be misclassified. There are, however, a number of other possible explanations. It may result from reporting errors in the change in employer variable, since this relies on retrospective recall. It is also possible for employees to change sector without changing employer. This is the case when a public corporation is privatised. In any case, the conservative approach is taken here, by limiting the sample to employees who reported a change in employer.

Table 1 Sample selection in W456 model

	Men	Women
Sample of employees in Wave 6 with nonzero weight	3430	3496
with missing Wave 6 data	81	118
Employees in Wave 6 without missing data	3349	3378
not in sample of Wave 5 employees	574	677
not a job changer between Waves 5 and 6	2300	2251
missing Wave 5 data	11	14
Employee job changers between Waves 5 & 6, no missing data	464	436
not in sample of Wave 4 employees	92	119
missing Wave 4 data	10	11
Education changed between Waves 5 & 6	16	24
Final sample	346	282

Notes: This table outlines the exclusions of records from the model estimated on Waves 4, 5 and 6 of the HILDA data

The sector movers (between Waves 5 & 6) consist of 33 men and 53 women.[9] These people identify $\bar{\delta}$ and ψ. Returns to experience cannot be separately identified. Each member of the sample was employed in three consecutive Waves. Their increase in experience between the last two observations are in most cases equal to the passage of time, or very close to it. Similarly, the number of people whose highest educational attainment changed between Waves 5 and 6 is too small to identify the education effect. For example, only 2 females would identify the parameters which measure returns to education in the public sector. Thus experience and education are included in θ, and their effects are identified by sector movers, as discussed in the previous section. Any people whose highest educational qualification changed between Waves 5 and 6 were excluded to ensure that education is time invariant. Experience was assumed to increase by one year for all, also as discussed in the previous section.

Casual status changed between Waves 5 and 6 for 90 men and 85 women. These records identify the estimated casual loading, assumed to be equal in both sectors.

Table 2 shows weighted means for this sample in 2006 by sex and sector. This table shows that the raw public-private difference in mean log wages is 0.17 for men and 0.24 for women.[10] Public sector

[9] In the W345 models, sector movers consist of 37 men and 47 women. In the W234 model, sector movers consist of 23 men and 50 women. In the W123 model, the sector movers consist of 35 men and 52 women.

[10] The corresponding raw difference in the W345 sample is -0.05 for men and 0.06 for women. In the W234 sample it is 0.16 for men and 0.21 for women. In the W123 sample it is 0.12 and 0.20. This variation reflects the relatively small samples.

employees are much more likely to hold a degree or higher qualification. They also have slightly more experience on average. Private sector employees are more likely to be employed in casual jobs.

Table 2 Sample means (2006)*

	Men		Women	
Variable	Public	Private	Public	Private
ln wage	3.26	3.09	3.13	2.89
Experience (years)	15.88	14.48	15.82	14.98
Education				
University degree	0.54	0.21	0.58	0.22
Trade	0.27	0.36	0.09	0.27
Year 12	0.12	0.26	0.15	0.26
less than Year 12	0.06	0.17	0.18	0.25
Casual	0.07	0.27	0.21	0.31

* The sample is limited to that of the main analysis as reported in the text.

Table 3 shows the results of OLS regressions using the sample described above at Wave 6. It suggests that for both sexes, the public sector wage premium is positive, but not significantly different from zero. The return to experience is about 1.7% per year for men and 0.5% for women. The return to university education is estimated to be large for both sexes. The estimated effect of a casual contract is negative for both sexes, despite the loading that compensates a lack of entitlements. This suggests that casual status is correlated with unobserved characteristics that are associated with lower wages.

Table 4 shows the results of fixed effects regressions using observations at 2006 and 2005 for the sample described above. For the same reasons discussed above for the main model, education and experience are excluded as regressors. The estimated public sector premium is similar for both sexes to the OLS estimates for both sexes. This suggests that for this sample at least, time invariant unobserved characteristics of employees do not lead to a major bias in the OLS estimates. The estimated public sector premium is not statistically significant for either sex. The effect of casual status is positive, as expected, as opposed to the OLS estimates and is statistically significant. This confirms that casual status is correlated with unobserved characteristics that are associated with lower wages.

Table 3 Results of OLS Regressions (2006)*

	Men		Women	
	coefficient	SE	coefficient	SE
Public	0.016	0.070	0.080	0.058
Experience	0.017	0.002	0.005	0.003
Education				
degree	0.447	0.075	0.431	0.065
trade	0.170	0.065	-0.043	0.072
year 12	0.071	0.071	0.054	0.064
Casual	-0.017	0.058	-0.037	0.051
constant	2.686	0.072	2.726	0.063
R squared	0.305		0.263	

* The dependent variable is the log wage. The sample is limited to that of the main analysis as reported in the text.

Table 4 Results of Fixed Effects (2006 and 2005) Regressions

	Men		Women	
	coefficient	SE	coefficient	SE
Public	0.014	0.053	0.112	0.059
Casual	0.090	0.043	0.012	0.055
Wave 6 dummy	0.098	0.022	0.089	0.027

* The dependent variable is the log wage. The sample is limited to that of the main analysis as reported in the text.

V Results

The parameters of the wage equation estimated using GMM on Waves 4, 5 and 6 are shown in Table 5. Corresponding results are shown for the other three specifications in the Appendix. The constant effect ($\bar{\delta}$) of public sector employment on wages is estimated to be close to zero for males and a statistically significant positive (0.145) for women. These parameters are estimated to be positive in all the other models and they are statistically significant in several (see Appendix). Thus there is evidence to suggest that the public sector pays a constant wage premium to its workers, independently of skills.

Overall, there is little or no evidence to suggest sectoral differences in returns to skills. A value of ψ that is less than 1 suggests that returns to skills are smaller in the public sector than the private sector. In the W456 model for females, ψ is estimated to be 0.70, and is significantly different from 1. However, this parameter is not significantly different from 1 in any of the other seven models across both sexes. Further, ψ is estimated to be greater than 1 in three of the eight models (see Appendix). For men, ψ is estimated to be close to 1 in the GMM model for males (0.95). If ψ is restricted to equal 1, the model simplifies to the fixed effects model, the results of which are reported above in Table 4. Thus it is not surprising that the GMM estimate of $\bar{\delta}$ is small, similarly to the 'Public' coefficient in the fixed effects model. The standard errors are also similar in the two models. This demonstrates that there is little efficiency loss due to the instrumental variable approach.

The W456 models suggest a positive loading for casual work for both genders, and it is significantly different from zero for men. The estimates in the other specifications are also positive, ranging from 0.03 to 0.17. As discussed above, the estimated casual loadings are constrained to be equal across sectors, but there is little change in the main results if this is relaxed, as will be shown subsequently.

Table 5 GMM regression estimates of wage equations (Waves 4, 5 & 6)

	Men		Women	
	coefficient	SE	coefficient	SE
constant effect ($\bar{\delta}$)	0.005	0.052	0.145	0.038
Returns to time invariant skills in public sector (ψ)	0.952	0.185	0.700	0.102
Casual	0.125	0.037	0.038	0.037
δ_t^R	3.078	0.018	2.901	0.018
δ_{t-1}^R	2.973	0.027	2.806	0.017

* The dependent variable is the log wage. The sample is limited to that of the main analysis as reported in the text.

Decomposition of the Average Sectoral Wage Gap

The decomposition based on the W456 results is shown in Table 6. The main result is that the average public sector wage premium is estimated to be close to zero (-0.003) for men and positive for women (0.113). Statistically, this estimate is significantly different from zero for women (p=0.018) and not for men.[11]

In the three alternate specifications, the estimates of the average public sector premium are all positive for both sexes. For men, the other point estimates are 0.018, 0.117 and 0.120. For women

[11] The results of the decomposition are a function of the estimated coefficients and the sample means. The standard errors of the decomposition take account of the variance-covariance matrix of the estimated parameter vector. They also take account of the standard errors on the sample means. They also account for the fact that the estimated mean time invariant characteristics of workers in each sector ($\bar{\theta}_P$ and $\bar{\theta}_R$) are functions of the estimated parameters and the sample means.

they are 0.113, 0.062 and 0.075 (Table 7). For both sexes, the confidence intervals of these estimates all overlap. The four models are assumed to be equally valid and so the overall estimate is calculated as the weighted average of the four. The weighting is inversely proportional to the variance of each estimate. This maximises the precision of the overall estimate. The four pairs of estimates are treated as independent, since they are each identified by different movements between sectors.[12] The overall estimate is thus 0.065 for men and 0.100 for women. These imply a public sector wage premium of $e^{0.065} - 1 = 6.7\%$ for men and $e^{0.100} - 1 = 10.5\%$ for women. The estimates are statistically significant ($p=0.024$ for and $p<0.001$ for women). The 95% confidence intervals are (0.009, 0.121) for men and (0.058, 0.141) for women. These estimates do not change greatly if casual loadings are allowed to vary between sectors (0.064 for men; 0.088 for women).

Table 6 Decomposition of Sectoral Wage Gap from GMM results (Waves 4, 5 & 6)

	Men		Women	
	Estimate	SE	Estimate	SE
Public Sector Wage Premium:				
constant effect ($\overline{\delta}$)	0.005	0.052	0.145	0.038
differences in returns to fixed characteristics	-0.008	0.036	-0.033	0.017
Total average wage premium	-0.003	0.086	0.113	0.048
Effect of differences in characteristics:				
casual status	-0.025	0.010	-0.004	0.004
fixed characteristics	0.202	0.085	0.134	0.048
Total effect of different characteristics	0.177	0.087	0.131	0.048
Unadjusted Wage Gap	0.174		0.243	

Returning to Table 6, the largest components of the decomposition are due to sectoral differences in the stock of time invariant skills (which include education, experience and unobserved characteristics). For both sexes, this is a positive effect, suggesting that the average public sector employee is more skilled than his or her private sector counterpart. This is consistent with Table 2, which shows that they are more educated and more experienced.

[12] Strictly speaking, the estimates are not independent. Across the four specifications and both sexes, the key parameters of the models are identified by 330 employees who changed sector. Of these, 38 employees changed sectors twice and hence contribute to the identification of two of the estimates. Nevertheless, the assumption of independence should produce reasonable estimates for the standard errors.

Table 7 Summary of estimated average public sector wage premiums across all GMM models

	Men		Women	
Model	Estimate	SE	estimate	SE
Waves 4, 5 & 6	-0.003	0.086	0.113	0.048
Waves 3, 4 & 5	0.018	0.046	0.062	0.050
Waves 2, 3 & 4	0.117	0.049	0.075	0.051
Waves 1, 2 & 3	0.120	0.073	0.118	0.031
Overall estimate	0.065	0.029	0.100	0.021

* The overall estimates are weighted arithmetic means of the estimates from the three models. The weights are inversely proportional to the variance of the estimates, as described in the text.

VI Conclusion

This analysis suggests that the average Australian public sector employee is paid more than he or she would be paid in the private sector. The best estimates of this public sector wage premium are 6.7% for men and 10.5% for women. This does not include the value of benefits such as superannuation and paid maternity leave which are also more generous in the public sector. This positive average premium is consistent with most of the international literature on this topic. It may result from the higher rates of unionisation in the public sector. It is also possible that this 'premium' compensates public sector workers for unfavourable working environments. However, the evidence for Australia suggests little or no sectoral difference in levels of work-related stress or job satisfaction (Lewig and Dollard, 2001; Macklin et al., 2006). The estimate is thus slightly higher for women than for men, though their difference is not statistically significant. This is also consistent with most previous research internationally.

The results also suggest that this premium results primarily from a constant effect across all employees that is independent of skills. No evidence was found to suggest that the public sector provides lower returns to skills, which would imply that it compresses the wage distribution of its workers. This contrasts with studies that have addressed this issue for other countries, which typically find that the public sector does compress the wage distribution (Gregory and Borland, 1999; Melly, 2006).

Appendix: Detailed Results from Alternative Specifications

This Appendix presents the results of alternate specifications of the GMM model. In the body of the text, the detailed results are shown for a model estimated on Waves 4, 5 and 6. This Appendix shows the results of corresponding analyses on Waves 3, 4 and 5, on Waves 2, 3 and 4, and on Waves 1, 2 and 3, respectively. The main features of these results are discussed in the body of the text. The results of the regression and the decomposition using Waves 3, 4 and 5 are shown in Table 8 and Table 9. Corresponding results using Waves 2, 3 and 4 using Waves 1, 2 and 3 are shown in the subsequent tables.

Table 8 GMM regression estimates of wage equations (Waves 3, 4, 5)

	Men		Women	
	coefficient	SE	coefficient	SE
constant effect ($\bar{\delta}$)	0.027	0.064	0.061	0.045
Returns to time invariant skills in public sector (ψ)	1.186	0.278	0.899	0.147
Casual	0.080	0.042	0.060	0.048
δ_t^R	3.058	0.015	2.884	0.019
δ_{t-1}^R	2.923	0.014	2.778	0.021

Table 9 Decomposition of Sectoral Wage Gap from GMM results (Waves 3, 4, 5)

	Men		Women	
	Estimate	SE	Estimate	SE
Public Sector Wage Premium:				
constant effect ($\bar{\delta}$)	0.027	0.064	0.061	0.045
differences in returns to fixed characteristics	-0.010	0.020	0.001	0.005
Total average wage premium	0.018	0.046	0.062	0.050
Effect of differences in characteristics:				
casual status	-0.006	0.006	-0.015	0.012
fixed characteristics	-0.060	0.046	0.018	0.052
Total effect of different characteristics	-0.066	0.047	0.003	0.050
Unadjusted Wage Gap	-0.048		0.065	

Table 10 GMM regression estimates of wage equations (Waves 2, 3, 4)

	Men		Women	
	coefficient	SE	coefficient	SE
constant effect ($\overline{\delta}$)	0.114	0.056	0.110	0.032
Returns to time invariant skills in public sector (ψ)	1.069	0.194	0.702	0.188
Casual	0.029	0.040	0.111	0.061
δ_t^R	2.876	0.023	2.820	0.022
δ_{t-1}^R	2.793	0.013	2.776	0.029

Table 11 Decomposition of Sectoral Wage Gap from GMM results (Waves 2, 3, 4)

	Men		Women	
	Estimate	SE	Estimate	SE
Public Sector Wage Premium:				
constant effect ($\overline{\delta}$)	0.114	0.056	0.110	0.032
differences in returns to fixed characteristics	0.003	0.011	-0.035	0.031
Total average wage premium	0.117	0.049	0.075	0.051
Effect of differences in characteristics:				
casual status	-0.003	0.004	-0.020	0.014
fixed characteristics	0.049	0.049	0.152	0.051
Total effect of different characteristics	0.047	0.050	0.132	0.052
Unadjusted Wage Gap	0.164		0.207	

Table 12 GMM regression estimates of wage equations (Waves 1, 2, 3)

	Men		Women	
	coefficient	SE	coefficient	SE
constant effect ($\overline{\delta}$)	0.121	0.069	0.039	0.086
Returns to time invariant skills in public sector (ψ)	0.975	0.327	1.777	0.851
Casual	0.170	0.046	0.015	0.041
δ_t^R	2.863	0.020	2.797	0.017
δ_{t-1}^R	2.789	0.026	2.695	0.020

Table 13 Decomposition of Sectoral Wage Gap from GMM results (Waves 1, 2, 3)

	Men		Women	
	Estimate	SE	Estimate	SE
Public Sector Wage Premium:				
constant effect ($\bar{\delta}$)	0.121	0.069	0.039	0.086
differences in returns to fixed characteristics	-0.002	0.021	0.079	0.082
Total average wage premium	0.120	0.073	0.118	0.031
Effect of differences in characteristics:				
casual status	0.045	0.074	0.119	0.031
fixed characteristics	-0.027	0.011	-0.003	0.009
Total effect of different characteristics	-0.002	0.025	0.079	0.082
Unadjusted Wage Gap	0.118		0.197	

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