The gender wage gap within the managerial workforce: an investigation using Australian panel data

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Abstract

This paper examines the gender pay gap among full-time managers in Australia over the period 2001 to 2007. It finds that women full-time managers earn about 25 per cent less than their male counterparts. Decomposition methods show that between 70 and 90 per cent of this earnings gap cannot be explained by recourse to a large range of demographic and labour market variables. A large part the earnings gap is simply due to women managers being female. Despite the characteristics of male and female managers being remarkably similar, their earnings outcomes are very different, suggesting that discrimination plays a major part. The paper uses seven waves of HILDA data to fit both OLS and multilevel models to a sample of full-time managers. The regression results become the basis for a number of decompositions, using a variety of Blinder-Oaxaca-style methods. In addition, a recent 'simulated change' approach, developed by Olsen and Walby in the UK is also implemented using this Australian data.

1 Introduction

Until the early 1970s the gender wage gap in Australia was wide, and was kept that way by 'institutionalised gender wage discrimination', in the words of Paul Miller (1994, p. 371).[1] The historic equal pay decisions of 1969, 1972 and 1974 ended this, and helped close the gap considerably (see, for example, Gregory and Duncan (1981); Borland (1999)). Nevertheless, a gender pay gap of considerable size has remained, as Borland noted in his overview at the end

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[1] This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views reported in this paper, however, are those of the author and should not be attributed to either FaHCSIA or the MIAESR.

of the 1990s. He summarised a number of studies, which showed estimates for the wage gap during the 1980s and 1990s ranging from about 8 per cent through to about 25 per cent (Borland, 1999, p. 267). Borland also summarised the 'discriminatory component' of this gap as ranging from about 7 per cent to about 19 per cent, a considerably portion of the actual gap. He concluded that most of the reduction in the wage gap since the early 1970s was due to a 'decrease in wage discrimination' (Borland, 1999, p. 268).

The early equal pay cases did not fully pursue the labour market dimension of the gender pay gap, particularly occupational-based gender segregation. By the 1990s, this had become the focus for pay equity inquiries (such as that in NSW) and the concept of comparable worth became central Pocock (1999). Using data from the late 1980s, Miller (1994) found a gender wage gap of about 13 per cent, with a large component of that gap (6 percentage points) due to occupational concentration . As Miller noted: 'about 40% of the differential might be removed by the implementation of true comparable worth' (1994, p. 367). Using a comparable, but later data set, Wooden (1999) also examined the issue of comparable worth. While the actual wage gap was smaller in Wooden's study (11.5 per cent), his results were broadly similar to Miller's. Wooden found that occupational concentration accounted for 4.2 percentage points, that is, about one third (1999, p. 167).

Wooden, however, argued that including the managerial workforce in such studies was unwarranted. When he removed managers from the sample, he found that the gender wage gap fell to 8.9 per cent, with the occupational concentration component now accounting for 3.6 percentage points. Wooden noted that the under-representation of women in senior management positions in Australian companies was likely to widen the gender wage gap, because managers earned much more than the all-occupational average. As a consequence, he concluded, this removed the scope for industrial tribunals to eliminate a considerable part of the gender wage gap because 'the earnings of managers typically lie outside the purview of industrial awards'. Wooden further added, 'the problem is not necessarily one of unequal earnings, but rather of unequal access to promotion' (Wooden, 1999, p. 167). The implications of this argument will be pursued at length in the discussion section of this paper.

While much of the research on the gender pay gap has focussed on the workforce more generally, or at least the full-time workforce, recent studies have begun to examine the gap across the entire wage distribution, pursuing the recognition that the gap is not uniform across this distribution. Innovations in the use of quantile regression methods (for example, Buchinsky (1998); Koenker and Hallock (2001)) has opened up this field of research. In Australia, both Miller (2005) and Kee (2006) have used this approach to explore the gender pay gap.

Miller found that the wage gap was much greater among high wage earners than among low wage earners:

> the gender wage gap generally widens as one moves up the wage scale. The wage differentials are below 10 per cent from the 5th to the 35th quantile, and then the gap increases from 12 percentage points at the 40th quantile to 23 percentage points at the 95th quantile (2005, p. 412).

This led him to argue: 'while the policy debate on the gender wage gap needs to focus on all parts of the wage distribution, there is a particular need for attention among high-wage earners' (2005, p. 412).

Kee's study extended Miller's by separately analysing the public and private sectors. She found that the gender pay gap increased at higher levels in the private sector—leading to her conclusion that a 'glass ceiling' existed there—but that the gap in the public sector was 'relatively constant' over all percentiles (Kee, 2006, p. 424).

In this paper I look more closely at the top of the wages distribution by examining the gender pay gap among full-time managers.[2] Among this subpopulation, this gap is distinctively larger, while at the same time confounders like occupational-based gender segregation and part-time/full-time wage ratios are largely absent (see, for example, Whitehouse (2001)). The approach I take implements various classic Blinder-Oxacaca-style decompositions, but I also consider a more recent 'simulated change' approach, developed by Wendy Olsen and Sylvia Walby in the UK (Olsen and Walby, 2004; Walby and Olsen, 2002). This approach is particularly relevant, because it allows researchers to examine more closely some of the policy-related dimensions of the gender pay gap.

2 The decomposition of wage differentials

2.1 The Blinder-Oaxaca tradition

The use of Blinder-Oaxaca-style decompositions have been a mainstay of sociological and economic analysis for the last 35 years. Since their pioneering work in the early 1970s, the core approach of Blinder (1973) and Oaxaca (1973) has been reproduced many times, though with variations and extensions to accommodate methodological weaknesses and different assumptions. The core technique is quite straightforward. After fitting separate regressions for men and women, the predicted wage gap is decomposed into that component based on the differing characteristics of each group, and another component based on how those characteristics are rewarded in the labour market (the regression coefficients). Only the difference in characteristics can be readily explained, and in this sense, the unexplained portion of the wage gap can be regarded as discriminatory. From within a human capital framework, the differences in characteristics have usually been referred to as a difference in 'endowments' (Blinder, 1973) or as a 'productivity differential' (Oaxaca and Ransom, 1994). The unexplained component has been variously referred to as the 'coefficients effect' or, more generally, the 'discrimination' component.

While it is common to see the terminology of 'endowments' and 'discrimination' used throughout the literature, it is important to keep in mind several caveats around these terms. The first term is usually based on human capital assumptions about wages and productivity, giving rise to a preference for a more neutral term like 'characteristics'. The term 'discrimination' can be misleading: within the decomposition method it is only ever identified as a residual, the part that cannot be explained by the characteristics of the sample. In the words of Dolton and Makepeace (1986, p. 332), 'the residual is really a measure of our ignorance'. In this paper, my own preference is to use the terms 'characteristics' and 'unexplained'.

[2] The terms wages, pay and earnings are used interchangeably in this report. The analysis focuses on annual wage and salary income, so the term earnings is probably more accurate than wages (which implies an hourly rate), but the relevant literature generally uses the terms 'pay gap' and 'wages gap'.

The core decomposition approach can be illustrated as follows. The wage gap between the two groups can be viewed as the difference in the predicted means of the (natural) logs of male (m) and female (f) wages, and following the fitting of separate regression functions, it can be represented by:

$$\hat{w}_m - \hat{w}_f = \Sigma\beta_m\bar{X}_m - \Sigma\beta_f\bar{X}_f \tag{1}$$

where the βs are the regression coefficients and the $\bar{X}$s are the vectors of mean characteristics. Re-arranging the terms, and representing the wage gap by G_{mf}, it is straightforward to show that there are at least two ways of decomposing this wage gap:

$$G_{mf} = \Sigma\beta_f(\bar{X}_m - \bar{X}_f) + \Sigma\bar{X}_m(\beta_m - \beta_f) \tag{2}$$

$$G_{mf} = \Sigma\beta_m(\bar{X}_m - \bar{X}_f) + \Sigma\bar{X}_f(\beta_m - \beta_f) \tag{3}$$

In each case, the first part of the right-hand sides of these equations contain estimates of the differences in the characteristics of males and females, *weighted* by the female (2) and male (3) coefficients. In other words, the differences in the characteristics of each group are rewarded according to the wage structure of females or males (depending on which decomposition is used). The second set of terms in these equations capture the 'discrimination' component: they measure the differences in each wage structure—how the labour market differentially rewards each group—applied to the male (2) and female characteristics respectively (3). (See Neumark (1988, p. 281) and Cotton (1988, p. 236)).

It is clear from these two equations that a key choice within the decomposition approach is deciding what constitutes the non-discriminatory benchmark against which to weight the differences. Regarding the female wage structure as non-discriminatory leads to a 'privilege model' of discrimination, in that males earn more than they should in a non-discriminatory world. On the other hand, regarding the male wage structure as the norm leads to a 'deprivation model' in which females earn less than they would in a non-discriminatory world (Jones and Kelley, 1984, p. 331).[3]

Lying behind these equations are different assumptions about the operations of the labour market. In the case of equation (2), males earn an undeserved premium in the labour market, and an absence of discrimination would see the female wage structure applied uniformly across the labour market. In the case of equation (3), females are penalised in the labour market, and ending discrimination would see the rate of return on their characteristics come to match that of the male wage structure. In either case, a non-discriminatory wage structure would result in a wages gap which reflected only (non-discriminatory) differences in characteristics.

Much of the literature subsequent to the early work of Blinder and Oaxaca has concentrated on examining different non-discriminatory benchmarks. These have gone beyond equating non-discrimination with either the male or female wage structure. Reimers (1983, p. 573), for example, suggested that in 'non discriminatory world' the wage structure by which to weight the differences would most likely lie somewhere in between. Cotton (1988, p. 238), in the context of racially based wage gaps, took a similar view:

[3] Jones and Kelley present their decomposition with an 'interaction term', which they define as $\Sigma(\beta_m - \beta_f)(\bar{X}_m - \bar{X}_f)$. They note that the deprivation model allocates this interaction term to the unexplained differences component while the privilege model allocates it to the characteristics component (1984, p. 331).

> ... not only is the group discriminated against undervalued, but the preferred group is overvalued, and the undervaluation of the one subsidizes the overvaluation of the other. Thus, the white and black wage structures are both functions of discrimination and we would not expect either to prevail in the absence of discrimination.

Where Reimers took the average difference between the male and female wage structures, Cotton weighted the white and black wage structures by the proportions of each group in the labour force (1988, p. 239). Neumark (1988) regarded these benchmarks as unsatisfactory and argued that the choice of a non-discriminatory wage structure should be based on theoretical grounds. Using Beckers' theory of employer discrimination (Becker, 1971), Neumark derived an 'estimable no-discrimination wage structure' (1988, p. 283) which he used as his weighting scheme. In a similar fashion Oaxaca and Ransom (1994, p. 9) criticised both Reimers and Cotton for adopting a non-discriminatory wage structure which was basically 'arbitrary'. Like Neumark they proposed as their non-discriminatory wage structure a weighting matrix based on the OLS estimates from a pooled regression (of both males and females), arguing that these pooled estimates reflected 'the wage structure that would exist in the absence of discrimination' (1994, p. 11).

These approaches are summarised in Table 1, which draws upon the presentation of results developed by Oaxaca and Ransom (1994, p. 13). It is useful because it makes the non-discriminatory benchmark explicit, and it also shows that the unexplained or 'discriminatory' component can be further decomposed:

$$G_{mf} = \Sigma\beta^{*}(\bar{X}_m - \bar{X}_f) + \Sigma\bar{X}_w(\beta_m - \beta^{*}) + \Sigma\bar{X}_f(\beta^{*} - \beta_f) \qquad (4)$$

Here β^{*} makes explicit the non-discriminatory wage structure. As before, the first term on the right-hand side shows the differences in male and female characteristics weighted by a particular wage structure, in this case, the non-discriminatory benchmark β^{*}. The second and third terms represent the last part of equations (2) and (3) in which the unexplained component is now decomposed into that part which reflects male privilege and that part which reflects female disadvantage. The last two columns in Table 1 show the weighting matrix which is applied in each of the approaches listed. The diagonals of this matrix consist of either 1s or 0s (identity matrix and the null matrix) in the first two approaches; a set of ratios (0.5 and the female-male ratio) in the Reimers and Cotton approaches; and a set of weights based on the differences between the pooled regression coefficients and the separate male and female regression coefficients (the Neumark and Oaxaca and Ransom approaches).

Table 1: Decomposing wage gaps: conceptual framework

Approach	Non-discriminatory benchmark	Unexplained ('discrimination') decomposed into: Male advantage	Female disadvantage
Deprivation	Male	0	I
Privilege	Female	I	0
Reimers	Male-female average	0.5	0.5
Cotton	Female-male ratio	f/m	$1 - f/m$
Pooled	Pooled coefficients (p)	$m - p$	$p - f$

Note: There is actually no further decomposition in the privilege and deprivation models (since the null matrix removes the non-applicable term) but they are shown in this table in this way so that all approaches can be compared within the one framework.
Source: Based on Oaxaca and Ransom (1994, p. 13).

As well as the tradition outlined here, other decomposition approaches have been taken within labour economics. Another popular strategy has been to implement a Juhn-Murphy-Pierce decomposition (see Juhn et al. (1991)), but as Neuman and Oaxaca (2004, p. 3–4) argue, the estimation results using JMP decomposition are largely the same as those produced by using the pooled approach developed by Oaxaca and Ransom (1994) and shown in Table 1 above.

Which of the approaches shown in Table 1 used be used for analysing the gender pay gap among managers? One might argue that if the focus were those workers at the bottom of the wage distribution, then a principle of 'equalizing upwards' (Supiot, 2009, p. 62) should apply and a deprivation model approach would be appropriate. Given that managers occupy the opposite niche—at the top of the wage distribution—then a privilege model is probably more appropriate and the interests of social justice would favour an 'equalizing downwards' principle.

There framework outlined in Table 1 does not utilise a detailed breakdown of the unexplained component, neither for individual variables nor for the intercept. The earliest decomposition formulations, such as Oaxaca (1973), presented detailed results, and also separated the intercept, regarding it as a 'group membership' component. However, it soon became apparent that such an approach was subject to an identification problem. As early as 1984, Jones and Kelley (1984, pp. 334–337) noted that the use of continuous variables which did not have a 'natural' zero point, and the use of categorical variables, could produce arbitrary results. In particular, recoding a dummy variable to have a different omitted category could change the relative contributions of the intercept and the other terms in the unexplained component. Oaxaca and Ransom (1999, pp. 154) showed that this identification problem also bedevilled attempts to isolate the separate contributions of any of the dummy variables within the unexplained component. They did, however, show that this problem did not apply to the summed terms of the unexplained component (as set out in Table 1 above). Until recently, this identification problem has left attempts at detailed decompositions in something of a limbo. As Yun observed:

> Economists have innocently ignored the identification problem when applying decomposition analysis empirically or have simply given up the detailed decomposition of the coefficients effect (2005, p. 771).

Yun herself provides one solution, as do Gardeazabal and Ugidos (2004, p. 1035): use a normalized equation and employ the mean characteristics of each categorical variable. Yun does this through a restricted least-squares estimation approach (2005, p. 771), while Gardeazabal and Ugidos (2004, p. 1035) achieve the same goal by restricting the coefficients to sum to zero, that is, through a transformation of the dummy variables. In practice this amounts to using so-called deviation contrast coding (also called 'effect coding'), such that for any particular categorical variable, the coefficient of each category reflects a deviation from the grand mean. This is the approach adopted in this paper for producing the detailed decomposition tables shown below.[4]

2.2 A simulated change approach

As noted earlier the Blinder-Oaxaca approach is not the only way to decompose the gender pay gap. A recent innovation developed by Sylvia Walby and Wendy Olsen in the UK (Walby and Olsen, 2002; Olsen and Walby, 2004) has emphasised the importance of pooled regressions, rather than the separate regressions which are at the core of many of the traditional methods.[5] As they argue: 'using separate regressions for women and men implies untenable assumptions as to the separation of male and female labour markets' (Olsen and Walby, 2004, p. 5). In the case of managers, this argument has considerable purchase, particularly given the similar profiles which male and female managers exhibit (with the exception of their industry distinctiveness).

The approach developed by Olsen and Walby (Olsen and Walby, 2004, pp. 63–70) entails fitting a pooled regression and then using simulated changes in the characteristics of the sample to quantify the contribution made by gender to the actual wages gap. In practices, one multiplies the (pooled) model coefficients by the gender difference in the mean values for each of the variables in the model. This can be represented by:

$$\bar{w}_m - \bar{w}_f = \sum \beta' \Delta X \tag{5}$$

where ΔX represents the difference in two means ($\bar{x}_m - \bar{x}_f$) for each variable. In the case of dummy variables—such as gender itself—the difference represents a switch from one category to another (eg. male to female). Olsen and Walby term ΔX a 'change factor' and by multiplying it by β they calculate a 'simulation effect' (that is, $\beta' \Delta X$). This simulation effect can be expressed as a percentage of the pay gap, and also, conveniently, as a monetary equivalent of the actual pay gap. (Glancing forward to Table 11 may make this exposition clearer.)

Olsen and Walby note that their approach is similar to using standardised regression coefficients, but without the incoherent treatment of binary variables entailed in that method. Instead,

> an explicit simulation, in which is variable is treated substantively and is examined to see how far a reasonable hypothetical change would affect the outcome, is even better than beta coefficients (Olsen and Walby, 2004, p. 69).

[4] Note that all the regression results shown in the appendix use the more conventional treatment contrast coding, since the interpretation of dichotomous dummy variables is more straightforward (for example, the coefficient is a simple contrast with the omitted category, rather than a contrast with the average between the two.)

[5] With the exception of Oaxaca and Ransom (1994); Neumark (1988) who also used pooled regressions, as shown in the last row of Table 1.

One can apply this approach to all of the variables in the regression, or to just a subset. Olsen and Walby, for example, argue that some variables should just be regarded as controls (such as region, or industry) while others are regarded as having more policy relevance (such as working hours or education). By hypothesising a change in the latter, the researcher can examine those factors which influence the wages gap and which are amenable to policy initiatives. In practice, this approach makes it possible to estimate the change in earnings 'that would occur if women's conditions changed to reflect the best or the average situation among men'(Olsen and Walby, 2004, p. 66). In this respect, they come closer to the assumptions of the 'deprivation' approach discussed earlier.

As an example, one can examine the simulation effect of any particular variable—such as years of part-time work—and express this as a percentage of the pay gap. Using British Household Panel Survey data, Olsen and Walby (2004, p. 65) find that this particular variable has a simulation effect of 0.02, which accounts for 10 per cent of the gross wages gap of 0.23. This variable can then be given a monetary value, namely 24 pence per hour (10 per cent of the £2.28 wages gap). In the final section of this paper, I implement the Olsen/Walby approach and illustrate its relevance in the Australian setting.

3 Modelling issues

3.1 Sample selection bias

The sample of persons under scrutiny in this paper are only a subset of all persons contained in the HILDA survey dataset. Only employees working as full-time managers are included in the modelling dataset and these exclusions have important implications for fitting earnings equations. The modelling must deal with problems of sample selection bias, that fact that only a subset of individuals are observed within this category of interest, and only some of these are observed in all years. If such selectivity were purely random this would not be an issue, but the factors which influence selection into the sample may to be correlated with the regressors which predict the outcome of interest, namely earnings. If such factors are observable, then they can be included in the regression model and bias in the estimates can be overcome. However, the possibility that unobservable factors influence selection into the sample remains an obstacle. A large literature has evolved devoted to this problem (see, for example, the overview in Vella (1998)). The issue is particularly pertinent to studies of women's wages, given the labour force participation decisions entailed (see, for early examples, Dolton and Makepeace (1986); Bloom and Killingsworth (1982)). Sample selection bias was also an obvious issue confronted at an early stage in the decomposition literature (for example, Reimers (1983).)

It is important to be clear about what is at stake. In much of the literature on sample selection, illustrated by women's wages, the issue is one of being able to generalise to what all women would earn when we only observe a subset of them actually working. However, in the case of this study, we are not seeking to generalise to a larger group, of which managers are a subset. Rather, managers are the population of interest, and the sample is a sample of managers.[6] Despite this difference, the underlying predicament of selection bias remains: it is still the case that some unobservable factors may influence both who becomes a

[6] Though it could be argued that the exclusion of part-timers makes this a comparable analogy, but for practical purposes, the numbers involved are very small.

manager, and what they are paid. In this respect, the necessity to correct for sample selection among managers is as important for males as for females.[7]

While maximum likelihood estimators are often used to model both selection and earning equations simultaneously, in this study I make use of the Heckman two-step approach (Heckman, 1979). It has a number of advantages when it comes to more complex models, such as multilevel models, not least its computational simplicity. The most common selection models are binary—working or not working—and are fit using probit regression. In this case, the potential outcome is threefold—working as a full-time manager, not working as a manager, or not working at all, and a multinomial logit model is more appropriate (see, for example, Rodgers (2002)). The following selection equation for individual, i, in each group j (males and females) takes the form:

$$\begin{aligned} Pr(Y_{ij} = 0) &= \frac{1}{1 + e^{\gamma_1' Z_{ij}} + e^{\gamma_2' Z_{ij}}} + \epsilon_{ij} \\ Pr(Y_{ij} = k) &= \frac{e^{\gamma_k' Z_{ij}}}{1 + e^{\gamma_k' Z_{ij}} + e^{\gamma_2' Z_{ij}}} + \epsilon_{ij} \qquad k = 1,2 \\ \epsilon_{ij} &\sim N(0,1) \end{aligned} \tag{6}$$

where $k = 0, 1, 2$ for not working at all, working, and working as a full-time manager, respectively. ϵ_{ij} is the usual error term and Z represents a matrix of characteristics likely to influence whether an individual is observed in the particular category of interest. The details of the variables used in this model are discussed below; suffice it to note that after running this model separately for each group (that is, males and females), the inverse of Mills ratio (for working as a full-time manager) is calculated for each observation in the sample, and this term is then incorporated into the earnings equation in the second stage as a 'correction' term.[8]

The main equation—the OLS earnings equation which is also fitted separately for males and females—takes the classic form:

$$\ln W_{ij} = X_{ij}\beta_j + c_j\lambda_{ij} + \epsilon_{2ij} \tag{7}$$

where

$$\epsilon_{2ij} \sim N(0, \sigma)$$
$$\text{corr}(\epsilon_{ij}, \epsilon_{2ij}) = \rho$$

and where $\ln W_{ij}$ is the (log) of the annual earnings for each individual, i, in each group, j. The term X is a matrix of relevant demographic and labour market explanatory variables, λ is the correction term for the selection effect, and ϵ is the usual error term. If the error term for the earnings equation (ϵ_{2ij}) and the error term for the selection equation (ϵ_{ij}) are correlated (if $\rho \neq 0$), then a

[7] For example, in some labour-market wide studies, the correcting for sample selection bias is only applied to women workers.

[8] For details on the construction of the inverse of Mills ratio, see Cameron and Trivedi (2005, p. 550) For its construction following multinomial logit, see Rodgers (2002, p. 235) Hamilton and Nickerson (2001, pp. 38–39). To ensure identification, without relying on the functional form, variables related to the presence of young children (which were not included in the earnings model) were included in the multinomial logit model. The full details are discussed later in the paper.

'selection effect' would appear to be operating. This can be tested with a Wald test on the coefficient c_j in the earnings equation. A statistically significant result endorses the presence of a selection effect.

This approach is useful because it 'corrects' the coefficients in the earnings equation for the effect of selection bias, and in that respect, plays an important role. Where the debate lies, from the point of view of the decomposition literature, is where to assign the selection effect itself within the final decomposition. The selection effect takes the following form:

$$\hat{c}_m \bar{\lambda}_m - \hat{c}_f \bar{\lambda}_f \tag{8}$$

where m refers to males and f to females. Reimers (1983), for example, regarded (8) as a separate category from the characteristics and discrimination effects and proceeded to decompose an 'adjusted wage gap', that is, the wage gap which had been corrected for selection bias. Nevertheless, as Neuman and Oaxaca (2004) observe, where to assign the selection effect is a complex issue, involving a range of assumptions about how discrimination operates in the labour market. They note that the Reimers' approach is 'noncommital' about whether to assign this term to characteristics or discrimination, and it avoids some of the identification problems which can arise if one tries to assign the term in a more unequivocal fashion (2004, p. 8). As will be discussed below, I find that the selection effect is not statistically significant, so the decompositions carried out for this paper do not deal with this issue.

3.2 Panel data and multilevel modelling

There are a number of advantages in using panel data for this study. Because the category of interest is such a small group—full-time adult managers—sample size considerations are paramount. There are major gains in the precision of the estimates for the decomposition results from using a larger number of observations from pooling the data across all waves. Moreover, the use of multilevel modelling (also called mixed-effects modelling) with panel data also provides a correction to the coefficients.

Using a multilevel modelling strategy (see Pinheiro and Bates (2004) and Gelman and Hill (2007) for the approach taken in this paper) entails fitting a model with a fixed component—the usual set of earnings regression controls—as well a random component. The actual dataset observations can be regarded as 'earnings episodes', which are clustered within individuals, who themselves are clustered within households. On the one hand, this hierarchical data structure poses challenges for calculating standard errors—because of the violation of the *iid* assumption—but it also offers distinct advantages. Multilevel modelling provides a kind of 'partial pooling' of the data. In this respect, it avoids the pitfalls of complete pooling—which would lead us to ignore differences between individuals and suppress variation in the data—and, on the other hand, no pooling with its problems of unreliable estimates (Gelman and Hill, 2007, pp. 7, 256). One can, of course, fit a fixed-effects model to panel data, but a particular advantage of the multilevel approach is its ability to make use of sparse observations. Because the population of interest is small, the loss of every observation matters. A fixed-effects approach requires at least two observations on the same individual across the panel, whereas a multilevel approach can suffice when there is only one observation (Gelman and Hill, 2007, p. 276). In the case of the HILDA panel of managers used in this study, there are a large number of individuals (44 per cent) who only appear once in the panel, with females more likely to be in this situation (48 per cent) than males (41 per cent). Their omission does not just reflect absence from the labour market, but occupational mobility, and the fact that becoming a manager is a step some distance along the career pathway.

The coefficients for the fixed-effects from the multilevel model are used as the basis for the decomposition of the earnings gap. The error terms from the model can also be decomposed into their appropriate levels—episode, individual and household—for additional insights into the sources of earnings variability.

For the multilevel modelling, the earnings equation takes the form:

$$\ln W_{ijt} = X_{ijt}\beta_j t + c_j t \lambda_{ijt} + \epsilon_{ijt} \tag{9}$$

where $\ln W_{ijt}$ is the (log) the annual earnings for each individual i, in each group j, in period t. The term X_{ijt} is a matrix of relevant demographic and labour market explanatory variables, $c_{jt}\lambda_{ijt}$ is the correction term for the selection effect as discussed earlier, and ϵ_{ijt} is the usual error term. The *iid* assumption regarding this error term is violated, since the model contains repeated observations for the same individual.

In practice, the inverse of Mills' ratio is calculated for each wave of the data, and then incorporated into the pooled dataset. Equation (9) is then fitted to this dataset, using the specification required by a multilevel approach for varying intercepts (more details on this are provided below).

4 Data and descriptive overview

This paper draws on the Australian Government/Melbourne Institute's *Household, Income and Labour Dynamics in Australia Survey* (HILDA). This is an ongoing longitudinal survey of Australian households which began in 2001 and which is representative of the Australian population.[9] The data for this paper comes from Release 7.0. The descriptive data, and the single wave models, come from Wave 7 (2007). While this descriptive data uses cross-sectional respondent weights, the panel models are unweighted and make use of unbalanced panels.

There are two possibilities in choosing a sample of managers: all adult employees and all adult full-time employees (the choice of employee and adult is axiomatic if one wants to focus on labour market earnings without the complications of self-employment and junior rates of pay). Managerial occupations are one of the few occupational groups where most employees do work as full-timers: among males the percentage is 96 per cent and females it is 83 per cent. By way of comparison, the all-occupational percentages are, respectively, 87 per cent for males and 57 per cent for females.

The differing profiles of all managers and full-time managers are shown in Table 2 and there are several notable features of the data. The profile of *female full-time* managers differs little from that of *all female* managers, except for marital status—the former are more likely to be single—and organisational size—the former are more likely to be in smaller organisations.

[9] For more information on the HILDA survey, see the HILDA Survey User Manual, (Watson, 2008).

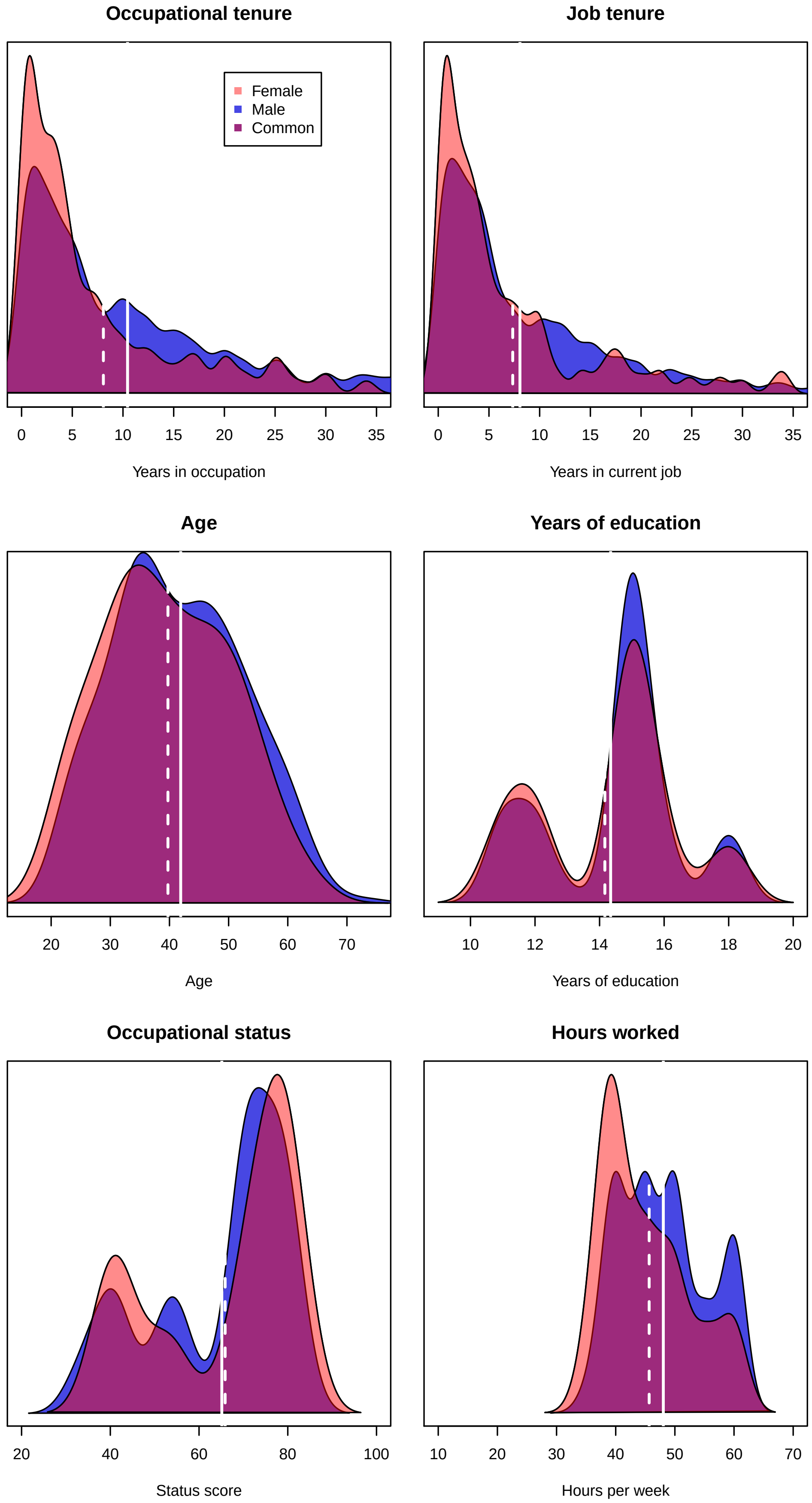
Table 2: **Overview of characteristics of managers: Australia 2007 (%)**

	All persons†			Full-timers‡		
	Female	**Male**	**Total**	**Female**	**Male**	**Total**
Age group						
Aged 21-24	7	6	7	8	4	7
Aged 25-29	8	9	10	9	9	10
Aged 30-34	22	15	16	20	15	16
Aged 35-39	16	17	17	16	18	17
Aged 40-44	11	13	12	11	14	12
Aged 45-49	14	11	15	13	11	15
Aged 50-54	11	12	11	12	12	12
Aged 55 or above	11	17	13	10	16	12
Education						
Uni	36	34	38	39	35	40
Vocational	29	37	33	27	37	33
Year 12	16	16	14	18	15	14
Year 11 or below	19	13	14	17	13	14
Marital status						
Couple	72	79	77	69	80	77
Single	28	21	23	31	20	23
Industry						
Primary industry	2	7	6	1	7	6
Manufacturing	3	18	12	4	19	13
Utilities	1	1	1	1	1	1
Construction	0	5	4	0	5	4
Wholesale	2	8	4	3	8	4
Retail	19	12	15	18	12	15
Accommodation, cafes etc	9	4	6	7	4	5
Transport	1	2	2	0	3	2
Information services	3	3	3	3	3	3
Finance & insurance	10	8	7	10	8	8
Business services	14	13	12	14	12	12
Government	10	9	9	11	10	10
Education	9	5	7	8	5	7
Health & community	12	3	7	12	3	7
Other services	5	1	3	6	1	3
Sector						
Private	77	85	82	75	86	81
Public	23	15	18	25	14	19
Organisational size						
Under 20	17	22	20	11	21	17
20 to 99	14	14	12	16	14	13
100 to 499	16	18	19	18	18	19
500 plus	53	46	49	56	47	51
Hours status						
Full-time	83	96	92	100	100	100
Part-time	17	4	8	0	0	0
Sample size	226	391	627	190	377	573

Notes: Weighted data (weighted by cross-sectional weights).
Source: Unit record data, HILDA, Release 7.
Population: Wave 7, 2007. † All adult respondents working as employees and in management occupations.
‡ All adult respondents working as employees, in management occupations and working 35 hours or more per week.

Figure 1: Profile of full-time managers, 2007

(Source: as for Table 2)



On the other hand, the differences between *male* and *female* full-time managers are more pronounced. Compared with their male counterparts, female managers are younger, are less likely to have vocational qualifications, are more likely to be single, are more likely to work in the public sector, and are more likely to work in larger organisations. Their industry profiles are also distinct: compared to male managers, females are less likely to be found in manufacturing and much more likely to be found in health and community services.

Some of the other characteristics of male and female full-time managers are shown in Figure 1, which also emphasises these differences. These graphs show kernel density distributions for a number of continuous variables, with male (blue plus mauve) and female (orange plus mauve) distributions overlaid. This allows one to see where the distributions are common (mauve) and where they are distinctive (blue and orange, respectively). Male means are shown as a solid line, females means as a dashed line. Compared to the male managers, females have less occupational and job tenure and are more likely to cluster at the lower end of the full-time hours distribution. In terms of years of education, and occupational status scores, their profiles are reasonably close.

What is most striking about the comparison between male and female managers is their similarity. Apart from industry location, and the public sector / private sector split, they really are quite comparable. Indeed, much more so than would be the case with an all-occupational comparison.

These differences in the characteristics of male and female managers are one of the key reasons that their earnings differ. One of the aims of this paper is, of course, to decompose how much of the gender earnings gap can be explained by these differing characteristics.[10]

As to the gap pay gap itself, its size depends on what is being measured and where it is being measured. As Table 3 shows, using hourly rates of pay produces a much smaller gap (14 per cent) compared with annual salaries (25 per cent). Moreover, the pay gap is greater at the top of the distribution, but only mildly so for hourly rates of pay (13 to 15 per cent variation between first and third quartile). With annual salaries this pay gap varies from 15 per cent to 24 per cent between the first and third quartiles. The highly skewed nature of these distributions is also notable, and is illustrated in Figure 2, which again uses kernel density distributions in the same fashion as described earlier.

A likely reason for the lower hourly wages gap is the difference in hours worked between male and female full-time managers. The former work on average 48 hours per week, the latter 45.7. Because the hourly rate is based on a simple arithmetic division of weekly wage divided by usual hours, the obvious effect of working longer hours is a reduction in the hourly wage measure. Thus longer hours by males results in a lower hourly rate for them and a consequent reduction in the gender gap. In reality, managerial jobs are rarely paid on an hourly basis, and the hours requirements are usually open-ended, so it makes little sense to pursue an analysis based on hourly rates. However, to make earnings comparable between males and females, the sample needs to be restricted to full-timers. Fortunately, as we have just seen, the profile of part-timers and full-timers differs little, and the number of lost observations is also minimal. To make for greater comparability, all of the models discussed

[10] In this descriptive section, the familiar term 'gap' is used and the measure is either dollars, or percentage points. In the modelling section, below, the term 'differential' is used and it refers to the difference in log annual wage and salary income (or earnings).

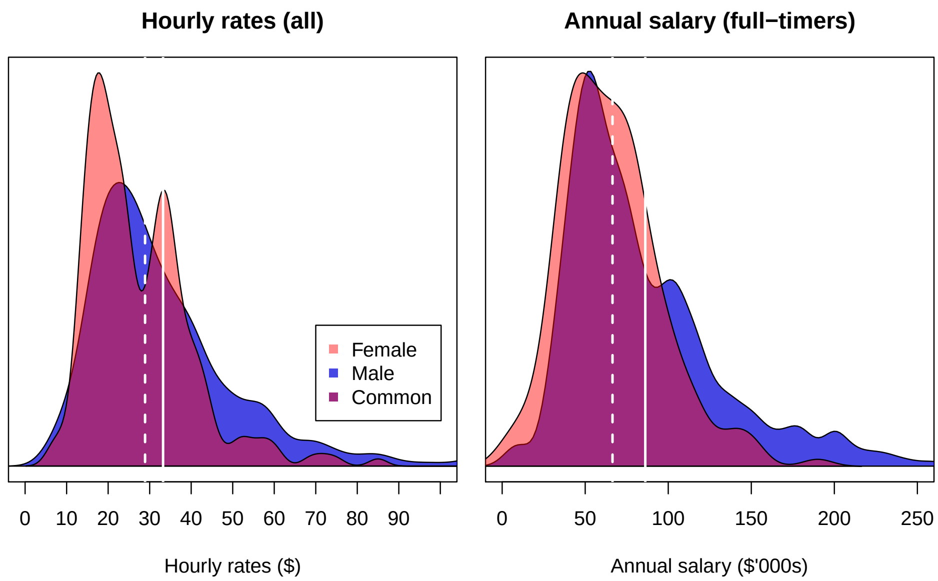
below include a control for weeks worked in the year, to take account of the likely gender differences in annualised labour force participation.

Table 3: Earnings gap: hourly rates and annual salaries (all and full-timers)

	All (hourly rate $)				Full-timers (annual salary $)			
	Mean	1st Qu	Median	3rd Qu	Mean	1st Qu	Median	3rd Qu
Male	34	21	28	40	87,800	52,000	71,000	106,000
Female	29	18	24	34	65,900	44,400	62,000	81,000
Gap	5	3	4	6	21,900	7,600	9,000	25,000
Gap (%)	14	13	13	15	25	15	13	24

Notes: Weighted data.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as employees and in management occupations: all (n = 617) and full-timers (n = 567).

Figure 2: Earnings distributions: hourly rates and annual salary, 2007
(Source: As for Table 3)



The size of the gender pay gap shown here is what one would expect, given earlier research. In his analysis of the full-time workforce using 2001 Census data, Miller found that the gender pay gap at the 95th percentile was about 23 percentage points. The equivalent figure from the HILDA dataset (Wave 7) for all occupations is 25 percentage points.[11] Given that most managers are likely to be found in vicinity of the 95th percentile, one would expect that the size of the gap among the managerial workforce will be of this order of magnitude. While not directly comparable—because of her public/private sector split—Kee's quantile analysis of the HILDA data also found comparable results. She found a differential (in log wages) at the 90th percentile of about 0.27 for the private sector and 0.12 for the public sector Kee (2006, p. 416).

[11] The age restriction is greater in Miller's dataset 20 to 64, compared to 21 and over here; Miller uses the full-time workforce, this figure is based on all full-time *employees*.

5 Results

5.1 Regression modelling

Description and summaries for the variables used for these models can be found in the appendix as Tables 13 and 14. The main variation in the coding of these variables is the use of a 'blue collar' industry grouping. This comprises a range of industries where women managers are seldom found—manufacturing, mining, utilities, wholesale and transport—and is a necessary aggregation to deal with sparse observations.

The modelling strategy in this paper involved increasing the complexity of the models, by moving from OLS to multilevel models and then to selectivity-corrected multilevel models. Models are fit separately for males and females and interest centres on the earnings differential between males and females, and how this might be decomposed in various ways. In order to allow for a 'pooled' decomposition—the Oaxaca and Ransom (1994) approach—and in order to implement the Olsen-Walby approach, a model using pooled male and female data is also fit. Following Jann (2008, pp. 457–458), a dummy for sex was included in the pooled sample, to avoid possible distortion of the decomposition results.

Before discussing the results of the earnings models, it is worth briefly summarising the results of the selection models, using the results of the 2007 data for illustration.[12] As noted earlier, these were multinomial logit models, with three possible outcomes: working as a full-time manager, working otherwise, or not working at all. The predictors in this model were age, years of education, marital status, number of children aged 0 to 4, number of children aged 5 to 9, and whether city or non-city resident. The model was run for males and females, and the inverse of Mills ratio was calculated for each person in each wave to provide a Heckman correction term (λ) for use in the final multilevel model. The multinomial model results for the 2007 data are shown in the appendix as Table 15.

The results of these models are consistent with expectations. The selection model for males shows that the likelihood of entering management increases with age, peaking in the middle years, before dropping off in the later years of life. Years of education is also positively associated with becoming a manager. Marriage (or de facto status) also has a strong association: being in this situation (compared with being single) increases men's odds of being a manager by a factor of 3.8. On the other hand, the presence of young children slightly reduces a man's odds of entering management (though the results are only statistically significant for children aged 0 to 4).

The female selection model shows that age is also positively associated with entering management, as is marriage (or defacto status). Similarly, the number of years of education is also positively associated with female entry into management. On the other hand, the presence of young children has strong negative associations. Compared with a woman with no children aged 0 to 4, someone with one child in that age group has only about one quarter the odds of becoming a manager. If they have two children in that age group, the odds shrink to about one eighth. If the children are somewhat older—in the 5 to 9 age group—the odds improve, but only slightly. For one child, it is just under

[12] The multinomial logit model was fitted separately to each year of data, but the example given in the appendix is for the latest wave, 2007.

one third and for two children it is about one fifth.

These results are interesting in their own right, and I return to them more fully in the final discussion. It is worth noting, at this stage, what these findings mean in terms of probabilities. Becoming a manager, overall, is about twice as likely for a man as a woman. The HILDA data allows us to quantify this over time. For example, the unconditional probability of someone in 2001 being a manager in 2007[13] is about 17 per cent for men, and 9 per cent for women. If their status in 2001 was not in the labour force, the respective figures are 11 per cent and 4 per cent. If employed in 2001, then the figures are 20 per cent and 12 per cent.

To illustrate the impact of parenting, the predicted probabilities from the 2007 model can be calculated.[14] If a man has no children, then his predicted probability of being a manager is 15 per cent. If he has two children, one of them aged 0 to 4, the other aged 5 to 9, this predicted probability barely changes, rising slightly to 18 per cent. For a woman, with the same characteristics, the predicted probability for being a manager is she has no children is 11 per cent, and this falls to 4 per cent if she has two children in these age groups.

Turning now the core modelling—the earnings equations—I discuss them in increasing order of complexity. The simplest model—the OLS model for annual wages—used 2007 data, with the dependent variable the log of annual wage and salary income. Controls consisted of age, marital status, number of weeks working in that year, state, whether city or non-city residence, years of education, occupational tenure, job tenure, occupational status, usual hours worked, union membership status, industry, sector, organisational size, single or multiple workplace organisation. One of the main issues in this research is occupational comparability: not all managers are doing the same kind of work. The ANZSCO category of 'Manager' includes both skill levels 1 and 2 (ABS, 1221.0, p. 14) and the gender mix here could be quite crucial to the size of the gender pay gap. The inclusion of a variable for occupational status score—which is based on a finer level of occupational disaggregation—controls for some this.[15] There remains, however, an issue of how one might control for seniority, apart from age. I return to this issue in the discussion section below. As for age, its likely non-linearity was captured by fitting this variable as a grouped categorical variable, rather than a quadratic, since interest lay in particular age groupings. The sample was restricted to adults, working full-time and classified as managers in the ANZSCO framework. This model was run for males, females and a pooled sample, with the latter required for the 'pooled' version of the decomposition. The detailed results of this modelling are shown in the appendix as Table 16.

The male OLS models for the 2007 data suggests that age is non-linear, with earnings for male managers rising to a peak in the 35 to 39 age group. Being married (or defacto) brings an earnings premium of about 17 per cent.[16] Years

[13] For this example, the outcome is simply a manager, with full-time status and employee status ignored.

[14] It is the relative probabilities which matter here, not the absolute. For prediction, the other regressors in the model are set at certain fixed levels and it is the overall combination which determines the absolute probabilities. The other regressors were set at married (or defacto), living in a city, aged 30 to 34, and 15 years of education.

[15] The measure of occupational status score is based on AUSEI06. See McMillan et al. (2009).

[16] Percentages for categorical variables are calculated from their coefficient, x, using the formula:

of education are rewarded well among men, with each additional year of study increasing their earnings by 5.2 per cent. Some of the industry differences are striking: men who work as managers in finance and insurance earn about 27 per cent more than their counterparts who work in 'blue collar' industries. An unusual finding is that organisational size does not appear to matter, except for male managers in mid-range organisations (100 to 499 employees). This group earn about 20 per cent more than their counterparts in small workplaces.

When the 2007 OLS model is rerun with the inclusion of the Heckman correction term (lambda), the magnitude of the coefficients change (as well as their standard errors), but the overall patterns are not dramatically different. The Heckman correction term is not, however, statistically significant, suggesting selection bias is not a major issue with this model. While the coefficient is quite large, the size of the standard error is considerable.

The female OLS model suggests that age is close to linearity, with little change in the latter years. Being married (or defacto) confers no earnings premium. Each additional year of education is associated with a 3.9 per cent increase in earnings. Organisational size appears to have no association with earnings, with none of the coefficients of large magnitude nor statistically significant. The inclusion of the Heckman correction term does not change any of these results in any substantial way. The coefficient for lambda is not statistically significant.

The multilevel models follow the same specification as the OLS models, with the addition of two varying-intercept terms: individual cross-wave identifier and household identifier. These terms, along with the usual error term, represent the variance components in the multilevel model and can be usefully interpreted as providing insights into the sources of variability in the outcome. The detailed results of this modelling are shown in the appendix as Table 17.

The differences between the simple OLS and the multilevel model are quite considerable. Looking first at the male models it is clear that the effect for age is no longer non-linear, but increases steadily right through a male manager's working life. Moreover, the magnitude of the coefficients for age are larger than in the OLS models. As an example, a male manager in his early 40s earns about 55 per cent more than a manager in his early 20s. By his late 50s, this has increased to about 60 per cent more. While the earnings premium for male managers in being married (or defacto) remains, its effect is much weaker (but still statistically significant). Perhaps the most interesting difference is organisational size: there is now a statistically significant effect and a linear one: working in larger organisations increases a manager's earnings considerably. When the same multilevel model is run with the inclusion of a Heckman correction term, the overall patterns do not change, though there is one notable difference. The marriage premium for males in no longer evident. The coefficient for selection bias is much smaller than was the case in the equivalent OLS model and is now statistically significant (but not strongly so).

Turning now to the female models, there are few changes worth noting. The linearity in age is still evident, with little change in earnings as female managers age. The magnitudes of the coefficients are not much larger in the multilevel model than in the OLS. By way of example, a female manager in her early 40s earns about 30 per cent more than a manager in her early 20s. By her late 50s, the figure is still just 30 per cent. The one change of note is organi-

$100 * (exp(x) - 1)$.

sational size: for female managers there is now a statistically significant effect and a linear one, with working in larger organisations increasing earnings. The inclusion of the Heckman correction term has only one impact: it increases the magnitude of the age premium, but it does not change its linearity. The coefficient for selection bias is similar in magnitude to the equivalent OLS model and is weakly statistically significant.

The final models, the ones used for applying the decompositions, differ from the ones just discussed in one respect. They include an additional regressor—the presence of young children—and they leave out the Heckman correction term. This term is removed because it is unlikely to be statistically significant. In the case of the OLS models this is clearcut, while in the multilevel models the situation is more uncertain. The standard errors shown in the appendix are conventional standard errors which take account of the clustered observations, but not the two stage estimation method. However, as the literature shows, these standard errors are not accurate in a two-stage estimation and are likely to be an under-estimate. This is confirmed when these multilevel models are bootstrapped. The standard errors increase substantially and none of the coefficients for selection bias come close to statistical significance.[17] Given that the inclusion of the Heckman selection term has little substantive effect on the coefficients in these models, the decision to drop it from the final model is a reasonable one.

This decision has the advantage that the presence of children can now be included in the earnings models. As mentioned earlier, this factor was required for model identification when using the two-stage estimation approach. In the earnings models it now takes the form of two variables: the presence of children aged 0 to 4, and the presence of children aged 5 to 9. The full details of both the OLS models and the multilevel models with this specification are shown in the appendix as Table 18.

In the male models, the presence of children is positive, but not statistically significant in the OLS model. In the multilevel model, the presence of children aged 0 to 4 is statistically significant, and moderately positive. In the female OLS models, the coefficients are both negative, and reasonably large for the younger age group. But the standard errors are also large—no doubt due to the small sample—and so the results are not statistically significant. On the other hand, the multilevel results—with their much larger sample—produce statistically significant results for children aged 5 to 9 (though not for children aged 0 to 4). In summary, the presence of children aged 5 to 9 is associated with a wages penalty for female managers of about 11 per cent.

Finally, one of the advantages of a multilevel model with varying-intercepts is the insights it provides into the sources of variability in earnings. If we view an observation as an 'earnings episode', then about one third of the total variability in earnings is due to fluctuations in earnings episodes from year to year. A small amount of variability—about 12 per cent—is due to differences between households; and the major component of the variability—about 56 per cent—is due to differences between individuals.

[17] The bootstrap standard errors are not shown in the appendix, but are available from the author.

5.2 Decomposition results

The decomposition results discussed in this section are based on the models which exclude the Heckman correction term (as just discussed). In the case of the OLS models, only summary decomposition results are presented, but these are done for 2007 and (in an abbreviated fashion) for the period from 2001 to 2007. In the case of the multilevel models, a detailed decomposition is also presented.

Looking first at the OLS results, Table 4 shows the 2007 results and Table 5 shows those for the period 2001 to 2007. In the case of the former, the proportion of the gender earnings differential which is unexplained—and potentially due to discrimination—varies from about 33 per cent to about 87 per cent, depending on one's assumptions about the labour market. If we adopt the 'privilege' approach, which suggests that male managers earn an unwarranted premium by virtue of their gender, then the relevant figure is 87 per cent. This is also a consistent figure over time, as the mean column in Table 5 shows.

Table 4: Decomposing earnings gaps: OLS results for 2007

	Differential due to:		Unexpl decomp into:		
Approach	**Charact-eristics**	**Unexpl-ained**	**Male advant**	**Female disadvant**	**Unexpl as %**
Deprivation	0.137	0.067	0.000	0.067	33.0
Privilege	0.026	0.178	0.178	0.000	87.2
Reimers	0.081	0.123	0.089	0.034	60.1
Cotton	0.100	0.104	0.059	0.045	51.1
Pooled	0.080	0.124	-0.000	0.124	60.9

Notes: Male prediction: 11.223; female prediction: 11.019, differential: 0.204. (All log of annual wage and salary income.) Decomposition of OLS models shown in appendix Table 16.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 557 (male n = 371, female n = 186).

Table 5: Unexplained as percentage of differential: OLS results for 2001-2007

Approach	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**Mean**
Deprivation	59.7	52.8	57.2	53.9	57.3	73.8	33.0	55.4
Privilege	74.6	87.9	96.8	72.2	107.8	89.5	87.2	88.0
Reimers	67.1	70.4	77.0	63.0	82.6	81.6	60.1	71.7
Cotton	64.1	63.5	69.3	59.6	73.5	78.8	51.1	65.7
Pooled	67.4	64.3	63.2	56.2	67.2	73.0	60.9	64.6

Notes: Based on OLS models for each year, with same specification as for 2007 (shown in Table 16).
Source: Unit record data, HILDA Release 7.
Population: Adult respondents working as full-time employees and in management occupations. Waves 1 to 7, 2001 to 2007.

Table 6: Decomposing earnings gaps: multilevel model results

	Differential due to:		Unexpl decomp into:		
Approach	Charact-eristics	Unexpl-ained	Male advant	Female disadvant	Unexpl as %
Deprivation	0.087	0.187	0.000	0.187	68.3
Privilege	0.030	0.244	0.244	0.000	89.2
Reimers	0.058	0.216	0.122	0.094	78.8
Cotton	0.069	0.205	0.076	0.129	74.8
Pooled	0.074	0.200	0.103	0.097	73.1

Notes: Male prediction: 11.18; female prediction: 10.908, differential: 0.274. (All log of annual wage and salary income.) Decomposition of multilevel models shown in appendix Table 17.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 3,851 (male n = 2,650, female n = 1,201). Wave 1 to 7, 2001 to 2007.

Turning to the multilevel model—which pools the data for all years while recognising the hierarchical nature of this data—the decomposition results are shown in Table 6. The figures which measure the unexplained component as a proportion of the differential are also somewhat higher than those figures which were averaged over 2001 to 2007 (shown in Table 5). In the case of the privilege approach, this is less so, with the figure of 89 per cent shown in Table 6 close to that shown in the OLS results (87 per cent).

The detailed results for the 'privilege' approach allow us to pursue this further (see Table 7). This figure of 87 per cent represents 0.24, out of a total (log) earnings differential of 0.27. Looking first at characteristics, only .03 of the gap is due to differences between male and female managers (evaluated using the male wage structure) and most of these differences relate to working fewer hours in the week, and fewer weeks in the year. On many of the other attributes, the differences are negative—which mean they help close the gap—though the magnitudes of these are minimal, except for the presence of young children.

When it comes to the unexplained component of the wage differential, the figures are of larger magnitude. The gender differences in coefficients, when applied to the characteristics of female managers, show that the gap is closed by hours worked and weeks worked (these have negative signs). The differences in returns on occupational status score—the variable which provides a finer measure of managerial category—also helps close the gap. What widens the gap? Not very much. Those variables with positive signs have quite small magnitudes, with differences on coefficients for working in the public sector and being married (or defacto) being the only notable ones. So, with the coefficient differences for most variables helping to close the gender differential, why does the unexplained component remain so large, at 0.24? The answer lies in the intercept, a figure of considerable magnitude: 0.72. As noted earlier, the intercept represents 'group membership': it is the component of the wage differential which reflects being female rather than male. In the earliest decomposition studies, it was viewed as the most 'blatant' measure of discrimination (see, for example, Blinder (1973)).

Table 7: Detailed decomposition: multilevel model results

	Deprivation		Privilege		Reimers		Cotton		Pooled	
Variables	**Charact-eristics**	**Unexpl-ained**	**Charact-eristics**	**Unexpl-ained**	**Charact-eristics**	**Unexpl-ained**	**Charact-eristics**	**Unexpl-ained**	**Charact-eristics**	**Unexpl-ained**
Intercept	0.000	0.721	0.000	0.721	0.000	0.744	0.000	0.721	0.000	0.721
Age	0.023	-0.004	0.012	0.007	0.017	0.001	0.019	-0.001	0.019	-0.001
Couple	0.009	0.011	-0.002	0.022	0.004	0.016	0.006	0.015	0.005	0.015
Young children	0.009	-0.093	-0.021	-0.063	-0.004	-0.121	-0.001	-0.084	0.004	-0.089
Weeks emp in yr	0.009	-0.217	0.011	-0.220	0.010	-0.207	0.010	-0.218	0.011	-0.219
State	-0.000	-0.005	-0.003	-0.002	-0.002	-0.004	-0.001	-0.004	-0.001	-0.004
Non-city resid	-0.003	0.009	-0.002	0.008	-0.002	0.008	-0.002	0.009	-0.002	0.009
Yrs of educatn	0.007	-0.005	0.007	-0.005	0.007	-0.004	0.007	-0.005	0.008	-0.005
Occup tenure	0.001	-0.006	0.002	-0.008	0.002	-0.006	0.002	-0.007	0.002	-0.007
Job tenure	0.003	-0.029	0.009	-0.035	0.006	-0.031	0.005	-0.031	0.005	-0.030
Occup status	-0.006	-0.144	-0.009	-0.141	-0.007	-0.137	-0.007	-0.143	-0.007	-0.143
Usual wkly hrs	0.025	-0.071	0.030	-0.076	0.028	-0.070	0.027	-0.073	0.028	-0.073
Union member	0.001	0.002	0.000	0.002	0.001	0.002	0.001	0.002	0.001	0.002
Industry	0.008	-0.009	0.002	-0.003	0.005	-0.006	0.006	-0.007	0.006	-0.007
Public sector	0.007	0.023	-0.003	0.033	0.002	0.028	0.004	0.026	0.003	0.027
Organisat size	-0.007	0.004	-0.006	0.003	-0.007	0.003	-0.007	0.004	-0.007	0.004
Org with single wp	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Total	0.087	0.187	0.030	0.244	0.060	0.215	0.069	0.205	0.074	0.200

Notes: Male prediction: 11.18; female prediction: 10.91, differential: 0.27. (All log of annual wage and salary income.) Decomposition of multilevel models shown in appendix Table 17.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 3,851 (male n = 2,650, female n = 1,201).

One of the key advantages of to using panel data for a study such as this is the increased precision of the estimates. Because managers comprise such a relatively small section of the workforce, sample size considerations become paramount when drawing inferences from the point estimates. In analysing a single wave of data, as was done for the simple OLS model, the sample size for both male and female managers was just 557. On the other hand, using all 7 waves of data provided a sample size of 3,850. Valid statistical inference requires some measure of uncertainty in the modelling and the decomposition approach in this paper is no exception. As Jann (2008, pp. 458–460) argues, variability enters the decomposition results through both the variances of the coefficients and the use of random variables from survey sample data. Because the decomposition method involves multiplying the coefficients and the means of these random variables, one must take account of both sources of variation. Following Sinning et al. (2008, pp. 489–90), the approach used in this study involves bootstrapping to obtain standard errors for the final decomposition results. This approach has advantages when the computation of analytical standard errors is complex, and is well suited to panel data models like those employed here (Cameron and Trivedi, 2005, p. 377).[18]

The gender wages differential examined in this study—of 0.27—has a standard error of about 0.02, giving a confidence interval of between 0.24 and 0.30 (Table 8). The figures reported earlier in Table 6 are reproduced below in Tables 9 and Tables 10, with their standard errors and confidence intervals shown beside them. The figure of 89 per cent calculated using the privilege approach has a standard error of 10.2 percentage points, giving a confidence interval of between 67 per cent and 111 per cent. Looking across all approaches, except the pooled approach, this proportion never drops below 52 per cent. The pooled approach has a much larger standard error—nearly 23 percentage points—and produces a much wider confidence interval: from 28 per cent to 118 per cent.

Finally, the observation made earlier that differences in characteristics do not explain much of the differential is reinforced by Table 10. We saw earlier that, using the privilege approach, this figure was 0.03. Its confidence interval is -0.03 to 0.09. With the exception of the pooled approach, the highest upper bound figure for characteristics is 0.13. On the other hand, the unexplained component, which measured 0.24 in the privilege approach, has a confidence interval of 0.18 to 0.31. Again, with the exception of the pooled approach, the smallest lower bound for this figure never drops below 0.14.

[18] Bootstrapping, using 1200 repetitions, was carried out for the multilevel model using the R routine, `boot`, see Canty and Ripley (2009) and Davison and Hinkley (1997). For efficiency, the R package, `snow`, was used to parallelise the bootstrapping, see Tierney, Rossini, Li and Sevcikova (2009); Tierney, Rossini and Li (2009).

Table 8: Confidence intervals for gender pay differential

Approach	Est	SE	LB	UB
Predicted male	11.18	0.01	11.17	11.20
Predicted female	10.91	0.01	10.88	10.94
Differential	0.27	0.02	0.24	0.30

Notes: Est = estimate; SE = standard error; LB = lower confidence interval bound; UB = upper bound. 95% confidence intervals.
Based on bootstrapping the unadjusted multilevel models shown in Table 17.
The predicted earnings are shown as the natural log of annual wage and salary income, and the differential is also on this scale.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 3,851 (male n = 2,650, female n = 1,201).

Table 9: Confidence intervals for Unexplained as percentage of differential (as %s)

Approach	Est	SE	LB	UB
Deprivation	68.3	8.1	52.5	84.2
Privilege	89.2	11.1	67.4	111.0
Reimers	78.8	7.2	64.7	92.9
Cotton	74.8	6.9	61.4	88.3
Pooled	73.2	23.0	28.1	118.4

Notes: 95% confidence intervals. Based on bootstrapping the unadjusted multilevel models shown in Table 17.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 3,851 (male n = 2,650, female n = 1,201).

Table 10: Confidence intervals for characteristics and unexplained components

	Characteristics				Unexplained			
Approach	Est	SE	LB	UB	Est	SE	LB	UB
Deprivation	0.087	0.024	0.040	0.133	0.187	0.023	0.143	0.232
Privilege	0.030	0.030	-0.030	0.089	0.244	0.032	0.182	0.307
Reimers	0.058	0.020	0.018	0.098	0.216	0.021	0.174	0.257
Cotton	0.069	0.020	0.030	0.108	0.205	0.020	0.166	0.244
Pooled	0.073	0.063	-0.050	0.197	0.201	0.063	0.077	0.324

Notes: 95% confidence intervals. Based on bootstrapping the unadjusted multilevel models shown in Table 17.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 3,851 (male n = 2,650, female n = 1,201).

5.3 Simulated change results

In the Olsen-Walby approach, the emphasis is on simulated change, and its consequences for closing the gender pay gap. By hypothesising various changes—some of which may have policy relevance—one can estimate how much the gap would close in percentage terms, and how much this would be worth to women, in dollar terms.

Looking first at Table 11, which is based on the pooled version of the 2007 OLS regression, it is notable that usual weekly hours is prominent. The difference between male and female managers in this respect accounts for 21 per cent of the wages gap. Were women managers, as a group, to increase their weekly hours to match the male average—a change of 2.9 hours—then this would be worth an additional $4,732 per annum. Similarly, if they increased their average for the weeks employed in the year to match men's, then this would reduce the wages gap by about 7 per cent and be worth $1,463 per annum.

Some of these hypothesised changes have little policy relevance. For example, it was noted earlier that marriage (or defacto status) confers an advantage on male managers. If female managers were to match their male counterparts in this regard—something requiring a 17 percentage point increase—then this would reduce the wages gap by 7 per cent, and be worth $1,520 to them.

On the other hand, the policy relevance of some hypothesised changes is quite clear. For example, if the representation of women in the ranks of older managers was the same as that of men—something requiring just under a 5 percentage point increase—then the gender pay gap would shrink by 8 percent, and be worth $1,755 per annum.

Ultimately, however, it is the intercept term which proves most resistant to policy interventions. Simply being a woman accounts for 61 percent of the wages gap. If the hypothesised change saw female managers become male managers overnight, then this 'sex change' would be worth $13,516 to them.

The simulated change results for the multilevel model, again using the pooled version, are shown in Table 12. These largely follow those just discussed, but the magnitudes differ quite considerably. The multilevel model attributes much more of the wages gap to the intercept—about 73 per cent—and less to changes in usually weekly hours (10 per cent) or weeks employed in the year (4 per cent). Interestingly, it highlights an age effect which is less evident in Table 11. Not only is the under-representation of women in the 55 and older age group a liability—worth about $1,179—but so is their under-representation in their middle years. If they achieved the same presence in the managerial workforce as men in the 40 to 44 year age range, then this would be worth an additional $1,147 per annum.

While the OLS results suggest a simulated change in marital status is worth about $1,520, the multilevel model only rates this change as worth $442. Neither model puts much emphasis on simulated changes in the presence of children: the OLS results value such a change at $676 per annum; the multilevel results value it at $355 per annum.

Table 11: Olsen-Walby simulated change: OLS model

	Male avg	Female avg	ΔX Change factor	β Overall coeff	$\beta'\Delta X$ Simul effect	Simul chng as % gap	Ann $ equival
Female	0.000	1.000	-1.000	-0.124	0.124	0.609	13,516
Aged 25-29	0.100	0.091	0.008	0.127	0.001	0.005	115
Aged 30-34	0.146	0.177	-0.032	0.309	-0.010	-0.048	-1,069
Aged 35-39	0.167	0.167	0.000	0.345	0.000	0.001	17
Aged 40-44	0.127	0.113	0.014	0.307	0.004	0.021	460
Aged 45-49	0.154	0.145	0.008	0.350	0.003	0.015	323
Aged 50-54	0.119	0.118	0.000	0.306	0.000	0.000	11
Aged 55 plus	0.137	0.091	0.046	0.350	0.016	0.079	1,755
Couple	0.822	0.656	0.166	0.084	0.014	0.068	1,520
Children 0 to 4	0.208	0.145	0.062	0.015	0.001	0.005	105
Children 5 to 9	0.213	0.065	0.148	0.035	0.005	0.026	571
Weeks emp in yr	51.881	51.043	0.838	0.016	0.013	0.066	1,463
Vic	0.264	0.263	0.001	-0.115	-0.000	-0.000	-9
Qld	0.181	0.204	-0.024	-0.084	0.002	0.010	217
SA	0.070	0.048	0.022	-0.005	-0.000	-0.001	-13
WA & NT	0.092	0.086	0.006	0.009	0.000	0.000	5
Tas & ACT	0.065	0.059	0.006	-0.097	-0.001	-0.003	-58
Non-city resid	0.342	0.296	0.047	-0.100	-0.005	-0.023	-509
Yrs of educatn	14.493	14.339	0.155	0.039	0.006	0.029	652
Occup tenure	9.841	7.769	2.072	0.005	0.010	0.049	1,094
Job tenure	8.272	6.981	1.292	-0.001	-0.002	-0.008	-170
Occup status	64.555	65.826	-1.272	0.011	-0.014	-0.070	-1,550
Usual wkly hrs	48.116	45.215	2.901	0.015	0.044	0.213	4,732
Union member	0.156	0.226	-0.069	-0.075	0.005	0.025	565
Retail	0.132	0.194	-0.061	0.027	-0.002	-0.008	-182
Acc, cafes, rec	0.040	0.081	-0.040	-0.012	0.000	0.002	53
IT & bus serv	0.148	0.145	0.003	0.149	0.000	0.002	50
Fin & insurance	0.065	0.097	-0.032	0.192	-0.006	-0.030	-670
Government	0.094	0.102	-0.008	-0.010	0.000	0.000	8
Education	0.062	0.081	-0.019	-0.085	0.002	0.008	173
Health & community	0.046	0.204	-0.158	-0.087	0.014	0.067	1,498
Public sector	0.151	0.263	-0.112	0.024	-0.003	-0.013	-290
Org size: 20–99	0.132	0.113	0.019	0.007	0.000	0.001	15
Org size: 100–499	0.194	0.199	-0.005	0.161	-0.001	-0.004	-85
Org size: 500 plus	0.480	0.575	-0.095	0.149	-0.014	-0.070	-1,546
Org with single wp	0.229	0.183	0.046	-0.113	-0.005	-0.026	-567
Intercept	1.000	1.000	0.000	7.961	0.000	0.000	0
Totals					0.204	1.000	22,200

Notes: Based on the pooled 2007 OLS model shown in Table 18.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 557 (male n = 371, female n = 186). Wave 7, 2007.

Table 12: **Olsen-Walby simulated change: multilevel model**

	Male avg	Female avg	ΔX Change factor	β Overall coeff	$\beta'\Delta X$ Simul effect	Simul chng as % gap	Ann $ equival
Female	0.000	1.000	-1.000	-0.200	0.200	0.732	16,254
Aged 25-29	0.093	0.137	-0.044	0.180	-0.008	-0.029	-643
Aged 30-34	0.162	0.156	0.007	0.274	0.002	0.007	146
Aged 35-39	0.164	0.135	0.029	0.337	0.010	0.036	788
Aged 40-44	0.155	0.118	0.037	0.384	0.014	0.052	1,147
Aged 45-49	0.140	0.172	-0.032	0.381	-0.012	-0.045	-988
Aged 50-54	0.123	0.125	-0.001	0.378	-0.001	-0.002	-46
Aged 55 plus	0.117	0.082	0.035	0.416	0.015	0.053	1,179
Couple	0.822	0.664	0.158	0.034	0.005	0.020	442
Children 0 to 4	0.218	0.092	0.126	0.024	0.003	0.011	247
Children 5 to 9	0.214	0.076	0.139	0.010	0.001	0.005	108
Weeks emp in yr	51.628	51.116	0.513	0.021	0.011	0.039	861
Vic	0.257	0.242	0.015	-0.047	-0.001	-0.003	-58
Qld	0.180	0.208	-0.028	-0.061	0.002	0.006	138
SA	0.078	0.057	0.021	-0.090	-0.002	-0.007	-154
WA & NT	0.092	0.092	0.000	-0.076	-0.000	-0.000	-0
Tas & ACT	0.058	0.057	0.001	-0.035	-0.000	-0.000	-2
Non-city resid	0.332	0.312	0.019	-0.121	-0.002	-0.009	-191
Yrs of educatn	14.426	14.246	0.180	0.043	0.008	0.028	629
Occup tenure	8.780	7.199	1.582	0.001	0.002	0.006	136
Job tenure	8.433	7.018	1.414	0.003	0.005	0.017	370
Occup status	64.810	66.110	-1.299	0.005	-0.007	-0.025	-550
Usual wkly hrs	48.548	45.296	3.252	0.008	0.028	0.101	2,235
Union member	0.194	0.250	-0.056	-0.010	0.001	0.002	43
Retail	0.095	0.154	-0.059	-0.034	0.002	0.007	163
Acc, cafes, rec	0.058	0.074	-0.016	-0.138	0.002	0.008	183
IT & bus serv	0.126	0.161	-0.035	0.085	-0.003	-0.011	-238
Fin & insurance	0.074	0.072	0.002	0.113	0.000	0.001	18
Government	0.105	0.110	-0.005	0.038	-0.000	-0.001	-15
Education	0.069	0.103	-0.035	-0.008	0.000	0.001	23
Health & community	0.067	0.195	-0.128	-0.030	0.004	0.014	315
Public sector	0.192	0.288	-0.096	-0.026	0.002	0.009	198
Org size: 20–99	0.178	0.162	0.016	0.110	0.002	0.006	144
Org size: 100–499	0.182	0.180	0.002	0.192	0.000	0.001	26
Org size: 500 plus	0.477	0.517	-0.040	0.217	-0.009	-0.032	-712
Org with single wp	0.247	0.243	0.004	0.014	0.000	0.000	4
Intercept	1.000	1.000	0.000	8.259	0.000	0.000	0
Totals					0.274	1.000	22,200

Notes: Based on the pooled multilevel model shown in Table 18.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 3,851 (male n = 2,650, female n = 1,201). All waves, 2001 to 2007.

6 Discussion

The results discussed in the last section are reasonably unambiguous, though their interpretation may be less so. Whichever way you look at the data, whether for individual years or pooled, the overall story is much the same. Women full-time managers earn about 25 per cent less than their male counterparts and somewhere between 70 and 90 per cent of this wage gap cannot be explained. Indeed, the characteristics of male and female managers—at least as measured in this sample—are remarkably similar. One is left with the stark conclusion that as much as 70 per cent of the gap is simply due to women managers being female.

While the characteristics of each group are so similar, the rewards which attach to these characteristics differ. Where male managers are rewarded for additional years of ageing, for female managers there is a distinct plateau. While male managers are rewarded for being married, this is not the case for female managers. Young children are a 'liability' for women managers, but not so for men.

There is, of course, the possibility that the modelling fails to capture some decisive factors which determine earnings. Career seniority and job specialisation come to mind. Ordinarily, seniority might be captured through an age effect—and that is included in the model—and specialisation might be captured by an occupational status score—again something in the model. However, it seems likely that these aspects of career progression for managers are not well represented in the available data. Were the models to include adequate proxies for managerial seniority, then it is likely that the unexplained component of the wage gap would decline. I doubt, however, that it would decline sufficiently to erase figures of this magnitude.

Moreover, as the notion of the 'glass ceiling' suggests, women's career progression often stalls between middle and upper management levels (see, for example, Adair (1994); Jeavons (2002)). In terms of modelling the gender pay gap, a truncated career progression is likely to see a well-crafted seniority variable 'take-on' a large part of the differential, shifting it from the unexplained to the characteristics side of the ledger. But, even were this to reduce the magnitude of the unexplained component, the same factors behind the glass ceiling are likely to still influence what remains. In particular, the magnitude of the pay differential attributable to the intercept—the group membership aspect—is likely to remain high. In other words, even better data, and a better model specification, would be unlikely to overturn the conclusion that sexual discrimination is at work within the managerial labour market.

The glass ceiling studies suggest why this is so, and help explain why 'group membership' is likely to have such a large impact on earnings. One of the early insights into managerial culture was the recognition that senior managers 'treat all workers as if they are men', and in so doing, fail to provide support in the form for their staff in the form of child care, parental leave or flexible work schedules (Newman, 1993). This is exacerbated by the current domestic division of labour, which leaves most women with the greater share of that burden (see, for example, Bittman and Lovejoy (1993); Baxter et al. (2005); Noonan (2001)). The findings above reinforce this: for women the presence of young children are negatively correlated with both their entry into management jobs and their level of earnings. The longer hours worked by male managers—evident in this study—are also made possible by these kinds of domestic arrangements, as is the opportunity to travel for work (such as interstate or overnight trips). Both of these can be assets when it comes to career progression.

Moreover, moving into senior management jobs is contingent on certain aspects of workplace culture, an area where 'group membership' again features. Researchers have identified the operations of 'exclusionary masculine practices' (Sinclair, 1994) which include the recruitment of 'similar' persons into higher positions. This 'cloning effect', also termed a 'mateship thing' or a 'comfort thing', can come into play at great expense to women's career progression:

> Many managers favor candidates who appear to be like themselves. It makes them feel that they understand the person and can trust him or her. They often use words like comfort, fit, and team to express that desire ... Those are code words for the 'in group', the 'club', or the 'old boys' network' (Jeffalyn Johnson in Gentile (1991, pp. 22)).

Exploring in greater depth why 'group membership' matters so much in sustaining a large gender pay gap among managers is clearly an important research task.

7 Appendix

Table 13: Summary statistics for sample in multinomial model

	Males		Females	
	Mean	**SD**	**Mean**	**SD**
Aged 25-29	0.091	0.288	0.083	0.275
Aged 30-34	0.095	0.293	0.094	0.291
Aged 35-39	0.099	0.299	0.103	0.304
Aged 40-44	0.105	0.307	0.105	0.306
Aged 45-49	0.115	0.319	0.109	0.311
Aged 50-54	0.091	0.287	0.094	0.292
Aged 55 plus	0.322	0.467	0.334	0.472
Yrs of educatn	13.765	2.036	13.279	2.098
Couple	0.721	0.449	0.657	0.475
One child 0–4	0.094	0.292	0.103	0.304
Two plus child 0–4	0.048	0.213	0.046	0.210
One child 5–9	0.094	0.292	0.106	0.308
Two plus child 5–9	0.035	0.183	0.038	0.192
Non-city resident	0.427	0.495	0.411	0.492

Note: Wave 7 data: 2007.
Source: Unit record data, HILDA, Release 7.
Population: All adult respondents.

Table 14: Summary statistics for sample in final models

	OLS 2007				Multilevel 2001 to 2007			
	Males		Females		Males		Females	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Aged 25-29	0.100	0.300	0.091	0.289	0.093	0.291	0.137	0.344
Aged 30-34	0.146	0.353	0.177	0.383	0.162	0.369	0.156	0.363
Aged 35-39	0.167	0.374	0.167	0.374	0.164	0.370	0.135	0.342
Aged 40-44	0.127	0.333	0.113	0.317	0.155	0.362	0.118	0.323
Aged 45-49	0.154	0.361	0.145	0.353	0.140	0.347	0.172	0.378
Aged 50-54	0.119	0.324	0.118	0.324	0.123	0.329	0.125	0.331
Aged 55 plus	0.137	0.345	0.091	0.289	0.117	0.321	0.082	0.274
Couple	0.822	0.383	0.656	0.476	0.822	0.383	0.664	0.473
Children 0–4	0.208	0.406	0.145	0.353	0.218	0.413	0.092	0.289
Chidren 5–9	0.213	0.410	0.065	0.246	0.214	0.410	0.076	0.265
Weeks emp in yr	51.881	0.908	51.043	4.814	51.628	2.229	51.116	4.184
Vic	0.264	0.441	0.263	0.442	0.257	0.437	0.242	0.429
Qld	0.181	0.385	0.204	0.404	0.180	0.385	0.208	0.406
SA	0.070	0.256	0.048	0.215	0.078	0.269	0.057	0.233
WA & NT	0.092	0.289	0.086	0.281	0.092	0.290	0.092	0.290
Tas & ACT	0.065	0.246	0.059	0.237	0.058	0.234	0.057	0.233
Non-city resid	0.342	0.475	0.296	0.458	0.332	0.471	0.312	0.464
Yrs of educatn	14.493	2.033	14.339	2.105	14.426	2.002	14.246	2.062
Occup tenure	9.841	9.451	7.769	9.168	8.780	8.669	7.199	8.225
Job tenure	8.272	8.199	6.981	8.033	8.433	8.472	7.018	7.793
Occup status	64.555	15.057	65.826	15.925	64.810	14.716	66.110	15.627
Usual wkly hrs	48.116	7.346	45.215	7.345	48.548	7.380	45.296	7.209
Union member	0.156	0.364	0.226	0.419	0.194	0.395	0.250	0.433
Retail	0.132	0.339	0.194	0.396	0.095	0.294	0.154	0.361
Acc, cafes, rec	0.040	0.197	0.081	0.273	0.058	0.233	0.074	0.262
IT & bus serv	0.148	0.356	0.145	0.353	0.126	0.332	0.161	0.367
Fin & insurance	0.065	0.246	0.097	0.296	0.074	0.261	0.072	0.258
Government	0.094	0.293	0.102	0.304	0.105	0.306	0.110	0.313
Education	0.062	0.241	0.081	0.273	0.069	0.253	0.103	0.304
Health & community	0.046	0.209	0.204	0.404	0.067	0.250	0.195	0.396
Public sector	0.151	0.358	0.263	0.442	0.192	0.394	0.288	0.453
Org size: 20–99	0.132	0.339	0.113	0.317	0.178	0.383	0.162	0.369
Org size: 100–499	0.194	0.396	0.199	0.400	0.182	0.386	0.180	0.384
Org size: 500 plus	0.480	0.500	0.575	0.496	0.477	0.500	0.517	0.500
Org with single wp	0.229	0.421	0.183	0.388	0.247	0.431	0.243	0.429

Note: Waves 1 to 7: 2001 to 2007 for multilevel; Wave 7 for OLS.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations; OLS 2007 models: n = 557 (male n = 371, female n = 186); multilevel models: n = 3,851 (male n = 2,650, female n = 1,201).

Table 15: Multinomial Logit Results, 2007

	Male		Female	
	Manager	Other	Manager	Other
Intercept	-3.907	-0.477	-6.073	-2.059
	(0.442)	(0.287)	(0.539)	(0.244)
Aged 25-29	0.930	0.331	-0.203	-0.206
	(0.341)	(0.220)	(0.360)	(0.167)
Aged 30-34	1.205	0.217	0.713	-0.142
	(0.336)	(0.228)	(0.322)	(0.165)
Aged 35-39	1.107	0.025	0.874	0.124
	(0.328)	(0.219)	(0.326)	(0.165)
Aged 40-44	1.027	0.041	0.105	-0.301
	(0.325)	(0.214)	(0.329)	(0.161)
Aged 45-49	1.018	-0.131	0.181	-0.278
	(0.316)	(0.207)	(0.319)	(0.162)
Aged 50-54	0.498	-0.657	-0.181	-0.632
	(0.319)	(0.203)	(0.324)	(0.160)
Aged 55 plus	-1.860	-3.048	-2.262	-2.715
	(0.290)	(0.165)	(0.305)	(0.135)
Yrs of educatn	0.181	0.163	0.340	0.268
	(0.027)	(0.019)	(0.034)	(0.016)
Couple	1.363	0.873	0.482	0.393
	(0.147)	(0.098)	(0.154)	(0.071)
One child 0–4	-0.480	-0.540	-1.250	-1.334
	(0.217)	(0.180)	(0.238)	(0.110)
Two plus child 0–4	-0.589	-0.557	-1.989	-2.015
	(0.286)	(0.236)	(0.336)	(0.150)
One child 5–9	0.314	0.138	-1.146	-0.348
	(0.218)	(0.189)	(0.266)	(0.110)
Two plus child 5–9	-0.307	-0.476	-1.702	-0.502
	(0.300)	(0.250)	(0.481)	(0.168)
Non-city resid	0.070	-0.178	0.109	-0.094
	(0.108)	(0.079)	(0.138)	(0.066)
AIC	7643		7949	
Deviance	7583		7889	
N	5237		6003	

Notes: Outcome variable: working as a full-time manager; or working otherwise; or not working at all. Base (reference) category: not working at all. Standard errors in brackets. Omitted categories are: Aged 21 to 24; Single; No child 0–4, No child 5–9, City resident.
Odds ratios (also known as relative risk ratios) can be calculated for these coefficients by taking their exponents.
Source: Unit record data, HILDA, Release 7.
Population: All adult respondents.

Table 16: OLS results for annual earnings, 2007

	Unadjusted			Adjusted		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Intercept	6.618	8.458	7.960	7.715	8.909	8.351
	(1.250)	(0.398)	(0.340)	(1.928)	(0.876)	(0.486)
Aged 25-29	0.075	0.165	0.127	-0.045	0.165	0.105
	(0.112)	(0.109)	(0.078)	(0.149)	(0.131)	(0.085)
Aged 30-34	0.302	0.274	0.314	0.101	0.227	0.260
	(0.108)	(0.098)	(0.074)	(0.207)	(0.140)	(0.089)
Aged 35-39	0.326	0.322	0.356	0.098	0.289	0.303
	(0.109)	(0.100)	(0.075)	(0.224)	(0.124)	(0.090)
Aged 40-44	0.240	0.338	0.311	0.041	0.319	0.267
	(0.113)	(0.105)	(0.078)	(0.216)	(0.136)	(0.090)
Aged 45-49	0.260	0.385	0.348	0.031	0.358	0.295
	(0.111)	(0.102)	(0.076)	(0.225)	(0.133)	(0.091)
Aged 50-54	0.245	0.291	0.301	0.035	0.266	0.253
	(0.119)	(0.109)	(0.082)	(0.223)	(0.132)	(0.092)
Aged 55 plus	0.292	0.362	0.343	0.260	0.392	0.348
	(0.117)	(0.135)	(0.085)	(0.109)	(0.156)	(0.088)
Couple	0.160	0.025	0.090	0.015	0.014	0.061
	(0.057)	(0.050)	(0.038)	(0.141)	(0.054)	(0.041)
Weeks emp in yr	0.038	0.014	0.016	0.040	0.015	0.016
	(0.024)	(0.005)	(0.005)	(0.032)	(0.009)	(0.006)
Vic	-0.140	-0.094	-0.114	-0.141	-0.093	-0.115
	(0.054)	(0.062)	(0.040)	(0.053)	(0.061)	(0.042)
Qld	-0.085	-0.134	-0.084	-0.079	-0.133	-0.083
	(0.062)	(0.072)	(0.046)	(0.064)	(0.087)	(0.047)
SA	0.024	-0.119	-0.003	0.020	-0.116	-0.008
	(0.088)	(0.116)	(0.068)	(0.082)	(0.130)	(0.058)
WA & NT	-0.035	0.072	0.010	-0.034	0.072	0.011
	(0.077)	(0.091)	(0.059)	(0.074)	(0.119)	(0.061)
Tas & ACT	-0.144	0.006	-0.089	-0.156	0.010	-0.090
	(0.093)	(0.109)	(0.072)	(0.074)	(0.123)	(0.059)
Non-city resid	-0.091	-0.089	-0.098	-0.144	-0.096	-0.112
	(0.046)	(0.056)	(0.035)	(0.065)	(0.063)	(0.037)
Yrs of educatn	0.052	0.017	0.039	0.042	0.009	0.034
	(0.012)	(0.013)	(0.009)	(0.014)	(0.021)	(0.010)
Occup tenure	0.006	0.001	0.005	0.006	0.001	0.005
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Job tenure	-0.003	0.000	-0.001	-0.003	0.000	-0.001
	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.002)
Occup status	0.011	0.012	0.011	0.011	0.012	0.011
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Usual wkly hrs	0.017	0.011	0.015	0.017	0.011	0.015
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)
Union member	-0.098	-0.015	-0.078	-0.096	-0.016	-0.077
	(0.066)	(0.076)	(0.049)	(0.060)	(0.068)	(0.043)
Retail	0.062	-0.053	0.024	0.062	-0.057	0.026
	(0.071)	(0.112)	(0.056)	(0.074)	(0.107)	(0.059)
Acc, cafes, rec	-0.047	0.055	-0.016	-0.048	0.050	-0.021
	(0.109)	(0.128)	(0.078)	(0.125)	(0.125)	(0.079)
IT & bus serv	0.144	0.175	0.148	0.143	0.176	0.150
	(0.063)	(0.096)	(0.051)	(0.064)	(0.105)	(0.053)
Fin & insurance	0.267	0.089	0.193	0.257	0.092	0.194
	(0.090)	(0.107)	(0.065)	(0.095)	(0.114)	(0.070)
Government	-0.009	-0.012	-0.012	-0.008	-0.019	-0.012
	(0.112)	(0.135)	(0.082)	(0.106)	(0.134)	(0.073)
Education	-0.082	-0.069	-0.082	-0.101	-0.072	-0.085
	(0.109)	(0.136)	(0.081)	(0.106)	(0.140)	(0.074)
Health & community	-0.210	-0.063	-0.085	-0.213	-0.062	-0.085
	(0.099)	(0.100)	(0.063)	(0.071)	(0.097)	(0.053)

	Unadjusted			Adjusted		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Public sector	-0.052	0.071	0.022	-0.045	0.074	0.026
	(0.098)	(0.098)	(0.068)	(0.092)	(0.093)	(0.060)
Org size: 20–99	-0.003	-0.035	0.008	-0.002	-0.034	0.010
	(0.081)	(0.107)	(0.063)	(0.090)	(0.104)	(0.066)
Org size: 100–499	0.201	0.038	0.160	0.204	0.040	0.159
	(0.081)	(0.103)	(0.063)	(0.078)	(0.107)	(0.059)
Org size: 500 plus	0.159	0.054	0.147	0.162	0.052	0.147
	(0.082)	(0.101)	(0.062)	(0.083)	(0.104)	(0.060)
Org with single wp	-0.130	-0.119	-0.115	-0.130	-0.123	-0.116
	(0.067)	(0.079)	(0.051)	(0.066)	(0.078)	(0.049)
Female			-0.129			-0.081
			(0.037)			(0.133)
Lambda				-0.497	-0.152	-0.150
				(0.430)	(0.237)	(0.056)
R squared	0.532	0.642	0.547	0.534	0.643	0.548
Adjusted R squared	0.486	0.564	0.517	0.486	0.563	0.517
N	371	186	557	371	186	557

Notes: Outcome variable: Log of annual wage and income salary. Standard errors in brackets. Standard errors for adjusted results calculated by bootstrapping (1000 repititions).
Omitted categories are: Aged 21 to 24; Single; NSW; City resident; Blue collar industries; Org size under 20; Org with multiple wps; Male.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 557 (male n = 371, female n = 186).

Table 17: Multilevel modelling results for annual earnings

	Without adjustment			With adjustment		
	Male	Female	Pooled	Male	Female	Pooled
Fixed effects:						
Intercept	8.471	7.875	8.263	8.862	8.505	8.826
	(0.162)	(0.170)	(0.114)	(0.235)	(0.289)	(0.163)
Aged 25-29	0.176	0.193	0.181	0.138	0.149	0.134
	(0.040)	(0.047)	(0.030)	(0.043)	(0.049)	(0.032)
Aged 30-34	0.285	0.267	0.280	0.227	0.216	0.213
	(0.041)	(0.050)	(0.032)	(0.048)	(0.053)	(0.035)
Aged 35-39	0.368	0.290	0.343	0.302	0.252	0.274
	(0.042)	(0.052)	(0.033)	(0.051)	(0.054)	(0.036)
Aged 40-44	0.437	0.264	0.386	0.367	0.236	0.315
	(0.044)	(0.053)	(0.034)	(0.054)	(0.053)	(0.036)
Aged 45-49	0.427	0.279	0.380	0.357	0.227	0.302
	(0.045)	(0.052)	(0.034)	(0.054)	(0.055)	(0.037)
Aged 50-54	0.430	0.261	0.374	0.356	0.207	0.293
	(0.046)	(0.055)	(0.035)	(0.056)	(0.058)	(0.039)
Aged 55 plus	0.472	0.262	0.412	0.467	0.285	0.418
	(0.050)	(0.062)	(0.039)	(0.050)	(0.063)	(0.038)
Couple	0.073	-0.014	0.040	0.025	-0.032	-0.007
	(0.020)	(0.025)	(0.016)	(0.029)	(0.026)	(0.018)
Weeks emp in yr	0.018	0.022	0.021	0.018	0.022	0.021
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Vic	-0.056	-0.034	-0.047	-0.056	-0.035	-0.048
	(0.028)	(0.037)	(0.022)	(0.028)	(0.036)	(0.022)
Qld	-0.077	-0.043	-0.061	-0.076	-0.043	-0.061
	(0.030)	(0.040)	(0.024)	(0.030)	(0.040)	(0.024)
SA	-0.064	-0.176	-0.090	-0.062	-0.173	-0.088
	(0.044)	(0.066)	(0.037)	(0.044)	(0.065)	(0.037)
WA & NT	-0.088	-0.043	-0.075	-0.086	-0.035	-0.069
	(0.038)	(0.051)	(0.030)	(0.038)	(0.050)	(0.030)
Tas & ACT	-0.046	0.001	-0.034	-0.048	-0.000	-0.036
	(0.046)	(0.061)	(0.037)	(0.046)	(0.060)	(0.037)
Non-city resid	-0.132	-0.089	-0.121	-0.150	-0.112	-0.144
	(0.022)	(0.031)	(0.018)	(0.024)	(0.032)	(0.019)
Yrs of educatn	0.041	0.042	0.043	0.039	0.029	0.036
	(0.006)	(0.007)	(0.004)	(0.006)	(0.009)	(0.005)
Occup tenure	0.001	0.002	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Job tenure	0.002	0.006	0.003	0.002	0.006	0.003
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Occup status	0.005	0.007	0.005	0.005	0.007	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Usual wkly hrs	0.008	0.010	0.008	0.008	0.009	0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Union member	-0.014	-0.007	-0.010	-0.014	-0.007	-0.011
	(0.021)	(0.028)	(0.017)	(0.021)	(0.028)	(0.017)
Retail	-0.028	-0.029	-0.034	-0.028	-0.030	-0.033
	(0.029)	(0.047)	(0.024)	(0.029)	(0.047)	(0.024)
Acc, cafes, rec	-0.140	-0.122	-0.139	-0.142	-0.124	-0.137
	(0.042)	(0.058)	(0.033)	(0.042)	(0.057)	(0.033)
IT & bus serv	0.079	0.104	0.084	0.081	0.102	0.086
	(0.024)	(0.041)	(0.020)	(0.024)	(0.041)	(0.020)
Fin & insurance	0.152	0.057	0.113	0.150	0.064	0.116
	(0.037)	(0.056)	(0.031)	(0.037)	(0.055)	(0.030)
Government	0.042	0.061	0.038	0.041	0.060	0.038
	(0.036)	(0.053)	(0.029)	(0.036)	(0.053)	(0.029)
Education	0.010	-0.006	-0.008	0.008	-0.004	-0.006
	(0.043)	(0.058)	(0.034)	(0.043)	(0.058)	(0.034)
Health & community	-0.056	-0.005	-0.031	-0.056	-0.005	-0.033

	Without adjustment			With adjustment		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
	(0.032)	(0.044)	(0.025)	(0.032)	(0.044)	(0.025)
Public sector	-0.072	0.031	-0.026	-0.073	0.032	-0.026
	(0.029)	(0.035)	(0.022)	(0.029)	(0.035)	(0.022)
Org size: 20–99	0.104	0.116	0.110	0.103	0.119	0.109
	(0.023)	(0.038)	(0.020)	(0.023)	(0.038)	(0.020)
Org size: 100–499	0.194	0.185	0.192	0.194	0.190	0.192
	(0.028)	(0.041)	(0.023)	(0.028)	(0.040)	(0.023)
Org size: 500 plus	0.221	0.210	0.217	0.222	0.216	0.218
	(0.028)	(0.042)	(0.023)	(0.028)	(0.042)	(0.023)
Org with single wp	0.010	0.015	0.013	0.010	0.018	0.013
	(0.020)	(0.030)	(0.016)	(0.020)	(0.030)	(0.016)
Female			-0.203			-0.129
			(0.020)			(0.025)
Lambda				-0.168	-0.197	-0.220
				(0.073)	(0.072)	(0.046)
SD of error terms:						
Household	0.05	0.11	0.07	0.05	0.11	0.07
Individual (Repeated)	0.34	0.30	0.33	0.34	0.30	0.33
Episode (Residual)	0.20	0.18	0.19	0.20	0.18	0.19
AIC	1398.55	777.62	1981.65	1398.64	775.74	1964.69
Deviance	1102.23	501.76	1662.31	1096.86	494.16	1638.75
No. observations	2650	1201	3851	2650	1201	3851
No. household groups	2409	1149	3260	2409	1149	3260
No. individuals	1101	582	1683	1101	582	1683

Notes: Outcome variable: Log of annual wage and income salary. Standard errors in brackets. Omitted categories are: Aged 21 to 24; Single; NSW; City resident; Blue collar industries; Org size under 20; Org with multiple wps; Male.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations, n = 3,851 (male n = 2,650, female n = 1,201).

Table 18: Models used for decomposition

	OLS model 2007			Multilevel model 2001–2007		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Intercept	6.605	8.481	7.961	8.481	7.916	8.259
	(1.257)	(0.399)	(0.340)	(0.162)	(0.170)	(0.114)
Aged 25-29	0.073	0.142	0.127	0.171	0.197	0.180
	(0.112)	(0.110)	(0.078)	(0.040)	(0.047)	(0.030)
Aged 30-34	0.292	0.275	0.309	0.270	0.279	0.274
	(0.109)	(0.098)	(0.075)	(0.042)	(0.050)	(0.032)
Aged 35-39	0.313	0.336	0.345	0.352	0.319	0.337
	(0.110)	(0.103)	(0.076)	(0.043)	(0.053)	(0.033)
Aged 40-44	0.243	0.331	0.307	0.433	0.270	0.384
	(0.114)	(0.105)	(0.079)	(0.044)	(0.052)	(0.034)
Aged 45-49	0.269	0.366	0.350	0.430	0.277	0.381
	(0.112)	(0.102)	(0.077)	(0.045)	(0.052)	(0.034)
Aged 50-54	0.257	0.264	0.306	0.438	0.252	0.378
	(0.120)	(0.111)	(0.083)	(0.046)	(0.054)	(0.035)
Aged 55 plus	0.307	0.340	0.350	0.482	0.252	0.416
	(0.119)	(0.136)	(0.085)	(0.050)	(0.062)	(0.039)
Couple	0.141	0.030	0.084	0.058	-0.010	0.034
	(0.061)	(0.050)	(0.039)	(0.021)	(0.025)	(0.016)
Children 0–4	0.043	-0.105	0.015	0.042	-0.045	0.024
	(0.058)	(0.071)	(0.044)	(0.017)	(0.035)	(0.015)
Chidren 5–9	0.032	-0.049	0.035	0.024	-0.111	0.010
	(0.056)	(0.102)	(0.047)	(0.017)	(0.038)	(0.016)
Weeks emp in yr	0.038	0.014	0.016	0.018	0.022	0.021
	(0.024)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Vic	-0.143	-0.100	-0.115	-0.056	-0.033	-0.047
	(0.054)	(0.062)	(0.040)	(0.028)	(0.036)	(0.022)
Qld	-0.086	-0.131	-0.084	-0.077	-0.039	-0.061
	(0.062)	(0.072)	(0.046)	(0.030)	(0.040)	(0.024)
SA	0.024	-0.109	-0.005	-0.065	-0.172	-0.090
	(0.088)	(0.116)	(0.068)	(0.044)	(0.066)	(0.037)
WA & NT	-0.040	0.081	0.009	-0.087	-0.035	-0.076
	(0.077)	(0.091)	(0.059)	(0.038)	(0.050)	(0.030)
Tas & ACT	-0.154	0.008	-0.097	-0.050	0.005	-0.035
	(0.095)	(0.109)	(0.072)	(0.046)	(0.060)	(0.037)
Non-city resid	-0.093	-0.095	-0.100	-0.135	-0.086	-0.121
	(0.047)	(0.057)	(0.036)	(0.022)	(0.031)	(0.018)
Yrs of educatn	0.051	0.018	0.039	0.041	0.041	0.043
	(0.012)	(0.013)	(0.009)	(0.006)	(0.007)	(0.004)
Occup tenure	0.006	0.001	0.005	0.001	0.002	0.001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Job tenure	-0.003	0.001	-0.001	0.002	0.006	0.003
	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)	(0.001)
Occup status	0.011	0.012	0.011	0.004	0.007	0.005
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Usual wkly hrs	0.017	0.011	0.015	0.008	0.009	0.008
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Union member	-0.089	-0.020	-0.075	-0.014	-0.007	-0.010
	(0.067)	(0.076)	(0.049)	(0.021)	(0.028)	(0.017)
Retail	0.067	-0.037	0.027	-0.030	-0.038	-0.034
	(0.071)	(0.114)	(0.056)	(0.029)	(0.047)	(0.024)
Acc, cafes, rec	-0.042	0.061	-0.012	-0.138	-0.133	-0.138
	(0.109)	(0.129)	(0.078)	(0.042)	(0.057)	(0.033)
IT & bus serv	0.147	0.188	0.149	0.080	0.102	0.085
	(0.064)	(0.096)	(0.051)	(0.024)	(0.041)	(0.020)
Fin & insurance	0.267	0.112	0.192	0.152	0.055	0.113
	(0.090)	(0.109)	(0.065)	(0.037)	(0.055)	(0.031)
Government	-0.008	0.015	-0.010	0.043	0.056	0.038
	(0.112)	(0.138)	(0.082)	(0.036)	(0.053)	(0.029)

	OLS model 2007			Multilevel model 2001–2007		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Education	-0.091	-0.043	-0.085	0.010	-0.013	-0.008
	(0.109)	(0.137)	(0.081)	(0.043)	(0.058)	(0.034)
Health & community	-0.209	-0.041	-0.087	-0.054	-0.009	-0.030
	(0.100)	(0.101)	(0.063)	(0.032)	(0.044)	(0.025)
Public sector	-0.050	0.055	0.024	-0.071	0.035	-0.026
	(0.099)	(0.099)	(0.068)	(0.029)	(0.035)	(0.022)
Org size: 20–99	-0.004	-0.028	0.007	0.105	0.113	0.110
	(0.081)	(0.108)	(0.063)	(0.023)	(0.038)	(0.020)
Org size: 100–499	0.206	0.057	0.161	0.195	0.179	0.192
	(0.081)	(0.104)	(0.064)	(0.028)	(0.040)	(0.023)
Org size: 500 plus	0.162	0.052	0.149	0.223	0.207	0.217
	(0.082)	(0.101)	(0.062)	(0.028)	(0.041)	(0.023)
Org with single wp	-0.124	-0.128	-0.113	0.012	0.014	0.014
	(0.068)	(0.080)	(0.052)	(0.020)	(0.030)	(0.016)
Female			-0.124			-0.200
			(0.037)			(0.020)
OLS statistics						
R squared	0.533	0.648	0.548			
Adjusted R squared	0.484	0.565	0.516			
N	371	186	557			
Multilevel statistics						
SD of error terms:						
Household				0.05	0.11	0.07
Individual (Repeated)				0.34	0.30	0.33
Episode (Residual)				0.20	0.18	0.19
AIC				1407.74	781.50	1995.95
Deviance				1094.74	491.71	1659.56
No. observations				2650	1201	3851
No. household groups				2409	1149	3260
No. individuals				1101	582	1683

Notes: Outcome variable: Log of annual wage and income salary. Standard errors in brackets. Omitted categories are: Aged 21 to 24; Single; No children; NSW; City resident; Blue collar industries; Org size under 20; Org with multiple wps; Male.
Source: Unit record data, HILDA, Release 7.
Population: Adult respondents working as full-time employees and in management occupations; OLS 2007 models: n = 557 (male n = 371, female n = 186); multilevel models: n = 3,851 (male n = 2,650, female n = 1,201).

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