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The Effect of Children on Women's Earnings: Evidence from Australian Data

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Abstract

This paper examines the effect of the presence of children on women's hourly wages in Australia. A two-stage Heckman sample selection model is used to estimate an earnings function for women using the Household, Income and Labour Dynamics in Australia (HILDA) survey for 2001-2004. The results show that the wage penalty associated with motherhood is smaller than indicated by many previous estimates, and can be entirely explained by differences in education, occupation and labour market experience.

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1. Introduction

The aim of this paper is to estimate the wage effect of motherhood for Australian women and assess the likely sources of any such effect. Previous studies have consistently found a negative effect of children on women's earnings. Among more recently published works, Phipps, Burton and Lethbridge (2001) estimated that women with children earn, on average, 17% less than childless women. If having children has a significant negative impact on the amount a woman can expect to earn in the labour market, this represents an important source of gender wage inequality. Having evidence on the magnitude of such an effect, and the extent to which it can be explained by productivity differences between mothers and childless women, would assist in any policymaking that seeks to improve equality of labour market opportunities.

Existing research offers several explanations for the existence of a negative wage effect of motherhood, or 'motherhood wage penalty' (Anderson, Binder & Krause, 2003). The foremost reason cited is that mothers are more likely than childless women to take time out of the labour market, and thus may tend to accumulate less experience or even have their skills deteriorate, as discussed in Jacobsen and Levin (1995) and Baum (2002). Another hypothesis is that mothers might have less energy to devote to paid work, and as a result could be less productive on the job, as examined in Phipps *et al.* (2001). A third explanation is that women with children might tend to choose jobs with 'mother-friendly' characteristics, such as close proximity to home or flexible hours, and might trade higher wages for these non-wage benefits (Budig & England, 2001). A fourth possible reason is that unobserved systematic differences between mothers and childless women, such as motivation or career ambition, might be responsible for an observed wage gap (Korenman & Neumark, 1992; Waldfogel, 1997). Finally, mothers might earn less due to employer discrimination (Phipps *et al.*, 2001).

The empirical approach of studies such as Phipps *et al.* (2001), Budig and England (2001) and Anderson *et al.* (2003) involves first regressing the logarithm of wages on a measure of the number or presence of children, to find the total impact of children on mean wages. Using this as a benchmark, these researchers would then add other variables affecting wage determination, and observe how this changes the estimated coefficient on the ‘children’ variable. The aim is to assess the extent to which such control variables can explain part of the estimated wage effect of children.

This paper takes a similar empirical approach, but seeks to build on it by focusing on the Australian context, using a newer data set, and correcting for sample selection bias. Previous studies have been based on data from the United States (US), United Kingdom, Canada and some European countries. Few researchers have looked at Australian data. Arun, Arun and Borooah (2004) examined the effect of work interruptions on women’s earnings in the Australian state of Queensland, but used a different empirical approach. Thus, one aim of this paper is to compare estimates based on Australian data with the results of studies from other countries which use a similar methodology.

This paper uses data from the Household, Income and Labour Dynamics in Australia (HILDA) annual survey for the period 2001-2004. Most previous research uses data from the 1980s-1990s or earlier, so the results of this paper might also offer insight on whether the wage gap estimated for previous decades has continued in recent years.[1] The HILDA survey also has the advantage of including many variables relevant to this area of research. For example, it includes direct measures of time spent out of the labour force, hours spent on housework and caring for children, and whether the respondent’s employer offers flexible hours or parental leave. Finally, this paper extends the empirical approach outlined above by using a two-stage sample selection model to correct for possible bias due to the sample of working women being a non-random sample of the population.[2]

Section 2 discusses theoretical explanations for the observed motherhood wage penalty, and summarises previous estimates of this penalty. Section 3 describes the statistical model, estimation procedures and sample data used. Section 4 presents the estimation results and discusses the implications in the context of previous findings. Finally, Section 5 offers some concluding remarks.

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[1] As the econometric model used in this paper is not identical to those of previous works, care should be taken in attributing entirely any differences between previous research and the results of this paper to cross-country or temporal variation.

[2] Most studies do not adjust for selection bias, but exceptions are Gupta and Smith (2002), Baum (2002) and Korenman and Neumark (1992).

2. Background and previous research

A few studies have begun by estimating the total motherhood wage penalty, defined as the marginal effect of the number or presence of children on predicted log-wages, when most relevant variables affecting wages (such as labour market experience and education) are omitted. This represents the sum of the direct effect of children on earnings and the indirect effect (the effect associated with the omitted regressors) (Budig & England, 2001).

Previous work suggests a total motherhood wage penalty of about 7-10% per child (Anderson *et al*., 2003; Budig & England, 2001; Phipps *et al*., 2001; Korenman & Neumark, 1992). As a starting point, these results indicate that on average, women with children do earn less than women without children, and the wage inequality is of an economically significant magnitude.

2.1 Explanations and evidence

Several hypotheses about the reasons why mothers earn less than childless women have been advanced.

2.1.1 Human capital explanation

The most common explanation is that mothers tend to accumulate less human capital, and so are offered lower wages, on average, than childless women.

Mothers might acquire less labour market experience, education and skills than childless women for several reasons. Many mothers take time out of the labour force, and so obtain fewer years of work experience than women of the same age who have worked continuously. By interrupting their careers, mothers might also suffer a 'depreciation' in existing human capital as skills are forgotten or expertise rendered obsolete, as suggested by Jacobsen and Levin (1995) and Baum (2002). In addition, mothers might tend to work part time for more of their working lives, and thus achieve fewer years of equivalent full-time work experience (Waldfogel, 1997).

Motherhood can also affect human capital accumulation indirectly. Women who plan to have children in the near future, and who anticipate future child-related career interruptions, might invest less in education and training because they have a shorter expected working life over which to recoup the investment (Gupta & Smith, 2002). Employers might invest less in the human capital of mothers, if they believe motherhood makes women more likely to leave their jobs and so render the investment less profitable (Gupta & Smith, 2002; Baum, 2002).

To the extent that labour market experience and education are productivity-enhancing and assuming workers are paid their marginal revenue products, a larger stock of human capital would be associated with higher wages. Additional years in the same occupation or with the same employer might also increase the likelihood of promotion to a higher-paying position (Jacobsen & Levin, 1995).

The attainment of education and experience could also have signalling effects. Higher education might be interpreted as a signal of high-ability — and thus, high-productivity — workers, and so might command a wage premium unrelated to any productivity increase induced by the qualification (Spence, 1973). Employers might view a history of career interruptions as a signal of weak career commitment, and thus expect an individual to be less productive (Baum, 2002) or more likely to leave the labour force again (Jacobsen & Levin, 1995). Or, as Phipps *et al.* (2001) suggested, it may take time for workers to find good job matches after leaving and returning to the workforce. For all these reasons, a smaller stock of human capital is likely to be associated with lower wage offers.

To test the human capital explanation empirically, researchers have typically included measures of human capital as explanatory variables in an estimated earnings equation. If their inclusion reduces the estimated motherhood wage penalty, this suggests that part of the wage penalty is attributable to human capital differences.

Overall, empirical evidence suggests that the motherhood wage penalty after controlling for human capital differences is in the range of 1-5% per child, substantially less than the total penalty of about 7-10% per child discussed earlier (Anderson *et al*., 2003; Avellar & Smock, 2003; Gupta & Smith, 2002; Budig & England, 2001; Korenman & Neumark, 1992). This indicates that a large part of the wage effect of children is associated with human capital differences.

2.1.2 Work effort hypothesis

Another explanation for the motherhood wage penalty is that mothers might exert less effort at work than childless women, because their energy levels are depleted by the demands of child-rearing (Budig & England, 2001; Becker, 1991). If greater effort is associated with increased productivity, and workers are paid the value of their marginal product, then lower effort could be one reason for lower observed wages.

There is some evidence that mothers tend to do more unpaid work than childless women. For example, Phipps *et al.* (2001) reported that mothers spend more than three times as many hours per week on unpaid work compared with childless women. However, it is not clear that this causes them to exert less effort in their jobs than do childless women. Although childless women spend fewer hours on housework and childcaring activities, leisure or social activities might take up a great deal of their energy (Phipps *et al*., 2001; Budig & England, 2001).

A rare study that tests the work effort hypothesis empirically is Phipps *et al.* (2001), who included hours per week spent on housework, child care and elderly care in an estimated wage equation. These variables reduced the estimated wage penalty for the presence of children from 12.5% (after human capital controls) to 7.8% in one specification and to 5.2% and statistically insignificant in another. These results suggest that a substantial part of the wage gap can be explained by differences in time spent on unpaid work and, if hours of unpaid work is a good proxy for domestic responsibilities, this may be taken as support for the work effort hypothesis.

2.1.3 Compensating differentials hypothesis

Compensating differentials theory implies that employers must pay workers higher wages to compensate for undesirable job attributes, and conversely, can pay lower wages for jobs that offer desirable characteristics. Mothers might be more likely than childless women to choose jobs paying lower wages but offering flexible hours, childcare, or other such features, and so could be receiving lower wages in return for these job characteristics (Budig & England, 2001).

Budig and England (2001) sought to test this hypothesis by including in their wage specification a wide range of job characteristics, including part-time status, commuting time, and so forth. This reduced the estimated motherhood wage penalty by only a small amount, from 1.8% (after human capital controls) to 1.2% per child and still statistically significant. Their results imply that the compensating differentials theory does not explain a large part of the motherhood wage penalty.

2.1.4 Unobservable heterogeneity

Korenman and Neumark (1992) and Waldfogel (1997), among others, argued that mothers and childless women might differ systematically in terms of unobservable characteristics affecting earnings potential, such as motivation and career ambition. For example, women with lower motivation for paid work might be more likely to have children and also more likely to earn less (Waldfogel, 1997). If this is the case, standard regression procedures would give biased estimates of the motherhood wage penalty.

Many studies have attempted to overcome this problem by using fixed-effects models. These models include a different intercept term for each individual in the sample, designed to capture the effects of unobserved, time-invariant personal characteristics. Fixed-effects estimation appears to have an ambiguous impact on the estimated motherhood wage penalty compared with ordinary least squares (OLS) estimation. Anderson *et al.* (2003) found estimated wage penalties were lower under fixed-effects specifications than comparable OLS models, while Budig and England (2001) reported the reverse situation. Moreover, in Waldfogel (1997), fixed-effects models had little impact on the estimated wage penalties, compared with OLS models. Hence, the importance of unobservable heterogeneity as an explanation of the motherhood wage penalty is uncertain.

2.1.5 Discrimination

It is possible that employers discriminate against mothers by paying them lower wages than childless women of equivalent productivity. Budig and England (2001) identified two forms of employer discrimination. One type is “statistical discrimination”, where employers expect the average productivity of mothers to be lower, and/or more variable, than that of childless women (see also Joshi, Paci & Waldfogel, 1999). Employers are assumed to be imperfectly informed about an individual’s productivity, and so they are prepared to pay only a wage based on the expected average productivity of their group. The other type is “taste discrimination”, where employers simply prefer to hire childless women, not because of any assumptions about productivity but based on the perceived preferences of employees or customers (Budig & England, 2001).

Employer discrimination is a difficult hypothesis to test empirically, and so is often associated with the residual motherhood wage penalty estimated after all observed factors are included (Phipps *et al.*, 2001). However, the size of the residual wage penalty is an unreliable measure of employer discrimination. There will always be some personal characteristics or job characteristics affecting wages that cannot be measured, are measured with error, or are unavailable in the data. If any of these factors interact with motherhood status, they will contribute to the residual wage penalty. Furthermore, if employer discrimination is of the statistical type, and employer expectations are correct on average, then it may be difficult to distinguish the effect of discrimination on the wage penalty from the effect of differences in human capital (Budig & England, 2001). Discrimination would only form part of the residual wage penalty if it is taste-based discrimination, or if employers consistently under-estimate mothers' average productivity (Budig & England, 2001).

2.2 Focus of this paper

This study builds on previous research by estimating the total motherhood wage penalty and testing the human capital, work effort and compensating differentials theories, but using Australian data and a sample selection model. A first step was to estimate a selection-corrected total wage penalty, and compare the result with previous (non selection-corrected) estimates. Next, the human capital hypothesis was assessed by including measures of experience, education and occupation in the wage equation. The HILDA data set has the advantage of detailed measures of educational attainment, occupation classification, actual labour market experience and years spent with the current employer and in the current occupation. This estimation yielded an estimate of the 'net' motherhood wage penalty, defined here as the wage effect of children after controlling for human capital differences..

Following this, additional variables were included in the wage equation to test supplementary hypotheses. The hypothesis that human capital depreciates during career interruptions was tested by including a measure of total duration of work interruptions in the wage specification. The work effort hypothesis was assessed by including a measure of hours spent on unpaid work. Finally, the compensating differentials hypothesis was tested by including commuting time, measures of job complexity, and availability of flexible hours and parental leave in the wage equation.

Fixed-effects estimation has not been used. In the four-year sample, there was too little variation in many of the explanatory variables, such that the fixed-effects estimator would be highly inefficient. It was also judged that the combination of selection correction and fixed-effects estimation might place too great a demand on the data.

3. Research method and data

This section describes the econometric model and data used in this paper. Subsection 3.1 outlines the sample selection model and how it was estimated, and subsection 3.2 describes how the sample data were obtained from the HILDA data set.

3.1 The sample selection model

The widely known problem of selection bias arises because the dependent variable, wages, is observed only for individuals who are working, and the sample of workers is a non-random sample of the population. Individuals are not randomly assigned into employment or non-employment, but self-select into or out of the labour market. Consequently, estimates from a standard least-squares wage regression yield biased statistical inferences about the population.

Heckman’s (1979) two-stage sample selection model can be used to adjust for selection bias. The first ‘stage’ of Heckman’s model consists of a selection equation representing the probability that an individual is employed at a given time, conditional upon a set of personal characteristics. The selection equation is estimated using a probit or similar model, and the fitted values are used to construct an estimate of the Inverse Mills Ratio (IMR). This term is included as an explanatory variable in the second ‘stage’ wage equation. The disturbances in the wage equation are heteroskedastic (Creedy, Duncan, Harris & Scutella, 2001) and may be correlated over time for each individual, so efficient least squares estimation should allow for this. To achieve identification in this model, it is preferable to include one or more variables in the selection equation that do not also affect wages, such as non-labour income.

In the present study, the probability that an individual was employed in a given sample year was modelled as a function of age, education, children, partnership status, non-wage income, hours per week spent on housework and childcaring activities, and duration of periods out of the workforce.[3] In both the selection and wage equations, the children variables were included as two dummies, one representing women with one child and the other, women with more than one child (the omitted category being childless women). This was designed to allow for possible non-linearity in the effects of the number of children. Identification for the two-stage model was achieved by including welfare benefits and investment income in the selection equation. As sources of non-labour income, these variables are assumed to affect the probability of employment but not to affect wage determination. Following estimation, the fitted values from the selection equation were used to construct an estimate of the IMR.

The log of hourly wages was regressed on children, partnership status, labour market experience, education, tenure, occupation and the estimated IMR.[4] The interpretation of dummy variable marginal effects in a log-linear regression, the percentage effects on a woman's hourly wage associated with having one child or two or more children, relative to having no children, are given by

$$g_i = 100 * \left(\exp\left\{ \hat{\beta}_i - \frac{1}{2} Var(\hat{\beta}_i) \right\} - 1 \right) \qquad \text{for } i = 1, 2 \tag{1}$$

where $\hat{\beta}_i$ are the estimated coefficients on the two children variables. In estimating different specifications of the wage equation, the aim was to observe the effect of changing the set of regressors on these estimated wage effects of children.

The log-linear functional form was chosen to remove most of the positive skewness in the distribution of hourly wages, and to enable the coefficient estimates to be interpreted as approximate percentage effects (after the transformation in (1), in the case of the dummy variables).

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[3] The probit model for the selection equation was estimated by maximum likelihood in the software package EVIEWS 5.1, using a Huber-White robust coefficient covariance matrix.

[4] The wage equation was then estimated in EVIEWS by pooled least squares, with a White heteroskedasticity-consistent coefficient covariance matrix to allow for heteroskedasticity among individuals in a given sample year, as well as for heteroskedasticity caused by the inclusion of the IMR. In addition, a generalised least squares weighting matrix was used to allow for correlation of residuals over time for each cross-section.

3.2 Data

The data used to estimate the model were taken from the first four waves of the HILDA survey, collected annually over the period 2001-2004, which contain detailed information on a sample of Australian individuals and households.[5]

The sample used in this paper was obtained from the HILDA data by the following transformations. First, the HILDA data set was restricted to female respondents who participated in all four waves of the survey. An age restriction was applied, to retain only those observations in which respondents were aged between 25 and 55. The lower cut-off of 25 years was chosen to exclude most full-time students, who are not of interest in the wage model, and the upper bound of 55 years, to exclude most retirees. In addition, if women's prime child-bearing age range is between 18 and 45 years, the age range of 25 to 55 allows observation of women some years after they may have had children. The age restriction generated an unbalanced panel of 12,664 observations. Of these, 1,282 observations in which the respondent was self-employed, or worked in her own business, were excluded. Self-employed individuals may report little or no salary, or irregular earnings, so including them could create inconsistencies or bias in the results.

The resultant sample of 11,382 included both workers and non-workers. The hourly wage was constructed by dividing the weekly wage earned in the respondent's main job by the number of hours usually worked in that job. Using this construction, only those observations where a zero wage was recorded (i.e. where the individual was not employed[6]) or an hourly wage of between \$5 and \$200 were kept. Observations with missing data, positive wages but missing values for hours, or positive hours but missing values for wages, were dropped. In total, 656 observations were dropped due to missing values, 67 were omitted because the hourly wage was below \$5, and six were dropped for having hourly wages above \$200.

The final sample used to estimate the selection equation contained 10,653 woman-year observations in which respondents were either not working, or were

[5] The HILDA data includes population weights that may be used to weight observations during estimation to ensure the sample is representative of the Australian population. However, EVIEWS does not include an estimation option for this, and so population weighting was not done here. This should not be a substantial problem, since the distribution of the population weights is relatively flat, suggesting that the sample is reasonably representative of the population.

[6] In the HILDA data, observations where the respondent was not working displayed weekly wages as 0 and hours worked as -1, representing 'not applicable', so dividing wages by hours conveniently gives a value of 0.

earning an hourly wage between $5 and $200.[7] The sample used to estimate the wage equation consisted of the 6,926 observations in which respondents were employed, defined as earning an hourly wage between $5 and $200.

4. Estimation results

This section presents estimation results for the two-stage model and for supplementary hypothesis tests. Subsection 4.1 shows the estimated selection equation. Subsection 4.2 presents several estimated specifications of the wage equation, with particular attention given to the estimated total and net motherhood wage penalties. Subsection 4.3 examines the effects of including time out of the labour force, unpaid hours of work and job attributes in the wage equation.

4.1 Selection equation

Table 4-1 gives definitions of the variables used in the selection equation. (Sample means of all variables used in the selection and wage equations are given in Tables 6-1 and 6-2 in the Appendix.) Table 4-2 shows the estimation results for the selection equation. All regressors are significant at the 5% level, with the exception of TWOCHILDPLUS. Prior expectations were that both children variables should have negative coefficient estimates (i.e., that having children would make a woman less likely to be in paid work) but this is only the case for ONECHILD. A possible explanation is that many women with one child have not completed their planned childbearing and so their child may be very young, making the woman less likely to be employed, while women with two or more children may have older children (perhaps school-aged), and so may have returned to the workforce. Alternatively, a larger number of children may imply greater household expenses, increasing the need for both parents to work.

[7] During estimation of the selection equation, EVIEWS dropped 2,718 observations (leaving 7,935) because the variables HOUSEWORK and CHILDCARING were not observed in Wave 1 of the HILDA survey.

Table 4-1: Variable definitions (selection equation)

Variable	*Definition*
EMPLOYED	Dummy = 1 if respondent earned an hourly wage between $5 and $200
AGE	Age at 30th June of the survey year
PARTNERED	Dummy = 1 if married or in a defacto relationship
	(Reference category: Respondents who are separated, divorced, widowed or never married)
ONECHILD	Dummy = 1 if respondent has exactly one child
TWOCHILDPLUS	Dummy = 1 if respondent has two or more children
	(Reference category: Respondents who have never had children)
HOUSEWORK	Number of hours per week usually spent on housework
CHILDCARING	Number of hours per week usually spent looking after own children
BENEFITS	Value of Australian pensions and benefits received by respondent's household in the last financial year
INVINCOME	Value of investment income received by respondent's household in the last financial year
TIMEOUT	Years spent neither working nor looking for work, since leaving full-time education
ED1	Dummy = 1 if highest education level attained is Master's degree or PhD
ED2	Dummy = 1 if highest education level attained is a postgraduate diploma or postgraduate certificate
ED3	Dummy = 1 if highest education level attained is a bachelor's degree
ED4	Dummy = 1 if highest education level attained is a diploma or advanced diploma
ED5	Dummy = 1 if highest education level attained is a Certificate III or IV
ED6	Dummy = 1 if highest education level attained is a Certificate I or II
ED7	Dummy = 1 if highest education level attained is Year 12
	(Reference category: Respondents who did not finish high school, or whose highest qualification is an undefined TAFE certificate)

Table 4-2: Estimated selection equation

Dependent Variable: EMPLOYED		
Variable	*Coefficient*	*p-value*
constant	-1.6622	0.0000
AGE	0.1546	0.0000
AGE^2	-0.0016	0.0000
PARTNERED	-0.4076	0.0000
ONECHILD	-0.1566	0.0226
TWOCHILDPLUS	0.0962	0.1357
HOUSEWORK	-0.0174	0.0000
CHILDCARING	-0.0127	0.0000
BENEFITS	-0.0001	0.0000
INVINCOME	-0.000007	0.0451
TIMEOUT	-0.1079	0.0000
TIMEOUT^2	0.0012	0.0000
ED1	0.4631	0.0001
ED2	0.5340	0.0000
ED3	0.4664	0.0000
ED4	0.1691	0.0061
ED5	0.2342	0.0000
ED6	0.3902	0.0474
ED7	0.1376	0.0079
McFadden R-squared	0.3348	
LR statistic (19 df)	3431.9030	
Probability(LR stat)	0.0000	

Besides TWOCHILDPLUS, all other regressors have coefficient signs that are consistent with prior expectations. For example, having a partner and having greater non-wage income both reduce the probability of working, while having higher levels of education increase this probability. The McFadden R-squared of 0.33 and the large value of the likelihood ratio statistic, both measures of joint significance of the regressors in the model, as well as the individual significance of the explanatory variables, suggest that the estimated model has reasonable explanatory power.

4.2 Wage equations

Subsections 4.2.1 and 4.2.2 present estimation results for the total motherhood wage penalty and the net penalty after human capital variables are included.

Table 4-3 defines those variables used in the wage equations and supplementary hypothesis tests which were not also included in the selection equation.

Table 4-3: Variable definitions (wage equation, additional variables)

Variable	*Definition*
HWAGE	Hourly wage earned in main job
LOGWAGE	Natural logarithm of HWAGE
EXPER	Years spent in paid work since leaving full-time education
TENURE	Years spent working for current employer
YEARSOCC	Years spent in current occupation
OCC1	Dummy = 1 if a manager or administrator
OCC2_BUSIT	Dummy = 1 if a business or IT professional
OCC2_EDUC	Dummy = 1 if an education professional
OCC2_HEALTH	Dummy = 1 if a health professional
OCC2_SCIENG	Dummy = 1 if a science, engineering, or building professional
OCC2_SOCIAL	Dummy = 1 if a social, arts or miscellaneous professional
OCC3	Dummy = 1 if an associate professional
OCC4	Dummy = 1 if a tradesperson
OCC5	Dummy = 1 if an advanced clerical or service worker
OCC6_CLERICAL	Dummy = 1 if an intermediate clerical worker
OCC6_SALES	Dummy = 1 if an intermediate sales worker
OCC6_SERVICE	Dummy = 1 if an intermediate service worker
OCC7	Dummy = 1 if an intermediate production or transport worker
OCC8	Dummy = 1 if an elementary clerical, sales or service worker
	(Reference category: Labourers and related workers)
COMMUTE	Number of hours per week usually spent commuting to and from work
FLEXTIME	Dummy = 1 if employer offers flexible start and finish times
PARENTAL	Dummy = 1 if employer offers parental leave
COMPLEX2	Dummy = 1 if respondent rates their job as between 3 and 5 on a 7-point scale of complexity and difficulty, with 7 being the most complex/difficult
COMPLEX3	Dummy = 1 if respondent rates their job as 6 or 7 on this 7-point scale
	(Reference category: Respondents who rate their job as 1 or 2 on this scale)
SUPERVISOR	Dummy = 1 if respondent normally supervises the work of others
MILLS	Inverse Mills Ratio, an adjustment for selection bias

4.2.1 Estimated total motherhood wage penalty

Table 4-4 shows the results of a pooled least squares estimation of the wage equation without human capital controls. Two specifications are shown. Model 1 gives unadjusted least squares estimates, while Model 2 corrects for selection bias by including the estimated IMR obtained from the selection equation. In both models, all regressors are significant at the 5% level, and the coefficient signs on the age, children and partner status variables are consistent with prior expectations. The estimated coefficient on the IMR has a negative sign, which suggests there is a negative correlation between the unobservables that affect employment participation and those that affect wages. Creedy *et al.* (2001) also find negative coefficient estimates on the IMRs in wage equations for married women and for sole-parent men and women in Australia, and Ermisch and Wright (1994, p. 189) show that a negative sign is theoretically reasonable and “need not be indicative of specification error”.

Table 4-4: Estimated wage equations – total wage penalty

Dependent Variable: LOGWAGE				
	Model 1		Model 2	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
constant	2.0665	0.0000	2.4311	0.0000
AGE	0.0416	0.0000	0.0262	0.0013
AGE^2	-0.0004	0.0000	-0.0003	0.0064
ONECHILD	**-0.0855**	**0.0001**	**-0.0538**	**0.0274**
TWOCHILDPLUS	**-0.1413**	**0.0000**	**-0.0947**	**0.0000**
PARTNERED	0.0390	0.0019	0.0481	0.0004
MILLS			-0.1738	0.0000
Weighted R-squared	0.0162		0.0380	

Before adjusting for selection bias, the estimated total motherhood wage penalty is approximately 8.21% for women with one child and 13.19% for women with two children.[8] This is consistent with previous estimates of the total wage penalty which, as discussed in Section 2, fall in the range of 7-10% per child. However, adjusting for selection bias reduces the estimated total wage penalties to 5.27% for one child and 9.06% for two or more children. These estimates are lower than the non-selectivity corrected estimates in Korenman and Neumark (1992), Budig and England (2001), Anderson *et al.* (2003), and Phipps *et al.* (2001). However, they are

[8] All estimated wage penalties were computed using equation (1) from Section 3.1, and so will not be equal to the estimated coefficients on the children variables reported in the tables.

consistent with the findings of Gupta and Smith (2002), who estimate lower wage penalties for children after correcting for selection bias. Thus, one implication of the results obtained here is that failure to correct for selection bias might have led previous estimates to overstate the total motherhood wage penalty.

4.2.2 Estimated net motherhood wage penalty

Having estimated the total effect of children on wages, measures of education, tenure and occupation were added to the wage equation to see how much of the total wage gap could be explained by differences in human capital. Table 4-5 shows three estimated wage equations that include human capital controls.

Table 4-5: Estimated wage equations – human capital controls

Dependent Variable: LOGWAGE						
	Model 3		Model 4		Model 5	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
constant	2.8717	0.0000	2.5808	0.0000	2.5026	0.0000
ONECHILD	**-0.0418**	**0.0758**	**-0.0129**	**0.5501**	**-0.0039**	**0.8434**
TWOCHILDPLUS	**-0.0653**	**0.0005**	**-0.0218**	**0.2009**	**-0.0155**	**0.3233**
PARTNERED	0.0359	0.0068	0.0279	0.0236	0.0220	0.0570
MILLS	-0.1542	0.0000	-0.0284	0.2175	0.0012	0.9572
EXPER	0.0093	0.0126	0.0140	0.0001	0.0118	0.0004
EXPER^2	-0.0003	0.0010	-0.0003	0.0005	-0.0003	0.0007
TENURE	0.0084	0.0000	0.0062	0.0000	0.0058	0.0000
YEARSOCC	0.0042	0.0000	0.0032	0.0000	0.0021	0.0037
ED1			0.4659	0.0000	0.3203	0.0000
ED2			0.3793	0.0000	0.2313	0.0000
ED3			0.3220	0.0000	0.1786	0.0000
ED4			0.1831	0.0000	0.1035	0.0000
ED5			0.0354	0.0734	0.0147	0.4397
ED6			-0.0261	0.7039	0.0122	0.8491
ED7			0.0996	0.0000	0.0641	0.0004
OCC1					0.3816	0.0000
OCC2_BUSIT					0.3201	0.0000
OCC2_EDUC					0.2248	0.0000
OCC2_HEALTH					0.3900	0.0000
OCC2_SCIENG					0.2430	0.0007
OCC2_SOCIAL					0.2601	0.0000
OCC3					0.1724	0.0000
OCC4					0.0447	0.2125
OCC5					0.1808	0.0000
OCC6_CLERICAL					0.1193	0.0000
OCC6_SALES					0.1574	0.0041
OCC6_SERVICE					0.0311	0.2530
OCC7					0.0366	0.3906
OCC8					0.0355	0.1744
Weighted R-squared	0.0689		0.1827		0.2611	

Model 3 contains measures of experience: in particular, total labour market experience as a quadratic, tenure (years with current employer), and years in current occupation. Model 4 encompasses Model 3 with the addition of education variables; and Model 5 adds occupational dummies to the specification of Model 4. All three models were estimated using pooled least squares corrected for selection bias. In Models 4 and 5, the IMR is not significant at the 5% level but is included for comparability.

The estimation results for Model 3 show that total labour market experience, tenure and years in occupation are all highly significant in the wage equation, and the estimated coefficient signs are consistent with prior expectations (positive signs on labour market experience, tenure and years in occupation, negative sign on experience squared). The inclusion of these variables reduces the estimated motherhood wage penalties to 4.12% for one child and 6.33% for two or more children, compared with the total wage penalties of 5.27% and 9.06% from the previous section. The wage penalty for one child is marginally insignificant at the 5% level, but the penalty for two or more children is still highly significant. Thus, differences in measures of work experience explain only about one-fifth to one-third of the total motherhood wage penalty.

In Model 4, most of the education dummy variables are significant at the 5% level and have the anticipated positive coefficient signs. (An exception is ED6, representing TAFE Certificates I and II, which is estimated to have an insignificant effect on wages relative to the base category, individuals who did not finish high school.) The experience variables remain statistically significant and correctly signed. More importantly, the addition of the education measures reduces the estimated motherhood wage penalties to 1.31% for one child and 2.17% for two children, and renders them insignificant at the 5% level. This implies that after controlling for differences in experience and education, the presence of children has no significant effect on women’s earnings.

The results for Model 5 show that most of the occupational dummy variables have positive and statistically significant effects on earnings. A few occupational categories were insignificant relative to the base category (labourers and related workers), but this was often because there were too few women in some categories (such as OCC4, which represents tradespersons). After including occupational controls in the wage equation, the estimated coefficients on the ‘children’ variables became smaller and highly insignificant, reinforcing the Model 4 results. This strongly suggests that the entire motherhood wage penalty can be explained by differences in experience, education and occupation.

These results were robust to different specifications of the children variables. Two alternative wage equations were estimated, one with presence of children as a single dummy variable, the other with a variable for the number of children. In both cases, the coefficient on the children variable became highly insignificant after the inclusion of experience, education and occupation variables.

The estimation results of the present study differ substantially from those reported in the literature. Nearly all previous studies have found a residual motherhood wage penalty after including human capital variables in the estimated wage function. It is generally concluded that differences in human capital can explain only part of the observed wage gap (Phipps *et al.*, 2001; Budig & England, 2001; Avellar & Smock, 2003; Anderson *et al.*, 2003, among others). Gupta and Smith's (2002) study, based on Danish data, found that the wage effects of children disappear with the inclusion of human capital controls, but only in a fixed-effects model that also accounts for unobservable heterogeneity. (The least-squares selectivity-corrected model in Gupta and Smith (2002) found an insignificant wage effect for one child, but a significant penalty for two or more children.) In contrast, using an Australian data set, the present study found that the inclusion of measures of experience, education and occupation in a least squares selectivity-corrected model was sufficient to render the motherhood wage penalty insignificant.

This result may have occurred for a few reasons. Firstly, the empirical results were based on Australian data, whereas previous studies were based on data from other countries (primarily, the US). It might be that the Australian labour market differs substantially from that of the US and other countries. Secondly, this paper used 2001–2004 data, which is more recent than the data used in previous research; in some cases, by over 20 years. Perhaps the motherhood wage penalty has changed over time, and has become more closely aligned with productivity or human capital-related differences. Lastly, the measures of human capital used in this paper might have captured more of the individual variation in actual human capital than those used in previous studies. For example, this paper uses detailed categorical measures of educational attainment, which contributed substantially to explaining the motherhood wage gap. Many previous studies used a single measure of years of education (Anderson *et al.*, 2003; Budig & England, 2001; Waldfogel, 1997; and others). Similarly, multiple measures of experience and numerous categories of occupation were used in the wage specification in this paper.

4.3 Testing other hypotheses

Although, using this data set, the motherhood wage penalty can be entirely attributed to human capital differences, additional hypothesis tests were carried out to assess some of the other theories discussed in Section 2. A base model was first estimated, containing only measures of motherhood, partnership status and labour market experience, and in which the estimated wage penalties for children are 4.26% for one child and 6.74% for two children. Additional variables were then included to determine whether they could explain any part of the motherhood wage gap in the base model. The aim was to test in turn the human capital depreciation theory, the work effort hypothesis, and the compensating differentials hypothesis.

To test the hypothesis that periods out of the labour market cause human capital to depreciate (and not merely halt its accumulation), TIMEOUT, a measure of years spent neither employed nor looking for work, was added to the base model. From Table 6-1 in the Appendix, mothers spend more time out of the labour force (7.59 years on average) than do childless women (2.18 years). If the human capital depreciation theory is correct, the variable TIMEOUT should have a significantly negative coefficient (representing a negative impact on wages even after controlling for differences in total labour market experience) and its inclusion should reduce the estimated motherhood wage penalty.

However, as the estimation results for Model 6 in Table 4-6 show, TIMEOUT is highly insignificant in the estimated wage equation. This suggests there is no evidence that periods out of the labour force affect earnings, after controlling for total work experience. Furthermore, the estimated wage penalties for children are not reduced at all, but are actually slightly larger than in the base model.

These results indicate that the theory that human capital depreciates during career interruptions is not supported by this data. This stands in contrast to the results of Anderson *et al*. (2003) and Phipps *et al*. (2001), which found that controlling for the duration of career interruptions, as well as total years of work experience, reduced the estimated motherhood wage penalty compared with controlling for work experience only.

Table 4-6: Supplementary tests – human capital depreciation

Dependent Variable: LOGWAGE				
	Base model		Model 6	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
constant	2.8772	0.0000	2.8735	0.0000
ONECHILD	**-0.0432**	**0.0743**	**-0.0441**	**0.0686**
TWOCHILDPLUS	**-0.0695**	**0.0003**	**-0.0762**	**0.0002**
PARTNERED	0.0427	0.0016	0.0445	0.0012
MILLS	-0.1635	0.0000	-0.1742	0.0000
EXPER	0.0141	0.0002	0.0142	0.0002
EXPER^2	-0.0003	0.0010	-0.0003	0.0010
TIMEOUT			0.0018	0.3571

Following Phipps *et al*. (2001), the work effort hypothesis was tested by adding measures of unpaid work to the specification of the base model. These measures are, respectively, the number of hours per week spent on housework and on caring for the woman's own children. Since neither work effort nor energy levels are directly observable, hours of unpaid work is intended to be a proxy for the impact of domestic responsibilities on a woman's productivity in paid work. From Table 6-1 in the Appendix, the average mother in the sample spends 19 hours per week on housework and 15 hours caring for her children, while the average childless woman spends only 8 hours on housework. If the work effort hypothesis is correct, and hours of unpaid work is a good proxy, then the housework and childcaring variables should have negative estimated coefficients and their inclusion should reduce the estimated motherhood wage penalty.

The results for Model 7 in Table 4-7 show that contrary to prior expectations, the estimated coefficients on HOUSEWORK and CHILDCARING are both positive, although HOUSEWORK is insignificant at the 5% level. The two unpaid work variables do not reduce the estimated wage penalties for children, but actually increase them. These results suggest there is no evidence in support of the work effort hypothesis in this data set. This differs from Phipps *et al*. (2001), who found that including measures of unpaid work in the wage equation reduced the estimated wage penalty by more than one-third.

Table 4-7: Supplementary tests – work effort hypothesis

Dependent Variable: LOGWAGE				
	Base model		Model 7	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
constant	2.8772	0.0000	2.9100	0.0000
ONECHILD	**-0.0432**	**0.0743**	**-0.0703**	**0.0036**
TWOCHILDPLUS	**-0.0695**	**0.0003**	**-0.0878**	**0.0000**
PARTNERED	0.0427	0.0016	0.0376	0.0054
MILLS	-0.1635	0.0000	-0.2201	0.0000
EXPER	0.0141	0.0002	0.0110	0.0042
EXPER^2	-0.0003	0.0010	-0.0002	0.0157
HOUSEWORK			0.0010	0.0951
CHILDCARING			0.0024	0.0000

Following Budig and England (2001), the compensating differentials hypothesis was tested by including in the wage specification job attributes for which mothers and childless women might have systematically different preferences. These attributes were hours per week spent commuting to and from work, whether the individual had access to flexible work schedules or parental leave, whether the individual held a supervisory position, and the extent to which the individual rated her job as ‘complex and difficult’. (Full definitions are given in Table 4-3.) According to the compensating differentials hypothesis, the estimated coefficients on these variables should be positive for commuting time, job complexity and supervisor status; and negative for the availability of flexible hours and parental leave. If mothers are more likely than non-mothers to choose jobs that are less demanding, closer to home, and which offer flexible schedules and parental leave, then including these variables in the wage equation should reduce the estimated motherhood wage penalty.

Estimation results for Model 8 in Table 4-8 show that commuting time and the availability of flexible hours are statistically insignificant, but the other four variables are significant at the 5% level. The measures of job complexity and supervisor status have the expected positive coefficient signs, while the estimated coefficients on parental leave, flexible hours and commuting time are all contrary to prior expectations. However, the inclusion of the group of variables reduces the estimated wage penalties for one child and two or more children to 2.59% and 5.31% respectively, and the penalty for women with one child is now highly (rather than marginally) insignificant.

Table 4-8: Supplementary tests – compensating differentials hypothesis

Dependent Variable: LOGWAGE				
	Base model		Model 8	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
constant	2.8772	0.0000	2.7892	0.0000
ONECHILD	**-0.0432**	**0.0743**	**-0.0260**	**0.2598**
TWOCHILDPLUS	**-0.0695**	**0.0003**	**-0.0544**	**0.0032**
PARTNERED	0.0427	0.0016	0.0383	0.0035
MILLS	-0.1635	0.0000	-0.1449	0.0000
EXPER	0.0141	0.0002	0.0106	0.0034
EXPER^2	-0.0003	0.0010	-0.0002	0.0087
COMMUTE			-0.0005	0.6944
FLEXTIME			0.0107	0.3013
PARENTAL			0.0452	0.0000
COMPLEX2			0.0822	0.0000
COMPLEX3			0.1607	0.0000
SUPERVISOR			0.0305	0.0035

These results give qualified support to the compensating differentials argument. On one hand, the measures of commuting time, parental leave and flexible hours are either insignificant or have estimated signs that are inconsistent with the theory. On the other hand, the variables measuring how demanding the job is (in terms of job complexity and supervisory responsibilities) are ‘correctly’ signed and highly significant, and the inclusion of the job characteristics renders the estimated wage penalty for one child strongly insignificant and reduces the penalty for two or more children by about 20%. On balance, it seems that there is some evidence in favour of the compensating differentials hypothesis. This differs somewhat from Budig and England (2001), who found that the inclusion of a larger set of job characteristics explained only a very small fraction of the wage gap.

5. Conclusion

This study set out to assess the extent of wage inequality between mothers and childless women in Australia, with a focus on correcting for sample selection bias. A two-stage sample selection model was used, with a probit model to estimate the probability of self-selection into employment, and a pooled least squares model to estimate a wage equation, adjusted for selection. Using this model and the 2001–2004 HILDA data, the aim was to estimate the total effect of children on women’s earnings, to determine how much of this effect could be attributed to differences in human capital, and to test some of the theoretical explanations for the observed motherhood wage penalty.

The results of this investigation differed substantially from previous empirical findings. After adjusting for selection bias, the total wage penalties associated with motherhood were found to be 5.27% for women with one child and 9.06% for women with two or more children. These estimates were lower than the non-selectivity corrected estimates reported in previous studies, indicating that selection bias may have overstated previous estimates of the effect of children on women's wages. More importantly, after including detailed measures of human capital variables in the wage equation, the estimated negative effect of children became insignificant. This implies that in the Australian context, wage inequality between mothers and childless women could be entirely explained by differences in work experience, education and occupation, a departure from nearly all empirical results based on data from other countries. Finally, supplementary hypothesis tests showed that the human capital depreciation and work effort explanations for the motherhood wage penalty were not supported by the data, a finding that differed from the results of previous research. Apart from the human capital hypothesis, the only other explanation of the wage penalty supported by this data set was the compensating differentials hypothesis.

The main finding of this paper — that differences in experience, education and occupation can fully explain the negative effect of children on women's earnings — has implications for any policy measures designed to improve the labour market outcomes of women with children. In particular, the importance of the education variables in explaining the wage gap implies that ensuring greater access to education and vocational training among women with children might be an effective way of overcoming this wage inequality. Although this is not the focus of this paper, it is likely that family responsibilities affect women's ability to undertake further education and training. Measures to improve education opportunities might include childcare programs or subsidies for women undertaking further education, increased availability of distance education, or greater incentives for employers to conduct on-the-job training. Improved quality and availability of childcare programs, and increased access to maternity leave provisions, might also assist women with children to balance their family responsibilities with continued labour market participation in their chosen field.

6. Appendix: Descriptive statistics

Table 6-1: Sample means of selection equation terms

Variable	*All Women*	*Mothers*	*Childless*
EMPLOYED	0.65	0.60	0.85
AGE	40.02	41.31	35.26
ONECHILD	0.15	0.19	0.00
TWOCHILDPLUS	0.63	0.81	0.00
PARTNERED	0.73	0.78	0.53
CITY	0.63	0.60	0.73
BENEFITS	$2,004.92	$2,244.75	$1,124.68
INVINCOME	$1,068.53	$1,103.87	$938.82
HOUSEWORK^	16.36	18.59	8.04
CHILDCARING^	11.73	15.05	0.00
ED1	0.03	0.02	0.06
ED2	0.08	0.07	0.11
ED3	0.16	0.13	0.27
ED4	0.10	0.09	0.13
ED5	0.12	0.13	0.10
ED6	0.01	0.01	0.00
ED7	0.16	0.16	0.16
TIMEOUT	6.43	7.59	2.18
Observations	**10,653**	**8,372**	**2,281**

Means of dummy variables indicate proportion of the sample for which the dummy takes the value 1.
^ HOUSEWORK and CHILDCARING were observed only in Waves 2, 3 and 4, so sample means for these two variables are taken over those observations.

Table 6-2: Sample means of wage equation terms

Variable	*All Working Women*	*Working Mothers*	*Working Childless*
HWAGE	$20.04	$19.67	$21.00
LOGWAGE	2.92	2.90	2.97
AGE	40.15	42.29	34.64
ONECHILD	0.15	0.20	0.00
TWOCHILDPLUS	0.57	0.80	0.00
PARTNERED	0.72	0.79	0.54
CITY	0.64	0.60	0.74
ED1	0.04	0.03	0.07
ED2	0.10	0.09	0.12
ED3	0.20	0.16	0.29
ED4	0.11	0.10	0.14
ED5	0.13	0.14	0.09
ED6	0.01	0.01	0.00
ED7	0.15	0.15	0.16
EXPER	18.42	19.62	15.31
TIMEOUT	4.29	5.42	1.37
TENURE	6.12	6.31	5.64
YEARSOCC	8.75	9.27	7.40
OCC1	0.04	0.04	0.06
OCC2_BUSIT	0.06	0.04	0.10
OCC2_EDUC	0.13	0.12	0.14
OCC2_HEALTH	0.09	0.09	0.09
OCC2_SCIENG	0.01	0.01	0.02
OCC2_SOCIAL	0.05	0.04	0.07
OCC3	0.13	0.12	0.16
OCC4	0.02	0.02	0.02
OCC5	0.06	0.06	0.06
OCC6_CLERICAL	0.14	0.15	0.13
OCC6_SALES	0.01	0.01	0.01
OCC6_SERVICE	0.10	0.12	0.05
OCC7	0.02	0.02	0.01
OCC8	0.09	0.10	0.06
Observations	**6,926**	**4,994**	**1,932**

Means of dummy variables indicate proportion of sample for which the dummy takes the value 1.

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