THE ECONOMIC RECORD, VOL. 84, NO. 267, DECEMBER, 2008, 496–510

Union Wage Effects in Australia: Is There Variation along the Distribution?*

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This study uses quantile regression models to examine whether the union wage effect varies across the conditional wage distribution. Although for men it is evident that the union wage effect decreases when moving up the conditional wage distribution, the effect for women is relatively stable except at the extremities of the distribution. Overall, unions are found to have a larger effect on men than on women wages. The decomposition results show that for men, the union wage effect explains a substantial proportion of the observed wage gap between union and non-union workers; this is not the case for women.

I Introduction

Before the early 1990s the Australian 'award' system set the increase in award wages for all workers covered by those awards, irrespective of their union status. Despite the unique wage setting system, a number of Australian studies find that union workers enjoy significantly higher wages than non-union workers with comparable characteristics (Mulvey, 1986; Crockett & Hall, 1987; Miller & Rummery, 1989; Christie, 1992; Kornfeld, 1993; Miller & Mulvey, 1993). The estimated union wage effect varies from 3 to 10 per cent.[1] In a series of studies attempting to explain the wage differential, Miller and Mulvey (1991, 1992, 1993) examine the role of overtime pay differentials, over-award pay and differences in the distribution of union and non-union workers across industries. They find that these factors together explain no more than a quarter of the estimated wage differential. However, a subsequent study by Miller and Mulvey (1996) finds that after controlling for workplace size the union wage differential disappears. This leads them to suggest that omitted variable bias is responsible for the union wage premium found in earlier Australian studies.

Since the early-1990s, through a ruling of the Australian Industrial Relations Commission, the Australian wage setting started to shift from industry-based awards towards enterprise-based (or workplace-based) agreements (Waddoups, 2005). The introduction of the Workplace Relations Act

* The authors thank Trevor Breusch, Tue Gorgens, Kostas Mavromaras, Paul Miller, Jacques Poot, Mark Wooden, and two anonymous referees for useful comments on an earlier version of the paper. The paper uses the data in the confidentialised unit record file from the Department of Families, Community Services and Indigenous Affairs (FaCSIA) Household, Income and Labour Dynamics in Australia Survey, which is managed by the Melbourne Institute of Applied Economic and Social Research. The findings and views reported in the paper, however, are those of the authors and should not be attributed to either FaCSIA or the Melbourne Institute.

JEL classifications: J31, J51

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[1] Although the size of the effect estimated is small compared to the USA (about 18 per cent), it is roughly similar to that found in European countries with highly centralised collective bargaining systems, such as Germany and Austria (5–8 per cent) (Blanchflower & Freeman, 1992; Blanchflower & Bryson, 2002; Waddoups, 2005).

doi: 10.1111/j.1475-4932.2008.00513.x

(WRA) in 1996 further legitimised this practice. As a result, the proportion of workers covered by the traditional award system has fallen dramatically. For example, in May 2000 only 23.2 per cent of employees were paid under an award compared to 67.6 per cent in May 1990 (Department of Employment & Workplace Relations, 2002).[2] If anything, the new system could have increased the union wage effect for at least two reasons (Wooden, 2001; Waddoups, 2005). First, the decentralised wage setting system offers opportunities for unions to exert their powers in negotiating over rent sharing. This is reflected by a strong union presence evident in the new enterprise agreements (Hawke & Drago, 1998; Wooden, 2001). Second, due to the reduction in the influence of arbitration, union-bargained wage benefits are now less likely to spread to non-union workers compared to the previous award system. Indeed, recently Waddoups (2005) finds that relative to 1993, the overall union wage effect increased significantly by 2001.[3]

Like Waddoups (2005), this study examines union wage effects in the changed Australian industrial relations environment. However, in addition to estimating the effects at the mean of the conditional wage distribution, as all previous Australian studies have done, we also examine how the union wage effects vary across the conditional wage distribution using quantile regression models. Internationally it is often found that that the effects are generally larger at the lower than at the upper end of the conditional wage distribution (e.g. Chamberlain, 1994; Disney *et al.* 1995; Hildreth, 1999; O'Leary *et al.* 2004). Little is known about how the union wage effects vary along the conditional wage distribution before the industrial relations reform. However, the new industrial relations system could potentially exacerbate any variation that exists. In decentralised wage setting, the bargaining power of workers is clearly important in determining wage levels. Low wage earners often have little bargaining power because they tend to be low-skilled and are subject to a high degree of substitutability. However, if low-skill workers are represented by unions their bargain power would be expected to increase substantially compared with low-skill workers not represented by unions. On the other hand, high wage earners have high bargaining power due to their high skills and low substitutability; association with unions makes little difference for them in terms of bargained wage outcomes. In addition, due to the potential wage compression effects of unions (Freeman & Medoff, 1984), highly skilled union workers might earn less than their non-union counterparts.

This study contributes to the Australian literature on union wage effects in two ways. First, we examine union wage effects in a changed industrial relations environment where decentralised wage setting is more extensive than in the period covered by most previous studies. Second, using quantile regression models, we examine how the union wage effects vary across the conditional wage distribution. Nevertheless, the present study has limitations. Notably in our data, aside from the union membership status as reported by survey respondents, we have no information on the firm-level wage setting process. This means that we cannot distinguish union (or non-union) workers covered by enterprise-based agreements from those not covered by such agreements. This also implies that the data we use do not allow us to examine how union wage effects vary across workplaces with different levels of union activity. This is an important line of research contained in Wooden (2001) that uses the Australian Workplace Industrial Relations Survey (AWIRS) 1995.[4] If it is the combined effect of active unions and enterprise-based agreements that generates the wage differential (as found in Wooden, 2001), our estimates are likely to provide a lower bound for the union wage effects. We could not use the AWIRS data for our analysis for two reasons. First, the AWIRS survey was not continued after 1995. Second, wages in the AWIRS survey were reported on an interval basis, rather than as a continuous variable. This makes comparisons of the wage distributions between union and non-union workers difficult. For example, from the AWIRS data we cannot estimate the difference of median wages between union and non-union workers since

[2] In May 2000, 35.2 per cent of employees were on registered collective agreements, 1.5 per cent on unregistered collective agreements, and 40 per cent were covered by individual agreements (Department of Employment and Workplace Relations, 2002).

[3] In another study Waddoups (2007) finds that, following the industrial relations reforms, a reverse relationship between firm size and the union wage effect has emerged in Australia.

[4] Using matching workplaces and employee data collected in the 1995 AWIRS, Wooden (2001) finds that workers in firms with active unions, and covered by enterprise-based agreements, earn a significant wage premium not enjoyed by otherwise comparable workers who are not covered by enterprise-based agreements, or are not employed in firms with active unions present.

we do not know the exact median wages of each group. At most, we can infer which intervals the median wages fall into. More accurate estimates of the union wage effects require data that provide more detailed information on both the new industrial relations framework and wages.

The rest of the article is arranged as follows. Section II describes quantile regression models and the semi-parametric decomposition method. Section III discusses the data source and model specification. Section IV presents estimation results. Finally, in Section V, we set out our conclusions.

II Method

(i) Quantile Regression

To investigate whether the union wage effects vary at different points of the conditional wage distribution, we employ the quantile regression models of Koenker and Bassett (1978). Following Buchinsky (1998), we specify the θth ($0 < \theta < 1$) conditional quantile of the distribution of the (log) wage w, conditional on a vector of covariates x, as

$$Q_\theta(w \mid x) = x\beta(\theta). \quad (1)$$

Equation (1) assumes a linear relationship between the population conditional quantile of w, $Q_\theta(w \mid x)$, and the covariate x. For a random sample of (w_i, x_i) for $i = 1, \dots, N$, Equation (1) implies

$$w_i = x_i\beta(\theta) + \varepsilon_{\theta_i}, \quad \text{with} \quad Q_\theta(\varepsilon_{\theta_i} \mid x) = 0, \quad (2)$$

where ε_{θ_i} is the error term of the θth conditional (on x_i) quantile. In quantile regressions the only distributional assumption on ε_{θ_i} is that the θth conditional (on x_i) quantile of the error term equals zero.

For a given $\theta \in (0,1)$, $\beta(\theta)$ can be estimated by

$$\hat{\beta}(\theta) = \arg\min_{\beta} \frac{1}{N} \sum_{i=1}^{N} (w_i - x_i\beta)(\theta - 1(w_i \le x_i\beta)), \quad (3)$$

where $1(\cdot)$ is the indicator function (Koenker and Bassett, 1978). $\beta(\theta)$ is estimated separately for each $\theta \in (0,1)$.

Following the tradition, we first estimate a single equation quantile regression model of the form similar to Equation (2),

$$w_i = \alpha(\theta)U_i + x_i\beta(\theta) + \varepsilon_{\theta_i}, \quad \text{with} \quad Q_\theta(\varepsilon_{\theta_i} \mid U_i, x_i) = 0, \quad (2')$$

where U_i is a dummy variable indicating union status of an individual i and x_i is a vector of other variables that are expected to affect wages, such as education and experience. The quantile regression coefficients can be interpreted as the rates of return to the respective characteristics at the specific quantile of the conditional wage distribution (Buchinsky, 1998; Koenker, 2005). Therefore, $\alpha(\theta)$ measures the union effect at the θth conditional quantile of wages and $\beta(\theta)$ measures the effect of other variables at that point. If the effects of unions are the same across the conditional wage distribution, we would expect $\alpha(\theta)$ not to vary for different θs. On the other hand, if unions have no effect on wages, then $\alpha(\theta)$ should not be significantly different from zero for any θ.

Intuitively, we use quantile regression to examine the interaction between independent variables and the spread of the distribution of the unobservables. For example, unobserved ability may be related to the spread of the union wage premium and this may be different at different quantiles of the distribution of unobservables. In order to identify this effect, we need to assume that the *mean* of the unobservables (at each quantile) is unrelated to the independent variables. So for the example of the union wage premium, we need to be able to assume that rates of unionisation are independent of unobserved ability in order to interpret our results in the way that we do.

Under these identifying assumptions, quantile regression provides a richer data description tool than OLS. The standard approach in OLS is to correct for heteroscedasticity and focus on effects on the conditional mean. One way to view our approach is as a non-parametric mapping of the heteroscedasticity to which we then provide an interpretation. However, it is important to note that consistent coefficient estimates depend on similar assumptions about the relationship between observables and unobservables.

The single equation model in Equation (2′) assumes that the wage determination process is identical for both union and non-union workers. However, test results shown later suggest that the assumption is violated; the wage determinants affect union and non-union workers differently. To account for the differences in the returns to wage determining factors between union and non-union workers, separate wage determination equations for each group are required. As in the OLS framework, after estimating the wage equation separately for union and non-union workers using quantile regressions, the differences at various quantiles of the wage distributions between the two groups of workers can be decomposed into differences in returns and differences due to observed characteristics.

(ii) Decomposition in Quantile Regression

A decomposition method for quantile regression models was developed by Machado and Mata (2005). For an application of the method to analyse the gender wage gap in Australia see Kee (2006). Here we use a modified procedure proposed by Melly (2005) and Autor *et al*. (2005). In the modified procedure, instead of randomly drawing θ and x, we simply estimate quantile regressions for a large number of selected θs, such as θ_1 θ_2 … θ_j, and use the observed sample x to form required marginal distributions of wages. In summary, the following steps are involved in decomposing the wage gap between union and non-union workers at different points of the wage distributions.

Step 1: Estimate $\beta^u(\tau_j)$ and $\beta^n(\tau_j)$, for $\tau_j \in (0,1)$ and $j = 1, \ldots, J$, using the union and non-union samples, respectively, to form $\{\{x_i^u\beta^u(\tau_j)\}_{j=1}^{J}\}_{i=1}^{N_u}$, and $\{\{x_i^u\beta^n(\tau_j)\}_{j=1}^{J}\}_{i=1}^{N_u}$, where x_i^u refers to the observed characteristics of union worker i; x_i^n refers to the observed characteristics of non-union worker i; N_u and N_n refer to the numbers of union workers and non-union workers, respectively. $\{\{x_i^u\beta^u(\tau_j)\}_{j=1}^{J}\}_{i=1}^{N_u}$ provide the predicted wage density of union workers; $\{\{x_i^u\beta^n(\tau_j)\}_{j=1}^{J}\}_{i=1}^{N_u}$ provide the counterfactual wage density of union workers that would arise if they retained their own characteristics but were paid as non-union workers.

Step 2: Estimate the θth quantile of the sample $\{\{x_i^u\beta^u(\tau_j)\}_{j=1}^{J}\}_{i=1}^{N_u}$, denoted as $Q_\theta(x^u, \beta^u(\tau))$, and of the sample $\{\{x_i^u\beta^n(\tau_j)\}_{j=1}^{J}\}_{i=1}^{N_u}$, denoted as $Q_\theta(x^u, \beta^n(\tau))$.

Step 3: Obtain $Q_\theta(x^u, \beta^u(\tau)) - Q_\theta(x^u, \beta^n(\tau))$. This difference represents the wage gap due to different returns at the θth quantile; that is, the union wage effects.[5]

To estimate the standard errors and confidence intervals of the differences, the bootstrap method can be used to replicate the above procedure. In this study 100 replications are carried out to estimate the confidence intervals and repeated observations for the same person in different waves (i.e. clustering) are taken into account in re-sampling.

III Data and model specification

(i) Data

The empirical analysis is based on the first four waves (2001–2004) of the Household, Income and Labour Dynamics in Australia (HILDA) survey. The survey is a national household panel survey focused on families, income, employment and well-being.[6] The first wave was conducted between August and December 2001. Then, 7683 households representing 66 per cent of all in-scope households were interviewed, generating a sample of 15 127 persons 15 years or older and eligible for interview. Of them, 13 969 were successfully interviewed. Subsequent interviews for later waves were conducted about one year apart.

The HILDA survey contains detailed information on individuals' current labour market activity including labour force status, earnings and hours worked, and employment and unemployment history. For those employed, information on job characteristics, such as the size of the workplace and the industry to which the employee belongs is also collected. The wages used in this study refer to hourly wages derived from pre-tax total weekly earnings and hours worked.[7] One comparative advantage of HILDA is that the earnings data are not grouped, thus avoiding possible measurement error due to grouped data. To increase the sample size and thus the accuracy of the estimated distribution, we pool four waves of data. Wages are deflated to the first quarter of 2001 using quarterly wage growth rates for men and women separately. Another reason for pooling the data is that sufficiently large sample sizes are important in bootstrapping the standard errors of the decomposition results.[8]

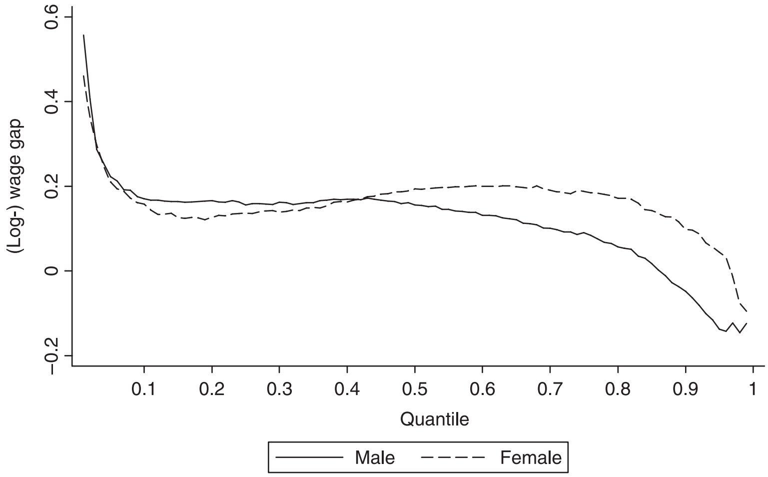
[5] An alternative decomposition using $Q_\theta(x^n, \beta^u(\tau))$ and $Q_\theta(x^n, \beta^n(\tau))$ shows a similar result.

[6] Detailed documentation of the survey is in Wooden *et al*. (2002).

[7] We use hourly wages in this study to avoid complications arising from the potential effects of unions on hours worked (Andrews *et al*., 1998).

[8] Initially we used only the first wave of the HILDA data and found that the bootstrap methods were difficult to carry out because sampling draws did not always contain observations that had the characteristics used in the model. For example, since only a few union workers are indigenous, a redrawn union worker sample may not have an indigenous worker. As a result, the original model that includes indigenous status as a covariate cannot be estimated using this redrawn sample. Some industry and firm size variables were also found to cause such a problem. While STATA goes ahead to estimate βs by automatically dropping these variables, the number of variables for union and non-union samples, x^u and x^n, respectively, will no longer be the same. As a result, one could not calculate the counterfactual wages of union workers in bootstrapping, since $x^u\beta^n$ becomes unconformable. Pooling the four waves of data helps to avoid the problem.

FIGURE 1
Raw Wage Gap at Different Quantiles



Pooling four waves of HILDA raises two econometric issues. One relates to repeated observations, as most individuals are surveyed more than once. The other is an increase in real wages over time. We include year dummies and use bootstrap methods (that account for clustering) in the empirical work to address these issues.

Our sample includes those wage earners who worked in non-agricultural industries. It includes men aged between 25 and 64 years and women aged 25 to 61 years. Full-time students are excluded. There are 18 547 individuals: 9381 men and 9166 women. About 35.6 per cent of the men in the sample are union workers as are 32.5 per cent of the women.

The raw wage gap between union and non-union workers at different percentiles are presented in Figure 1. Clearly, for both men and women the wage gap between union and non-union workers is much larger at the lower than at the upper end of the wage distribution. While the wage gap for men appears to decrease when moving up along the wage distribution, this is not the case for women. The women wage gap narrows at wages below the 20th percentile and then widens. It narrows again at wages above the 60th percentile. The variation of the wage gap across the wage distribution provides a case for using quantile regressions to analyse the union wage effects. Results from OLS may mask the variation of the union wage effects across the wage distribution.

(ii) Model Specification

The specification of the wage equation is an extension of the standard Mincer model of wage determination (Mincer, 1974). Essential to his model are human capital variables. Therefore, we include in the wage equation four education dummies, work experience (lifetime employment and its square) and a dummy on whether one has long-term health conditions (representing health capital). In addition to human capital, variables on the following characteristics are also included in the model: demographic characteristics (three dummies for whether one is a migrant born in an English speaking or non-English speaking country; a race dummy to identify whether an individual is an Aborigine or Torres Strait Islander; a marital status dummy); and employment characteristics (three dummies to identify casual, part-time or full-time employment); three occupation dummies for white-collar work (managers and professionals), other white-collar work and blue-collar work; and fourteen industry dummies.[9] These variables are fairly similar to those used in other Australian studies (Miller & Mulvey, 1996; Wooden, 2001). To control for heterogeneity of local labour markets and the differential effects of regional living costs

[9] For women, the mining, electricity and gas, and construction industries are grouped into the category 'other industries' due to the small number of observations.

on wages, we also include six state dummies and a dummy indicating capital city residence. There are six dummies to identify workplace size ranging from < 20 to over 500 employees. The positive relationship between workplace size and wages is well-documented (Idson & Feaster, 1990; Morissette, 1993; Miller & Mulvey, 1996). Increasing monitoring costs (which result in higher wages according to efficiency wage theories), greater importance of workplace-specific human capital and teamwork are some explanations discussed in the literature. Finally, year dummies are included to control for the trend of increasing real wages over the four waves of the HILDA data.

Summary statistics for the variables used are presented in Appendix Table A1. The sample means reveal very little that is not already well-known. For instance, larger workplaces (generally) have a higher incidence of unionisation; union workers tend to participate in the workforce longer; are less likely to be migrants from non-English speaking countries; are more likely to be from the ACT, NSW and Victoria but are less likely to hold casual and part-time jobs. There is some evidence of gender differences. As expected, more women have casual or part-time jobs. This is especially apparent among non-unionised workers. In addition, blue-collar jobs are mostly male-dominated; women are relatively more concentrated in white-collar related jobs. Furthermore, men workers have a high representation in manufacturing. Most women union workers are in the education and health industries. More women union workers are degree holders than are their male counterparts.

(iii) Econometric Issues

The estimation of a union wage gap typically involves two complications resulting from two selection processes. One is the problem of sample selection arising from the work choice decision; the other is the selection into union status. If these two selection processes are determined by some unobserved factors that also affect wages, the union wage effects estimated from models that do not account for these possibilities are likely to be biased. However, within a quantile regression framework it is not easy to deal with either of the two selection processes, although standard approaches are available in the OLS framework. In addition, identifying instruments for the determination of union membership status are not available in the data. Consequently, in this study we do not control for potential biases arising from the two selection processes. We leave this issue for future research.[10] Accordingly, the results reported here must be interpreted with caution.

Another issue is possible measurement error of union status. Without the workplace level data (employer-based or matched employer–employee data), we rely on self-reported union membership status, which could be problematic if respondents incorrectly identify their union status. In addition, as we focus on individual differences, rather than differences across bargaining units, we cannot distinguish between active and inactive unions. As a result, we may under-estimate the union wage effects (Wooden, 2001). Other than workplace size and industry we cannot include workplace-specific characteristics (such as capital–labour ratio and product market characteristics).

IV Results

(i) Single Equation Estimation

Figure 2 presents the coefficient estimates and their 95 per cent confidence intervals for the union dummy variable from both the quantile regression and OLS models. For quantile regression, the model is estimated at each 0.01 percentile point. From the 95 per cent confidence interval estimates in Figure 2, for men the union wage effects at quantiles below 0.1 are significantly larger than at other quantiles at the 5 per cent significance level; the effects at quantiles above 0.8 appear to be significantly smaller than at other quantiles. For women the differences of the estimated union wage effects at various quantiles appear to be insignificant.[11]

For ease of reading, Table 1 lists the coefficient estimates for the union dummy at selected percentiles and also the estimates from OLS for

[10] Using Heckman's two-stage approach within the OLS framework, we found that the sample selection term arising from employment status is not significant for men or women. This does not mean that the selection process is exogenous to the determination of wages at other points of the conditional wage distribution.

[11] Interquantile equality tests were also conducted to see whether the difference in the estimated coefficients for the union dummy at various, selected, quantiles is statistically significant. It was found that for men the differences were statistically different at the 5 per cent level between the 10th and the 25th, the 75th and the 90th, the 10th and the 50th, as well as the 50th and the 90th quantiles. However, among the quantiles selected, only the difference between the 50th and the 75th was statistically significant for women.

FIGURE 2
Coefficient Estimates for Union Dummy by Sex

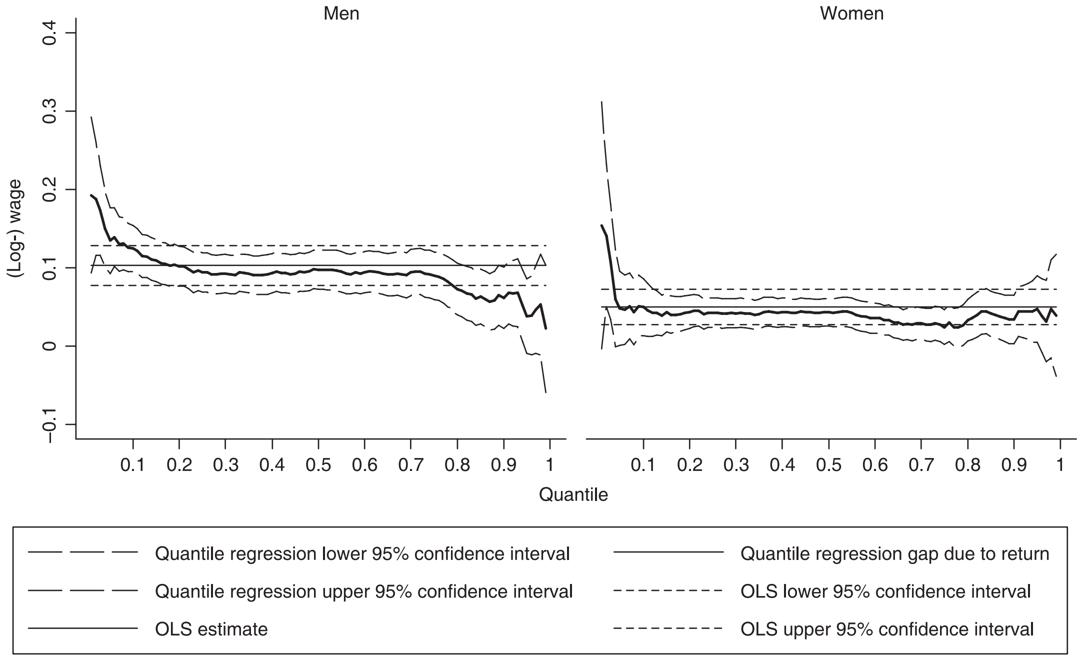


TABLE 1
Union Wage Effects in the Single Equation Model

	10%	25%	50%	75%	90%	OLS
Men	0.1249***	0.0941***	0.0974***	0.0898***	0.0616***	0.1032***
	(0.0151)†	(0.0129)	(0.0127)	(0.0155)	(0.0201)	(0.0130)‡
Women	0.0500***	0.0430***	0.0436***	0.0244**	0.0345**	0.0501***
	(0.0185)	(0.0097)	(0.0092)	(0.0114)	(0.0157)	(0.0113)

Note: *** Significant at 1 per cent level; ** 5 per cent level; and * 10 per cent level. † Standard errors for quantile regressions are bootstrapped using 500 replications and accounting for clusters in re-sampling. ‡ Standard errors for OLS estimates account for clusters.

men and women.[12] The OLS estimates in the last column show a 10 per cent wage premium for men union workers and 5 per cent for women union workers. These estimates are in line with the findings of most previous Australian studies.[13] More importantly the significant wage premium is found in our OLS models, even after controlling for workplace size. This contradicts the findings in Miller and Mulvey (1996) wherein the effects disappeared after they controlled for workplace

[12] Coefficient estimates for other variables are not shown here but are obtainable on request from the authors.

[13] Using the Survey of Training & Education 1993, Miller and Mulvey (1996) estimate union wage effects using the specifications from several earlier studies. Their results for the Mulvey (1986) model show that men (women) union workers are rewarded an hourly wage rate of 8.5 (4.9) per cent more relative to non-union workers. For the Blanchflower and Oswald (1989) specification, they find a union wage effect of 10.39 and 6 per cent for men and women, respectively. They also find a similar result for the Miller and Rummery (1989) model. The union wage effects for the Miller and Mulvey (1994) specification are 7.9 and 5.8 per cent (and 11.6 and 6.6 per cent after correction for selectivity in the manner of Christie (1992)) for men and women, respectively.

size. One explanation may be that widespread decentralised collective bargaining might have increased the influence of unions on wages, even though the unionisation rate declined (Wooden, 2001; Waddoups, 2005).[14]

As for the quantile regression results, ceteris paribus, both men and women union workers are found to have higher wages than non-union workers at all quantiles. These tend to be larger at the lower than at the upper end of the conditional wage distribution, particularly for men. For example, at the 10th percentile, men union workers enjoy a premium of about 12 per cent, while at the 90th percentile the premium is only about 6 per cent. These different effects may reflect the different unobserved determinants of wages between union and non-union workers at various parts of the conditional wage distribution.

Studies from the UK also find a larger union wage effect at the lower end of the conditional wage distribution and a smaller effect at the upper end of the conditional wage distribution (see Disney *et al.* 1995; O'Leary *et al.* 2004). Focusing on blue-collar workers in the USA, Chamberlain (1994) finds that for workers with 20 to 29 years of work experience, the estimate for the union dummy is much larger at the lower end (36 and 32 per cent at the 10th and 25th quantiles, respectively) than at the upper end (16 and 9 per cent at the 75th and 90th quantiles, respectively) of the conditional wage distribution; for workers with < 9 years work experience no such pattern is found.

Comparing the estimates from quantile regression estimates with those from OLS, it appears that for both men and women OLS tends to overestimate the union wage effect for most parts of the conditional wage distribution, except at the very bottom where the OLS model underestimates it. However, from Figure 2 the differences between OLS and quantile regression estimates appear insignificant for the entire conditional wage distribution for women; for men, the differences appear significant at some quantiles at the bottom and top ends of the conditional wage distribution.[15] The quantile regression estimation suggests that the rate of change of the unobservables is different at different quantiles for men but it is not the case for women. One possible explanation for the difference between men and women is that women may be reluctant to bargain aggressively, either due to the virtue of being women or gratitude of a few at the top end at getting a top job which is usually dominated by men. Or it may simply be the lack of information about what men with similar jobs are paid. This could explain the relatively small and stable pattern in the rate of change of the observed wage differences between union and non-union women workers at different quantiles in contrast to that between union and non-union men workers. This by itself is an interesting finding that OLS fails to offer.

The single equation estimation results must be interpreted with caution, because they rely on the assumption that the wage determination process is identical for both union and non-union workers. This assumption may be violated if unions also affect the returns to factors such as education. To see whether the model should be estimated separately for union and non-union workers, we experimented through making interactions of each independent variable with the union dummy. If the interaction terms are jointly significant, the independent variables affect union and non-union workers differently. The test statistics are reported in Appendix Table A2. The results overwhelmingly reject the hypothesis that workers are subject to the same wage determination process, irrespective of union membership. Therefore, the union wage effects estimated using the single equation model are likely to be misleading; separate wage determination equations for union and non-union workers and decomposition methods are required to provide a more reliable picture of the union wage effects.

(ii) Quantile Regression Decomposition

Previous research has shown that while the union wage differential can be partially explained by observed differences in personal, job, and workplace characteristics, a significant proportion

[14] Christie (1992) also finds a significant union wage effect after controlling for firm size. However, she defines firm size as the number of workers employed Australia-wide by firms, and thus it is not the size of the establishment (or workplace). Miller and Mulvey (1996) argue that what matters in the relationship between firm size and wages is the workplace, not the corporate entity. After including a more appropriately defined firm size variable in the equation estimated by Christie (1992), Miller and Mulvey (1996) find that there is only a small union wage effect. They hence attribute the significant effect reported by Christie (1992) to the deficiency of the firm size variable she used.

[15] For example, for men the quantile regression estimates at the 2nd, 3rd, 82nd to 88th and 95th to 97th percentiles are statistically different from the OLS estimate at the 5 per cent significance level.

remains unexplained. For example, in Canada the differences in such characteristics account for a large part of the pay differentials (about 75 per cent) (Fang & Verma, 2002). On the contrary, the differences in characteristics only explain 27.5 per cent in the United Kingdom (Arabsheibani & Martin, 2001). We follow the procedure described in Section II to examine to what extent the union wage differential could be explained by differences in observed worker characteristics and to what extent it could arise from differences in the returns to the observed worker characteristics.

To generate the samples for decomposition purposes, we estimate models for quantiles at [0.001, 0.003 … 0.997, 0.999] and at the median. There are 501 regressions for each gender and union membership status group and thus not all of the estimation results are reported.[16] There are clear differences in the coefficient estimates between union and non-union workers. For example, union workers start off, on average, with higher wages than do non-union workers. This is reflected by the larger intercept term of the union wage equations. Returns to marital status are lower for union workers than non-union workers. Returns to university degrees and experience are lower for male union workers than male non-union workers, with the opposite being true for women. For both men and women who are in a workplace of the same size, non-union workers earn higher wages than union workers. These differences further justify the estimation of separate models for union and non-union workers.

The decomposition attributes the total union wage gap to two components: one explained by the differences in observed wage determining factors (e.g. personal, job and workplace characteristics) and the other explained by the differences in returns to those factors. It is the latter component that can be regarded as union wage effects, because otherwise there should not be any difference in the returns. For this reason the reported results focus on the gap due to returns differences.[17]

Figure 3 shows the union wage gap attributable to returns differences at each 0.01 percentile point, together with bootstrapped 95 per cent confidence intervals. In bootstrapping the 95 per cent confidence intervals, 100 replications were used and the clustering of the observations resulting from the panel data was also taken into account. For men the union wage effect decreases monotonically, with a sharp fall from about 60 per cent to about 17 per cent occurring within the lowest 10 percentile range. At the 0.85 percentile point and above, the union wage effects become insignificant. For women there is also a sharp fall in the union wage effect at the bottom of the wage distribution.[18] But the decrease in the effect is not monotonic over the distribution. From about the 0.2 percentile point, the effect appears to increase up to the 0.6 percentile point and decreases again thereafter. But the changes in the effects do not appear significant between the 0.1 and 0.8 percentile range. This suggests that the union wage effects for women are quite stable in most part of the wage distribution. For women, the effect becomes insignificant at the 0.8 percentile point and above. Overall, the union wage effect is larger for men than for women workers, consistent with the findings using the single equation quantile regression and the OLS model.

The horizontal line in the figure shows the union wage effect estimated using the OLS decomposition method.[19] It masks the variations of the union effect, particularly at the bottom and top ends of the male wage distribution. The 95 per cent confidence intervals in Figure 3 indicate that for men the OLS estimate appears statistically smaller than the quantile regression estimate for percentiles below 0.1, and statistically larger than the quantile regression estimate for percentiles above 0.8. For union workers in the bottom 10 per cent of the wage distribution, the OLS estimate understates

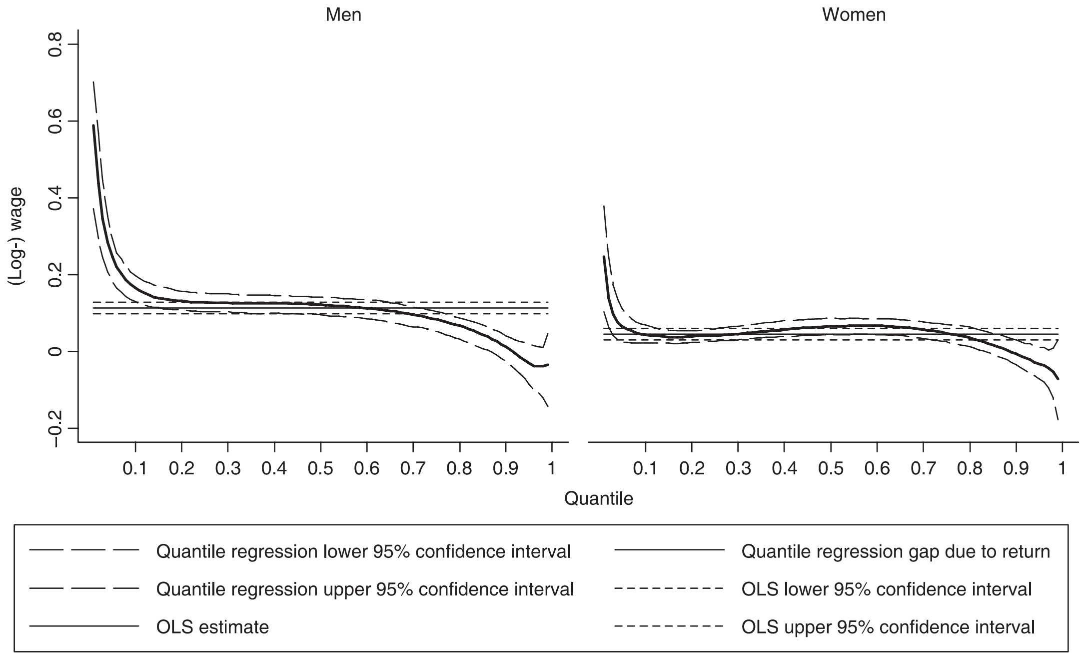
[16] Selected quantile regression results, together with OLS estimates, can be obtained from the authors.

[17] We also compared the decomposition results using the pooled data to those obtained using each of the four waves. Although the point estimates from each wave are not identical, there are no systematic differences between the waves. In addition, except for the 0.2 to 0.4 quantile range of wave 2 and the very top end of wave 4 for women, the estimates from each wave fall within the confidence intervals of the pooled data estimates.

[18] It is not clear what causes the extremely large union effect and thus the sharp fall of the effect at the very bottom of the wage distribution. Wages paid at below the legally specified minimum to illegal migrants who are not represented by unions may be a possible explanation; union workers are far less likely to be subject to illegal wage payments than are non-union workers.

[19] The OLS estimate is computed as $\bar{x}^u(\beta^u - \beta^n)$, using the Blinder–Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973), where $\bar{x}^u$ refers to the means of the union sample; β^u and β^n refer to the OLS coefficient estimates from union worker and non-union workers, respectively.

FIGURE 3
Wage Difference due to Union Effects by Sex



the union effects. For union workers in the top 20 per cent of the wage distribution, the OLS result overstates the union effects. Altogether the OLS model provides misleading estimates of the union effect for about 30 per cent of male union workers. However, the proportion of female union workers for which the union effects are underestimated or overestimated is much smaller.

How much does the difference in returns account for the total wage gap between union and non-union workers? Table 2 reports the results at selected percentile points. Two total wage gaps are shown in the table; one is estimated from raw data and the other from simulated data. The simulated data are generated from the model, as described in Section II. If one believes that the model is correctly specified, the simulated data should better describe the underlying distribution of wages. This is because the simulated data have a much larger number of observations and the raw data can be viewed as a random draw from the underlying distribution. Nonetheless, we report the total wage gap from both datasets. The general conclusion does not change whichever total gap is used.[20]

Table 2 shows that a substantial proportion of the wage premium enjoyed by male union workers can be explained by differences in the returns to worker characteristics, but it is not the case for women. Although there are variations at different quantile points, the returns differences account for more than 70 per cent of the total wage gap for most men. However, for women the differential explained by the returns difference only accounts for about one-third or less of the total wage gap. These findings are in line with Wooden (2001) and Pocock (1995). They also find evidence to support the proposition that unions are more effective in generating wage premiums for men than for women workers.

Comparing Table 1 with Table 2 and Figure 2 with Figure 3, we notice some differences in the

[20] We compared the wage distributions between raw data and simulated data. The two distributions were found to be very close, although there were some discrepancies.

TABLE 2
Decomposition of Union Wage Gap

	Men			Women		
	Total wage gap†		Gap due to difference in returns‡	Total wage gap†		Gap due to difference in returns‡
Percentile	Raw data	Simulated data		Raw data	Simulated data	
0.10	0.1700 (97.57)	0.2032 (81.62)	0.1659 (0.1294, 0.1974)	0.1579 (27.53)	0.1699 (27.19)	0.0435 (0.0218, 0.0682)
0.25	0.1562 (81.92)	0.1679 (76.22)	0.1280 (0.1038, 0.1513)	0.1365 (30.60)	0.1423 (29.34)	0.0418 (0.0276, 0.0590)
0.50	0.1560 (77.50)	0.1395 (86.72)	0.1209 (0.0954, 0.1413)	0.1938 (33.46)	0.1853 (34.99)	0.0648 (0.0437, 0.0865)
0.75	0.0902 (91.99)	0.0712 (116.62)	0.0830 (0.0525, 0.1037)	0.1878 (25.16)	0.1769 (26.72)	0.0473 (0.0244, 0.0701)
0.90	−0.0481 (−23.99)	−0.0262 (−44.02)	0.0115 (−0.0259, 0.0409)	0.0984 (−6.18)	0.1019 (−5.96)	−0.0061 (−0.0353, 0.0294)
OLS	0.1197 (94.78)		0.1134 (0.0955, 0.1314)	0.1613 (28.02)		0.0452 (0.0274, 0.0630)

Note: † In parentheses is the percentage of the total gap explained by the difference in returns (the union effect), ‡ In parentheses are bootstrapped 95 per cent confidence intervals. Confidence intervals for quantile regression decomposition were bootstrapped using 100 replications and accounting for clusters in re-sampling. Confidence intervals for OLS decomposition used standard errors computed from the delta methods.

estimated union wage effects between the single equation model and the model that estimates the wage equations separately for union and non-union workers. For men, the single equation model tends to underestimate the union wage effect for the lower parts of the wage distribution and to overestimate it for the upper parts of the distribution. For women, there is no such pattern but still the single equation model overestimates the effect at the 90th percentile and underestimates it at the 50th percentile.

IV Conclusion

Previous research on union wage effects in Australia has only focused on the effect at the mean of the conditional wage distribution. Using the first four waves of the HILDA survey, this paper employs quantile regressions and a semi-parametric decomposition method to examine the union wage effects over the entire conditional wage distribution. The identification of the union wage effect at different conditional quantiles relies on the assumption that union status is independent of unobservables, such as ability. We found significant union wage effects over most of the conditional wage distribution. For men, the union wage effects are significantly higher at the lower than at the upper end of the conditional wage distribution, a result similar to a number of international studies. However, for women, the union wage effect is very stable, except at the very bottom and top ends of the conditional wage distribution. One explanation for why the union wage effects are larger at the lower end of the conditional wage distribution might involve the bargaining power of workers at different skill levels. Low wage earners have low skills and also low bargaining power. However, if low-skill workers are represented by unions, their bargaining power would be increased substantially compared with non-unionised low-skill workers. On the other hand, high wage earners have high bargaining power due to their specific skills; association with unions or not makes little difference in terms of bargained wage outcomes. In addition, due to the potential wage compression effects of unions (Freeman & Medoff, 1984), highly skilled union workers might earn less than their non-union counterparts.

We also found that across almost the entire conditional wage distribution unions have a larger effect on men than on women wages, which is a result similar to previous Australian studies using OLS models. The decomposition results show that for men, the union wage effects explain a substantial proportion of the observed wage gap between union and non-union workers; this is not the case for women. There may be several reasons for the larger union effects for men than for women. First, women's interests may not be effectively represented by mainstream union activity (Sap, 1993), perhaps due to the marginal nature of some women employment (part-time or casual workers). Second, even if unions could effectively represent women's and men's interests equally, because some women may be more interested in non-wage benefits such as maternity leave and child care arrangements than high wages per se, the effects of unions in the case of women may not show up in their wages as much as they do for men. Third, the distributional differences of men and women across industries may lead to the difference in the union wage effects between men and women if union wage effects vary across industries (Waddoups, 2005). For example, if women are more concentrated in industries with less union activity, the union wage effects for women will be smaller than otherwise. While we included industry dummies in our model, the effects of the distributional differences in industries might not have been fully accounted for by the dummies. Finally, as discussed earlier, different unobservables between men and women could also be an attributing factor. The exact reasons for the difference of the union wage effects between men and women require further investigation.

The significant effect of unions on wages in this study is found even after controlling for workplace size. This result is in contrast to Miller and Mulvey (1996) who, within an OLS framework, find that when the firm size variables are included in the wage model, the effect of unions becomes negligible. One possible explanation for such a difference may lie in the decentralisation of wage setting that occurred over the last decade. This reduced the effect of arbitration and offered opportunities for unions to exert their power in wage negotiation (Wooden, 2001; Waddoups, 2005).

This study has limitations. First, due to the data constraint the problem of selectivity, particularly selection into union status, could not be dealt with entirely satisfactorily. If wages and selection into unions are affected by some correlated unobservables, the estimates reported here might be biased. Second, we could only examine the effect of individual union membership on wages in this study. It is likely that this estimate does not reflect the true effect of unions if union negotiated wages in collective bargaining apply to both union and non-union workers (a spillover effect). Future research with richer data would perhaps provide deeper insight into the union wage effects over the period when Australia is undertaking important industrial reforms. Third, the quantile regression results rely on the assumption that the covariates, particular union status, are not related to the mean of the unobservables. The estimated union wage effects would be biased if this assumption does not hold.

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Appendix

TABLE A1
Summary Statistics of the Samples

	Men						Women					
	Union		Non-union		All		Union		Non-union		All	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Log-wage	3.0543	0.3807	2.9345	0.4914	2.9771	0.4587	2.9584	0.3793	2.7972	0.4284	2.8498	0.4203
Married	0.7869	0.4096	0.7486	0.4339	0.7622	0.4258	0.7047	0.4563	0.7211	0.4485	0.7158	0.4511
Degree	0.2539	0.4353	0.2708	0.4444	0.2648	0.4412	0.4540	0.4980	0.2445	0.4298	0.3126	0.4636
Other post-school qualification	0.4197	0.4936	0.3921	0.4883	0.4019	0.4903	0.2285	0.4200	0.2492	0.4326	0.2424	0.4286
Year 12	0.0986	0.2982	0.1168	0.3212	0.1103	0.3133	0.0906	0.2871	0.1732	0.3784	0.1463	0.3534
Lifetime employment	2.4508	1.0103	2.1519	1.0782	2.2582	1.0642	2.1227	0.8878	1.8227	0.9124	1.9203	0.9153
Lifetime employment^2	7.0267	5.1658	5.7932	5.2647	6.2319	5.2627	5.2936	4.0466	4.1547	3.8115	4.5253	3.9256
Indigenous	0.0105	0.1019	0.0109	0.1039	0.0108	0.1032	0.0138	0.1165	0.0123	0.1102	0.0128	0.1123
Immigrants from English speaking country	0.1028	0.3038	0.1300	0.3364	0.1203	0.3254	0.1067	0.3088	0.1104	0.3134	0.1092	0.3119
Immigrants from non-English speaking country	0.1124	0.3159	0.1247	0.3304	0.1203	0.3254	0.1077	0.3101	0.1272	0.3333	0.1209	0.3260
NSW/ACT	0.3471	0.4761	0.3047	0.4603	0.3198	0.4664	0.3735	0.4838	0.3041	0.4601	0.3266	0.4690
VIC	0.2548	0.4358	0.2559	0.4364	0.2555	0.4362	0.2134	0.4098	0.2762	0.4471	0.2557	0.4363
QLD	0.2011	0.4009	0.2046	0.4035	0.2034	0.4025	0.2037	0.4028	0.2060	0.4045	0.2052	0.4039
SA	0.0728	0.2599	0.0928	0.2902	0.0857	0.2799	0.0862	0.2808	0.0831	0.2761	0.0841	0.2776
WA/NT	0.0923	0.2895	0.1198	0.3247	0.1100	0.3129	0.0822	0.2747	0.1025	0.3033	0.0960	0.2946
TAS	0.0318	0.1754	0.0222	0.1472	0.0256	0.1579	0.0409	0.1982	0.0281	0.1654	0.0323	0.1768
Capital city	0.5914	0.4916	0.6604	0.4736	0.6359	0.4812	0.6121	0.4874	0.6333	0.4819	0.6263	0.4838
Part-time	0.0423	0.2012	0.0834	0.2765	0.0688	0.2531	0.3181	0.4658	0.4454	0.4971	0.4041	0.4907
Casual	0.0573	0.2324	0.1704	0.3760	0.1302	0.3365	0.0930	0.2904	0.3093	0.4622	0.2390	0.4265
Part-time and casual	0.0171	0.1296	0.0622	0.2415	0.0462	0.2098	0.0725	0.2593	0.2445	0.4298	0.1886	0.3912
White collar workers	0.2803	0.4492	0.3408	0.4740	0.3193	0.4662	0.5326	0.4990	0.2674	0.4426	0.3536	0.4781
Other white collar workers	0.2788	0.4485	0.3098	0.4625	0.2988	0.4578	0.3829	0.4862	0.6189	0.4857	0.5422	0.4982
Blue collar workers	0.4400	0.4965	0.3487	0.4766	0.3812	0.4857	0.0846	0.2783	0.1137	0.3174	0.1042	0.3055
Having health conditions	0.1571	0.3639	0.1471	0.3542	0.1506	0.3577	0.1436	0.3508	0.1295	0.3358	0.1342	0.3409
Workplace size <20	0.2167	0.4121	0.3911	0.4880	0.3291	0.4699	0.1977	0.3983	0.4454	0.4971	0.3649	0.4814
Workplace size 20–99	0.3132	0.4639	0.3067	0.4612	0.3090	0.4621	0.3574	0.4793	0.2857	0.4518	0.3090	0.4621
Workplace size 100–199	0.1556	0.3625	0.0943	0.2923	0.1161	0.3203	0.1349	0.3417	0.0800	0.2714	0.0979	0.2971
Workplace size 200–499	0.1472	0.3543	0.0923	0.2895	0.1118	0.3152	0.1372	0.3442	0.0770	0.2666	0.0966	0.2954
Workplace size 500+	0.1604	0.3670	0.1080	0.3104	0.1266	0.3326	0.1601	0.3667	0.0985	0.2980	0.1185	0.3232
Workplace size unknown	0.0069	0.0828	0.0076	0.0869	0.0074	0.0855	0.0128	0.1122	0.0134	0.1151	0.0132	0.1141
Mining†	0.0423	0.2012	0.0281	0.1653	0.0332	0.1790						

Table A1
Continued

	Men						Women					
	Union		Non-union		All		Union		Non-union		All	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Manufacturing	0.1799	0.3841	0.1969	0.3977	0.1908	0.3930	0.0460	0.2095	0.0755	0.2642	0.0660	0.2483
Electricity/gas[†]	0.0297	0.1697	0.0121	0.1092	0.0183	0.1342						
Construction[†]	0.0770	0.2667	0.0781	0.2683	0.0777	0.2677						
Whole sale	0.0207	0.1423	0.0763	0.2654	0.0565	0.2309	0.0081	0.0894	0.0404	0.1970	0.0299	0.1703
Retail	0.0336	0.1802	0.1055	0.3073	0.0799	0.2712	0.0738	0.2615	0.1196	0.3246	0.1047	0.3062
Accommodation/restaurant	0.0192	0.1372	0.0394	0.1945	0.0322	0.1765	0.0134	0.1151	0.0574	0.2326	0.0431	0.2031
Transport	0.0884	0.2840	0.0605	0.2385	0.0705	0.2559	0.0188	0.1358	0.0239	0.1528	0.0223	0.1475
Community services	0.1067	0.3088	0.1998	0.3999	0.1667	0.3727	0.0960	0.2946	0.2039	0.4029	0.1688	0.3746
Government	0.1109	0.3141	0.0625	0.2421	0.0797	0.2709	0.0695	0.2543	0.0574	0.2326	0.0613	0.2399
Education	0.1328	0.3394	0.0455	0.2084	0.0765	0.2659	0.3117	0.4633	0.1266	0.3325	0.1868	0.3898
Health	0.0650	0.2466	0.0371	0.1889	0.0470	0.2117	0.3070	0.4613	0.2100	0.4074	0.2415	0.4280
Culture	0.0231	0.1502	0.0313	0.1740	0.0284	0.1660	0.0141	0.1179	0.0255	0.1578	0.0218	0.1461
Other industries	0.0698	0.2549	0.0260	0.1591	0.0416	0.1996	0.0406	0.1974	0.0590	0.2357	0.0530	0.2241
Year dummy for Wave 2	0.2527	0.4346	0.2541	0.4354	0.2536	0.4351	0.2483	0.4321	0.2521	0.4342	0.2508	0.4335
Year dummy for Wave 3	0.2455	0.4304	0.2475	0.4316	0.2468	0.4312	0.2466	0.4311	0.2461	0.4308	0.2463	0.4309
Year dummy for Wave 4	0.2305	0.4212	0.2392	0.4266	0.2361	0.4247	0.2376	0.4257	0.2348	0.4239	0.2357	0.4244
Number of observations	3336		6045		9381		2980		6185		9165	

Note: [†] For women, because of the very few observations, mining, electricity and gas, and construction industries are combined with the 'other industries'. SD, Standard deviation.

Table A2
F-Statistics on the Joint Significance of the Interactions between Union Status and other Independent Variables

	10%	25%	50%	75%	90%	OLS
Men	2.94***	4.02***	4.46***	5.65***	4.74***	3.38***
Women	2.08***	2.16***	3.81***	4.19***	3.22***	2.76***

Note: ***Significant at the 1 per cent level.