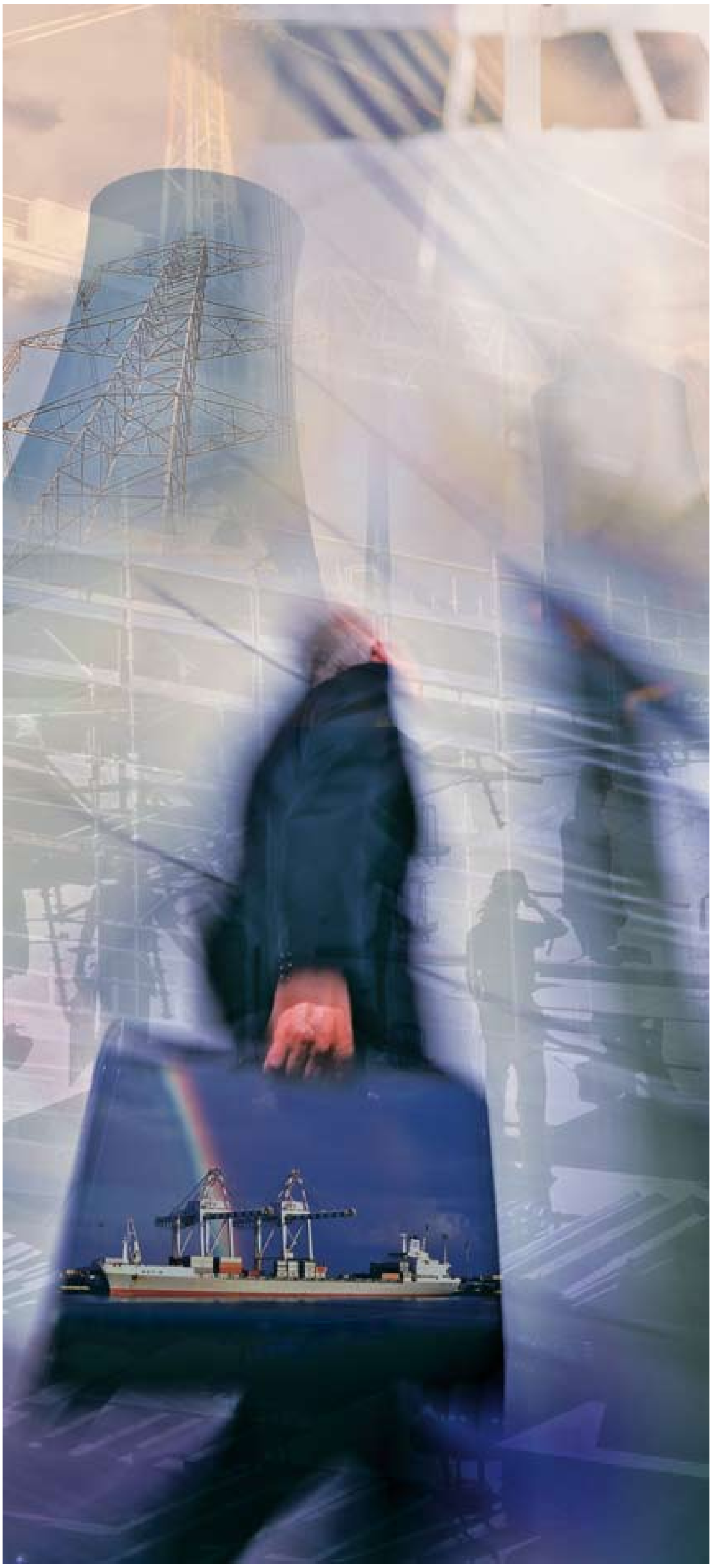

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The Paper following forms part of - *Proceedings of the 37th Australian Conference of Economists*
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What would the average public sector employee be paid in the private sector?

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September 2008

Abstract

I estimate the average Australian public sector wage premium and consider whether it varies with skill. The chosen approach is a quasi-differenced Generalised Method of Moments panel data model, which has not been previously applied to this topic, internationally. Its main advantage over competing models is that it accounts for sectoral differences in returns to unobserved characteristics. It thus facilitates a decomposition of the raw sectoral wage gap into the component explained by sectoral differences in returns to all (observed and unobserved) characteristics and the component explained by differences in the stock of those characteristics. The average premium is estimated to be 3.3% for men (95% CI: -2.5%, 9.1%) and 7.1% (95% CI: 3.0%, 11.3%) for women. No evidence is found to suggest that the size of the differential varies with skill.

JEL classification codes: J45, J31, J38

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

1 Introduction

The public sector accounts for 16% of total employment in Australia (Australian Bureau of Statistics, 2007b). This is similar to many other OECD countries (OECD, 2001). Public sector wage setting policy thus has major fiscal implications and it directly affects the living standards of many citizens. Much research has investigated the public sector wage ‘premium’, motivated primarily by concerns over efficiency as well as equity.[1] As discussed by Gregory & Borland (1999), wage setting in the public sector may not necessarily follow private sector principles. Many components of the public sector are insulated from market competition. To varying extents, all governments will seek to control employment costs in order to achieve efficiency goals. But their wage setting policies may also be motivated by equity goals. The influence of political incentives and bureaucratic budget-maximising (or minimising) incentives may also play a role.

The primary aim of this paper is to estimate the average Australian public sector wage premium. Specifically, I seek to estimate the average premium received by public sector workers as a result of working in the public sector. 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 raw sectoral wage gap may result from a constant wage premium that is independent of skills. 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, work ethic or attitudes towards risk. These effects need to be distinguished from sectoral differences in the stock of such characteristics. Sector selection is hence an important issue. A given employee may prefer 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.

A secondary aim is to investigate whether this differential varies with the level of skill. Most recent studies of sectoral wage effects have analysed differences across the entire wage distribution (especially through quantile regression approaches), rather than just the mean effect. Most find that the public sector wage premium is positive and relatively large at the bottom of the wage distribution, and small or negative at the top of the wage distribution (Birch, 2006; Cai and Liu, 2008; Lucifora and Muers, 2006; Melly, 2005; Mueller, 1998). Thus the public sector has been found to compress the wage distribution by providing a lower return to skills than the private sector. However, all previous studies have only examined differences in returns to observed skills.

The econometric approaches available to address these research questions are critically reviewed in Section 2. The chosen model is discussed in Section 3. 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

[1] The earlier literature is surveyed by Bender (1998) and Gregory & Borland (1999).

are estimated using the Generalised Method of Moments (GMM) after quasi-differencing the wage equation. To the author's knowledge, it has not previously been applied to this topic. Its main advantage over competing models is that it accounts for sectoral differences in returns to unobserved characteristics. It thus facilitates a decomposition of the raw sectoral wage gap into the component explained by sectoral differences in returns to all (observed and unobserved) characteristics and the component explained by differences in the stock of those characteristics. The data source is the Household Income and Labour Dynamics in Australia (HILDA) panel survey, which is described in Section 4. Section 5 presents results, including regression estimates, a decomposition of the average wage gap and comparisons with other estimators. Section 6 offers conclusions.

2 Review of Available Approaches and Their Limitations

In order to motivate the methods used in this paper, I first discuss the methods available to estimate the average public sector wage premium and their limitations. I then note that these limitations also apply to the analogous methods available to investigate the sectoral differential across the wage distribution, which has been the focus of related research in the last 10-15 years.

2.1 Models of the average wage premium

First consider the following model:

$$\ln(w_i) = a + bP_i + \beta X_i + \mu_i \qquad i = (1,\ldots,N) \qquad (1)$$

where w_i is observed hourly earnings of employee i and N is the number of observed employees. The model is linear in sector of employment (P = 1 if sector = public; P = 0 if sector = private) and other observed characteristics (X). In this model, b is the average public sector premium. The parameters can be estimated by OLS. This model assumes that P is uncorrelated with μ, implying that sectoral differences in unobserved characteristics do not affect wages. It also assumes that returns to observed (and unobserved) characteristics are equal in the two sectors.

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

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

where t denotes the time point of the observation, T is the number of time points and θ_i is a time-invariant individual effect. In a FE model, b is identified through variation in wages within people who move between sectors: 'movers'. FE accounts for differences in time-invariant unobserved characteristics of workers between sectors. It allows sector choice to be correlated with observables (X) and time-invariant unobservables (θ).

Perhaps the most common method for examining sectoral wage differentials is a decomposition method such as that of Oaxaca (1973). 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 raw mean sectoral (log) wage difference can be decomposed as follows:

$$\overline{\ln(w_P)} - \overline{\ln(w_R)} = \hat{\beta}_R \Delta\overline{X} + \Delta\hat{\beta}\overline{X_P} \tag{4}$$

where $\overline{X_P}$ represents average (observed) characteristics of employees in the public sector, $\hat{\beta}_R$ is the vector of estimated returns to observed characteristics in the private sector, $\Delta\hat{\beta} = \hat{\beta}_P - \hat{\beta}_R$ and $\Delta\overline{X} = \overline{X}_P - \overline{X}_R$. The first term of (4) represents the effect of differences in characteristics between sectors. The second term is the effect of differences in returns to observed characteristics between sectors. It also represents the estimated average public-private wage differential.

In the above decomposition, the estimated parameters ($\hat{\beta}_P$ and $\hat{\beta}_R$) will be biased if sector selection is made on unobserved characteristics that are correlated with wages (Heckman, 1979). In many studies, the Oaxaca decomposition has been extended with a Heckman-type sample selection correction. There are a number of reasons why this is a problematic approach. The first difficulty is the existence of plausible exclusion restrictions. Unless the model is identified purely through the nonlinearity in the probit selection model, it is necessary to choose a variable which is instrumental in the selection process, but does not directly affect wages. In many studies, this exclusion restriction is sector of father's occupation (e.g. Bender, 2003; Dustmann and van Soest, 1998; Hartog and Oosterbeek, 1993; Hou, 1993; Melly, 2006; Terrell, 1993). Such estimates are biased if intergenerationally transmitted attitudes to public sector employment are accompanied by intergenerationally transmitted (unobserved) skills. Others have used attitudes towards unions, since union membership is correlated with public sector status (eg. Bender, 2003; Heitmeuller, 2006; Melly, 2006). Such attitudes are likely to be endogenous to working in a unionised environment (as acknowledged by Melly). Some use parent's education (Hartog and Oosterbeek, 1993; Hou, 1993), which is also likely to be correlated with unobserved skills. Others have used age (Borland et al., 1998; Kanellopoulos, 1997). But age is correlated with risk aversion (Halek and Eisenhauer, 2001; Pålsson, 1996), which may be rewarded differently in the two sectors (Gregory and Borland, 1999).

In addition, this approach cannot distinguish between the effect of differences in the stock of unobserved characteristics from the effect of differences in their returns (Gyourko and Tracy, 1988; Neuman and Oaxaca, 2004). The selectivity corrected decomposition has additional terms, which are the sample selection correction terms in the wage equations:

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

where $\overline{\lambda}$ is the estimated mean Inverse Mills Ratio and $\hat{\theta}$ is its estimated coefficient for 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. One can take the selectivity correction terms to the left hand side of (5) and decompose the selectivity corrected wage difference: $\overline{\ln(w_P)} - \overline{\ln(w_R)} - (\hat{\theta}_P \overline{\lambda}_P - \hat{\theta}_R \overline{\lambda}_R)$. This 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 set 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 research question addressed in this paper.

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 this 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 applicants is modelled next (see Farber, 1983; and Lemieux, 1993 in relation to selection and unionisation). To implement this approach as part of a selection correction model, one would require a further exclusion restriction which influences employers' selection of workers, but not the worker's productivity in that sector.

2.2 Models of the distribution of the wage premium

All of the methods discussed so far estimate the average sectoral wage premium. This section serves to briefly highlight that the limitations of the methods discussed above are shared by the methods available to estimate the effect across the wage distribution.

All of the methods discussed above now have analogous methods in the quantile regression framework. Quantile regressions 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 the effect of working in the public sector (P) on the entire distribution of wages can be estimated using a series of quantile regressions. The model in equation (1), where sector enters as a constant term, can be estimated by quantile regression at any point of the conditional wage distribution. Such an approach shares the assumptions of the OLS model discussed above.

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 has also been used Birch (2006) and Cai & Liu (2008) to examine the Australian public sector wage differential. Melly (2006) has attempted to incorporate sample selection correction into a quantile regression decomposition. However, the method is complex and is yet to be published.

The development of panel data quantile regression methods is an active topic of research. A fixed effects quantile regression estimator has been proposed by Koenker (2004). It has been used to investigate French sectoral wage differentials by Bargain & Melly (2008). Abrevaya and Dahl (2006) propose an alternative model which is analogous to the correlated random effects model for least squares (Chamberlain, 1982). Both of these methods have the same restriction as the least squares FE approach, as they assume equal returns to unobserved characteristics in the two sectors.

The semiparametric approach used by DiNardo et al. (1996) to investigate the effects of de-unionisation on wages could also be applied to this topic. This method can not account for differences in unobserved characteristics between sectors or differences in their returns.

3 The Model

The adopted approach is based on the quasi-differenced panel data model used by Lemieux (1993; 1998) to estimate the effect of unions on wages.[2] Similarly to FE, it allows sector selection to be correlated with time-invariant unobserved characteristics. The main innovation of this approach is that unlike all the other approaches considered, it identifies differences between sectors in returns to unobserved characteristics. The method is described below, drawing on Lemieux (Lemieux, 1993, 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 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.[3] 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:

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

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

[3] 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.

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. These assumptions are generalised slightly by accounting for the wage compensation received for casual employment and shift work, as discussed in Section 4.

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 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 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.

3.1 Decomposition of the Raw Sectoral Wage Gap

If estimable, the parameters in (7) can be used in a decomposition of the raw wage gap, which distinguishes between the effects of differences in the stock of 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:

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

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

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

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

3.2 Estimation[4]

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

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

Substituting into (7):

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

where:

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

and

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

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}. It would seem natural for $\ln w_{it-1}$ to be instrumented by $\ln w_{it-2}$, which is available for this study. However, the likely serial correlation between ε_{it-2} and ε_{it-1} renders $\ln w_{it-2}$ an invalid instrument. This is because the sample (described in the Section 4) consists of job changers between *t-1* and *t*, most of whom did not also change jobs between *t-2* and *t-1*. Given that ε' will include a job-specific component, the correlation between ε_{it-2} and ε_{it-1} will be greater than between ε_{it-1} and ε_{it}. As such, $\ln w_{it-2}$ will also be correlated with e_{it}.

[4] Analysis was conducted using SAS V9 and Stata V10.

An alternative instrument is the interaction of the lagged and unlagged sector indicators: $P_{it}P_{it-1}$. The complete sector history indicators described by Lemieux (1998) are equivalent to the three sector variables: P_{it}, P_{it-1} and $P_{it}P_{it-1}$. The validity of $P_{it}P_{it-1}$ as an instrument follows from the exogeneity of P_{it} and P_{it-1}. The relevance of $P_{it}P_{it-1}$ as an instrument for $\ln w_{it-1}$ results from the correlation between $P_{it}P_{it-1}$ and θ_i. In other words, $P_{it}P_{it-1}$ is a relevant instrument if the average skill of public sector joiners is different to the average skill of public sector leavers (see Lemieux, 1993: Appendix 1 for further discussion of these issues). The three sector variables are also interacted with X_{it-1} and X_{it} to create further instruments.

Equation (9) can be estimated consistently using the method of Nonlinear Instrumental Variables (NLIV) (Amemiya, 1974). NLIV can be motivated by first-order moment conditions. Let Z denote the set of instrumental variables (including X and P). The first order population moment conditions are 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 $e(\alpha) = (e_{\mathrm{it}},\ldots,e_{\mathrm{Mt}})$, M is the number of people in the sample, and $Z = (Z_1{}':\ldots: Z_M{}')'$.

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

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

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 addition to the gains in efficiency, another advantage of GMM is that it generates standard errors which are robust to heteroskedasticity.

In order to separately identify δ_t^R, δ_{t-1}^R and $\overline{\delta}$, 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:

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

where *N* is the number of people and

$$\hat{\theta}_{is} = \{\ln w_{is} - (\delta_s^R + P_{is}\bar{\delta} + X_{is}[\beta^R + P_{is}(\beta^P - \beta^R)]\}/[1 + P_{is}(\psi - 1)] \text{ for } s \in (t, t-1) \quad (10)$$

This restriction involves the sum of a nonlinear function across the entire sample. However, it can be easily imposed by noting that the denominator of this expression can only take two values: 1 and ψ.

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 of θ_{is} (see Lemieux, 1993). This is because $\hat{\theta}_{is}$ is partly a function of ε_{is} as can be seen by comparing (8) with (10) for $s = t\text{-}1$.

3.3 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 $t\text{-}1$ 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 could thus be identified by the set of people whose experience increased by less than the time elapsed between observations.

An alternate identification strategy is used in this paper. 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 a 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. Thus differences in time invariant skills (including education) are identified by movers between sectors. One advantage of this identification strategy is that it does not require any 'changers'. By leaving education in θ, the approach also avoids several other problems characteristic of the standard panel data approach. These include the assumptions that returns to education are immediate rather than lagged and that returns to education for students who simultaneously work are representative of all employees. It also avoids ambiguity over whether the highest level of educational qualification is the appropriate human capital measure, or whether the total quantity of education (in years) is more appropriate. 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.

A similar strategy is available to incorporate the effects of experience. One can assume that experience increased by a constant 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 $\delta_t^R - \delta_{t-1}^R$.

An assumption of this approach 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 is problematic 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. Thus I do not follow Lemieux's approach of limiting the sample to the set of involuntary job changers. In any case, the number of job changers who reportedly changed jobs involuntarily is too small in HILDA to adopt this approach. Such a restriction would reduce the total sample size by approximately 75%, including a similar proportion of sector movers.

3.4 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 some public sector 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 unknown at the time that wages are earned 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).[5] 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 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, 2007a: 135). HILDA does include data on paid maternity leave entitlement. But it is poorly reported, with missing values recorded for approximately 40% of females in the sample used here, most of whom did not know whether they were entitled. 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. See Edwards (2006) for

[5] 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%.

recent evidence of a compensating wage differential associated with paid maternity leave in Australia.

There may also be sectoral differences in job security and flexibility and differences in the utility derived from the work itself. Such factors would induce compensating wage differentials in less attractive jobs. These are only partly measured by the casual status variable (which will capture some of the effects of job instability) and the shiftwork variable (which will capture the compensation paid for the disutility of shift work), as discussed below.

4 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 for an initial sample of 7682 households and 19,914 individuals. The analysis utilises all six available waves (2001-2006).

The sample is defined as the set of employees who changed employers between any two consecutive observations (e.g. between Waves 1 & 2; or between Waves 2 & 3; and so on).[6] The restriction to job changers is because sector of employment is self reported and thus may be measured with error.[7] Since only a small proportion of employees change sectors between consecutive years, a large proportion of apparent sector movers may be incorrectly identified due to reporting error. Indeed, preliminary analysis revealed that more than half of apparent sector movers did not report a change in employer in the same period, suggesting that a large proportion of movers may be misclassified.[8] To address this issue, the sample is limited to those who reported a change in employer, which follows Lemieux's (1998) approach in principle.

The dependent variable is the natural logarithm 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

[6] Employees employed by their own business at either observation were excluded.

[7] Public sector employees are those who identified their employer as a 'Government business enterprise or commercial statutory authority' or 'Other governmental organisation'.

[8] 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.

main job'. Wage inflation is accounted for by scaling observed wages in each year by gender specific full time ordinary time average weekly earnings to $2006.

The only observed characteristics included in the model (X) are dummy variables for shift or irregular work and for 'casual' employment contracts. The shift work variable captures any compensating wage differentials resulting from the disutility of shift work.[9] The casual status variable 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, because no significant difference is found between sectors when the parameter is allowed to vary. The results are not sensitive to the relaxation of this assumption.

Separate models are estimated for men and for women. Exclusions from the sample are detailed in Table 1. Observations were excluded due to missing data at either observation (missing wage, sector, highest educational qualification, casual or shift status). Observations were also excluded where the real wage was recorded to have changed by more than one log point between observations (i.e. by a factor of more than 2.72). People whose highest educational qualification changed between observations were excluded to ensure that education is time invariant, as discussed in the previous section. The final sample consists of 1868 men and 1688 women. Observations are weighted by the cross sectional probability weight provided on the responding person files.

The sector movers consist of 195 men and 314 women. These observations identify $\overline{\delta}$ and ψ. Casual status changed between observations for 519 men and 519 women. These records identify

[9] Current work schedule is self-reported. Shift work is defined as any schedule other than a 'regular daytime schedule'. Most employees classified as shift workers reported 'A rotating shift (changes from days to evenings to nights)'; an 'Irregular schedule'; or a 'Regular Evening Schedule'.

the estimated casual loading. Shift work status changed between observations for 446 men and 345 women. These records identify the estimated compensation for shift work.

Table 2 shows weighted means for the main sample by sex and sector. It also facilitates comparisons of the characteristics of sector movers to that of the full sample. This table shows that the raw public-private difference in mean log wages is 0.13 for men and 0.21 for women. Public sector employees are much more likely to hold a degree or higher qualification and to work in professional occupations. Amongst females, public sector employees also have more experience, while the difference is small for men. Private sector employees are more likely to be employed in casual jobs and to work in shift work arrangements. It is also clear that sector movers are similar to the rest of the sample, with their mean characteristics lying between the public and private means on most measures. Approximately half of job changers also changed occupation, regardless of sex or sector. This proportion is very similar for female sector movers, and slightly higher for male sector movers (61%).

Table 3 facilitates an evaluation of the extent to which sector movers resemble the set of all employees (not just job changers). It is based on Table 2, with the sample expanded to the set of all employees. The mean characteristics of sector movers are similar to that of all employees in many regards. The main difference is that sector movers are less experienced (especially amongst males). They are also slightly more likely to be 'Intermediate Clerical, Sales & Service' workers and less likely to be 'Managers & Administrators'.

The wage distribution of sector movers is compared to that of other groups in Figure 1 and Figure 2. Figure 1 shows that the wage distribution of sector movers is very similar to that of all job changers, especially those in the public sector. Figure 2 shows that the wage distribution of sector movers is slightly more densely concentrated around the mean of the distribution, as compared to that of all employees in either sector, especially amongst men.

It is noted that a slightly higher proportion of sector movers moved into the public sector rather than away from the public sector (64% of male sector movers and 57% of female sector movers). This is not surprising given that public sector workers are more experienced on average. There were no major changes in this proportion across the years included in the sample.

5 Results

The results of the GMM estimation are shown in Table 4. The constant effect ($\bar{\delta}$) of public sector employment on wages is estimated to be positive and small (0.037 for men and 0.034 for women). Neither estimate is statistically significant, though the standard errors are reasonably small.

There is also no evidence of 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. For males, ψ is estimated to be 0.951, while for females it is 1.268. This parameter is not significantly different from 1 in either model. Thus there is no evidence to suggest that the size of the public sector wage premium depends on the level of skill. This important result is considered in more detail in Section 6.

Positive and statistically significant loadings for casual status are estimated for both sexes. Compensation for shift work is not statistically significant for either sex. The coefficients of casual and shift were constrained to be equal across sectors in the results reported in, since Wald tests do not reject the hypothesis of equality across sectors for either parameter for either sex. The results are not sensitive to these restrictions, as will be shown.

The Hansen statistic, reported at the bottom of Table 4, is a test of instrument validity in overidentified GMM models. It is equal to the minimised value of the objective function multiplied by the sample size. Under the null hypothesis (instrument validity) the statistic follows a χ^2 distribution with degrees of freedom equal to the number of overidentifying restrictions, which is the difference between the number of instruments and the number of parameters (Hansen, 1982). In the models estimated here, there are 14 overidentifying restrictions. Since the p-value is greater than 0.05 for each sex, the null hypothesis is not rejected.

5.1 Decomposition of the Raw Wage Gap

The decomposition results are shown in Table 5. The main result is that the average public sector log wage premium is estimated to be positive but small for men (0.033) and slightly larger for women (0.069). Statistically, this estimate is significantly different from zero for women (p<0.001), but not for men (p=0.254).[10] The 95% confidence intervals are (-0.023, 0.089) for men and (0.031, 0.107) for

[10] 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.

women. These imply an average public sector wage premium of $e^{0.033} - 1 = 3.3\%$ for men and $e^{0.069} - 1 = 7.1\%$ for women.

Returning to Table 5, the majority of the raw wage gap is explained by differences in characteristics. In particular, the largest component of the wage gap is accounted for by 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 their private sector counterpart. This is consistent with Table 2, which shows that they are more educated and more experienced. Differences in casual and shiftwork status are not major factors.

5.2 Sensitivity Tests

This subsection considers the robustness of the results with respect to a number of modifications to the preferred model. As discussed by Stock et al. (2002: 527), sensitivity to minor methodological changes is suggestive of weak identification in nonlinear GMM models. The estimates of primary interest are $\bar{\delta}$ (the constant effect of public sector employment on wages), ψ (returns to skills in the public sector relative the private sector), and the total average effect of public sector employment on wages. These are shown for a range of alternate specifications in Table 6.

The first set of results are for a model where returns to 'casual' and 'shift' are not constrained to be equal in the two sectors. These estimates are similar to that of the preferred model, though they are slightly less precise, which reflects the increase in the number of parameters estimated by the model. As shown in the next two sets of results, if the models are estimated by NLIV or iterated GMM, the results are very similar to the preferred model. When sample weights are not applied, the estimates also remain similar to the preferred model, though $\bar{\delta}$ becomes statistically significant for men. In the next five sets of results, the sample is restricted to job changers between any single pair of consecutive waves (e.g. between Waves 1 & 2 only). Thus the sample size is approximately five times smaller in each of these models. Consequently, the estimates vary between these models. It is clear, however, that the changes to the estimates are always within reasonable realms of sampling error (most estimates are within one standard error of those in the preferred model, almost all are within two standard errors, and all are within three standard errors). Thus the results are robust to the methodological modifications considered.

The final set of results in Table 6 was generated by estimating the quasi-differenced wage equation (equation 9) by nonlinear least squares, thereby ignoring the endogeneity of $\ln w_{it-1}$. The standard errors on these estimates are smaller than in the preferred model (especially for ψ), but they are qualitatively similar. Like in the preferred model, the estimates of $\overline{\delta}$ are small positives for both sexes and the estimates of ψ are not significantly different from 1. The average wage premiums are also positive and similar to the preferred model, and only the estimate for women is statistically significant.

5.3 Comparison with other Methods

The estimated average public sector wage premiums are compared in Table 7 to corresponding estimates generated through other methods.

The OLS and Oaxaca decomposition models are estimated using observations for employees across all six waves of HILDA.[11] Observations are excluded if the real recorded wage was less that $5 per hour or more than $100 per hour. Control variables include experience, experience squared, highest educational qualification (6 dummy variables), casual status, shift work status, years with current employer, years in current occupation, occupation (28 dummy variables for men; 22 for women), proficiency in English (3 dummy variables), married, state or territory (7 dummy variables) and remoteness (3 dummy variables). The OLS and Oaxaca decomposition results do not differ greatly, suggesting that differences in returns to observed characteristics are not a major driver of the average wage differential. Using the dame data, Cai and Liu (2008) also estimated the average public wage premium using OLS and Oaxaca decompositions. Their estimates are lower than those in Table 7, and are in some cases negative. Much of this discrepancy is explained by their inclusion of control variables for employer size.

The fixed effects and first difference (full controls) models use the same variables and the same sample as the OLS model, with the following exceptions. Employees with only a single observation are excluded from the fixed effects model. Employees without consecutive observations are excluded from the first difference model. Employees whose wage changed by more than one log point were also excluded in each model. These results suggest that much of the apparent female public sector wage premium may be explained by higher unobserved skills of public sector employees. For males, the change in the estimate is much smaller.[12] However, these estimates are likely to be subject to considerable attenuation bias due to reporting error in the sector variable, as discussed above in the description of the data.

[11] The decompositions were estimated using the user-written Stata module –oaxaca– (Jann, 2008)

[12] The fixed effects models were estimated using the user-written Stata module –xtivreg2– (Schaffer, 2005)

The next estimates are also generated using a first difference approach. Here, the set of control variables is limited to those in the preferred model and education changers are excluded. The results here are very similar to the previous model, suggesting that the larger set of control variables makes little difference to the estimates.

To examine the issue of attenuation bias, a third pair of first difference results is estimated with the sample limited to job changers (the same sample as the preferred model). For females, the estimated wage premium is considerably larger than the previous estimate, which conforms to the hypothesised attenuation bias in the larger sample. For males, however, the estimate from the smaller sample is unchanged. This may reflect the loss in precision associated with the smaller sample. It may also suggest that the reporting error associated with the sector variable is non-classical.

The first difference model estimated on the job changer sample is equivalent to the preferred model with ψ restricted to equal 1. In the preferred model for males, ψ is estimated to be close to 1, so it is unsurprising that the estimated average wage premium is very similar to that of the first difference model. For women, the point estimate for ψ is greater than 1. As a result, the estimated premium is greater in the preferred model, since public sector employees have higher skills on average than private sector employees.

6 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 preferred estimates of this public sector wage premium are 3.3% for men and 7.1% for women, though the estimate is not statistically significant for men. 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 the difference between the two estimates is not statistically significant. This is also consistent with most previous research internationally.

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 the majority of studies that have addressed this issue using quantile regression methods for Australia (Birch, 2006; Cai and Liu, 2008) and for other countries (Lucifora and Muers, 2006; Melly, 2006; Mueller, 1998), which typically find that the public sector does compress the wage distribution. However, it is consistent with the recent results of Bargain & Melly (2008) for France, who are the first to implement a fixed effects quantile regression approach to address this question. Whilst they are unable to account for differences in returns to unobserved skills, they find that the apparent wage compression ascribed to the French public sector is mostly explained by sector selection on unobserved skills. French public sector workers were found to have higher unobserved skills at the bottom of the wage distribution, while the opposite is true at the top of the distribution. This is also a possible explanation for the results presented here, although the large standard errors for ψ must be taken into account. If this finding is accepted, it calls into question the ability of governments to use wage setting policies to achieve redistributive goals. If, for instance, the government aims to provide a wage premium to public sector workers in low skill occupations, it may simply be inducing the best workers (on unobserved characteristics) to join the public sector. Conversely, this finding is also consistent with concerns over the ability of the public sector to retain highly skilled employees. Further research is required to investigate these issues, since this literature has paid insufficient attention to sectoral differences in unobserved skills (and in their returns).

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Table 1 Sample selection

	Men	Women
Job changers between any consecutive waves	2158	2032
with missing data	106	149
outliers	78	57
changed education	106	138
Final sample	1868	1688

Table 2 Sample means – job changers*

	Men			Women		
Variable	Public	Private	Sector Movers	Public	Private	Sector Movers
ln wage	3.16	3.03	3.07	3.08	2.87	3.00
Experience (years)	14.8	14.5	14.7	15.7	12.5	14.5
Highest educational qualification						
University degree	0.46	0.17	0.33	0.49	0.20	0.40
Trade	0.26	0.38	0.34	0.17	0.28	0.24
Year 12	0.14	0.22	0.13	0.18	0.28	0.18
less than Year 12	0.14	0.23	0.20	0.16	0.24	0.18
Casual	0.16	0.28	0.20	0.21	0.38	0.25
Shift / irregular	0.19	0.24	0.20	0.19	0.28	0.24
Occupation						
Managers & Administrators	0.07	0.06	0.02	0.06	0.03	0.03
Professionals	0.38	0.12	0.29	0.40	0.14	0.33
Associate Professionals	0.14	0.12	0.10	0.12	0.12	0.12
Tradespersons & Related	0.12	0.23	0.20	0.00	0.03	0.00
Advanced Clerical & Service	0.01	0.01	0.02	0.11	0.08	0.11
Intermediate Clerical, Sales & Service	0.16	0.09	0.17	0.27	0.35	0.35
Intermediate Production & Transport	0.05	0.16	0.07	0.01	0.02	0.00
Elementary Clerical, Sales & Service	0.02	0.08	0.07	0.03	0.15	0.03
Labourers & Related	0.05	0.12	0.06	0.01	0.09	0.03
Changed occupation between observations	0.50	0.50	0.61	0.48	0.48	0.51
Sample size	1,652	216	195	1,362	326	314

* The sample is limited to that of the main analysis as reported in the text. 'Public' denotes all public sector employees who changed employer since the previous observation. 'Private' denotes all private sector employees who changed employer since the previous observation. 'Sector movers' denotes all employees who changed employer and sector since the previous observation.

Table 3 Sample means – all employees*

Variable	Men Public	Men Private	Men Sector Movers	Women Public	Women Private	Women Sector Movers
ln wage	3.25	3.00	3.07	3.13	2.85	3.00
Experience (years)	23.3	17.4	14.7	19.5	14.3	14.5
Highest educational qualification						
University degree	0.39	0.17	0.33	0.45	0.19	0.40
Trade	0.36	0.36	0.34	0.24	0.25	0.24
Year 12	0.11	0.19	0.13	0.13	0.23	0.18
less than Year 12	0.14	0.28	0.20	0.19	0.33	0.18
Casual	0.08	0.22	0.20	0.14	0.35	0.25
Shift / irregular	0.24	0.26	0.20	0.21	0.27	0.24
Occupation						
Managers & Administrators	0.09	0.07	0.02	0.05	0.03	0.03
Professionals	0.33	0.13	0.29	0.45	0.15	0.33
Associate Professionals	0.19	0.10	0.10	0.11	0.10	0.12
Tradespersons & Related	0.10	0.21	0.20	0.01	0.03	0.00
Advanced Clerical & Service	0.01	0.01	0.02	0.04	0.07	0.11
Intermediate Clerical, Sales & Service	0.13	0.10	0.17	0.26	0.30	0.35
Intermediate Production & Transport	0.06	0.17	0.07	0.00	0.03	0.00
Elementary Clerical, Sales & Service	0.06	0.09	0.07	0.04	0.20	0.03
Labourers & Related	0.04	0.13	0.06	0.03	0.09	0.03
Sample size	3,552	13,187	195	4,899	11,669	314

* 'Public' denotes all public sector employees. 'Private' denotes all private sector employees. 'Sector movers' denotes all employees who changed employer and sector since the previous observation.

Table 4 GMM estimates of wage equations*

	Men		Women	
	parameter	SE	parameter	SE
Constant effect ($\bar{\delta}$)	0.037	0.027	0.034	0.034
Returns to time invariant skills in public sector (ψ)	0.951	0.187	1.268	0.222
Returns to varying characteristics				
Casual	0.069	0.017	0.058	0.020
Shift Work	0.015	0.018	-0.040	0.025
δ_t^R	3.015	0.007	2.877	0.014
δ_{t-1}^R	2.966	0.011	2.843	0.011
Hansen overidentification test statistic	16.654		21.041	
(p-value)	(0.275)		(0.101)	
Sample size	1868		1688	

* The dependent variable is the log wage. The sample is limited to that of the main analysis as reported in the text. The Hansen overidentification test statistic follows a χ^2 distribution with 14 degrees of freedom.

Table 5 Decomposition of Raw Average Wage Gap from GMM results

	Men		Women	
	Estimate	SE	Estimate	SE
Public Sector Wage Premium:				
constant effect ($\bar{\delta}$)	0.037	0.027	0.034	0.034
differences in returns to fixed characteristics	-0.005	0.019	0.035	0.029
Total average wage premium	0.033	0.029	0.069	0.020
Effect of differences in characteristics:				
casual and shiftwork status	-0.010	0.004	-0.006	0.005
fixed characteristics	0.108	0.029	0.154	0.020
Total effect of different characteristics	0.098	0.029	0.147	0.020
Unadjusted Wage Gap	0.131		0.216	

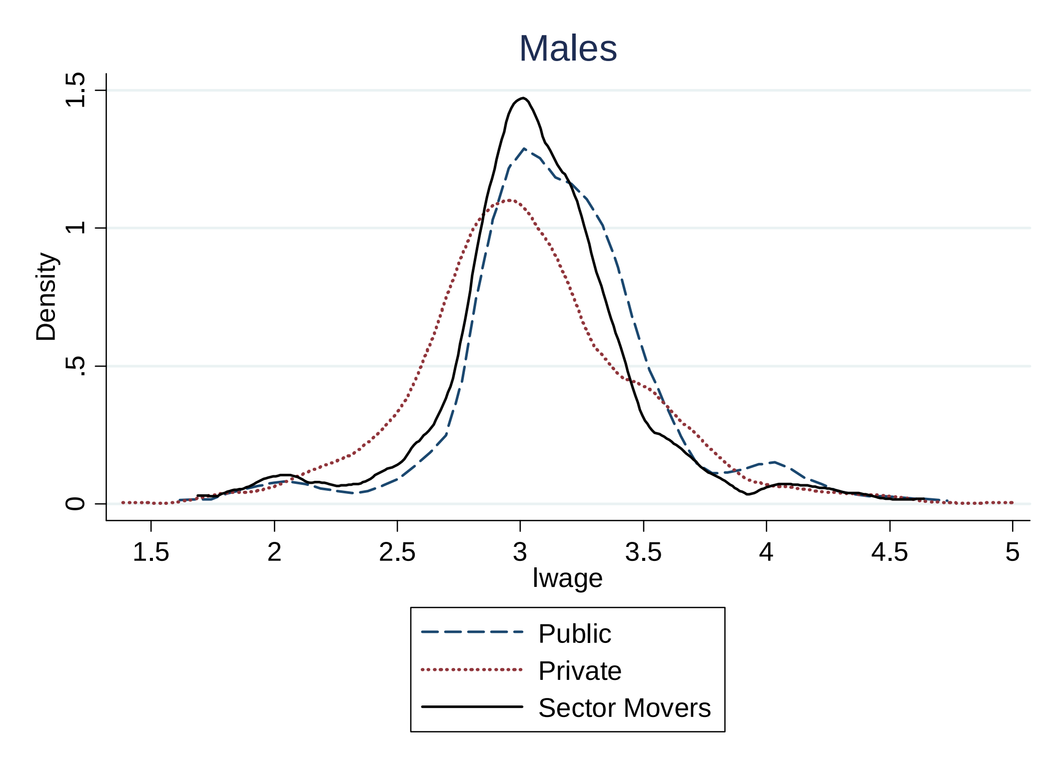
Table 6 Sensitivity Tests of Main Results

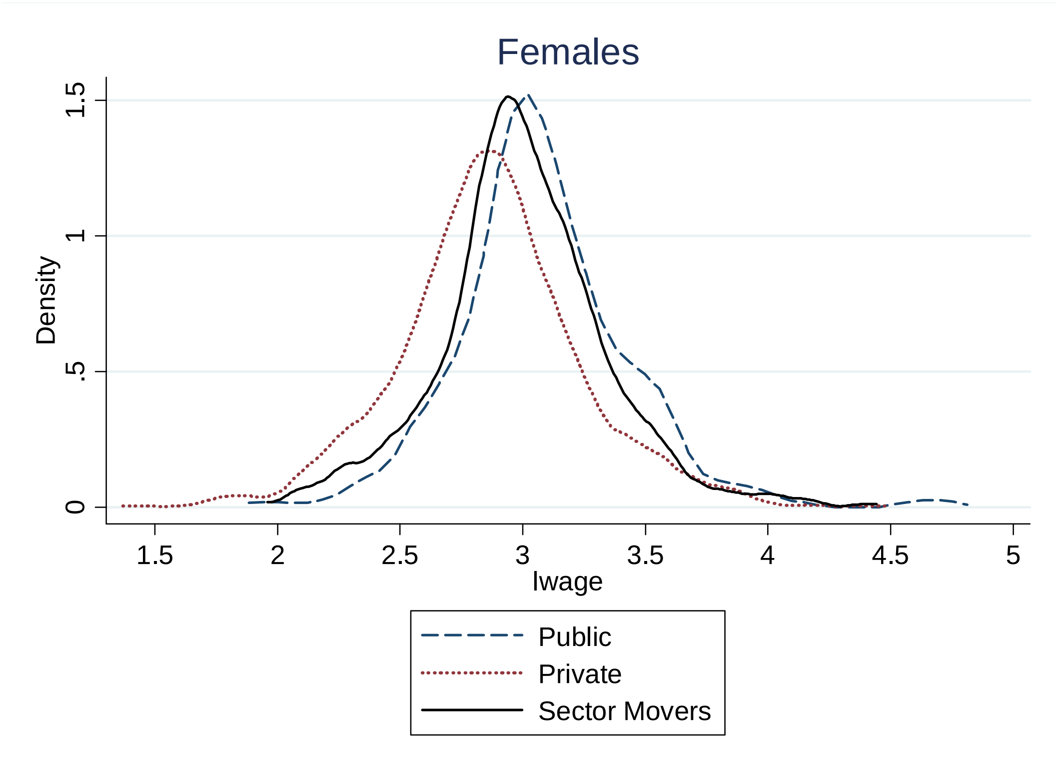
	$\bar{\delta}$	SE	ψ	SE	Average public wage premium	SE
Unrestricted returns to casual and shift						
Men	0.052	0.031	0.940	0.199	0.039	0.030
Women	0.010	0.047	1.330	0.281	0.068	0.020
NLIV						
Men	0.037	0.025	0.939	0.161	0.031	0.028
Women	0.029	0.029	1.198	0.188	0.057	0.020
ITGMM						
Men	0.037	0.027	0.951	0.186	0.033	0.029
Women	0.034	0.034	1.316	0.235	0.074	0.019
Unweighted						
Men	0.060	0.024	0.799	0.169	0.037	0.034
Women	0.030	0.031	1.267	0.194	0.069	0.018
Waves 1 & 2						
Men	0.124	0.044	0.601	0.172	0.127	0.070
Women	-0.004	0.061	1.815	0.375	0.100	0.027
Waves 2 & 3						
Men	0.005	0.081	1.768	0.585	0.088	0.046
Women	0.024	0.068	1.583	0.412	0.093	0.026
Waves 3 & 4						
Men	0.053	0.049	0.876	0.194	0.037	0.061
Women	0.081	0.037	0.874	0.192	0.066	0.036
Waves 4 & 5						
Men	0.041	0.041	1.407	0.241	0.033	0.028
Women	-0.012	0.071	1.059	0.332	-0.004	0.039
Waves 5 & 6						
Men	0.025	0.037	0.694	0.093	-0.037	0.069
Women	0.064	0.046	0.937	0.161	0.051	0.041
Nonlinear Least Squares						
Men	0.034	0.024	0.960	0.059	0.032	0.026
Women	0.060	0.021	0.910	0.053	0.047	0.022

Table 7 Estimated Average Public Sector Wage Premium - Comparison to other Methods

	Men			Women		
	Average public wage premium	SE	N	Average public wage premium	SE	N
OLS	0.030	0.013	18854	0.058	0.009	18583
Oaxaca decomposition	0.037	0.010	18854	0.046	0.008	18583
Fixed Effects	0.049	0.014	15130	0.020	0.012	14332
First Difference (full controls)	0.032	0.017	12527	0.007	0.012	11892
First Difference (limited controls)	0.034	0.017	12423	0.009	0.013	11618
First Difference (job changers only)	0.034	0.025	1868	0.050	0.020	1688
Quasi-Difference (preferred model)	0.033	0.029	1868	0.069	0.020	1868

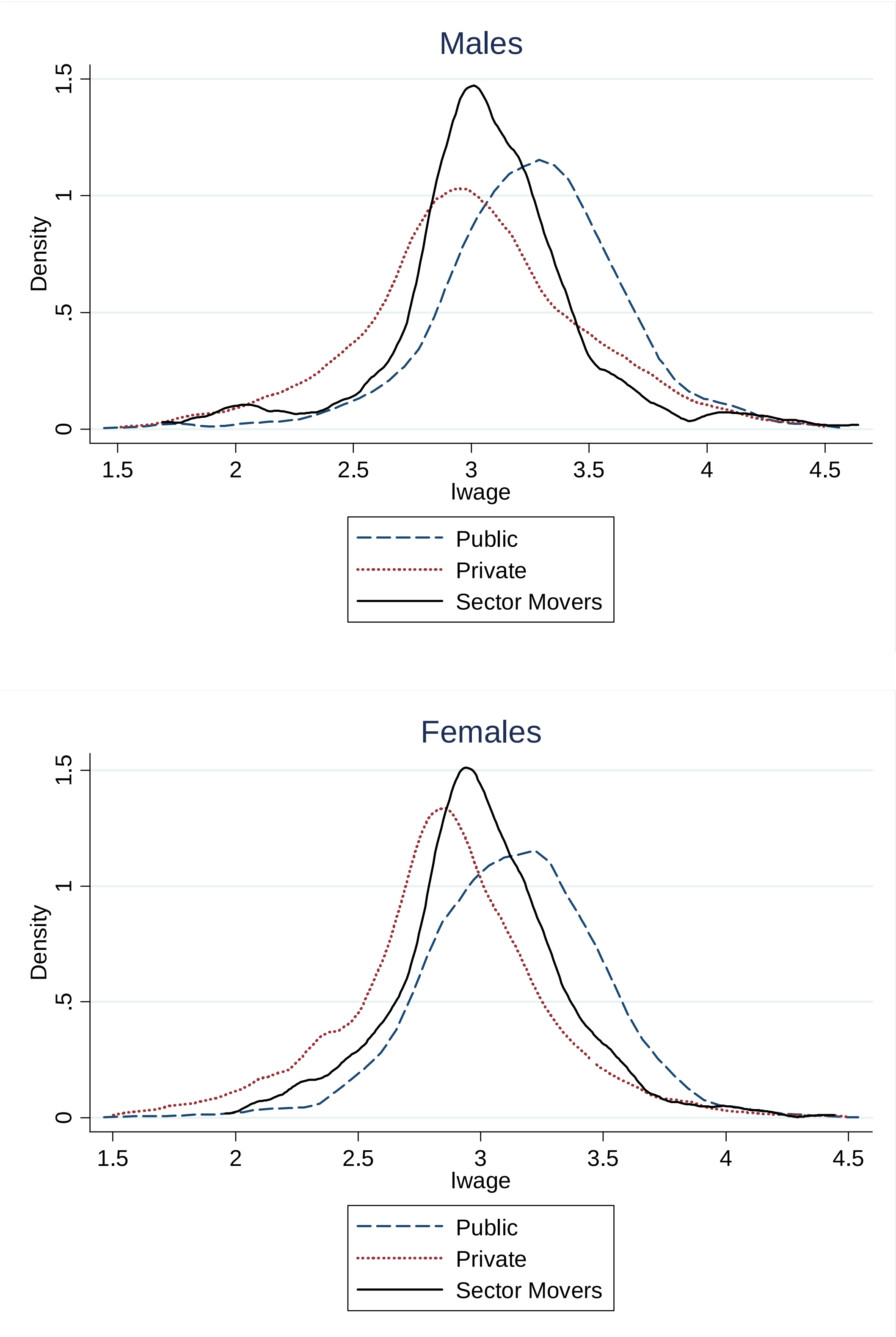
Figure 1 Density of ln wage distribution amongst job changers*





* The sample is limited to that of the main analysis as reported in the text. 'Public' denotes all public sector employees who changed employer since the previous observation. 'Private' denotes all private sector employees who changed employer since the previous observation. 'Sector movers' denotes all employees who changed employer and sector since the previous observation.

Figure 2 Density of ln wage distribution amongst all employees*



* 'Public' denotes all public sector employees. 'Private' denotes all private sector employees. 'Sector movers' denotes all employees who changed employer and sector since the previous observation.