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Decomposing the Gender Pay Gap in the Australian Managerial Labour Market

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Abstract

This article[1] examines the gender pay gap among full-time managers in Australia over the period 2001 to 2008. Using decompositions I explore the issue of discrimination, as well as the roles played by labour force experience and parenting. The results show that female managers earned on average about 27 per cent less than their male counterparts and the decompositions suggest that somewhere between 65 and 90 per cent of this earnings gap cannot be explained by recourse to a large range of demographic and labour market variables. A major part of the earnings gap is simply due to women managers being female. In addition, the presence of dependent children worsens the earnings gap, while the financial returns to labour force experience diminish in the latter years among female managers rather than stabilising, as they do for male managers. Despite the characteristics of male and female managers being remarkably similar, their earnings are very different, suggesting that discrimination plays an important role in this outcome. The article uses eight waves of HILDA data to fit mixed-effects models which are then used for Blinder-Oaxaca decompositions. In addition, a recent simulated change approach, developed by Olsen and Walby in the UK, is also implemented using this Australian data.

JEL Classification: J31, J70, J16

[1] This article 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 article, however, are those of the author and should not be attributed to either FaHCSIA or the MIAESR.

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1. Introduction

Until the early 1970s the gender pay gap[2] in Australia was wide, and was kept that way by 'institutionalised gender wage discrimination', in the words of Paul Miller (1994, p. 371). 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; and Borland, 1999). Nevertheless, a gender pay gap of considerable size has remained to this day. In his overview at the end of the 1990s, Borland summarised a number of studies covering the 1980s and 1990s which showed that the pay gap ranged from about 8 per cent to 25 per cent (Borland, 1999, p. 267). Borland observed that discrimination accounted for between 7 percentage points and 19 percentage points of the gap. He concluded that most of the reduction in the pay 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 in which the concept of comparable worth was a central plank (Pocock, 1999). Using data from the late 1980s, Miller (1994) found a gender pay 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 per cent 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 pay 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 of the gap (1999, p. 167).

However, Wooden argued that including the managerial workforce in such studies was unwarranted. When he removed managers from the sample, he found that the gender pay 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 pay 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 pay 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).

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 wages distribution. Using unit record data from the 2001 Australian census, Paul Miller found that the pay gap was much greater among high wage earners than among low wage earners. In the 5th to the 35th quantile it was below 10 per cent, at the 40th quantile it was about 12 per cent,

[2] The terms 'wages', 'pay' and 'earnings' are used interchangeably in this article to refer to labour market earnings. The term 'wages' is more commonly used when discussing the decomposition literature, or the labour force more generally; the term 'pay' is preferred when discussing managerial earnings, where 'wages' seems a somewhat inappropriate expression.

but at the 95th quantile it reached 23 per cent (2005, p. 412). This led Miller 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). Moreover, other research suggests that policy initiatives may work differently at different locations in the distribution. As Gardeazabal and Ugidos (2005, p. 167) argue:

> ...policies might have different impacts at different quantiles of the distribution of wages if, for example, as a result of the policies implemented more women enter into low paid occupations. Therefore, it is necessary to measure gender wage discrimination at different quantiles to determine the indirect effect of such policies.

Innovations in the use of quantile regression methods (for example, Buchinsky, 1998; and Koenker and Hallock, 2001) have opened up this field of research. Using the first wave of the HILDA data, Kee (2006) made use of quantile regression to explore the gender pay gap in Australia while Albrecht *et al*. (2003), Gardeazabal and Ugidos (2005) and Arulampalam *et al*. (2007) have used quantile regression coupled with decomposition methods to unpack the gender pay gap in Sweden, Spain, and the European Union, respectively.

Other decomposition approaches which don’t involve quantile regression have also examined the gender pay gap in Australia at different locations in the wages distribution. Recent research by Barón and Cobb-Clark (2008), using semi-parametric methods developed by DiNardo *et al*. (1996), have pursued this strategy using the first six waves of the HILDA data. As these authors observed:

> it is now becoming clear that the magnitude of the gender wage gap is generally not constant across the entire wage distribution and that the gap in mean wages obscures a great deal of the interesting variation in the data ...a much richer story about the role of gender in the labour market emerges once we move away from an exclusive focus on outcomes for ‘average’ men and women (2008, p. 2).

Barón and Cobb-Clark (2008) contrasted the private and public sectors, a strategy which Kee (2006) had also earlier pursued. Kee 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). While their methods differed, the study by Barón and Cobb-Clark (2008) reinforced Kee’s finding that the gap was ‘roughly constant’ across the public-sector wages distribution – at about 13 per cent – but they also found a somewhat surprising result which reflected poorly on public sector employment. Their decomposition method showed that the explanation for the public-sector gap was highly sensitive to location within the wages distribution, with the unexplained (or discriminatory) component of much greater influence at the top of the distribution:

> The proportion of the gender wage gap that cannot be explained by differences in wage-related characteristics is insignificantly different from zero in the bottom half of the distribution. Among high-wage workers, however, the portion of the wage gap not attributable to gender differences in endowments rises to over 90 per cent. Despite the fact that the magnitude of the public-sector gender wage gap is relatively constant, the extent to which it can be explained by the wage-related characteristics of men and women falls as we move up the wage distribution. Overall, it appears that high-wage public-sector employees in Australia may face more employer discrimination (i.e., glass ceilings) than low-wage workers (i.e., sticky floors) (2008, p. 17).[3]

In the private sector, on the other hand, they found that the unexplained component at top of the distribution is much smaller – at between 50 and 60 per cent – suggesting discrimination was less influential (though still of a considerable magnitude).

In this article I build upon this tradition of decomposing the pay gap at the top of the wages distribution. However, rather than contrasting different locations within that distribution, I focus specifically on the occupational grouping of managers. Defined according to the ANZSCO Major Group 1, this occupation is quite distinctive and lends itself to a gender comparison of earnings. The work which male and female managers do is highly comparable and there is no obvious reason for any kind of sub-occupational segregation. Levels of full-time work among female managers are exceptionally high, while the educational levels of male and female managers are remarkably similar. At the same time, however, the top echelons of management are disproportionately occupied by men, returning us to Wooden's point about the assumed link between inequality in access to promotion and the gender pay gap.

At noted earlier, some of the decomposition literature in this area has focused on quantile regression. There are, in addition, several studies which have used decomposition methods to unpack the gender pay gap in the managerial labour market. These include Lausten (2001) and Holst and Busch (2009) for Denmark and Germany respectively. The former used a combined gender and occupational decomposition approach and estimated the unexplained (or discriminatory) portion of the pay gap at between 23 per cent and 32 per cent (2001, p. 21). Holst and Busch compared decompositions with and without selection effects (that is, taking into account who becomes a manager). Inclusion of the selection effect had a major impact, increasing the unexplained portion of the gender pay gap among managers from about 30 per cent to two-thirds (2009, p. 26).

It is reasonable to regard the level of annual earnings as a rough proxy for seniority so the problem of the gender pay gap among managers also raises questions about discriminatory outcomes in long-term career paths between men and women. In other words, the phenomenon of the glass ceiling – which blocks the movement of women from middle into senior management – appears to be an integral part of the

[3] Sticky floors refer to the situation where the gender wage gap widens at the bottom of the wage distribution and glass ceilings refer to the situation where it widens at the top (see Arulampalam *et al*., 2007, p. 164).

gender pay gap at this level of the labour market. By unpacking some of the determinants of the gender pay gap, using a number of different decomposition methods, it should be possible to gain insights into this dimension of gender inequality within the managerial labour market. In particular, we know that it is common for women – but infrequent for men – to experience parenting as a major disruption in their working lives. While this may or may not translate into fragmented career paths, it does represent fragmentation in the duration and continuity of their job and labour force experience (Beblo and Wolf, 2002). The conventional earnings equations which examine the return on years of experience have often used age as a proxy for experience, a strategy which overlooks this important gender difference. Fortunately, the HILDA dataset used for this study makes use of a variable which directly measures years of labour force experience and avoids this gender bias. This provides the opportunity in this article to address a key research question. Among the determinants of the gender pay gap, what roles do labour force experience and parenting play in influencing this outcome?

As with the Barón and Cobb-Clark (2008) study, my analysis makes use of the HILDA data. In terms of method, the decomposition approach used here involves two different strategies. While they both assist in quantifying the extent to which the gender pay gap is based on discrimination, they do so in different ways. The first strategy uses Blinder-Oaxaca methods to provide a detailed breakdown of the variables which contribute most to the discriminatory component within the gender pay gap. The second strategy makes use of a simulated change methodology, developed by Wendy Olsen and Sylvia Walby in the United Kingdom (Olsen and Walby, 2004; and Walby and Olsen, 2002). This also allows for a detailed decomposition and it makes it possible to render the contribution of individual variables in dollar terms. With this strategy researchers can examine, for example, how much their parenting roles cost women in dollar terms. Both of these strategies point towards the same conclusion: simply being a female is the basis for the major part of the gender earnings gap found among managers. At the same time, family life and labour force experience are pivotal in understanding unequal outcomes in the managerial labour market. In summary, both direct and indirect forms of discrimination appear to be implicated in the maintenance of the gender pay gap.

2. Method

The Blinder-Oaxaca Tradition of Decomposing Wage Gaps

The use of Blinder-Oaxaca 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 method 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 males and females, 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' (or 'productivity differential') and 'discrimination' used throughout the literature, it is important to keep in mind several caveats around these terms. The first set of terms are based on human capital assumptions about wages and productivity, assumptions not universally shared among labour market researchers. Clearly, a more neutral term like 'characteristics' is preferable. 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'. While recognising the importance of this caveat, I will continue to use the term 'discrimination' because it is so central to this tradition of research.

The core decomposition method 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. 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. Rearranging 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:

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

and

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

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) for more details.

It is clear from these two equations that a key choice within the decomposition tradition is a normative criterion, that is, a decision about what should constitute a *non-discriminatory benchmark* against which to weight the differences. Regarding the current female wage structure as nondiscriminatory leads to a model of discrimination in which males earn more than they should. On the other hand, regarding the current male wage structure as the norm implies a model of discrimination in which females earn less than they should. 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 a '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:

> ...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). From a different perspective, 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 Becker's 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 ordinary least squares (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 methods 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:

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

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 methods listed. The diagonals of this matrix consist of either 1s or 0s (identity matrix and null matrix) in the first two methods; a set of ratios (0.5 and the female-male ratio) in the Reimers and Cotton method; 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 methods).

Table 1 - Decomposing Earnings Gaps: Conceptual Framework

		Discrimination Decomposed	
Method	*Non-discriminatory Benchmark*	*Male Disadvantage*	*Female Disadvantage*
Blinder (1973)	Male	0	I
Oaxaca (1973)	Female	I	0
Reimers (1983)	Male-female average	0.5	0.5
Cotton (1988)	Female-male ratio	f/m	1 - f/m
Pooled (Oaxaca & Ransom, 1994)	Pooled coefficients (p)	m - p	p - f

Note: There is actually no additional decomposition of the discrimination component for the Blinder and Oaxaca models (since the null matrix removes the non-applicable term) but they are shown in this table in this way so that all methods 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. One popular strategy has been to implement a Juhn-Murphy-Pierce (JMP) 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 method developed by Oaxaca and Ransom (1994) and shown in table 1 above.

The 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 arbitrarily coded categorical variables, could produce inconsistent 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. 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, 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 article for producing the detailed decomposition table shown below.[4]

A Simulated Change Approach

As noted earlier the Blinder-Oaxaca tradition 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; and 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).

The approach developed by 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. In their framework, the wage gap can be represented by:

$$\bar{w}_m - \bar{w}_f = \Sigma\beta'\Delta X \qquad (5)$$

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 (e.g. 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. Table 10 below illustrates how this works in practice.

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 each 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).

One can apply this approach to all of the variables in the regression, or to

[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) and Neumark (1988) who also used pooled regressions, as shown in the last row of table 1.

just a subset. Olsen and Walby, for example, argue that some variables should just be regarded as controls (such as 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). 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) found that this particular variable had a simulation effect of 0.02, which accounted for 10 per cent of their gross wages gap of 0.23. This variable could 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 article, I implement the Olsen/Walby approach and illustrate its relevance in the Australian setting.

Sample Selection Bias

The sample of persons under scrutiny in this article 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. The reason selectivity matters is that 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; and 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).

This issue is dealt with in this study through the use of the Heckman (1979) two-step approach by fitting a selection model to the data prior to fitting the main earnings equation. The selection equation seeks to model who becomes a manager – using multinomial logit estimation – and is used to construct a correction term (the inverse of the Mills ratio) which is then included with the other regressors in the main earnings equation. If this correction term is not statistically significant, then one can conclude that selection bias is not an important issue and modelling the earnings can proceed without the need for including the correction term. In the case of this study, this was the case, and the correction term was excluded from the final models used for the decomposition analysis.[6] As Barón and Cobb-Clark (2008, p. 6) suggest, studies

[6] For reasons of space, the full details of the selection equation modelling used for this article are not shown here but are available from the author.

based on panel data are less likely to find selection effects than those based on cross-sectional data. Longitudinal data, particularly for a large number of waves, clearly increases the range of individuals who are observed over the scope of the study. This may partly explain the different results obtained by Holst and Busch (2009), who find selection effects have a major impact on their cross-sectional decomposition results.

Panel Data and Mixed-effects 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 mixed-effects modelling with panel data also provides more consistent estimates and helps deal with unobserved heterogeneity.

Mixed-effects models, also called multilevel models, entail fitting a model with a fixed component – the usual set of earnings regression controls – as well a random component (Pinheiro and Bates, 2004; and Gelman and Hill, 2007). The actual dataset observations can be regarded as 'earnings episodes' which are clustered within individuals. This hierarchical structure induces dependence among observations, violating one of the key assumptions of ordinary least squares regression. While one can partially deal with this using various robust estimators to correct the standard errors, a more rigorous approach attempts to model the variance directly. Mixed-effects modelling provides for this by allowing for a random effect at the level of the individual and by allowing for the modelling of the variance and the covariance within the earnings episodes as well.

This approach avoids the pitfalls of complete pooling of panel data – which would lead us to ignore differences between individuals and 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). A mixed-effects approach can also deal with unbalanced panel data, such as when there is only one observation per individual subject. In the case of the HILDA panel of managers used in this study, there are a large number of individuals who only appear once in the panel, with females more likely to be in this situation (53 per cent) than males (44 per cent). Their omission does not just reflect absence from the labour market, but occupational mobility, and the fact that becoming a manager is usually some distance along an individual's career pathway.[7]

The coefficients for the fixed-effects from the mixed-effects model are used as the basis for the decomposition of the earnings gap while predictions from the model are used to explore returns to labour force experience. For a mixed-effects model, the earnings equation takes the form:

$$y_{it} = X_{it}\beta + u_i + \epsilon_{it} \tag{6}$$

where y_{it} is the log annual earnings for each individual i, in period t. The terms X_{it} and β are the usual matrix of covariates and the vector of model coefficients. The random component is expressed through the u_i term, and ϵ_{it} is the idiosyncratic error term (the residual). The former captures the random intercepts dimension of the modelling – at the level of the individual – while the latter captures the variability around each earnings episode. This residual is assumed to have an autoregressive correlation structure of order one (AR1). In other words, the error term for earnings in adjacent years is assumed to be more highly correlated than those separated by a larger number of years. The decomposition method works with the fixed effects from this model, which is the same strategy used for estimating marginal predictions from mixed-effects models (Pinheiro and Bates, 2004; and West *et al*., 2007). The actual decomposition routine is thus little different to that which applies when decomposing a conventional ordinary least squares regression.

Summary statistics for the variables used for the regression modeling can be found in table 11 and the regression coefficients and standard errors are shown in table 12. The mixed-effects models were fit using restricted maximum likelihood estimation (REML) and made use of the lme and lmer functions from the nlme and lme4 packages using the R statistical environment (Pinheiro *et al*., 2009; and Bates and Maechler, 2009; and R Development Core Team, 2009). Most of the explanatory variables represent the usual earnings equation variables, coded in the conventional way but with a few variations. Years of labour force experience, defined as the number of years in paid work, included a cubic, as well as a squared term. This captures the usual plateauing of earnings that occurs in the latter year, but moderates the drop-off at the very top end (a tendency which is empirically appropriate for managerial occupations). The inclusion of experience required that age be omitted (due to high collinearity). Some of the usual industry categories were collapsed (for example, construction and utilities were combined, as were wholesale and transport) because of the small number of women managers in these blue-collar industries. For reasons of sample size several of the states were combined. Finally, a finer measure of occupational differentiation within the broader managerial category of ANZSCO Major Group 1 was introduced by employing an occupational status variable.

As mentioned earlier, the selectivity-corrected models proved unnecessary so the results reported here deal only with the final mixed-effect models. Models were fit separately for males and females and interest centred 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) method – and in order to implement the Olsen-Walby approach, a model using pooled male and female data was 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.

[7] Is a random intercepts mixed-effects model appropriate when large numbers of individuals have only one earnings episode? According to Gelman and Hill (2007, p. 276), such models are certainly feasible; while for West *et al*. (2007, p. 48) only if the 'vast majority' of subjects have only one episode may this approach not be warranted. In the case of this study, both a random intercept mixed-effects model and a generalised least squares model were fit to the same data, using the same specification on the fixed effects and the covariance structure of the residuals. The latter model differed from the former by omitting the random intercept. The substantive results were essentially the same and the random intercept mixed-effects model was preferred as it provided a much better fit to the data.

3. Data and Descriptive Overview

As noted already, this article draws on the Australian Government/Melbourne Institute's *Household, Income and Labour Dynamics in Australia* (HILDA) Survey. This is an ongoing longitudinal survey of Australian households which began in 2001 and which is representative of the Australian population.[8] The data for this study comes from Release 8.0. The descriptive tables come from Wave 1 and Wave 8 while the mixed-effects models use pooled data from all eight waves. These regression models make use of unbalanced panels and are unweighted, while the descriptive tables make use of cross-sectional respondent weights.

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 97 per cent and among females it is 81 per cent. By way of comparison, the all-occupational percentages are, respectively, 87 per cent for males and 55 per cent for females (averages for the period 2001 to 2008). The gender difference in hours worked for managers is dealt with in the modelling by the inclusion of a control for weekly hours worked, while there is also a control for weeks worked in the year.

Some of the differences between male and female full-time managers are evident in the summary statistics shown in table 11. Compared with their male counterparts, female managers have fewer years of labour force experience, are less likely to have vocational qualifications, are more likely to be single, are considerably more likely to work in the public sector, and are slightly 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 retail and in health and community services. However, 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 exceptionally similar*. Indeed, much more so than would be the case with an all-occupational comparison.

The measure of earnings used in this study is annual wage and salary income expressed in 2008 dollar terms (with earlier years indexed by the CPI). Because the sample consists of full-time managers for whom salary income is normal, there is little to be gained in constructing an hourly rate of pay variable and, in fact, the long hours of work reported by managers would mean that such an hourly rate would be artificially deflated for a great many respondents. This earnings variable was bottom-coded at $10,000, a restriction which led to the loss of just three observations.[9]

The magnitude of the gender pay gap,[10] at the beginning and end of the period,

[8] For more information on the HILDA survey, see the HILDA Survey User Manual (Watson, 2010).
[9] Sensitivity analysis was also conducted on the effect of omitting observations above $500,000 and this showed no substantive differences. These observations were retained in the dataset because they did not represent outliers for this particular sample of managers.
[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 earnings.

is shown in Table 2. There is no closure in this gap when measured at the mean and a slight narrowing when measured at the median. The size of the gender pay gap shown here – of between 24 and 27 per cent – 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.[11] Because most managers earn somewhere in vicinity of the 95th percentile, it's likely that the size of the gap among the managerial workforce in his sample would be about this magnitude. While not directly comparable – because of her public/private sector split – Kee's quantile analysis of the HILDA data also found similar results. She found a differential (in log earnings) at the 90th percentile of about 0.27 for the private sector and 0.12 for the public sector Kee (2006, p. 416).

Table 2 - Earnings Gap - Mean and Median Annual Salaries Among Fulltime Managers, 2001 and 2008

	Mean		*Median*	
	2001	*2008*	*2001*	*2008*
Male	81,602	88,955	72,407	79,000
Female	59,603	65,173	53,666	60,000
Gap	21,999	23,782	18,741	19,000
Gap (%)	27.0	26.7	25.9	24.1

Notes: Weighted by cross-sectional weights. Earnings are in 2008 dollars (CPI indexed).
Source: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

When it comes to career paths, salary bands are a useful device for gaining insights into seniority. These are shown in tables 3 and 4 which show the gender distribution of managers both across and within salary bands. In terms of the former, some 14 per cent of male managers were in the highest salary band in 2001 (earning $120,000 or more per annum in 2008 dollars), while the equivalent figure for female managers was 2 per cent. By 2008 the male percentage in the top band had grown to 21 per cent; the female percentage had increased to 5 per cent. Figures like these are sensitive to what is happening lower in the distribution: a large increase in the proportion of women working as lower or middle level managers, for example, could result in the proportion at the top declining. For this reason, looking at the gender distribution *within* salary bands is also useful (table 4). These show that female managers made up 5 per cent of the top band in 2001, a proportion which had increased to 12 per cent by 2008. However one looks at it, the presence of women in senior positions is massively small, something recognised regularly in media reporting of business executives.[12]

[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*.
[12] For example, 'Only two in every 100 chief executives in Australia are female. Women hold 10.7 per cent of senior executive positions and chair just 2 per cent of ASX 200 companies' (Mahar and Hurst, 2010, p. 4).

Table 3 - Distribution of Managers Across Salary Bands, 2001 and 2008 (Column %)

	2001			2008		
	Male	*Female*	*Total*	*Male*	*Female*	*Total*
Under $40,000	10	22	14	8	18	12
$40,000 to $60,000	24	34	27	21	31	24
$60,000 to $80,000	25	25	25	22	26	23
$80,000 to $100,000	19	11	17	16	14	16
$100,000 to $120,000	8	6	7	11	6	9
$120,000 or over	14	2	10	21	5	16
Total	100	100	100	100	100	100
n	388	161	549	422	229	651

Notes: Weighted by cross-sectional weights. Earnings are in 2008 dollars (CPI indexed).
Source: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

Table 4 - Distribution of Managers Within Salary Bands, 2001 and 2008 (Row %)

	2001			2008		
	Male	*Female*	*Total*	*Male*	*Female*	*Total*
Under $40,000	10	22	14	8	18	12
$40,000 to $60,000	24	34	27	21	31	24
$60,000 to $80,000	25	25	25	22	26	23
$80,000 to $100,000	19	11	17	16	14	16
$100,000 to $120,000	8	6	7	11	6	9
$120,000 or over	14	2	10	21	5	16
Total	100	100	100	100	100	100
n	388	161	549	422	229	651

Notes: Weighted by cross-sectional weights. Earnings are in 2008 dollars (CPI indexed).
Source: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

4. Results

Decomposition Results

The extent to which discrimination accounts for the gender pay gap varies between 65 per cent and 94 per cent, depending on the approach one takes. The higher figure comes from using the Oaxaca method, while the lower figure comes from the Blinder method. These decomposition results are shown in summary form in table 5 and with a more detailed breakdown in table 6.

This figure of 94 per cent represents 0.260 out of a total (log) earnings differential of 0.278. The remaining .018 of the gap is due to differing characteristics between the sexes. In the case of the 65 per cent figure, the breakdown is 0.180 for discrimination and 0.098 for characteristics (see the Oaxaca and Blinder rows in table 5). The gender differences in coefficients, when applied to the characteristics of female managers, show that the gap is predominantly closed by hours worked and weeks worked (these have negative signs) (see table 6). The differences in returns on occupational status score also helps close the gap.

So what widens the gap? It is predominantly years of labour force experience, with positive figures in the range of 0.071 to 0.091. Just about all of the other variables with positive signs have quite small magnitudes (less than 0.015). Leaving aside labour force experience (to which I return in greater detail later), why does the unexplained component remain so large when most variables in the model help to close the gender differential? The answer lies in the intercept, a figure of considerable magnitude: 0.508. 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 early decomposition studies, it was viewed as the most blatant measure of discrimination (see, for example, Blinder, 1973).

Table 5 - Decomposing Earnings Gaps: Summary of Results

	Differential due to:		*Discrimination Decomp into:*		
	Characteristics	*Discrimination*	*Male advantage*	*Female disadvantage*	*Unexplained as %*
Blinder	0.098	0.180	0.000	0.180	64.8
Oaxaca	0.018	0.260	0.260	0.000	93.5
Reimers	0.058	0.220	0.130	0.090	79.1
Cotton	0.073	0.205	0.082	0.123	73.8
Pooled	0.082	0.196	0.099	0.097	70.5

Notes: Male prediction: 11.30; female prediction: 11.02, differential: 0.27. (All log of annual wage and salary income.) Decomposition is based on of mixed-effects models shown in appendix table 12. *Source*: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

One of the key advantages 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. In analysing a single wave of data the sample size for both male and female managers can be as low as 546. On the other hand, using all eight waves of data provides a sample size of 4,391.[13] Valid statistical inference requires some measure of uncertainty in the modelling and the decomposition approach in this article 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 entailed 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 involved 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

[13] Of course, many of these observations are the same person repeated and are not independent observations. This is the main reason why mixed-effects modelling is employed in the analysis.

Table 6 - Decomposing Earnings Gaps: Detailed Results

	Blinder		*Oaxaca*		*Reimers*		*Cotton*		*Pooled*	
	Character-istics	*Discrim-ination*	*Character-istics*	*Discrim-ination*	*Character-istics*	*Discrim-ination*	*Character-istics*	*Discrim-ination*	*Character-istics*	*Discrimin-ination*
Intercept	0.000	0.508	0.000	0.508	0.000	0.508	0.000	0.508	0.000	0.508
Couple	0.009	0.014	-0.003	0.026	0.003	0.020	0.005	0.018	0.005	0.018
Dependent childre	0.013	-0.092	-0.021	-0.058	-0.004	-0.075	0.003	-0.081	0.008	-0.087
Birthplace	0.000	-0.004	0.001	-0.004	0.001	-0.004	0.001	-0.004	0.000	-0.004
Educational level	-0.002	0.008	-0.001	0.006	-0.002	0.007	-0.002	0.007	-0.002	0.007
Years of experience	0.037	0.071	0.017	0.091	0.027	0.081	0.031	0.078	0.032	0.076
Years in current job	0.004	-0.011	0.006	-0.013	0.005	-0.012	0.004	-0.011	0.004	-0.011
Weeks emp in yr	0.006	-0.211	0.007	-0.212	0.006	-0.212	0.006	-0.211	0.007	-0.212
Usual wkly hrs	0.021	-0.105	0.028	-0.113	0.025	-0.109	0.023	-0.107	0.024	-0.108
Union member	0.001	0.010	-0.001	0.012	-0.000	0.011	0.000	0.010	0.000	0.010
Occup status	-0.005	-0.032	-0.006	-0.031	-0.005	-0.031	-0.005	-0.031	-0.005	-0.031
Industry	0.020	-0.008	0.001	0.011	0.010	0.001	0.014	-0.002	0.016	-0.004
Public sector	0.005	0.013	-0.001	0.019	0.002	0.016	0.003	0.015	0.003	0.016
Organisat size	-0.005	0.003	-0.005	0.002	-0.005	0.003	-0.005	0.003	-0.005	0.003
Org with single wp	0.000	-0.008	-0.000	-0.007	0.000	-0.007	0.000	-0.008	0.000	-0.008
Non-city resid	-0.003	0.013	-0.001	0.011	-0.002	0.012	-0.002	0.012	-0.002	0.012
Stat	-0.001	0.010	-0.001	0.011	-0.001	0.011	-0.001	0.010	-0.001	0.010
Time period	-0.002	-0.001	-0.003	0.000	-0.002	-0.000	-0.002	-0.001	-0.002	-0.001
Total	0.098	0.180	0.018	0.260	0.058	0.220	0.073	0.205	0.082	0.196

Notes: Male prediction: 11.30; female prediction: 11.02, differential: 0.27. (All log of annual wage and salary income.) Decomposition is based on mixed-effects models shown in appendix table 12. Note that for this table only those models were fitted using deviation contrast coding (also called `effect coding') whereas the coefficients shown in appendix table 12 use the conventional indicator contrast coding. See the discussion in the text for further details. *Source*: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

(Cameron and Trivedi, 2005, p. 377).[14]

This bootstrapping approach suggests that the gender pay differential has a standard error of about 0.02, giving a confidence interval of between 0.25 and 0.31 (table 7). The figures reported earlier in table 5 are also reproduced below in tables 8 and tables 9, with their standard errors and confidence intervals shown beside them. The Oaxaca method suggests that the discriminatory component of the gender pay gap lies between 80 per cent and 106 per cent, whilst the Blinder method suggests an interval of between 51 per cent and 72 per cent.

Table 7 - Confidence Intervals for Gender Pay Differential

Method	*Est*	*SE*	*LB*	*UB*
Predicted male	11.30	0.01	11.29	11.32
Predicted female	11.02	0.01	11.00	11.05
Differential	0.28	0.02	0.25	0.31

Notes: Est = estimate; SE = standard error; LB = lower confidence interval bound; UB = upper bound. 95 per cent confidence intervals. Based on bootstrapping the mixed-effects models shown in table 12 but without AR1 correlation of residuals. 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 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

Table 8 - Confidence Intervals for Discrimination as Percentage of Differential

Method	*Est*	*SE*	*LB*	*UB*
Blinder	61.7	5.3	51.2	72.2
Oaxaca	93.1	6.5	80.3	105.9
Reimers	77.4	4.6	68.3	86.5
Cotton	71.6	4.6	62.7	80.5
Pooled	68.9	4.2	60.6	77.2

Notes: 95 per cent confidence intervals. Based on bootstrapping the models shown in table 12 but without AR1 correlation of residuals hence the point estimates slightly differ from those shown in table 5. *Source*: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

[14] Bootstrapping, using 2400 repetitions, was carried out for the mixed-effects models using the boot function, (see Canty and Ripley, 2009; and Davison and Hinkley, 1997). For efficiency the snow package was used to parallelise the bootstrapping, (see Tierney *et al*., 2009a; and Tierney *et al*., 2009b). The AR1 correlation used for the mixed-effects modelling in the main decomposition results could not be repeated in the bootstrap, because any repetition of an observation from the same year violated the AR1 assumption. For this reason the point estimates in the confidence intervals differ from those in the main decomposition results.

Table 9 - Confidence Intervals for Characteristics and Discrimination Components

	Characteristics				*Discrimination*			
Method	*Est*	*SE*	*LB*	*UB*	*Est*	*SE*	*LB*	*UB*
Blinder	0.108	0.017	0.074	0.141	0.173	0.016	0.142	0.205
Oaxaca	0.019	0.019	-0.017	0.056	0.262	0.019	0.224	0.299
Reimers	0.064	0.014	0.035	0.092	0.218	0.014	0.190	0.245
Cotton	0.080	0.015	0.051	0.108	0.201	0.014	0.174	0.228
Pooled	0.087	0.014	0.060	0.115	0.194	0.013	0.168	0.220

Notes: 95 per cent confidence intervals. Based on bootstrapping the models shown in table 12 but without AR1 correlation of residuals. *Source*: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

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.

Table 10 shows the simulated change results for the pooled version of the mixed-effects model and highlights the key finding that group membership, that is, simply being female, counts for $12,899 of the $18,400 pay gap.[15] This represents about 70 per cent of the overall pay gap. Some of the individual components are also revealing. Less labour force experience is costly for female managers: were they to match male managers in this respect they would be earning an additional $2,153 per annum. If their family life – couple and children variables – were also rewarded in the same way, women managers would be earning about $870 more per annum. And if women managers could match the hours routine which male managers maintain, that would be worth an additional $1,607 per annum. These key areas – which reflect the interface between workplace and family life – are the major elements in the gender pay gap using this simulated change approach. Most of the other variables show either trivial amounts or amounts which favour women. Clearly, labour force experience and family life warrant closer inspect.

[15] Note that the gap here is not based on weighted figures, but comes from the unweighted modelling data.

Table 10 - Olsen-Walby Simulated Change: Detailed Results

	Male avg	*Female avg*	ΔX *Change factor*	β *Overall coef*	$\beta'\Delta X$ *Simul effect*	*Simul chng as % gap*	*Ann $ equival*
Female	0.000	1.000	-1.000	-0.192	0.192	0.701	12,899
Couple	0.825	0.679	0.146	0.036	0.005	0.019	349
One dep child	0.173	0.168	0.005	0.001	0.000	0.000	0
Two dep child	0.212	0.092	0.120	0.032	0.004	0.014	255
Three + dep child	0.081	0.017	0.064	0.061	0.004	0.014	266
Born Eng spk country	0.140	0.103	0.037	0.010	0.000	0.001	25
Born Non-Eng spk	0.085	0.087	-0.001	-0.057	0.000	0.000	6
Vocational quals	0.332	0.258	0.074	-0.261	-0.019	-0.071	-1,303
Year 12 quals	0.129	0.157	-0.028	-0.224	0.006	0.023	421
Year 11 or below	0.127	0.157	-0.031	-0.378	0.012	0.042	780
Years of experience*	22.951	19.830	3.121	0.053	0.032	0.117	2,153
Job tenure	8.606	7.128	1.478	0.003	0.004	0.016	287
Weeks employed in yr	51.615	51.183	0.431	0.015	0.007	0.024	440
Usual wkly hrs	48.527	45.215	3.311	0.007	0.024	0.087	1,607
Union member	0.193	0.253	-0.060	-0.004	0.000	0.001	17
Occup status	65.008	66.371	-1.363	0.004	-0.005	-0.020	-366
Primary industry	0.075	0.013	0.062	-0.014	-0.001	-0.003	-57
Construct/utilities	0.066	0.014	0.052	0.054	0.003	0.010	192
Wholesale/transport	0.101	0.040	0.061	0.010	0.001	0.002	39
Retail	0.099	0.157	-0.058	-0.064	0.004	0.013	247
Accommodation, cafes etc	0.056	0.073	-0.017	-0.156	0.003	0.010	183
Information services	0.035	0.030	0.006	0.082	0.000	0.002	31
Finance & insurance	0.073	0.075	-0.002	0.109	-0.000	-0.001	-16
Business services	0.090	0.133	-0.043	0.070	-0.003	-0.011	-200
Government	0.110	0.113	-0.002	0.036	-0.000	-0.000	-5
Education	0.068	0.105	-0.038	-0.038	0.001	0.005	97
Health & community	0.026	0.144	-0.117	-0.070	0.008	0.030	550
Other services	0.038	0.049	-0.011	-0.044	0.000	0.002	33
Public sector	0.196	0.290	-0.094	-0.028	0.003	0.009	174
Org size: 20-99	0.172	0.159	0.013	0.095	0.001	0.005	84
Org size: 100-499	0.184	0.178	0.006	0.149	0.001	0.003	64
Org size: 500 plus	0.485	0.529	-0.043	0.170	-0.007	-0.027	-496
Org with single wp	0.239	0.232	0.007	0.011	0.000	0.000	6
Non-city resid	0.330	0.309	0.021	-0.100	-0.002	-0.008	-143
Vic	0.261	0.242	0.019	-0.050	-0.001	-0.004	-65
Qld	0.182	0.210	-0.028	-0.066	0.002	0.007	123
SA, Tas	0.097	0.078	0.019	-0.108	-0.002	-0.007	-137
WA & NT	0.091	0.092	-0.000	-0.054	0.000	0.000	1
ACT	0.040	0.042	-0.002	-0.013	0.000	0.000	2
Year: 2002	0.126	0.118	0.008	0.118	0.001	0.004	67
Year: 2003	0.125	0.119	0.006	0.189	0.001	0.004	76
Year: 2004	0.128	0.128	0.000	0.303	0.000	0.000	6
Year: 2005	0.116	0.118	-0.002	0.413	-0.001	-0.002	-44
Year: 2006	0.127	0.123	0.004	0.096	0.000	0.002	28
Year: 2007	0.118	0.129	-0.011	0.130	-0.001	-0.005	-100
Year: 2008	0.131	0.151	-0.019	0.130	-0.003	-0.009	-171
Intercept	1.000	1.000	0.000	9.240	0.000	0.000	0
Totals					0.274	1.000	18,400

Notes: Based on the pooled model shown in table 12. *Except for the male and female averages, the labour force experience figures shown here represent the summation of each of the regressors (that is, experience, experience squared and experience cubed). *Source*: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

5. Discussion

Direct Discrimination

The results discussed in the last section are reasonably unambiguous, though their interpretation may be less so. Women full-time managers earn about 27 per cent less than their male counterparts and somewhere between 65 and 90 per cent of this pay gap cannot be explained by the characteristics of managers and is possibly due to discrimination. 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 the major part of the gap is simply due to women managers being female.

Despite quite different methodological approaches, these results are consistent with the findings of Barón and Cobb-Clark (2008), the study most similar in scope to this one. While their results are presented separately for the public and private sectors, the range of estimates for the unexplained (discriminatory) component of their decomposition is quite similar to these results. They find, for example, that the public sector figure is 92 per cent when occupation is excluded, and 88 per cent when it is included. For the private sector, the comparable figures are 59 per cent and 52 per cent. One would assume that were these results pooled, then the all-sector averages would lie squarely within the 65 to 90 per cent range found in this study.

The management literature which deals with the glass ceiling provides qualitative insights into how discrimination may operate at senior levels of management (Sinclair, 2005). It has been argued, for example, that women's movement into senior management jobs can be blocked by 'exclusionary masculine practices' (Sinclair, 1994). As with many in-groups, such practices include the recruitment of 'similar' persons into higher positions. This 'cloning effect', also termed a 'mateship thing' or a 'comfort thing', can restrict the range of people who end up being recruited or promoted:

> Many managers favour 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, cited in Gentile, 1991, pp. 22).

At its crudest, this reduces to 'Men employ men': 'Male executives support and promote other men looking like themselves and they use each others success to their own advantage' (Lausten, 2001, p. 3).

Even when the cultural norms are not this blatant, gender-stereotyping can still play its part in limiting women's advancement: 'the tendency to choose men may ...reflect a tendency to define leadership in terms of task-oriented contributions' (Eagly and Karau, cited in Beyer, 2007, p. 487). This insight is part of a broader analysis which argues that there is an inherent gender bias in the evaluation of men and women in the workplace, with 'greater social significance and general competence attributed to men over women' (Beyer, 2007, p. 494; and see also Chung, 2001).

Quantitative evidence on promotions and earnings suggests that the problem is indeed a complex one. A recent study on promotions (Booth *et al*., 2003) using the British Household Panel Survey found evidence that women were just as likely to be promoted as men, but that the pay increases they received from those promotions were smaller. These findings were consistent with a sticky- floors model of promotion:

'the mechanisms operating are not the simple glass ceilings ones of an unfavourable promotions rate for women, but involve lower wage returns to promotion for women' (2003, p. 297). The implications of this for the present study are subtle, but important: 'the promotion process...may very well increase the disadvantage, not through a lower promotion probability, but through a lower wage reward over time to promotion' (2003, p. 319). In other words, the assumption of a simple link between pay equity and seniority may be inadequate. Women may be climbing the corporate ladder at a similar rate to men, but still slipping behind on the earnings ladder, thereby leaving the gender pay gap largely undisturbed. Booth *et al*. (2003, p. 319) sum up these implications well: 'Women do not catch up on men from the promotions process, and the pay differential may widen as both men and women are promoted. The implication is that it is not sufficient for policy purposes to ensure equal opportunities in promotions. It is necessary as well to look at issues of pay within rank ...'

Is there evidence for this in Australia? The HILDA survey also asked respondents (from 2002 onwards) about whether they had received promotions in the previous year. Among the sample of managers used in this study, some simple descriptive tables (not shown) partly endorse the Booth *et al*. (2003) findings. Female managers were no less likely than male managers to gain a promotion during the year, and this also applied in the top salary bands. Moreover, the annual increase in earnings for those promoted were roughly equivalent between male and female managers.[16] The Booth *et al*. (2003) study was estimated for the sample as a whole, rather than just managers – as in this study – so its direct relevance for the managerial labour market may be limited. Their study did, however, entail a multivariate analysis, so its findings are more robust than simple descriptive tables from the HILDA data. Clearly, studies like those by Booth *et al*. (2003) emphasise the need for more nuanced accounts of the complexities around recruitment, promotions, seniority and pay equity.

Indirect Discrimination

The findings from this study also throw light on the interface between family life and working life and its implications for women's career advancement. The literature on the glass ceiling has suggested that managerial career paths are inherently gendered with an early insight being that senior managers 'treat all workers as if they are men'. In so doing, they fail to provide support for their staff in the form of child care, parental leave or flexible work schedules (Newman, 1993). What makes this discriminatory in its impact is the prevailing domestic division of labour, which leaves most women with the greater share of parenting and housekeeping tasks (see, for example, Bittman and Lovejoy, 1993; and Baxter *et al*., 2005; and Noonan, 2001). The results from this study, particularly around hours of work, labour force experience and parenting reinforce these arguments. The number of hours worked are one of the key differences between male and female managers – both of whom are working full-time – with the former doing 3.3 hours more per week than the latter. This does not necessarily mean that female managers, on average, achieved less. If we assume that earnings relate to productivity to some degree, then the higher return on hours worked for women (shown by the regression coefficients) means that they may be just as productive, as

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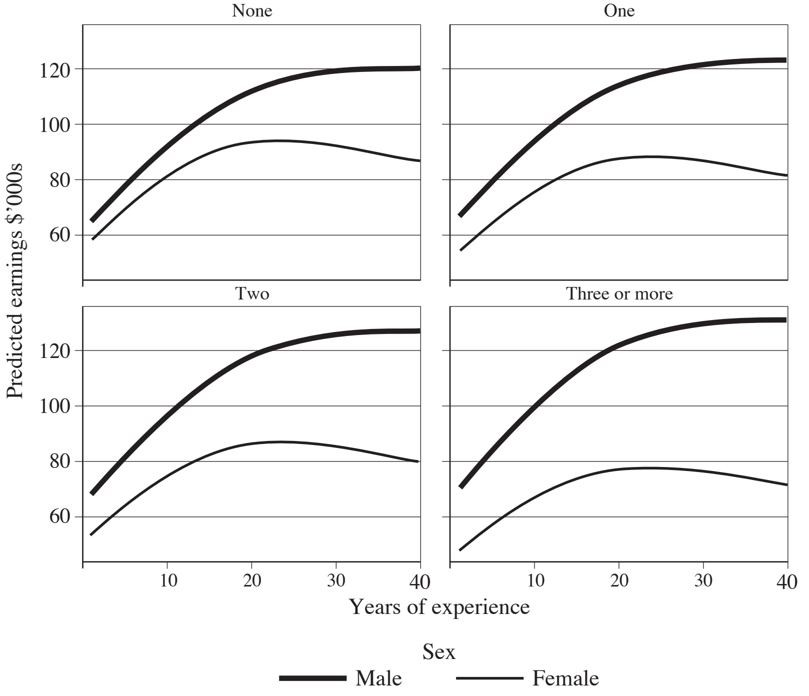
[16] The tables are not shown here but are available from the author.

a group, despite working fewer hours. Similarly, years of labour force experience is also an area where the male and female populations differ: male managers have, on average, 3.2 more years of labour force experience. However, their respective returns on experience differ considerably towards the latter years of working life, the period when seniority is usually achieved. A glass ceiling is evident in the way in which longer years of experience no longer count for as much among female managers when it comes to returns on experience. Finally, the presence of dependent children also makes a difference, evident in the regression coefficients (table 12) which show increasingly negative returns for each additional child, particularly the third.

In practice, these factors – hours worked, labour force experience and the presence of children – combine in such a way that the earnings of female managers fall well behind those of male managers, even when their other characteristics are equivalent. This can be seen quite clearly in earnings predictions from the regression modelling, in which returns on labour force experience are conditioned on the presence of children. These predictions take the average characteristics of the pooled sample – that is, the averages for both males and females – and apply the respective male and female regression coefficients. The results are shown in figures 1 and 2. The graph data is the same in both, but each presentation emphasises a different facet. In figure 1 the male and female lines are offset largely by the difference in intercepts (the group membership component) and can be overlooked for the purposes of this illustration. Interest centres on the trajectory of the lines and the influence of children. Looking at the first panel, where there are no dependent children in the picture, the graph shows that the returns on labour force experience are the same for men and women in the early years, but then plateau and decline at quite different rates. For male managers, their years of experience continue to provide a return right through their working lives (though at a diminishing rate of increase). By contrast, for female managers the rate of return begins to steadily decline after about twenty years. Each successive panel in figure 1 shows how the addition of children serves to widen the gap between men and women, and this applies in the early years as well as towards the end. The effect of children is also highlighted in figure 2 where the addition of each dependent child raises the line for men, but shifts it downwards for women, with the most decisive drops occurring for the first child and the third.

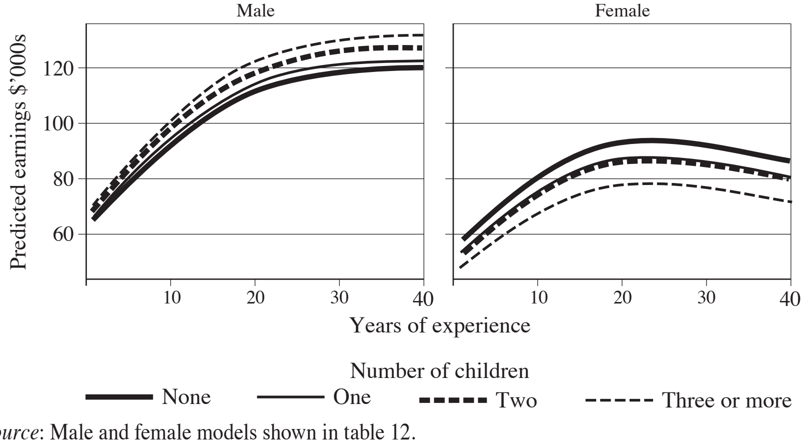
These results are also consistent with the qualitative findings on the glass ceiling which emphasises how gender arrangements shape the prospects of career advancement. These are the various ways in which gender discrimination works indirectly. The longer hours of work put in by male managers – which makes them more visible in the workplace – is made possible by the domestic division of labour whereby the bulk of parenting responsibilities fall on women. Similarly, such domestic arrangements provide an opportunity for male managers to travel as part of their work in ways which are often impossible or impractical for female managers. Finally, the unbroken years of labour force experience by men can also work in favour of managerial career paths, signalling a level of 'commitment' which may be deemed missing among female managers who have taken time out for parenting.

Figure 1 - Predicted Earnings by Years of Experience, Number of Children and Sex



Source: Male and female models shown in table 12.

Figure 2 - Predicted Earnings by Years of Experience, Sex and Number of Children



Source: Male and female models shown in table 12.

In conclusion, the intercept term – group membership – accounts for the vast majority of the discriminatory component in the gender pay gap. At the same time, those aspects of working life which intersect most profoundly with family life – hours worked, the presence of children and years of labour force experience – are also the variables in these regression models which appear to widen the gap most dramatically. However one looks at it, the evidence points towards both direct and indirect discrimination as major obstacles in achieving gender equity in the managerial labour market.

Appendix A

Table A.1 - Summary Statistics for Sample in Models

	Means/percentage			*Standard deviations*		
	Male	*Female*	*All*	*Male*	*Female*	*All*
Single	17.5	32.1	22.1			
Couple	82.5	67.9	77.9			
No children	53.5	72.4	59.4			
One dep child	17.3	16.8	17.1			
Two dep child	21.2	9.2	17.4			
Three + dep child	8.1	1.7	6.1			
Born Australia	77.5	81.1	78.6			
Born Eng spk country	14.0	10.3	12.8			
Born Non-Eng spk	8.5	8.7	8.6			
University quals	41.3	42.8	41.7			
Vocational quals	33.2	25.8	30.9			
Year 12 quals	12.9	15.7	13.8			
Year 11 or below	12.7	15.7	13.6			
Years of experience	23.0	19.8	22.0	11.0	10.3	10.9
Job tenure	8.6	7.1	8.1	8.5	7.9	8.4
Weeks employed in yr	51.6	51.2	51.5	2.5	4.0	3.0
Usual wkly hrs	48.5	45.2	47.5	7.4	7.2	7.5
Not union member	80.7	74.7	78.8			
Union member	19.3	25.3	21.2			
Occup status	65.0	66.4	65.4	14.7	15.6	15.0
Manufacturing	16.3	5.5	12.9			
Primary industry	7.5	1.3	5.6			
Construct/utilities	6.6	1.4	5.0			
Wholesale/transport	10.1	4.0	8.2			
Retail	9.9	15.7	11.7			
Accommodation, cafes etc	5.6	7.3	6.1			
Information services	3.5	3.0	3.3			
Finance & insurance	7.3	7.5	7.4			
Business services	9.0	13.3	10.4			
Government	11.0	11.3	11.1			
Education	6.8	10.5	7.9			
Health & community	2.6	14.4	6.3			
Other services	3.8	4.9	4.1			
Private sector	80.4	71.0	77.5			
Public sector	19.6	29.0	22.5			
Org size: under 20	15.9	13.5	15.1			
Org size: 20-99	17.2	15.9	16.8			
Org size: 100-499	18.4	17.8	18.2			
Org size: 500 plus	48.5	52.9	49.9			
Org with multiple wps	76.1	76.8	76.3			

Table A.1 - Summary Statistics for Sample in Models (continued)

	Means/percentage			*Standard deviations*		
	Male	*Female*	*All*	*Male*	*Female*	*All*
Org with single wp	23.9	23.2	23.7			
City resident	67.0	69.1	67.6			
Non-city resid	33.0	30.9	32.4			
NSW	32.8	33.6	33.1			
Vic	26.1	24.2	25.5			
Qld	18.2	21.0	19.1			
SA, Tas	9.7	7.8	9.1			
WA & NT	9.1	9.2	9.2			
ACT	4.0	4.2	4.1			
Year: 2001	12.8	11.5	12.4			
Year: 2002	12.6	11.8	12.3			
Year: 2003	12.5	11.9	12.3			
Year: 2004	12.8	12.8	12.8			
Year: 2005	11.6	11.8	11.7			
Year: 2006	12.7	12.3	12.6			
Year: 2007	11.8	12.9	12.1			
Year: 2008	13.1	15.1	13.8			
Male			68.5			
Female			31.5			

Note: All waves (2001 to 2008). *Source*: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

Table A.2 - Models Used for Decomposition: Coefficients and Standard Errors

	Male		*Female*		*Pooled*	
	Coef	*SE*	*Coef*	*SE*	*Coef*	*SE*
Intercept	9.418	(0.128)	8.882	(0.142)	9.240	(0.093)
Couple	0.063	(0.021)	-0.018	(0.022)	0.036	(0.015)
One dep child	0.024	(0.018)	-0.065	(0.024)	0.001	(0.015)
Two dep child	0.061	(0.022)	-0.071	(0.033)	0.032	(0.018)
Three + dep child	0.093	(0.030)	-0.181	(0.071)	0.061	(0.027)
Born Eng spk country	0.010	(0.033)	0.023	(0.043)	0.010	(0.026)
Born Non-Eng spk	-0.036	(0.038)	-0.062	(0.046)	-0.057	(0.030)
Vocational quals	-0.275	(0.025)	-0.220	(0.033)	-0.261	(0.020)
Year 12 quals	-0.207	(0.033)	-0.222	(0.039)	-0.224	(0.026)
Year 11 or below	-0.402	(0.035)	-0.301	(0.041)	-0.378	(0.027)
Years of experience	0.053	(0.009)	0.055	(0.011)	0.054	(0.007)
Years of experience squared	-0.001	(0.000)	-0.002	(0.001)	-0.002	(0.000)
Years of experience cubed	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Job tenure	0.002	(0.001)	0.004	(0.002)	0.003	(0.001)
Weeks employed in yr	0.013	(0.002)	0.017	(0.002)	0.015	(0.001)
Usual wkly hrs	0.006	(0.001)	0.009	(0.001)	0.007	(0.001)
Union member	-0.016	(0.019)	0.022	(0.025)	-0.004	(0.015)
Occup status	0.004	(0.001)	0.004	(0.001)	0.004	(0.000)
Primary industry	0.004	(0.036)	-0.101	(0.091)	-0.014	(0.033)
Construct/utilities	0.034	(0.031)	0.142	(0.079)	0.054	(0.029)
Wholesale/transport	0.007	(0.024)	0.045	(0.056)	0.010	(0.022)

Table A.2 - Models Used for Decomposition: Coefficients and Standard Errors (continued)

	Male		*Female*		*Pooled*	
	Coef	*SE*	*Coef*	*SE*	*Coef*	*SE*
Retail	-0.047	(0.029)	-0.066	(0.052)	-0.064	(0.025)
Accommodation, cafes etc	-0.185	(0.043)	-0.103	(0.060)	-0.156	(0.034)
Information services	0.058	(0.042)	0.138	(0.063)	0.082	(0.035)
Finance & insurance	0.145	(0.037)	0.046	(0.057)	0.109	(0.030)
Business services	0.042	(0.027)	0.149	(0.047)	0.070	(0.023)
Government	0.026	(0.035)	0.094	(0.057)	0.036	(0.029)
Education	-0.050	(0.043)	0.038	(0.059)	-0.038	(0.034)
Health & community	-0.093	(0.049)	0.008	(0.054)	-0.070	(0.033)
Other services	-0.062	(0.038)	0.032	(0.059)	-0.044	(0.031)
Public sector	-0.056	(0.027)	0.008	(0.032)	-0.028	(0.021)
Org size: 20-99	0.110	(0.022)	0.047	(0.033)	0.095	(0.018)
Org size: 100-499	0.155	(0.025)	0.133	(0.036)	0.149	(0.021)
Org size: 500 plus	0.179	(0.026)	0.142	(0.037)	0.170	(0.021)
Org with single wp	0.020	(0.018)	-0.008	(0.026)	0.011	(0.015)
Non-city resid	-0.120	(0.022)	-0.054	(0.029)	-0.100	(0.018)
Vic	-0.071	(0.027)	-0.016	(0.033)	-0.050	(0.021)
Qld	-0.085	(0.029)	-0.034	(0.036)	-0.066	(0.023)
SA, Tas	-0.116	(0.039)	-0.107	(0.052)	-0.108	(0.031)
WA & NT	-0.067	(0.037)	-0.011	(0.046)	-0.054	(0.029)
ACT	-0.038	(0.054)	0.055	(0.064)	-0.013	(0.042)
Year: 2002	0.110	(0.015)	0.138	(0.024)	0.118	(0.012)
Year: 2003	0.185	(0.017)	0.202	(0.026)	0.189	(0.014)
Year: 2004	0.299	(0.018)	0.313	(0.026)	0.303	(0.015)
Year: 2005	0.394	(0.019)	0.449	(0.027)	0.413	(0.016)
Year: 2006	0.083	(0.020)	0.119	(0.028)	0.096	(0.016)
Year: 2007	0.108	(0.020)	0.178	(0.028)	0.130	(0.016)
Year: 2008	0.110	(0.021)	0.176	(0.028)	0.130	(0.017)
Female -0.192 (0.019)						
Statistics						
Null log-likelihood	-1182.1		-594.0		-1841.9	
Model log-likelihood	-648.4		-305.9		-876.6	
Random effects (SD)	0.30		0.27		0.30	
Sigma (SD)	0.25		0.21		0.24	
Rho	0.56		0.30		0.49	
N	3,006		1,385		4,391	

Notes: Linear mixed-effects model fitted by REML with residual correlation modelled as AR1. *Outcome variable*: Log of annual wage and income salary in 2008 dollars (CPI indexed). Standard errors in brackets. Omitted categories are: Single; No children; Born in Australia, University qualifications; Manufacturing; Private sector, Org size under 20; Org with multiple wps; City resident; NSW; Male. *Source*: Unit record data, HILDA, Release 8. *Population*: Adult respondents working as full-time employees and in management occupations, n = 4,391 (male n = 3,006, female n = 1,385). All waves, 2001 to 2008.

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