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Abstract

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Keywords

era2015, differenced, quasi, overpaid, really, workers, sector, public, panel, skill, data, low, analysis

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ARE LOW SKILL PUBLIC SECTOR WORKERS REALLY OVERPAID? A QUASI-DIFFERENCED PANEL DATA ANALYSIS

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ABSTRACT

Public-private sectoral wage differentials have been studied extensively using quantile regression techniques. These typically find large public sector premiums at the bottom of the wage distribution. This may imply that low skill workers are 'overpaid', prompting concerns over efficiency. We note several other potential explanations for this result and explicitly test whether the premium varies with skill, using Australian data. We use a quasi-differenced GMM panel data model which has not been previously applied to this topic, internationally. Unlike other available methods, this technique identifies sectoral differences in returns to unobserved skill. It also facilitates a decomposition of the wage gap into components explained by differences in returns to all (observed and unobserved) skills and by differences in their stock. We find no evidence to suggest that the premium varies with skill. One interpretation is that the compressed wage profile of the public sector induces the best workers (on unobserved skills) to join the public sector in low wage occupations, *vice versa* in high wage occupations. We also estimate the average public sector premium to be 6% for women and statistically insignificant (4%) for men.

JEL classification codes: J45, J31, J38

Keywords: public sector, wages, quasi-differenced panel data, GMM, Australia

I INTRODUCTION

In developed countries, the distributions of wages in the public sector are typically more condensed than in the private sector (see for example the review of Gregory and Borland 1999; and cross-national evidence from Lucifora and Muers 2006). Studies using quantile regressions and quantile regression decompositions find that this is not fully explained by the mix of 'skill' (proxied by education and years of experience) in the two sectors (Birch 2006; Blackaby et al. 1998; Cai and Liu 2011; Gregory and Borland 1999; Lucifora and Muers 2006; Melly 2005; Mueller 1998). A typical finding across countries and sexes is that public sector workers at the bottom of the wage distribution receive a large pay premium (holding education and experience constant), whilst public sector workers near the top of the wage distribution receive a wage penalty, or a small premium. Such results motivate concerns that low-skill public sector workers are overpaid, resulting in public sector inefficiency, whilst high-skill public sector workers are underpaid, leading to difficulties in retainment (Birch 2006; Lucifora and Muers 2006; Mueller 1998). These concerns assume that the quantile regression findings reflect a public sector wage premium that varies with skill. In other words, the public sector may provide lower overall returns to skill (whilst paying a premium that is independent of skill). But there are other possible explanations for the quantile regression results. There may be greater variation in private sector wages for each given level of skill (Bender 2003). It is also possible that in this context, education and experience are inadequate proxies of skill which bias the results (we expand on this suggestion below). The source of these results has major implications for assessing public sector efficiency as well as for interpreting the effect of public sector employment on the distribution of wages. Are low skill public sector workers overpaid, whilst high skill public sector workers are underpaid? Our primary aim in this paper is to examine explicitly whether the public sector wage premium varies with skill.

We feel that insufficient consideration has been given in this literature to the role of 'unobservables' in the sorting of workers into sectors. In most studies, experience and education are the only proxies for skill. To illustrate the possible implication of this, consider the notion that workers with little experience or education are better paid in the public sector than in the private sector, *vice versa* for more educated and experienced workers. This is implicit in the results of studies which estimate separate wage equations for each sector which find that returns to education and earnings are lower in the public sector (see the review by Bender 1998; and recent evidence for Australia in Birch 2006). But economic theory (and common sense) suggests that less educated and inexperienced workers would hence prefer to work in the public sector, *vice versa* for more educated and experienced workers. If employers (in hiring, firing and promotions) observe better indicators of skill than are available to econometricians, the standard quantile regression results may be partially (or completely) explained by bias due to sector selection. There are many such indicators of skill available to employers, even at the stage of recruitment. These include the relevance of qualifications (field of study), the quality of the institution of study, relevance of work experience (firms and industries worked for), proxies of intelligence and work ethic (school grades), interpersonal skills (observed during the interview) and so on. Thus it is conceivable that the lower public sector returns to observables are offset by sector sorting on unobservables, due to the information that is available to employers (but not econometricians). This argument concords with the corresponding union wage effects literature. Reviewing the empirical evidence, Card *et al.* (2004) argue that failure to account for unobserved characteristics leads to overstating the extent to which union wage effect varies with skill (see also Card 1996).

Selectivity corrections would seem to be a potential solution to this problem. These have been used extensively in the related literature on decomposing the mean wage premium (Gregory and Borland 1999). They have also been attempted in a quantile regression context (Melly 2006). However, selectivity corrections have major limitations in this context. They cannot differentiate between sectoral differences in the stock of unobserved skills from sectoral differences in returns to such skills. They do not, therefore, facilitate Oaxaca-type decompositions which treat observed and unobserved skills symmetrically (Gyourko and Tracy 1988; Neuman and Oaxaca 2004). Secondly, there appears to be a lack of credible exclusion restrictions to implement such methods.[1] Further, sector selection is a non

[1] Some have used father's sector of employment as an exclusion restriction (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 correlated with intergenerationally transmitted (unobserved) skills. Others have used attitudes towards unions (eg. Bender, 2003;

standard selection problem, since workers select from a set of potential employers and *vice versa* (see Card 1996; Farber 1983 in the related context of union status). Fixed effects quantile regressions have also been developed (Bargain and Melly 2008). But they too do not allow for differences in returns to unobservables.

Here, we address these issues through an alternate approach. We implement an estimator proposed by Lemieux (1993; 1998), using Australian data. This is a quasi-differenced panel data model, estimated by GMM. To our knowledge, it is the only available estimator that fully disentangles returns from stocks of all (observed and unobserved) skills and it has not been applied to this topic before. In our adaptation, we use a single index of (latent) skill. Our main interest is in whether returns to this concept of skill vary between sectors. We find no evidence of differences in returns. This conforms to our expectations of sector sorting on unobserved characteristics and it informs the interpretation of established quantile regression results. We also decompose the average wage gap into the components explained by returns and stocks of (all) skills. We estimate a positive average public sector premium for women and an insignificant positive premium for men.

The estimator is discussed in Section **Error! Reference source not found.**. The data source is the Household Income and Labour Dynamics in Australia (HILDA) panel survey, which is described in Section III. Section IV presents results, including estimated parameters, a decomposition of the raw average wage gap, sensitivity tests and comparisons with other estimators. Section V offers conclusions.

Heitmeuller, 2006; Melly, 2006), which are likely to be endogenous to working in a unionised environment. 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).

II METHODS

The model is adapted from Lemieux (1993, 1998), who used a similar approach to estimate the effect of unions on wages.[2] The intuition of the model is in some respects similar to that of a first-difference model. The key parameters are estimated by sector movers and sector choice can be correlated with (unobserved) characteristics. The main innovation of Lemieux's approach is that unlike all other approaches used for this topic, it accounts for differences between sectors in returns to unobserved characteristics. The method is centred around a single wage equation of the following form:

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

The wage observed for employee *i* at time *t* is a function of sector (P = 1 if the employee is in the public sector and zero otherwise), job characteristics (X), a single (latent) index of skill (θ) and an idiosyncratic error. The coefficient $\overline{\delta}$ represents a constant public sector premium, independent of skill. Returns to skills are allowed to differ between sectors through ψ. If ψ = 1, returns to skills are equal across sectors. If ψ < 1, returns to skills are systematically lower in the public sector that the private sector, which would imply that any public sector wage premium is smaller for high skill workers than for low skill workers, *vice versa* if ψ > 1. Our main interest is thus to test whether ψ = 1. The only job characteristics (X) of interest are those which attract compensation for working conditions (such as shift work, or an absence of job security or leave entitlements). Returns to such job characteristics (β) are also allowed to differ by sector, with the superscripts *P* and *R* denoting returns in the public and private sectors, respectively.

A Decomposition of the Raw Sectoral Wage Gap

If estimable, the parameters in (1) can be used in a decomposition of the raw average wage gap, which distinguishes between the effects of differences in the stock of skills and job characteristics as well as the effects of differences in returns to both skills and job characteristics. Consider the mean wage difference between sectors:

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[2] See also Gibbons *et al.* (2005) who use a similar approach in the context of industry wage models.

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

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

$$= [\overline{\delta} + \overline{X}_P(\beta^P - \beta^R) + (\psi - 1)\overline{\theta}_R] + [(\overline{X}_P - \overline{X}_R)\beta^R + (\overline{\theta}_P - \overline{\theta}_R)] \qquad (2)$$

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.

B *Estimation*[3]

The first step to estimate (1) 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:

$$\theta_i = [\ln w_{it-1} - (\delta_{t-1}^R + P_{it-1}\overline{\delta} + X_{it-1}[\beta^R + P_{it-1}(\beta^P - \beta^R)] + \varepsilon_{it-1}]/[1 + P_{it-1}(\psi - 1)] \qquad (3)$$

Substituting into (1):

$$\ln w_{it} = F_t(X_{it}, P_{it}) + \frac{[1 + P_{it}(\psi - 1)]}{[1 + P_{it-1}(\psi - 1)]} \times [\ln w_{it-1} - F_{t-1}(X_{it-1}, P_{it-1})] + e_{it} \qquad (4)$$

where:

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

and

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

Equation (4) 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

3 Analysis was conducted using SAS V9 and Stata V11.

because the sample (described in Section III) is restricted to 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}.

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 assumed 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). Since θ_i is not observed, this is difficult to test.[4] However, an approximate alternative is to test whether the average wage of joiners is different to that of leavers (averaged across their public and private sector observations). The three sector variables are also interacted with X_{it-1} and X_{it} to create further instruments.

Equation (4) can be estimated efficiently by GMM. The 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 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 mean value of θ across all people and both years is constrained to be zero:

[4] In linear IV, instrument relevance can be determined by testing the significance of the instrument(s) in the first stage regression. This is not the case for nonlinear GMM (see Stock *et al.*, 2002).

$$\overline{\theta} = \left(\frac{1}{2N}\right)\sum_i (\hat{\theta}_{it} + \hat{\theta}_{it-1}) = 0 \tag{5}$$

where N is the number of people and

$$\hat{\theta}_{is} = \{\ln w_{is} - (\delta_s^R + P_{is}\overline{\delta} + X_{is}[\beta^R + P_{is}(\beta^P - \beta^R)]\}/[1 + P_{is}(\psi - 1)] \text{ for } s \in (t, t-1) \tag{6}$$

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.

C Identification

The estimates of $\overline{\delta}$ and ψ are identified only by movers between sectors. This can be seen by noting that both disappear from (4) when $P_{it} = P_{it-1}$. Thus reasonable estimates of $\overline{\delta}$ 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. In the present application, only job characteristics are included in X. In principle, observed time varying human capital variables could also be included in X. Consider the standard human capital variables: experience and education. Sectoral differences in returns to education could be identified by 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 people whose highest educational qualification changed between $t-1$ and t (of whom there are very few as shown in the following section) 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 education 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. A consequence of this strategy is that sectoral differences in returns to education are not separately identified from differences in returns to other time invariant skills.

A similar strategy is available to incorporate the effects of experience. Since the two observations are only one year apart, experience is almost completely time invariant and can thus be incorporated into θ , similarly to the treatment of education. The effect of the last one year increase in experience is incorporated into $\delta_t^R - \delta_{t-1}^R$.[5]

[5] It is acknowledged that the effect of a one year increase in experience may differ across the experience distribution, as reflected by the standard practice of including experience in quadratic form in wage equations (Mincer, 1974; Preston, 1997). It would be possible to include experience in quadratic form in the wage equation here. This is not pursued for a number of reasons. First, such an inclusion would make the interpretation of ψ more difficult. In the preferred model, ψ facilitates a simple assessment of whether differences in returns to skills differ between sectors. Second, the nonlinearity in returns to experience would only be identified through an increase in one year of experience for each employee. To reiterate the nature of this restriction, it assumes that returns to the *last single year* of experience do not vary across experience levels. However, there is no restriction to the functional form of returns to *all previous* years of experience. This restriction is thus unlikely to be of any substantive consequence.

D Exogenous Switching Assumption

The model relies on the assumption that sector choice is uncorrelated with e, conditional on X and θ. It allows sector selection to be correlated with θ. But it does not allow for the possibility that workers switch sectors due to changes in person and sector specific productivity (i.e. time-varying comparative advantage). Lemieux argues that this problem 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. Workers may be dismissed or laid off precisely due to a fall in sector-specific productivity (especially if institutional constraints prevent a wage reduction). Even if an involuntary job loss is assumed exogenous, there is no reason to believe that subsequent sector choice is unaffected by time-varying comparative advantage. Thus we 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 report changing jobs involuntarily is too small in HILDA to adopt this approach, as it would reduce the sample size by approximately 75%.

Instead, we provide empirical support (in the next section) for the exogenous switching assumption. The rationale is based on the following arguments. If time-varying comparative advantage were an important factor in sector switching, one would expect to find an apparent public sector premium for public sector joiners and a corresponding *private* sector premium for public sector leavers. In other words, switching sectors would be associated with an increased wage, regardless of the direction of the switch. With purely exogenous switching, one would expect to see a *public* sector premium (or penalty) that does not depend on the direction of the switch (public to private or private to public). This is indeed what we find in the data. Next, even if time-varying comparative advantage were an important factor in sector switches, it would only bias the key results in specific circumstances. The mean public sector premium would be biased up (down) only to the extent that the number of public sector joiners (leavers) in the sample dominate the number of leavers (joiners). A similar argument holds for ψ. Time-varying comparative advantage would lead to downward bias in ψ only to the extent that public sector leavers are concentrated at the top of the skill distribution (relative to joiners), *vice versa* for an upward bias. Whilst the distribution of θ is not attainable, the wage distribution of leavers and joiners (averaged across their public and private sector observations) is arguably a close substitute in the present context. We will show that this distribution is similar for leavers and joiners.

E Factors Not Included in the Model

Some factors that may affect sectoral wage differences have not been incorporated in the model and need to be taken into account when interpreting the results. 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 important considerations and both are more generous in the public sector.

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).[6] 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.

Paid maternity leave was not mandatory In Australia until January 2011 (after the period of data coverage used here). In the pre-2011 era at least, public sector employers were 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 2007: 135). HILDA includes 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 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 in the following section. No controls are included for industry and occupation. This implies an assumption that the

[6] 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, excluding employees of own business. 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%.

industries and occupations of jobs in one sector are not generally less appealing compared to the other sector, in the sense that they detract from utility directly. Some supporting evidence for this assumption is presented in the following sections. It is shown in Section IV that the inclusion of industry and occupation controls in related models makes almost no difference to the estimates. Further, there is no evidence of sectoral differences in work stress and work satisfaction in Australia, as discussed in Section V. At a practical level, the samples in the preferred models are too small to accurately identify compensating differentials off movers between industries and occupations.

We 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). We treat these as inherent features of the public sector which we 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.

III 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, with an initial sample of 7682 households and 19,914 individuals. The analysis utilises all eight available waves (2001-2008).

The estimation 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).[7] The restriction to job changers is because

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

sector of employment is self reported and thus may be measured with error.[8] 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.[9] To address this issue, the sample is limited to those who reported a change in employer, which follows Lemieux's (1998) approach.

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 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 2008 levels.

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.[10] 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

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

[9] 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.

[10] 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'.

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 this restriction as will be shown.

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). A small number of people whose highest educational qualification changed between observations were excluded to ensure that education is time invariant, as discussed in the previous section. The estimation sample consists of 2703 men and 2520 women.

The sector movers consist of 294 men and 461 women. These observations identify $\bar{\delta}$ and ψ. Casual status changed between observations for 741 men and 767 women. These records identify the estimated casual loading. Shift work status changed between observations for 628 men and 663 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 0.14 for men and 0.23 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, less so 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 male job changers also changed occupation, regardless of sector. This proportion is slightly higher for male sector movers (57%). Amongst females, the proportion of sector changers who changed occupation was similar to that of job changers overall.

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 most regards. The main differences are that sector movers are less experienced (especially amongst males) and had worked for their employer for a shorter period (at *t-1*). Amongst males, they are also less likely to be 'Managers'.

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 not strikingly different to that of all employees in each sector either, perhaps resembling the private sector distribution slightly more than the public sector distribution.

A slightly higher proportion of sector movers moved into the public sector rather than away from the public sector (60% 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.

It was suggested in Section **Error! Reference source not found.** that an approximate test of instrument relevance is to test whether the mean wage of public sector leavers is different to that of joiners. The results of such tests are shown in

Table 4, which shows the mean ln wage for public sector joiners and leavers, across both observations, so that both the public and private sector wage is included in the calculation for each employee. There is clear evidence that public sector leavers have a higher wage than public sector jointers amongst both males and females (a difference of 0.103 for males and 0.070 for females). These differences are statistically significant ($p = 0.030$ for males; $p = 0.012$ for females) which provides evidence for instrument relevance (see section II.B). If the male and female samples are pooled, the evidence is stronger still ($p = 0.002$). For this reason, the model is re-estimated for a pooled sample of males and females as a robustness test. It will be shown that the three sets of results, that for men, women and overall are similar and that the key estimates for the pooled model lie in between that of the male and female models.

The middle panel of Table 4 shows mean log wage changes leavers, joiners and job changers who did not change sector. Relative to job changers who did not change sector, the log wage of public sector joiners increased by a mean of 0.041. The corresponding change for leavers is a *decrease* of 0.054. Thus endogenous sector switching does not appear to have empirical support in this application. Table 4 also shows the numbers of leavers and joiners in the sample, which are fairly similar.

Figure 3 shows the wage distributions for leavers and joiners (averaged across their public and private sector observations). These are similar, strongly suggesting that leavers and joiners are similarly distributed across the skill distribution. The corresponding distributions by sex (not shown) are noisier, but lead to the same qualitative conclusion.

IV RESULTS

A Parameter Estimates

The results of the GMM estimation are shown in **Table 5**. There is 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 0.954, while for females it is 1.118. In the pooled model it is 0.960.

This parameter is not significantly different from 1 in any 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 V.

The constant effect ($\bar{\delta}$) of public sector employment on wages is estimated to be positive and small (0.044 for men and 0.042 for women). This parameter is statistically significant for men (p = 0.038), and borders on significance for women (p = 0.073). The estimate is slightly higher in the pooled model across sexes (0.052) and is highly significant.

Positive and statistically significant loadings for casual status are estimated for both sexes and in the pooled model. Compensation for shift work is not statistically significant. 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 in any model. The results are not sensitive to these restrictions, as will be shown.

The Hansen statistic, reported at the bottom of **Table 5**, facilitates partial tests 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 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. In the male and pooled models the p-values greatly exceed 0.05 and so the null hypothesis is not rejected. In the female model the p-value is slightly less than the critical value (0.044). However this may simply result from parameter heterogeneity in the population, with the different instruments picking up various local averages.

B Decomposition of the Raw Wage Gap

The decomposition results are shown in Table 6. The main result is that the average public sector wage premium is estimated to be positive but small for men (0.040), slightly larger for women (0.059), with the estimate from the pooled model lying between the two (0.048). Statistically, this estimate is significantly different from zero for women (p<0.001) and the pooled model (p<0.001), but not for men (p=0.072).[11] The 95% confidence intervals are (-0.004, 0.083) for men, (0.029, 0.089) for women and (0.022, 0.073) overall. These imply an average public sector wage premium of $e^{0.040} - 1 = 4.1\%$ for men, $e^{0.059} - 1 = 6.1\%$ for women and $e^{0.048} - 1 = 4.9\%$ overall.

Returning to Table 6, 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). In each model, 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.

C Robustness 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 $\overline{\delta}$ (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 7.

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, reflecting the increase in the number of parameters estimated by the model. The constant effect $\overline{\delta}$ becomes statistically insignificant. As shown in the next two sets of results, if the

[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 ($\overline{\theta}_P$ and $\overline{\theta}_R$) are functions of the estimated parameters and the sample means.

models are estimated by NLIV or iterated GMM, the results are very similar to the preferred model. When sample weights are applied, the estimates also remain similar to the preferred model.

In the next seven 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 severely restricted to approximately one seventh of the main 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 (the majority of point 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). This constitutes strong support for the validity of inference for the main set of estimates. Thus the results are generally robust to the methodological modifications considered.

The final set of results in Table 7 was generated by estimating the quasi-differenced wage equation (equation 7) 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 $\bar{\delta}$ are small positives for both sexes and the estimates of ψ are not significantly different from 1. The average wage premiums are also positive, statistically significant and similar to the preferred model.

D Comparison with other Methods

The estimated average public sector wage premiums are compared in

Table 8 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.[12] 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 (46 dummy variables for men; 43 for women), proficiency in English (3 dummy variables), married, state or territory (7 dummy variables) and remoteness (3 dummy variables).[13] 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 similar data, Cai and Liu (2011) also estimated the average public wage premium using OLS and Oaxaca decompositions. Their estimates are lower than those in

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

[13] Industry dummies are not included due to the heavy industrial segregation of public sector employment.

Table 8, 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 for both sexes, some of the apparent public sector wage premium may be explained by higher unobserved skills of public sector employees.[14] 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.

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 quite similar to the previous model, suggesting that the larger set of controls makes little difference to the estimates, thereby justifying their exclusion from our preferred model.

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 both sexes, the estimated wage premium is considerably larger than the previous estimate, which conforms to the hypothesised attenuation bias in the larger sample.

The first difference model estimated on the job changer sample is equivalent to the preferred model with ψ restricted to equal 1. Since ψ is estimated to be close to 1, so it is unsurprising that the estimated average wage premiums are similar in the first difference models.

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

V CONCLUSION

We have used an adaptation of Lemieux's (1993, 1998) quasi-differenced panel data estimator to test whether the public sector wage premium varies with skill in Australia. This estimator allows us to identify sectoral differences in returns to a latent index of overall skill. We find no evidence to suggest that the public sector wage premium varies with skill. This suggests that if low skill public sector workers receive a wage premium, it is no larger than that of high skill workers. This is despite the typical results of quantile regressions, which suggest that the premium is usually much larger at the bottom of the wage distribution. How can these results be reconciled? The quantile regression results could be explained by greater variance in private sector wages for a given level of skill. Another explanation is that the compressed wage profile of the public sector induces the best workers (on unobserved skills) to join the public sector in low wage occupations, *vice versa* in high wage occupations. This would be consistent with the recent work of Bargain & Melly (2008) for France, who use a fixed effects quantile regression approach. Whilst they are unable to account for differences in returns to unobserved skills, they find that the apparent variation in the French public sector wage premium across the wage distribution 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.

Our findings suggest that caution should be taken before inferring (from quantile regression) that low skill public sector workers are considerably overpaid. If the public sector does attract the best workers (on unobservables) in low skill occupations, this is likely to translate to higher productivity. The finding also calls into question the ability of governments to use wage setting policies to achieve redistributive goals. If, for instance, governments aim to provide a wage premium to public sector workers in low wage occupations, it may simply be inducing the best workers (on unobserved characteristics) to join the public sector.

Our results are consistent with concerns over the ability of the public sector to retain highly skilled workers. When compared to the results of Cai & Liu (2011), the lack of a public sector wage *penalty* for high skill workers in our study suggests that the best workers (on unobserved characteristics) in high wage occupations select into the private sector.

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). In particular, the standard errors for ψ must be taken into account. The 95% confidence intervals do not rule out moderate sectoral differences in returns to skills. It would thus be useful to conduct related studies using other data sources.

We also find that the average Australian public sector employee is paid slightly more than he or she would be paid in the private sector. The preferred estimates of this public sector wage premium are 4% for men and 6% 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).

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Table 1 Sample selection (number of observations)

	Men	Women	Pooled
Job changers between any consecutive	3116	3043	6159
with missing data	149	225	374
outliers	103	88	191
changed education	161	210	371
Final sample	2703	2520	5223

Table 2 Sample means – job changers*

Variable	Men Public	Men Private	Men Sector Movers	Women Public	Women Private	Women Sector Movers
ln wage	3.26	3.12	3.18	3.21	2.98	3.13
Experience (years)	15.4	14.5	14.8	15.4	12.6	14.1
Education						
University degree	0.46	0.17	0.34	0.52	0.21	0.43
Trade	0.22	0.38	0.29	0.19	0.29	0.23
Year 12	0.16	0.21	0.18	0.16	0.26	0.19
less than Year 12	0.16	0.24	0.19	0.13	0.24	0.16
Casual	0.17	0.27	0.20	0.21	0.37	0.26
Shift / irregular	0.20	0.23	0.22	0.18	0.26	0.23
Occupation						
Managers	0.06	0.10	0.03	0.05	0.07	0.06
Professionals	0.39	0.15	0.32	0.48	0.17	0.38
Technicians and Trades Workers	0.13	0.25	0.19	0.02	0.05	0.02
Community and Personal Service	0.12	0.05	0.12	0.14	0.16	0.18
Clerical and Administrative Workers	0.15	0.08	0.13	0.27	0.29	0.28
Sales Workers	0.02	0.10	0.05	0.01	0.17	0.04
Machinery Operators and Drivers	0.04	0.13	0.05	0.00	0.01	0.01
Labourers And Related Workers	0.09	0.16	0.11	0.02	0.08	0.03
Tenure (years) with employer at *t-1*	3.50	2.74	3.62	3.19	2.41	2.87
Changed occupation between	0.53	0.48	0.57	0.41	0.46	0.46
Sample size	300	2,403	294	479	2,041	461

* 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	3.37	3.12	3.18	3.26	2.97	3.13
Experience (years)	23.1	17.5	14.8	19.6	14.6	14.1
Education						
University degree	0.42	0.18	0.34	0.50	0.20	0.43
Trade	0.34	0.36	0.29	0.23	0.26	0.23
Year 12	0.11	0.18	0.18	0.11	0.22	0.19
less than Year 12	0.13	0.27	0.19	0.16	0.32	0.16
Casual	0.08	0.22	0.20	0.14	0.35	0.26
Shift / irregular	0.24	0.26	0.22	0.22	0.27	0.23
Occupation						
Managers	0.11	0.13	0.03	0.06	0.07	0.06
Professionals	0.37	0.15	0.32	0.51	0.17	0.38
Technicians and Trades Workers	0.12	0.24	0.19	0.02	0.05	0.02
Community and Personal Service	0.14	0.05	0.12	0.17	0.15	0.18
Clerical and Administrative Workers	0.14	0.07	0.13	0.20	0.25	0.28
Sales Workers	0.01	0.09	0.05	0.01	0.19	0.04
Machinery Operators and Drivers	0.06	0.13	0.05	0.00	0.01	0.01
Labourers And Related Workers	0.06	0.15	0.11	0.03	0.10	0.03
Tenure (years) with employer at *t-1*	10.57	4.92	3.62	7.93	3.82	2.87
Sample size	5,714	21,419	294	7,987	19,120	461

* '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 Mean wages of public sector leavers and joiners

	Males	Females	Pooled
	mean ln wage		
Leavers	3.213	3.141	3.168
Joiners	3.110	3.071	3.087
Difference	0.103	0.070	0.081
Standard error of difference	0.048	0.030	0.026
p-value of difference	0.030	0.012	0.002
	mean change in ln wage		
Leavers	-0.002	-0.009	-0.006
Joiners	0.082	0.093	0.089
Other job changers (not sector switchers)	0.053	0.042	0.048
	Number of observations		
Leavers	117	198	315
Joiners	177	263	440
Other job changers (not sector switchers)	2,409	2,059	4,468

* The upper panel shows the mean log wage for public sector leavers and joiners, where for each switcher, the log wage is averaged across one public sector observation and one private sector observation (the observations immediately before and after the sector switch).

Table 5 GMM estimates of wage equations*

	Men		Women		Pooled	
	coefficient	SE	coefficient	SE	coefficient	SE
Constant effect ($\bar{\delta}$)	0.044	0.021	0.042	0.024	0.052	0.014
Returns to time invariant skills in public sector (ψ)	0.954	0.146	1.118	0.159	0.960	0.104
Returns to varying characteristics						
Casual	0.062	0.014	0.066	0.013	0.063	0.009
Shift Work	0.010	0.014	-0.017	0.015	-0.003	0.010
δ_t^R	3.112	0.006	2.992	0.008	3.055	0.004
δ_{t-1}^R	3.060	0.007	2.949	0.008	3.008	0.005
Hansen overidentification statistic	16.616		24.146		17.350	
(p-value)	(0.277)		(0.044)		(0.238)	
Sample size	2703		2520		5223	

* 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 6 Decomposition of Raw Average Wage Gap from GMM results

	Men		Women		Pooled	
	Estimate	SE	Estimate	SE	Estimate	SE
Public Sector Wage Premium:						
constant effect ($\bar{\delta}$)	0.044	0.021	0.042	0.024	0.052	0.014
differences in returns to fixed characteristics	-0.005	0.015	0.017	0.022	-0.004	0.012
Total average wage premium	0.040	0.022	0.059	0.015	0.048	0.013
Effect of differences in						
casual and shiftwork status	-0.006	0.002	-0.009	0.003	-0.007	0.001
fixed characteristics	0.110	0.022	0.176	0.016	0.132	0.013
Total effect of different characteristics	0.104	0.022	0.166	0.016	0.124	0.013
Unadjusted Wage Gap	0.144		0.225		0.172	

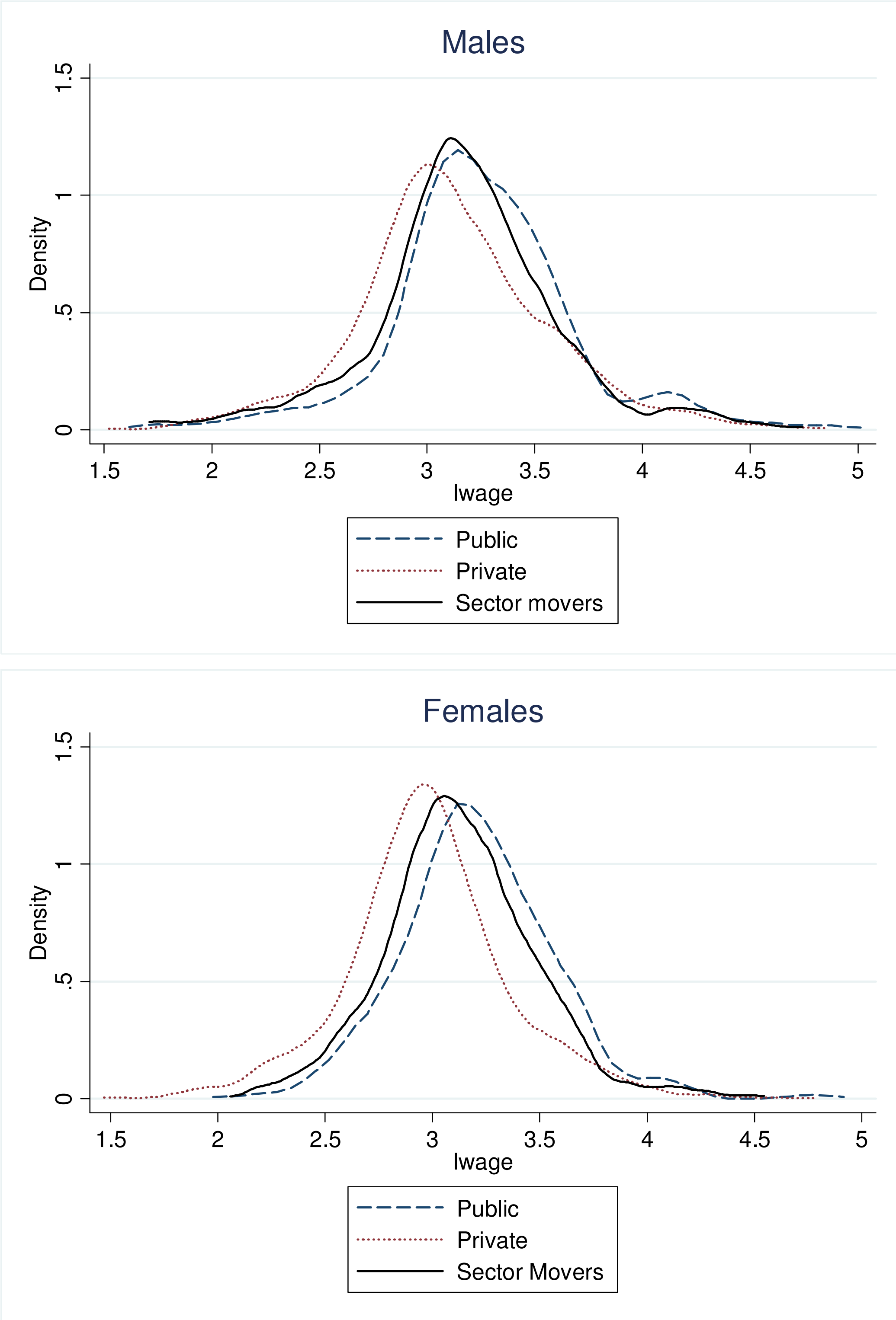
Table 7 Sensitivity Tests of Main Results

	$\bar{\delta}$	SE	ψ	SE	Average public wage premium	SE
Unrestricted returns to casual and shift						
Men	0.034	0.026	1.021	0.172	0.047	0.022
Women	0.011	0.034	1.262	0.212	0.062	0.015
NLIV						
Men	0.048	0.020	0.954	0.135	0.043	0.022
Women	0.039	0.021	1.174	0.153	0.063	0.016
ITGMM						
Men	0.044	0.021	0.954	0.145	0.040	0.022
Women	0.044	0.023	1.106	0.157	0.059	0.015
Weighted						
Men	0.020	0.024	0.974	0.163	0.018	0.023
Women	0.036	0.027	1.190	0.200	0.060	0.018
Waves 1 & 2						
Men	0.118	0.041	0.601	0.172	0.035	0.064
Women	0.003	0.059	1.815	0.375	0.108	0.027
Waves 2 & 3						
Men	0.011	0.079	1.771	0.587	0.084	0.045
Women	0.025	0.064	1.582	0.411	0.105	0.033
Waves 3 & 4						
Men	0.050	0.050	0.877	0.194	0.044	0.057
Women	0.082	0.038	0.874	0.192	0.065	0.037
Waves 4 & 5						
Men	0.036	0.039	1.415	0.244	0.045	0.031
Women	-0.011	0.067	1.059	0.332	-0.003	0.038
Waves 5 & 6						
Men	0.030	0.036	0.694	0.093	-0.042	0.070
Women	0.062	0.043	0.937	0.161	0.050	0.042
Waves 6 & 7						
Men	0.048	0.046	1.104	0.199	0.053	0.044
Women	0.027	0.038	0.778	0.227	-0.013	0.052
Waves 7 & 8						
Men	-0.108	0.129	2.494	0.841	0.024	0.042
Women	-0.008	0.060	1.530	0.454	0.055	0.027
Nonlinear Least Squares						
Men	0.047	0.020	0.957	0.042	0.043	0.020
Women	0.059	0.016	0.936	0.040	0.050	0.016

Table 8 Estimated Average Public Sector Wage Premium - Comparison to other Methods

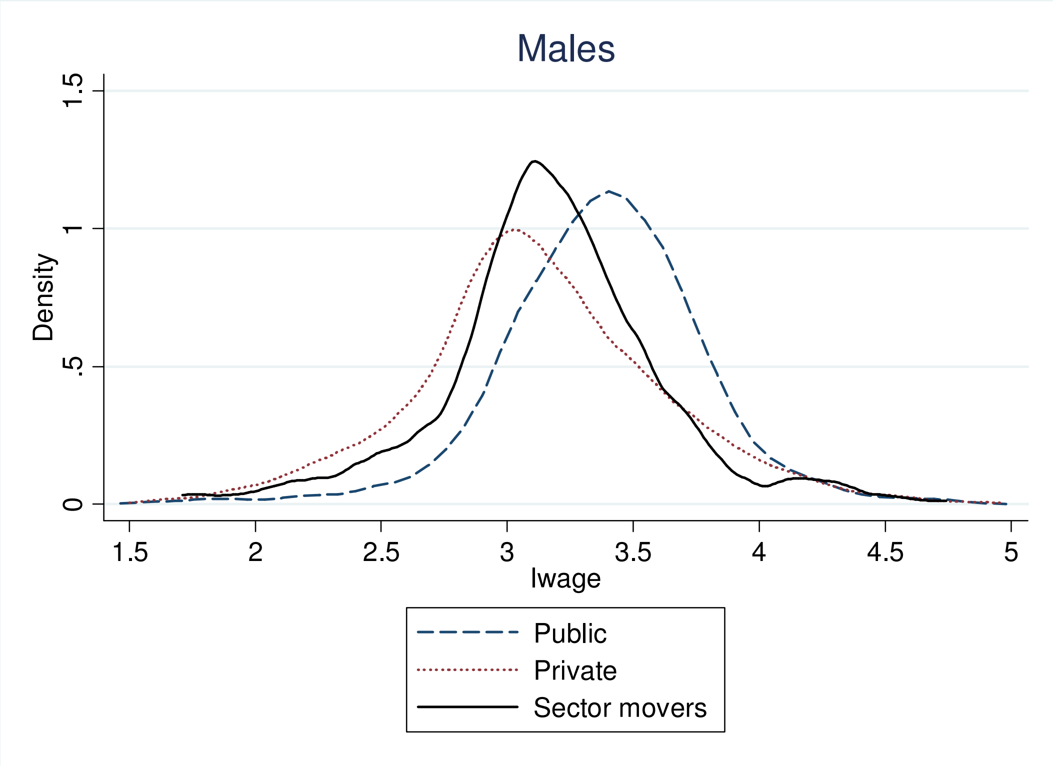
	Men			Women		
	Average public wage premium	SE	N	Average public wage premium	SE	N
OLS	0.037	0.011	25,178	0.065	0.008	25,116
Oaxaca decomposition	0.050	0.007	25,178	0.053	0.006	25,116
Fixed Effects	0.032	0.010	19,171	0.040	0.008	18,294
First Difference (full controls)	0.018	0.011	18,294	0.020	0.009	17,085
First Difference (limited	0.024	0.012	17,736	0.022	0.009	16,849
First Difference (job changers	0.046	0.020	2,703	0.054	0.007	2,520
Quasi-Difference (preferred	0.040	0.022	2,703	0.059	0.015	2,520

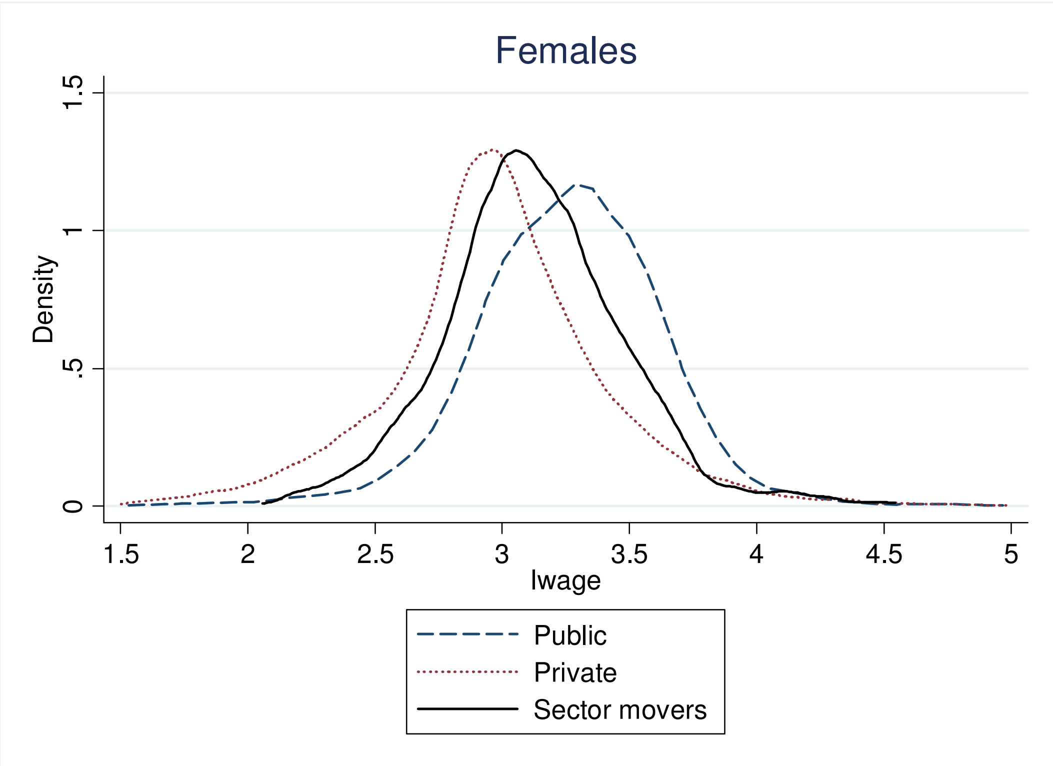
Figure 1 Density of ln wage distribution amongst job changers*



* 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.

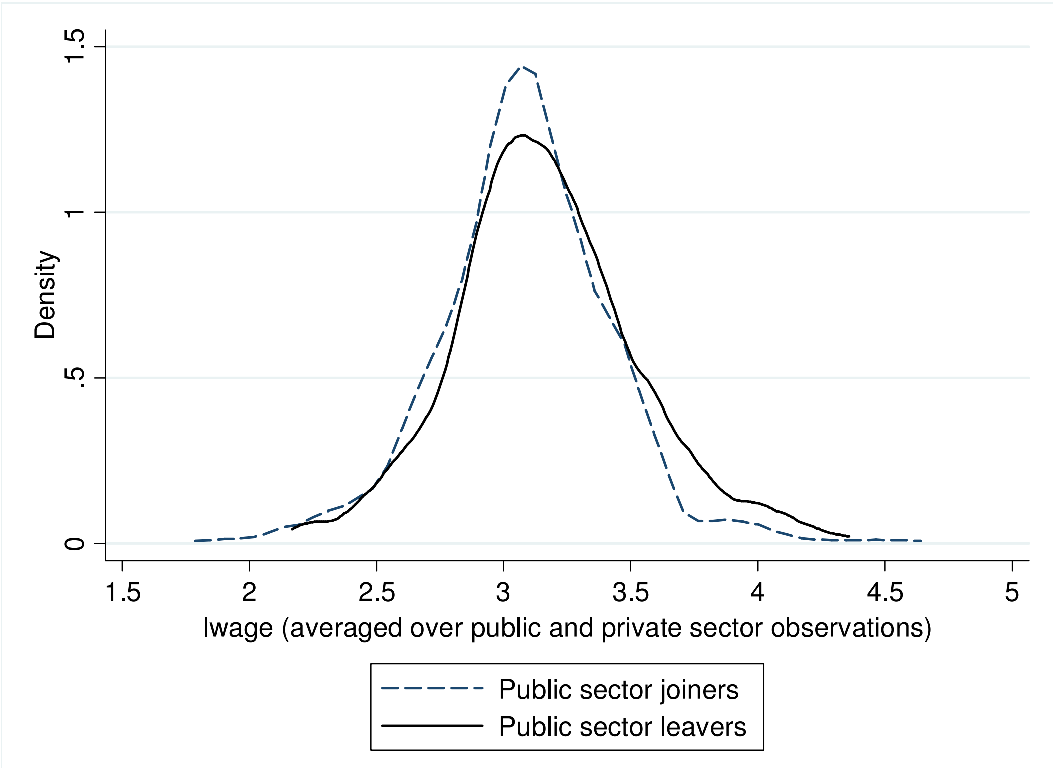
Figure 2 Density of ln wage distribution amongst all employees*





* '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.

Figure 3 Density of ln wage distribution amongst public sector joiners and leavers*



* The population is limited to sector switchers. For each switcher, the log wage is averaged across one public sector observation and one private sector observation (the observations immediately before and after the sector switch).