The Effect of Motherhood on Wages and Wage Growth: Evidence for Australia

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By

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Certificate of Originality

I, Tanya Livermore, declare that this thesis, submitted in partial fulfilment of the requirements for the award of Bachelor of Commerce (Honours), in the Department of Economics, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The work contained in this thesis has not been previously submitted for a degree or other qualification at any other higher education institution. To the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made.

Signed:

Date:

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List of Abbreviations

ABS	Australian Bureau of Statistics
AIHW	Australian Institute of Health and Welfare
CPI	Consumer Price Index
FaHCSIA	Department of Families, Housing, Community Services and Indigenous Affairs
HILDA	Household, Income and Labour Dynamics in Australia
LFP	Labour Force Participation
NLS	National Longitudinal Survey
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
TSLS	Two Stage Least Squares

Abstract

Labour market theory provides numerous reasons why mothers may earn lower hourly wages than non-mothers; however the empirical evidence for Australia is limited. Despite the importance of this issue to female labour supply and gender equality, and the large body of international literature, no Australian study to date has examined the effect of motherhood on women's wages taking account of unobserved heterogeneity, or examined the effect of motherhood on wage growth. As such, this thesis contributes to the literature by estimating the effect of motherhood on Australian women's wages and wage growth using a series of panel data models which account for unobserved factors affecting both wage levels and wage growth. Using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, an unexplained motherhood wage penalty of around five percent for one child, and nine percent for two or more children is found. Further analysis reveals that the wage penalty emerges over time through reduced wage growth, rather than through an immediate wage decline after birth. This reduction in wage growth is consistent with flatter wage profiles of part-time workers, discrimination and a reduction in mothers' work effort.

1 Introduction

1.1 Motivation and Objectives of the Thesis

A large body of international literature has found an unexplained wage differential between mothers and non-mothers (e.g. Anderson, Binder and Krause, 2002; Buligescu *et al.*, 2009; Drolet, 2002; Waldfogel, 1995); however the presence of a 'motherhood wage penalty' in Australia is less clear. No study to date has examined the effect of motherhood on Australian women's wages taking account of unobserved factors, and the effect of motherhood on wage growth has not been assessed.[1]

Understanding the effect of children on women's wages and wage growth however is important to current Australian policy. The Australian Treasury Department (2007) has identified increases in birth rates and female labour force participation (LFP) as two key ways of counteracting the negative effect on economic growth of an ageing population.[2] However to encourage both outcomes, it is important to determine the way in which the presence of children affects mothers' wages, which will in turn affect their LFP.

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[1] To the best of the author's knowledge.

[2] High female LFP will help support the current retired population, while higher birth rates will create a larger working age population in the future.

The effect of motherhood on wages is also important to the study of gender wage equality. The direct and indirect effects of children are often cited as a cause of the gender wage gap, and thus measuring the motherhood wage differential will shed light on this hypothesis (Waldfogel, 1998a). Determining the source of the motherhood penalty and how it may be avoided will inform policy to improve mothers', and hence women's wages overall.

Finally, the opportunity costs born by mothers are of social importance. Since good parenting provides positive externalities to the community, it has been argued that mothers disproportionately share the costs of childbearing (Budig and England, 2001). This is exacerbated when the costs of children go beyond the *direct* costs of food, clothing, health, education and shelter and include *indirect* opportunity costs of wages foregone.

Given the importance of the issue to Australian policy and the lack of prior Australian research, the first aim of this thesis is to determine whether mothers, on average, earn lower hourly wages than non-mothers. To investigate the source of the differential, a number of human capital, job and demographic characteristics will be progressively controlled for in the analysis. Moreover, unlike previous Australian work (Krepp, 2007; Whitehouse, 2002), panel data methods will be used to account for the influence of time invariant unobserved factors on wages.

The second aim of this thesis is study the effect of motherhood on wage growth. Although most international studies have focussed on wage levels, mothers' wage growth may also be affected by childbearing. This analysis will help to determine whether the wage differential arises immediately after birth, or develops over time through wage growth.

1.2 Data and Methodology

This thesis will use the first seven waves of data, collected from 2001 to 2007, of the Household, Income and Labour Dynamics in Australia (HILDA) survey. The large panel data set allows changes in labour market and family characteristics to be observed, and time invariant unobserved factors to be held constant. Moreover, HILDA provides the necessary data to calculate hourly wages, identify mothers, and control for actual work experience and other human capital, job and demographic characteristics. Finally, household information may be matched to each respondent allowing non-labour income to be used in the analysis.

To estimate the average wage differential between mothers' and non-mothers', the methods conventionally used in the international literature will be applied to Australian data. Estimates robust to time invariant unobserved factors will be obtained with a fixed effects model using an unbalanced panel from the seven waves of HILDA. The fixed effects results will be compared to Ordinary Least Squares

(OLS) and Heckman-corrected cross-sectional models to gauge the extent of heterogeneity and selection bias.

To study the effect of motherhood on wage growth, the first-difference methodology of Loughran and Zissimopoulos (2009) which accounts for the effect of unobserved heterogeneity on the wage level will be adopted. Furthermore, their fixed effects approach will be applied to account for the effect of unobserved factors on both the wage level and wage growth.

1.3 Structure of the Thesis

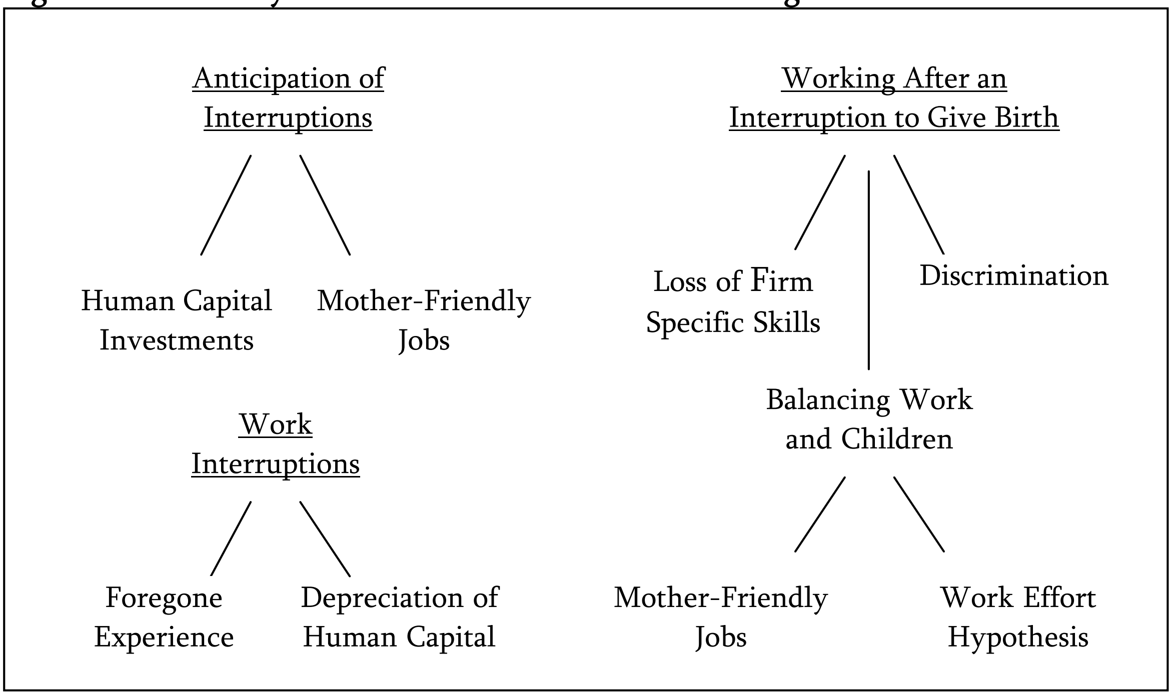
This thesis is structured as follows. Chapter 2 provides an overview of the theoretical reasons for a motherhood wage penalty, namely, work interruptions, work effort, mother friendly jobs and wage discrimination. Chapter 3 reviews the empirical literature. The first section summarises the international motherhood wage penalty literature while the second section focuses on the effect of children on wage growth. Subsequently, Australian studies on the motherhood penalty and related areas are reviewed. Chapter 4 discusses the methodologies generally used in the literature and the empirical issues of selection into employment, reverse causality between motherhood and wages and unobserved heterogeneity. Chapter 5 presents the empirical approach adopted in this thesis. The choice of control variables, potential for bias and the use of an unbalanced panel are also addressed. Chapter 6 describes the HILDA data, discusses the use of weights and describes the sample and variables used. Finally, Chapter 7 presents the empirical results and Chapter 8 concludes.

2 Review of Theory

This chapter reviews the theoretical explanations of why mothers, on average, may earn lower wages than non-mothers. The first section examines labour market interruptions as a source of the motherhood wage penalty. The second section discusses additional factors affecting wages: work effort, mother friendly jobs and discrimination.

The multiple ways in which a raw wage differential between mothers and non-mothers may arise are summarised in Figure 2.1. The effects are grouped in the mothers' work-life stage they primarily occur.

Figure 2.1. The Ways in Which Motherhood Affects Wages



2.1 Work Interruptions

One key difference in mothers' and non-mothers' work histories is the frequency and duration of work interruptions. As such, the age-wage profiles of continuous and non-continuous workers explained by Mincer and Ofek (1982, p.6), which are reproduced in Figure 2.2, can be used to analyse how the work histories and wage profiles of mothers and non-mothers may differ.

The age-wage profile for a continuous worker, which may represent that of a non-mother, is given by the strait line JKL, while the wage profile of a non-continuous worker, or a mother, is given by the kinked line ABCDEFG.[3] For simplicity, it is assumed that only one labour market interruption occurs which is taken to be one period long (T-V=1).[4] Following Mincer and Ofek, four stages of a mother's work history can be distinguished: the pre-interruption period (AB), the labour market interruption (BCDE), the restoration period (EF) and the post-interruption period (FG).

2.1.1 Pre-interruption Period

The pre-interruption period occurs between the completion of compulsory schooling at age S and the beginning of the work interruption at age V. Although

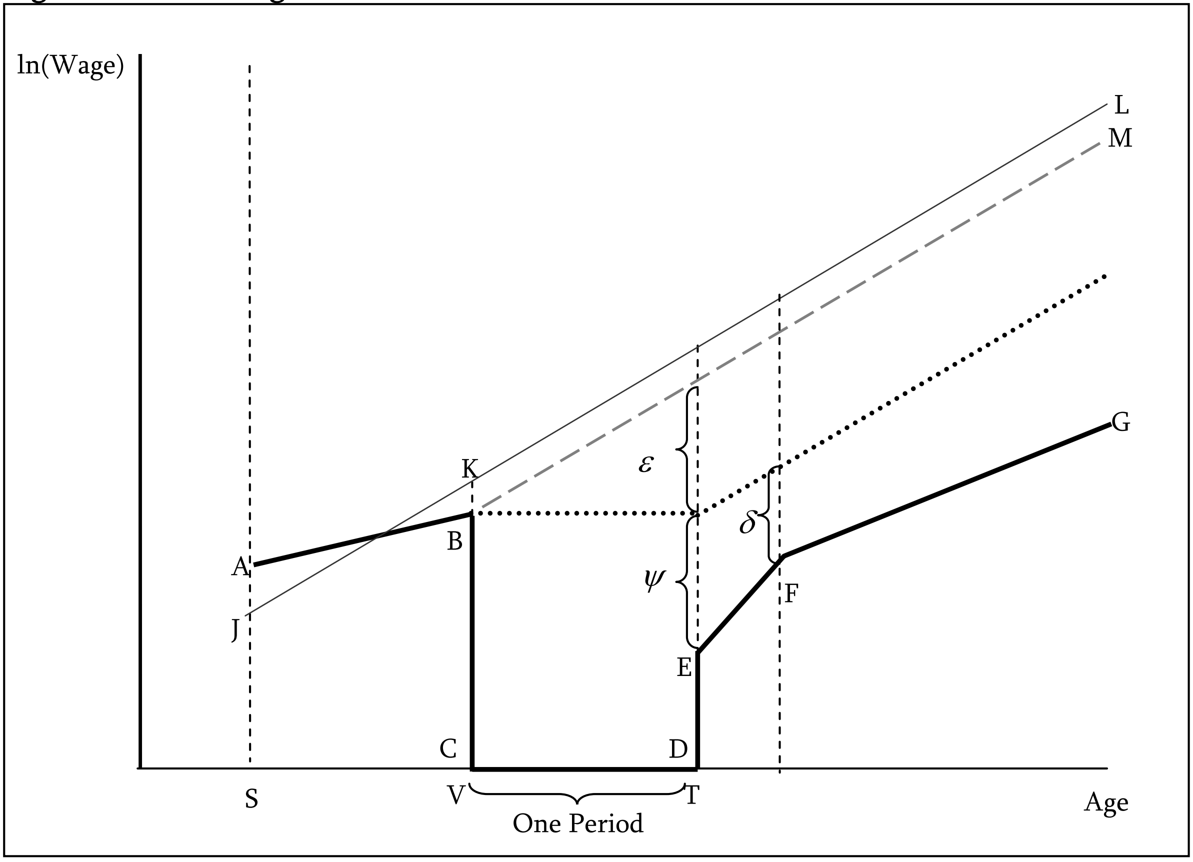
---

[3] Note that the profiles are drawn as strait lines for simplicity. Returns to experience (or age) are assumed to be concave.

[4] By assuming that the interruption lasts for one period, the distances ε , ψ and δ can be interpreted as the rates of wage loss due to lost experience, non-use in the short run and non-use in the long-run respectively.

work interruptions are yet to take place, the wage profile of mothers and non-mothers may differ if those who anticipate future work interruptions make fewer investments in human capital.

Figure 2.2. The Wage Profiles of Mothers and Non-Mothers



Source: Mincer and Ofek (1982, p.6)

The theoretical model of Ben-Porath (1967) posits that individuals decide whether to undertake an investment in human capital by comparing the present value of the costs of education or training, which includes direct costs and earnings foregone, with the present value of the stream of future additional earnings, that is, earnings in excess of what would have been earned had the investment in human capital not been made. Given this model, the greater the amount of work time a person has to accrue the benefits of human capital investment; the more likely it is the investment will be made. Since having children usually involves work interruptions, women who anticipate becoming mothers will expect to have fewer years over which to amortise their investment. Consequently, women who anticipate motherhood will make lower investments in human capital.[5]

Investments in On-the-Job Training

Mincer and Ofek's analysis treats pre-interruption human capital accumulation as investments in on-the-job training which consists of general human capital development and firm specific training.[6] The former will increase the productivity of the worker at all firms, whereas the latter only increases productivity at the current employer. Since the benefits of general training may be accrued by other firms, the employee must effectively pay for the general training by receiving wages which are less than their marginal productivity. As such, workers who invest in general human capital accumulation will initially receive lower wages (by amount AJ; Becker, 1985, p.34). However, over the period in which higher on-the-job training investments are made, the worker's productivity and thus wages will increase at a faster rate.

---

[5] This effect is accentuated for mothers who expect to work part-time hours following the birth of a child.

[6] Mincer and Ofek's analysis does not explicitly depict time spent in education; the wage profiles begin at the end of compulsory schooling (age S) and investments in post-school education are omitted. Nevertheless, investments in tertiary education can be viewed in a similar way to investments in on-the-job training. Instead of receiving lower wages in exchange for on-the job training, individuals investing in their education experience a period of no wages up until point V. After completing their education, they follow a wage profile which is parallel to but vertically above the profile of the non-continuous workers.

Since non-mothers are more likely to make larger investments than mothers in the pre-interruption period, non-mothers' wage profiles (JK) are characterised by a lower intercept and steeper slope than mothers' profiles (AB) in the pre-interruption period.

2.1.2 Labour Market Interruption and Re-entry

At age V, women who become mothers commence a work interruption while those women who will remain childless continue working.[7] During the labour market interruption, three main factors affect mothers' earning power.

Firstly, during leave mothers forego growth in experience. Assuming the interruption lasts for one period, the rate of wage decline due to foregone experience is distance ε. If this is the only source of a wage setback, mothers' re-entry wages will be lower than wages of non-mothers, but will not be lower than their own wages at exit (Mincer and Ofek, 1982, p.4).

In addition to foregoing experience, mothers' skills may depreciate during the break. Skill depreciation will lead to a reduction in the stock of human capital, and thus the wages received at the point of re-entry (age T) will be lower than the wage earned at the time the interruption commenced (age V). The rate of depreciation due to non-

[7] If women who anticipated becoming mothers at age V instead remain childless, their wage profile will become line BM. As long as no future work interruptions are anticipated, investments in on-the-job training will be the same as the investments made by non-mothers. As such, profile BM will have the same slope as the profile of women who never anticipated motherhood; however the wage level will remain below.

use in the short-run is given by ψ. In the long-run however, the depreciation effect will be lower if mothers experience a period of human capital restoration, as will be discussed further below.

Finally, if mothers return to a different employer after an interruption, the firm specific skills relevant to their previous employer will not earn rents at the new firm. Accordingly, there will be an additional wage loss effect beyond that attributed to skill depreciation.

2.1.3 Restoration and Post-restoration Periods

The restoration period which commences at the point of re-entry (age T) is characterised by higher rates of investment in human capital by recent returnees. Mincer and Ofek (1982, p.4) hypothesize that the restoration of depreciated human capital is less costly than the development of new human capital. They explain that the rate of decline of the rental value of depreciated human capital is greater than the 'physical' rate of decline as the market productivity is largely reduced even if minor parts of human capital are lost or become defective. However it may take relatively little effort to repair or replace the depreciated parts, after which the rental value returns to its original level (Mincer and Ofek, 1982, p.4).

Because their opportunity cost is lower, recent returnees invest more heavily in human capital than comparable continuous workers. Accordingly, the returnees' wage profile exhibits a steeper slope over the period of rapid restoration (line segment EF) than the profile of a continuous worker.[8]

According to Mincer and Ofek's model, once the human capital of returnees is restored to pre-interruption levels, investments in human capital level off at the same rate as continuous workers, provided that no future work interruptions are anticipated. However in the Australian context where many women return to part-time employment following the birth of a child (Hosking, 2007), this assumption may not apply. Women working part-time may accumulate less experience per year of age, and have fewer opportunities for promotion than non-mothers who work full-time. Thus the wage profiles of mothers (as shown in Figure 2.1) may be flatter than non-mothers' beyond point F. The vertical distance between the mothers' and non-mothers' profiles at point F represents the long run wage differential (δ).

2.2 Additional Explanations

In addition to work interruptions, mothers' wages may also be affected by a number of other factors associated with motherhood.

[8] For workers who separate from their previous employer, Baum (2002, p.4) provides additional reasons to believe that low return wages will rebound. Firstly, job search theory predicts that better job matches are found over time. While women returning to the work force may not initially find a good job match, their wages will rise towards pre-interruption levels as they seek out better matches. Secondly, signalling theory predicts that wages will increase as employers observe worker productivity. At first when productivity is only partially observed, employers may pay low wages, however as they observe the worker over time, they may become more willing to pay a wage closer to productivity.

2.2.1 Work Effort Hypothesis

A commonly cited theoretical reason for the existence of a motherhood wage penalty is the different amounts of effort available for mothers and non-mothers to expend at market work (Budig and England, 2001). This explanation is derived from Becker's (1985) allocation of effort hypothesis, commonly termed 'the work effort hypothesis'.

In Becker's effort allocation model, mothers and non-mothers have a given amount of energy to distribute between work and household activities. It is assumed that outside of time in market work, mothers undertake household duties related to caring for children whereas non-mothers spend their non-market time in leisure. Assuming leisure requires less energy than housekeeping and child care; mothers expend more energy outside of market work time than non-mothers. As a result, mothers have less energy to spend on market work and therefore earn a lower hourly wage than non-mothers with the same market human capital and working the same number of hours. Furthermore, the model also predicts that mothers will economise on their energy expenditure at market work by seeking less energy demanding jobs, which may in turn pay lower wages.

2.2.2 Discrimination

In addition to work effort, statistical and taste discrimination have also been put forward as explanations for the motherhood wage penalty.

Statistical discrimination arises in a market where there is imperfect information on worker productivity, and gathering information on the productivity of an individual is expensive. In the absence of full information, employers use the average productivity of a particular group as a 'signal' of worker productivity, and as a result, those with above average productivity are 'under-paid' (Hyclak, Johnes and Thornton, 2005, p.382).

If it is the case that mothers on average are less productive than non-mothers, a wage differential will result whether or not individual high-productivity mothers are subjected to statistical discrimination. However, if mothers and non-mothers are equally productive, yet employers assume childcare and housework responsibilities make mothers less productive, a wage penalty may arise through statistical discrimination (Hyclak, Johnes and Thornton, 2005, p.384).[9]

It is also possible that 'taste' discrimination may result in lower wage offers. In Becker's (1957) taste discrimination model employers with a prejudice against mothers will pay a wage below their productivity by an amount sufficient to compensate for their taste for discrimination (Hyclak, Johnes and Thornton, 2005,

[9] Similarly, Baum (2002, p.3) argues that the greater propensity of mothers to undertake work interruptions may lead employers to view mothers as less productive. If work commitment is used as a signal of productivity and work interruptions indicate weak commitment then mothers may be subject to statistical discrimination.

p.379).[10] Thus even if no productivity differential exists, mothers may receive lower wages.

2.2.3 Mother Friendly Jobs

Differences in the type of jobs chosen by mothers and non-mothers may also cause a wage differential. Mothers may choose a job which is considered 'mother-friendly', that is, has work flexibility, part-time hours, maternity leave entitlements or limited travel time.

The theory of compensating wage differentials presented by Rosen (1986) states that in competitive market equilibrium, an observed wage differential is that "required to equalise the total monetary and non-monetary advantages or disadvantages among work activities" (Rosen, 1986, p.641). The theory assumes that workers' are willing to trade off monetary compensation for non-wage benefits. Therefore, if there are two equally productive workers, one of whom chooses a job with monetary benefits only and the other chooses a job with wage *and* non-wage benefits, the latter worker will be paid less.

If mothers are willing to accept non-wage benefits as compensation for lower wages then the propensity of mothers to work in 'mother friendly' jobs may (partially) explain the motherhood wage differential.

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[10] Taste discrimination may also operate through employees and customers.

2.3 Summary

In summary, there are a number of non-mutually exclusive explanations for an observed raw wage differential between mothers and non-mothers. Following human capital theory, work interruptions may reduce women's wages through foregone experience, skill depreciation and loss of tenure, and the anticipation of career breaks may affect wages even before they occur. Moreover, the effort required to raise children and the type of jobs compatible with motherhood may also result in lower wages. Finally the real or perceived differences between mothers and non-mothers in the eyes of employers may contribute further.

The empirical evidence on the extent to which each explanation contributes to the motherhood wage penalty will be presented in the next chapter.

3 Empirical Literature Review

This chapter has four sections. Section 3.1 reviews the international empirical literature on the motherhood wage penalty. The second section reviews the evidence on the effect of motherhood on wage growth and the third section reviews Australian studies on the relationship between motherhood and hourly, annual and lifetime earnings. Finally, the fourth section summarises the current position of the Australian literature and reiterates the thesis objectives.

3.1 The Motherhood Wage Penalty

A large body of international literature has studied whether mothers earn lower wages than non-mothers (see Table 3.1 for key papers). While the evidence is mixed, the majority of studies have found a residual motherhood wage penalty. A significant wage penalty has been found in the United States[11], Britain (Waldfogel, 1995; Waldfogel, 1998b), Canada (Drolet, 2002) and Germany (Buligescu *et al.*, 2009).[12] While other studies in Denmark (Gupta and Smith, 2002) and Sweden (Albrecht *et al.*, 1999) have found motherhood or maternal leave to have no direct effect on wages.

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[11] Such as: Anderson, Binder and Krause (2002; 2003), Baum (2002), Budig and England (2001), Loughran and Zissimopoulos (2009), Lundberg and Rose (2000), Taniguchi (1999) and Waldfogel (1997; 1998b).

[12] Most studies which found a motherhood wage penalty control for marital status in their analysis (for example, Anderson, Binder and Krause, 2002; Anderson, Binder and Krause, 2003; Baum, 2002; Budig and England, 2001) which demonstrates that motherhood has a negative effect on wages, independent of the effects of marriage.

Table 3.1. Motherhood Penalty Literature: Selected International Studies

Study	Country (Data)	Relevant Research Questions/ Topics	Method	Main Findings
Amuedo-Dorantes and Kimmel (2005)	USA (NLSY79)	- Motherhood wage penalty	Pooled CS, Heckman CS, Heckman IV-FE. <u>DV</u>: ln(wage) . <u>Key Variables</u>: One + children. <u>Controls</u>: MS, Age, Age^2, Ra, Ed, Exp, Exp^2, Ten, Ten^2, Oc, Re, Unemployment Rate, Household Resources.	- Motherhood penalty- 5% - College educated mothers receive a wage boost from motherhood which is enhanced by fertility delay.
Anderson, Binder and Krause (2002)	USA (NLSYW)	- Motherhood wage penalty	FE. <u>DV</u>: ln(wage) . <u>Key Variables</u>: One, two + children. <u>Controls</u>: MS, Age, Ed, Exp, Exp^2, YO, Oc.	- Motherhood penalty- One child: 3%; two or more: 5% -The motherhood wage penalty increases with education level.
Anderson, Binder and Krause (2003)	USA (NLSYW)	- Motherhood wage penalty - Work effort hypothesis	FE. <u>DV</u>: ln(wage) . <u>Key Variables</u>: One, two + children. <u>Controls</u>: MS, Age, Age^2, Ra, Ed, Exp, Exp^2, PT, Oc, Household Resources.	- Motherhood penalty- One child: 3%; two or more: 5% - Wage penalties do not exist for the least and most educated groups; significant wage penalty for mothers with middle education.
Baum (2002)	USA (NLSY79)	- Motherhood wage penalty - Interruptions to give birth - Continuity	FD, Heckman FD. <u>DV:</u> Δln(wage) . *Motherhood Penalty:* <u>Key Variables:</u> Number of Children. <u>Controls:</u> MS, Exp, Exp^2, Ten, Ten^2, YO, PT, Re. *Birth Interruption:* <u>Key Variables:</u> Duration of Interruption, $duration^2$. <u>Controls:</u> Above controls + return to previous employer dummy.	- Motherhood penalty- Per child: 2% - Upon return to work after giving birth, wages are around 3% less than pre-birth levels. - Returning to the pre-child birth job reduces or mitigates a wage decline.
Budig and England (2001)	USA (NLSY79)	- Motherhood wage penalty	FE. <u>DV</u>: ln(wage) . <u>Key Variables</u>: One, two, three + children. <u>Controls</u>: MS, Ed, Exp(PT/FT), Ten(PT/FT), PT, Ind, U, Sec, Number of breaks, Work effort index.	- Motherhood penalty-One child: 3%; two children: 9%; three or more: 12% - Mother friendly job characteristics explain little of the penalty. -Married mothers experience a larger wage penalty.
Buligescu *et al.* (2009)	Germany (GSOEP)	- Wage penalty for maternity leave	Heckman IV-FE. <u>DV:</u> ln(wage) .<u>Key Variables:</u> Fraction of previous years spent on ML. <u>Controls:</u> Number of children, Ed, Exp(FT/PT), Exp^2(FT/PT), Ten, FS, Re, Temporary worker, Country of Origin.	- Maternal leave penalty: 10-14% net of foregone experience and tenure. - Women who took short breaks catch up quickly; those who extend beyond the legislated 3 years of protected leave receive a greater penalty.

Motherhood Penalty Literature: Selected International Studies (Continued)

Study	Country (Data)	Relevant Research Questions/ Topics	Method	Main Findings
Drolet (2002)	Canada (SLID)	- Motherhood wage penalty - Birth timing	CS (OLS). DV: ln(wage) . Key Variables: One + children. Controls: Exp, Exp², Ed, Ten, PT, U, Re, FS, Ind, Oc, Job responsibilities, Urban Class size, Area of study. *Timing of Childbirth:* Above model estimated for women who had children early, on-time, or delayed childbirth relative to the predicted age.	- Motherhood wage penalty: around 5%. - Mothers who delay motherhood earn wages at least 6% higher than women who have children early. -The wages of women who delay motherhood do not differ significantly from the wages of women without children.
Ejrnaest and Kunze (2004)	West Germany (IABS)	- Changes in mothers wages around first birth	Heckman IV-FD. DV: Δln(wage) . Key Variables: Exp (before first, between and after last birth), interruption duration, before birth dummy, job change dummy. Controls: Ind.	- A one year interruption around childbirth leads to a wage decline of around 3% for unskilled women and around 15% for skilled women. - The return to experience is greater after birth.
Gupta and Smith (2002)	Denmark (0.5% of Pop Panel)	- Motherhood wage penalty - Mothers' wage growth	Heckman RE & FE. DV: ln(wage) . Key Variables: One, two + children. Controls: Exp, Exp², Ed, MS, Re, Salary. *Wage Growth:* Exp (and quadratics) Split into: years before first birth, between children and after last child.	- No motherhood penalty controlling for UH. - The birth of a child leads to slower wage growth for mothers but mothers eventually 'catch up' as their post-birth return to experience is convex,
Hill (1979)	USA (PSID)	- Motherhood wage penalty	CS (OLS). DV: ln(wage) . Key Variables: Number of Children. Controls: Exp, Exp², Ed, Ten, YO, MS, Re, Disability.	- No penalty when controlling for actual work experience.
Joshi, Paci and Waldfogel (1999)	Britain (NCDS, MRC)	- The effect of part-time work on the motherhood wage penalty - Continuity	CS, Multinomial selection equation for selection into motherhood and PT/FT status. DV: ln(wage) . Key Variables: One + children. Controls: Exp, Ed, Ten, Re, Ability measure, Fathers social class at age 11. *PT:* Oaxaca decomp of penalty. *Continuity:* Child variables interacted with "continuous worker" dummy.	- PT work is a large source of the motherhood penalty. - FT working mothers returning to the workforce within one year of the birth avoid a penalty. FT working mothers who interrupt their career are paid around 20 percent less than other women. - Continuity does not mitigate penalty for PT workers.
Korenman and Neumark (1992)	USA (NLSYW)	- Motherhood wage penalty - Endogeneity of motherhood, UH, selection.	*Endogeneity:* CS, IV. DV: ln(wage) . Key Variables: One, two + children. Controls: Exp, Ed, Ten, MS, Re. *Unobserved Heterogeneity:* FD. DV: Δln(wage) . *Selection into Employment:* Heckman CS; Heckman FD - bivariate selectivity criterion for employment in both 1980 and 1982.	- FD estimates imply motherhood has no direct effect on wages. - The exogeneity of marriage and motherhood was not rejected. UH caused OLS CS to be biased; women with wage enhancing characteristics are less likely to have children. Marginally significant (t=1.86) inverse Mill's ratio in pooled CS. Insignificant in the FD model.

Motherhood Penalty Literature: Selected International Studies (Continued)

Study	Country (Data)	Relevant Research Questions/ Topics	Method	Main Findings
Loughran and Zissimopoulos (2009)	USA (NLSY79, NLSYW)	- Mothers' wages and wage growth	FD with fixed effects model; DV: $\Delta \ln(wage) - \Delta \overline{\ln(wage)}$. Key Variables: One +, two +children, years with one +, years with two + children. Controls: Exp, Exp^2, MS, years married, divorced status, years divorced.	- A birth reduces women's wages by 2-3% in year of birth and has no effect on wage growth. Marriage reduces wages by 2-4% in the year of marriage and further reduces wage growth by 2-4 percentage points in subsequent years.
Lundberg and Rose (2002)	USA (PSID)	- Changes in mothers wages around first birth - Continuity	FE & RE. DV: ln(wage) . Controls: Ed, Age, Re, Ra. *RE Model:* Key Variables: Before (=1 in years before birth), Born (=1 in year of birth), After (=1 in years after birth). *FE Model:* Key Variables: Born (equal 1 in year of birth), After (equal 1 in years after birth). Only women who gave birth included.	- Birth of 1st child leads to a 5% reduction in women's wages. Mothers earn 9% less than non-mothers before birth (negative heterogeneity). - Those women who worked in all years of the sample window except the year of birth received no wage drop following birth.
Taniguchi (1999)	USA (NLSYW)	- Motherhood wage penalty - Birth timing	FE. DV: ln(wage) . Key Variables: Number of children, number of children interacted with: gave birth as a teenager, 20-27 years of age, 28 + years of age. Controls: Exp, Ed, Age, Age^2, MS, Re, H, H^2, SMSA.	- Motherhood penalty- Per child: 3%. - Those who delay child bearing to 28 years or older do not receive wage penalty. Those who have their first child between 20 and 27 or during teenage years receive penalties of 4% and 2% respectively.
Waldfogel (1995)	Britain (NCDS)	- Motherhood wage penalty	FE. DV: ln(wage) . Key Variables: One, two + children. Controls: Exp, Ed, Age, MS.	- Motherhood penalty- One child: 9%; two or more: 16%.
Waldfogel (1997)	USA (NLSYW)	- Motherhood wage penalty	FE. DV: ln(wage) . Key Variables: One child, children. Controls: Exp(FT/PT), Exp^2 (FT/PT), Ed, Age, Age^2, MS, Ra, PT.	- Motherhood Penalty- One child: 4%; two or more: 12%.
Waldfogel (1998b)	USA (NLSY79) Britain (NCDS)	- Motherhood wage penalty - Continuity	FE. DV: ln(wage) . *Motherhood penalty:* Key Variables: One child, two or more children. Controls: Exp, Ed, Age, Ra. *ML coverage:* Key Variables: Covered by ML. Controls: Exp, Ed, Ra, U, FS.	- Motherhood Penalty- USA- One child: 5%; two or more: 13%. Britain- One child: 9%; two or more: 16%. - In both countries, maternity leave coverage provided an offsetting wage premium.

Key: Data Sets: NLSY/YW: National Longitudinal Survey of Youth/Young Women, NCDS: National Child Development Study, SLID: Survey of Labour and Income Dynamics, GSOEP: German Socio-Economic Panel, MRC: Medical Research Council's National Survey of Health and Development, IABS: Institut für Arbeitsmarkt und Berufsforschung Sample. Method: DV: Dependant variable, CS: Cross-sectional, FE: Fixed effects, RE: Random effects, FD: First-difference, 2SLS: Two stage least squares, UH: Unobserved Heterogeneity, ML: Maternity leave. Controls: Ed: Education, Exp: Experience, Ten: Tenure, Ra: Race, PT: Part-time, FT: Full-time, U: Union, FS: Firm size, MS: Marital status, Re: Region, H: Hours, Oc: Occupation, YO: Years out of the labour force, Sec: Sector, Ind: Industry.

Although the effects of children on wages may work indirectly through characteristics such as experience, tenure, education and job choices, most studies focus on estimating the direct effect of children. To that end, the 'residual' motherhood penalty is typically estimated with human capital, job characteristics and time invariant unobserved heterogeneity held constant. In studies which have found a residual penalty, estimates range from two to nine percent for one child and a further two to eight percent for additional children (Table 3.1).

3.1.1 Evidence on the Sources of the Motherhood Wage Penalty

Work Interruptions

To understand the sources of the wage penalty, many studies have examined the impact of work interruptions on mothers' wages. In accordance with Mincer and Ofek's analysis of intermittent workers, time out of the workforce has been found to be a key reason for the raw motherhood wage penalty. Controlling for experience and related variables such as tenure and time out of the labour force narrows the unexplained wage differential between mothers and non-mothers in a number of studies (Anderson, Binder and Krause, 2002; Anderson, Binder and Krause, 2003; Budig and England, 2001; Waldfogel, 1995) and eliminates the gap in another (Hill, 1979).

The role of labour market interruptions has been further investigated in studies looking at how employment continuity around birth affects mothers' wages. A study of the United States by Lundberg and Rose (2000) found that women who return to work within one year of the birth do not receive a wage penalty, whereas women who stay out of the work force longer experience a wage decline. Joshi, Paci and Waldfogel (1999) found a similar result for full-time working British women.

Other papers have studied the impact of returning to the same employer after a work interruption to give birth. In line with the expectations of human capital theory, women who return to their pre-birth employer receive higher wages than otherwise similar women who begin work at new firms (Baum, 2002; Waldfogel, 1995; Waldfogel, 1997). In fact, in separate regressions for the two sub-samples, Baum (2002) found that mothers who return to their pre-birth employer do not receive a wage decline around birth, whereas the wages of women who begin new jobs fall by 2.5 percent.

Employment continuity through job-protected maternity leave has also been examined.[13] In her study of the United States and Britain, Waldfogel (1998b) found a wage benefit accruing to women who use job-protected maternity leave which is almost large enough to offset the wage penalty for motherhood. Similarly, a Swedish study by Albrecht *et al.* (1999) found no effect on subsequent wages for women entering into formal maternity leave schemes, whereas time out of the workforce due to household tasks and unemployment has significantly negative effects. A

[13] Job-protected maternity leave enables women to return to their pre-birth employer and position within a certain time frame.

German study by Buligescu *et al.* (2009) also examined the effect of time out of the workforce for maternity leave on women's wages. However, in contrast to the abovementioned results, they found that the wages of women who return to work within the legislated 3 years of protected maternity leave fall by 10-14 percent upon return to work. Nevertheless, maternity leave still appears to provide benefits as women who extend their leave beyond the legislated period receive an additional 4-6 percent wage penalty.

In line with human capital theory, Waldfogel concludes that the wage advantage of job protected leave comes from the increased likelihood of return to the pre-birth employer. On the other hand, Albrect *et al.* (1999) and Buligescu *et al.* (2009) attribute their results to a signalling effect. Albrect *et al.* conclude that maternity leave has no effect on wages in Sweden as almost all women take formal leave around birth. As such, taking maternity leave does not serve as a signal of lack of worker commitment, and thus employers do not use it as a way to separate high and low productivity workers. Similarly, Buligescu *et al.* (2009) argue that taking more than the legislated leave duration may be used as a signal of weak worker commitment and result in lower wages.

Overall, it appears that work interruptions are a key source of the raw wage differential between mothers and non-mothers and employment continuity may reduce the effects of motherhood on wages. Nevertheless, with the exception of Hill

(1979), most studies find a wage differential even after controlling for experience and work interruption variables. As a result, many studies have explored other explanations for the motherhood wage penalty.

Work Effort Hypothesis

A common explanation for the residual wage penalty is differences in work effort between mothers and non-mothers (Budig and England, 2001), however few have studied whether this work effort hypothesis holds. One exception is Bielby and Bielby (1988) who examined whether mothers exert less effort at work than non-mothers using self-reported measures of effort from the 1973 and 1977 Quality of Employment Surveys in the United States. They found that mothers of pre-school age children report significantly lower effort while on the job than non-mothers, whereas mothers of older children do not. This finding therefore implies that responsibility for young children may contribute to the motherhood wage penalty, and suggests that the penalty should decrease as children get older.

Anderson, Binder and Krause (2003) extended upon Bielby and Bielby's finding by examining whether the motherhood wage penalty declines as children grow older. They also analysed whether the wage gap increases with education, hypothesising that higher skilled jobs require more work effort. The study found that the wage penalty diminishes as children grow older, however does not increase with education as hypothesised. No wage penalty exists for the least and most educated groups while the penalty experienced by the group with middle (high school) education persists as children age.

On account of the latter finding, the authors propose an alternative explanation for the motherhood wage penalty. They conclude that work schedule inflexibility in some type of jobs, rather than differential effort between mothers and non-mothers, is the cause of a wage differential. It is argued that women with high school education only are the most likely to work office hours in jobs offering little flexibility, and those also responsible for children face the greatest scheduling constraints.

Like Anderson, Binder and Krause (2003), other studies examining the relationship between education and the motherhood penalty have found no evidence of greater penalties for more educated women (Budig and England, 2001) and even a wage premium for college educated mothers (Amuedo-Dorantes and Kimmel, 2005).[14] In contrast, other studies have found the motherhood penalty increases with education (Anderson, Binder and Krause, 2002; Waldfogel, 1997) and that those with the highest skill levels face the greatest wage declines around birth (Ejrnaest and Kunze, 2004). These latter studies may provide some indirect support for the work effort hypothesis if the assumption that work effort rises with education holds true.

[14] Amuedo-Dorrantes and Kimmel found college educated mothers receive higher wages even when accounting for selection into employment and unobserved heterogeneity.

However without a direct measure of effort, the validity of this assumption cannot be tested.

Discrimination

Another explanation for the residual wage differential is discrimination (Anderson, Binder and Krause, 2003). However like work effort, discrimination is very difficult (or not possible) to measure and little research has been done on the contribution of discrimination to the motherhood wage penalty.

Kalist (2008) however used a panel data set on the performance of women professional golfers to get indirect evidence on discrimination. Since productivity is directly observed through tournament scores, ranking and prize money, the effect of motherhood on productivity and consequent earnings can be measured without the effect of taste or statistical discrimination confounding the results. Results from fixed effects models with average scores, earnings and rankings used as the dependant variables reveal that the birth of a child significantly reduces player productivity. While the professional sport industry differs from the general labour market, the study's results provide some indirect evidence that the motherhood wage penalty is at least partly due to productivity differences between mothers and non-mothers, and not entirely due to discrimination.

Budig and England (2001, p.218) also state that their results suggest the motherhood penalty is not completely due to discrimination as married mothers face a larger penalty than unmarried mothers. They argue that unless it is believed that employers discriminate more against married than unmarried mothers, the wage penalty is not completely due to discrimination.

Mother Friendly Jobs

Another explanation for the motherhood wage penalty studied is the propensity of mothers to work in jobs offering valued non-wage benefits. The study by Budig and England (2001) examined the proportion of the motherhood penalty explained by mother friendly job characteristics. Overall, they found that these variables explain only a small portion of the motherhood penalty (one percentage point), and of the variables included, current part-time work status is the most important.

Other studies of the United States (Waldfogel, 1997) and Britain (Joshi, Paci and Waldfogel, 1999) have also found part-time work to be important. Using an Oaxaca decomposition, Joshi, Paci and Waldfogel (1999) concluded that the source of the motherhood penalty lies more in the propensity of mothers to work in part-time jobs than any direct effect of children (Joshi, Paci and Waldfogel, 1999, p.551). Similarly, Waldfogel (1997) found controlling for part-time employment significantly reduces the wage penalty attributed to motherhood. However accounting for past part-time work by distinguishing part-time from full-time experience explains only a small portion of the gap.

Although the contribution of part-time work to the motherhood penalty has not been studied in Australia, studies of the part-time wage differential suggest it will not be an important factor. Using a cross-section from the first wave of HILDA, Rodgers (2004) found no evidence of a significant pay differential between part-time and full-time workers after correcting for self-selection into part-time and full-time employment. Extending upon Rodgers' analysis, Booth and Wood (2008) used a panel of the first four waves of HILDA and found that part-time workers receive a wage premium.[15]

Thus, in contrast to Britain (Ermisch and Wright, 1993; Main, 1988) and the United States (see Hirsch, 2005) where part-time workers receive lower wages, the propensity of Australian mothers to work in part-time jobs may not cause (or increase) a motherhood wage penalty. Nevertheless, even if no wage penalty exists, part-time work may still affect Australian mothers' wages in the long run through lower human capital accumulation (due to less time spent working) and fewer opportunities for promotion (Abhayaratna *et al.*, 2008).

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[15] Booth and Wood found that casual part-time female employees earn higher wages then part-time permanent employees who in turn earn more than full-time employees *ceteris paribus*. As such, the part-time pay premium is not entirely due to casual loading.

Another non-wage benefit presumably valued by women who anticipate motherhood is maternity leave entitlement. An Australian study by Edwards (2006) examined whether women eligible for paid and unpaid maternity leave receive lower wages than other women after controlling for worker and job characteristics. She found evidence of a compensating wage differential which suggests that women are willing to accept lower wages for the provision of maternity leave. Thus part of the motherhood wage differential may be explained by eligibility for maternity leave.

3.1.2 Heterogeneity between Mothers

Age at First Birth

A number of studies have examined whether the age a woman is when she has children affects her wage outcomes. Evidence on work interruptions in general has found that time out of the labour force has no significant effect on wage growth either early (in the first seven years) or later (in the eighth to fifteenth year) in one's career (Green and Ferber, 2008). However evidence from the motherhood penalty literature suggests that delaying childbearing creates positive wage outcomes.

Drolet (2002) found using Canadian cross-sectional data that mothers who delay childbearing earn wages at least six percent higher than women who have children early. Unobserved heterogeneity does not appear to be driving the finding as studies using fixed effects have obtained similar results. Taniguchi (1999) found that those who delay childbearing until after the age of 28 do not receive a motherhood wage penalty, whereas younger women earn wages two to four percent less than otherwise similar non-mothers. Similarly, Amuedo-Dorrantes and Kimmel (2005) found that delaying childbearing increases the wage advantage of college educated mothers.

Altogether, these studies suggest that women who delay childbearing until after their careers are established avoid the negative wage effects felt by women who enter motherhood at a younger age.

Marriage and Motherhood

While marriage and childbearing traditionally happen together, the combination of increasing numbers of births outside of marriage and higher divorce rates have resulted in a large proportion of mothers being unmarried in recent times (OECD, 2006). Despite this, the interaction between motherhood and marital status has received little attention. One study which did examine the interaction found that married women bear a greater motherhood penalty than otherwise similar unmarried women (Budig and England, 2001). The authors argue that having access to a husband's income may allow married mothers to focus more on childcare whereas unmarried mothers are more inclined to specialise in market work.

3.2 Motherhood and Wage Growth

While there have been many studies of the effect of children on wage levels, few studies have examined wage growth. Three exceptions however are Gupta and Smith (2002), Ejrnaest and Kunze (2004) and Loughran and Zissimopoulos (2009).

Gupta and Smith (2002) examined the effect of childbirth and length of the birth work interruption on wage growth by comparing the returns to experience before and after childbearing. Using a sample of women aged between 19 and 39 who were childless in the first wave of a Danish panel survey (1980-1995), the authors constructed three experience variables which measure work experience accumulated before the first birth, between children and after the last child is born.[16] Using these variables and their quadratics, it was found that mothers do experience slower wage growth initially after birth, however post-birth returns to experience display a convex path, and thus wage growth increases in time. Since the returns to experience before birth follow the usual concave trajectory, mothers' wages eventually 'catch up' to pre-birth levels.

A similar methodology was used by Ejrnaest and Kunze (2004) who broke experience into that attained before and after birth. They found mothers' return to experience to be greater after birth than before, which is taken as evidence of the wage rebound effect hypothesised by Mincer and Ofek (1982).

[16] For women who remained childless throughout the panel all experience was classified as 'before'.

Using a different methodology which allows for individual slopes in experience, Loughran and Zissimopoulos (2009) also examined the effect of childbirth on wage growth. They allow motherhood to affect wage growth by including regressors which count the number of years since the birth of a first or second child. By estimating a first-difference model with fixed effects, Loughran and Zissimopoulos account for the effect of time invariant unobserved heterogeneity on wage levels and wage growth. Overall, they found that motherhood reduces wages by two to three percent in the years of birth, but has no effect on subsequent wage growth.

While his study did not examine wage growth explicitly, Baum (2002) provides some indirect evidence on short-run wage growth after birth. Upon return to work after a work interruption to give birth, mothers' wages are reduced by three percent. However Baum finds that wages 'rebound' and the negative wage effect disappears after two years. This finding therefore suggests that women experience a period of rapid wage growth following their return to work in line with the findings of Ejrnaest and Kunze (2004) and Gupta and Smith (2002). The long-term wage growth however is not examined.

3.3 Australian Studies

In contrast to the large international literature, the effect of motherhood on wages or wage growth has received little attention in Australia. In fact, only two Australian studies (Krepp, 2007; Whitehouse, 2002) have sought to examine whether mothers earn lower hourly wages than non-mothers and no Australian study to date has examined the effect of motherhood on wage growth.[17]

Using cross-sectional data from the Australian Workplace Industrial Relations Survey collected in 1995, and a British survey conducted in 1998, Whitehouse (2002) examined whether the presence of dependent children affected mothers' and fathers' hourly wages. Controlling for some demographic, human capital and job characteristic variables, it was found that British and Australian fathers receive a pay premium, British mothers receive a pay penalty, and motherhood has no significant effect on Australian women's wages.

More recently, Krepp (2007) used the first four waves of HILDA to estimate the effect of children on Australia women's wages. Pooling the 2001-2004 cross-sections, Krepp estimated a Heckman-corrected wage equation accounting for selection into employment. With controls for martial status and age only, motherhood penalties of five percent for one child and nine percent for two or more children were found. However when experience, education and tenure were included, the motherhood penalties became insignificant.

A related study by Edwards (2006) examining whether maternity leave eligibility acts as a compensating differential included a control for the number of children

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[17] To the best of the author's knowledge.

aged zero to four years. In line with the other Australian results, Edwards found the coefficient of the number of children to be positive but insignificant. Like the above studies, cross-sectional data was used.

Although these Australian studies have found no direct effect of motherhood on wages, their results are potentially biased by the omission of key controls. Firstly, Whitehouse does not control for work experience, and if mothers in the sample have more years of experience than the non-mothers, the coefficient of the motherhood variable will be biased upwards (Anderson, Binder and Krause, 2003).[18] Similarly, Krepp's models do not control for part-time employment status. Given that mothers are more likely to be employed in part-time jobs, and part-time work attracts a pay premium (Booth and Wood, 2008), the motherhood coefficient may be biased towards zero.

Moreover, the results may suffer from heterogeneity bias as time invariant unobserved factors are not controlled for in the cross-sectional models. Although Krepp accounts for selection into employment, there may be other unobserved factors which are correlated with both motherhood and wages (Anderson, Binder

[18] If mothers had more years of experience simply because they were older, controlling for age should remove the bias. However, in Whitehouse's model age is controlled for by two categorical variables (30-39 and 40-49) and thus may not completely control for the effect of age on wages.

and Krause, 2002; Anderson, Binder and Krause, 2003; Korenman and Neumark, 1992).[19]

Finally, as highlighted in the paper, Whitehouse's estimates of the motherhood penalty may be biased as data is not collected from firms with fewer than 20 employees. If casual and part-time workers which are over-represented in small workplaces are the most likely to experience a motherhood penalty, Whitehouse's results may understate the negative effect of motherhood on wages.

The effect of motherhood on annual earnings has also been examined in Australia. Arun, Arun and Boorah (2004) using survey data from Queensland found that career breaks taken for reasons related to childrearing have a larger effect on annual earnings than other types of interruptions. Similarly, Baxter (1992) found married women's annual earnings are reduced by four to five percent per child.

In addition, two Australian studies have estimated the foregone lifetime earnings associated with childrearing. Breusch and Gray (2004) using HILDA and Chapman *et al.* (2001) using data from the Negotiating the Life Course Survey (NLCS; 1997) simulated lifetime earnings profiles of mothers and non-mothers. They estimate that

[19] If wage enhancing unobserved attributes are positively correlated with motherhood, the cross-sectional estimates will be biased upwards towards zero. Alternatively, if those with wage enhancing unobserved attributes are less likely to become mothers, the negative effect of motherhood will be overstated.

mothers' accumulated lifetime earnings are reduced by 19 (Breusch and Gray, 2004) to 27 percent (Chapman *et al.*, 2001).

These studies demonstrate that Australian mothers earn less on average per year and over their lifetime than non-mothers, however it is not possible to determine the extent to which this is due to differences in the hourly wage rate or hours worked.[20] Although it has been found that the presence of children reduces the hours worked by Australia mothers (Kawaguchi, 1994; Knudsen and Peters, 1994), evidence from other developed countries suggests hourly wages may also fall.

3.4 Summary and Restatement of Objectives

Despite the importance of the issue to the current Australian context and the large amount of research attention overseas, few studies have examined the effect of children on Australian women's hourly wages. Moreover, the studies thus far potentially suffer from heterogeneity and omitted variables bias. Accordingly, this thesis will fill a gap in the Australian literature by estimating the effect of motherhood on wages using a rich set of human capital and job characteristics controls and accounting for time invariant unobserved heterogeneity with fixed effects. Furthermore, the impact of motherhood on wage growth will be examined

[20] Breusch and Gray (2004) and Chapman *et al.* (2001) provide their earnings equation estimates, however the dependent variable is annual earnings rather than hourly wages. Baxter includes a control for weekly hours worked, however the earnings penalty cannot be interpreted as the effect of motherhood on women's hourly wages as the model does not account for the number of weeks worked in the year.

for the first time by applying the methodology of Loughran and Zissimopoulos (2009).

4 Review of Methodology

This chapter reviews the methodologies used in the motherhood penalty literature in two sections. The first section describes the basic specifications which have been used to estimate the effect of motherhood on wages. The second section addresses empirical issues that arise, namely, selection into employment, reverse causality between wages and motherhood and unobserved heterogeneity. The problems which each issue presents and the possible ways to overcome the issues are discussed. In addition, empirical evidence on the extent to which each issue causes the motherhood penalty estimates to be biased is presented.

4.1 Conventional Specifications

Some studies have begun by estimating the raw wage differential between mothers and non-mothers which is given by β in the following equation:

$$\ln(w_{it}) = \eta + \beta Mother_{it} + u_{it}$$

where $\ln(w_{it})$ is the natural logarithm of the hourly wage for individual i ($\forall i = 1, 2, ..., N$) at time t ($\forall t = 1, 2, ..., T$), $Mother_{it}$ is a dummy variable for the motherhood status of the i th individual ($Mother_{it}$ =1 if a mother, 0 otherwise) and μ_{it} is stochastic error term. The coefficient β captures the effect of differences in observable and unobservable characteristics between mothers and non-mothers on the hourly wage.

To gain an estimate of the effect of motherhood on wages, net of human capital differences, most studies proceed by including human capital controls:

$$\ln(w_{it}) = \eta + \beta Mother_{it} + \gamma_1 HC_{it} + u_{it}$$

where the vector HC_{it} typically includes education, experience, experience squared and tenure, and in some studies, time out of the labour force.

The majority of the motherhood penalty studies have used modern data sets which record the actual number of years spent in paid employment allowing them to control for actual rather than potential experience (calculated as age minus years of schooling minus 6). While potential experience provides a satisfactory measure of experience for continuous workers, it fails to accurately represent the experience of intermittent workers (Mincer and Polachek, 1974). Because mothers are likely to have spent time out of the workforce, potential experience will in most cases, overestimate actual experience. As a result, the variable for children will act as a proxy for having fewer years of actual experience and cause the motherhood wage penalty to be overstated (Hill, 1979; Waldfogel, 1998b).

To further increase the accuracy of the experience measure, some have distinguished between years of part-time and full-time work (Budig and England, 2001; Buligescu *et al.*, 2009; Waldfogel, 1997). Part-time employees work fewer hours per year and thus may accumulate less work experience than full-time workers employed for the same time span. Since mothers are more likely to be in part-time employment, separating experience into part-time and full-time years may increase the accuracy of the motherhood penalty estimate. However the one study which compared the motherhood penalty estimates with and without experience disaggregated found that disaggregation had no material effect on the results (Waldfogel, 1997).[21]

In addition to experience, some studies have also controlled for time spent out of the workforce (Anderson, Binder and Krause, 2002; Baum, 2002; Hill, 1979; Krepp, 2007; Simonsen and Skipper, 2006). With experience held constant, the coefficient of time out of the workforce provides the partial effect of interruptions on wages (Mincer and Ofek, 1982, p. 11), and has been interpreted as the effect of human capital depreciation (Baum, 2002).

Time out of the workforce has been controlled for by including the number of years spent not working in general since completing school (Anderson, Binder and Krause, 2002; Hill, 1979; Krepp, 2007; Simonsen and Skipper, 2006) or around the most recent birth (Baum, 2002) as explanatory variables. Alternatively, it has also been effectively controlled for by including age, actual experience and years in schooling (Anderson, Binder and Krause, 2003).[22] While the latter method controls

[21] Studies which have distinguished between part-time and full-time experience have found that the return to full-time experience exceeds the return to part-time experience as expected (Budig and England, 2001; Buligescu *et al.*, 2009; Waldfogel, 1997).

[22] Following the relationship:

$$\text{Time out of the labour force} = \text{age} - \text{years of experience} - \text{years of schooling} - 6$$

for time out of the labour force, it does not provide an estimate of the marginal effect of time out of the labour force on wages.[23]

Even after controlling for conventional human capital variables and time out of the workforce, a motherhood penalty still remains in a number of studies (Anderson, Binder and Krause, 2002; Anderson, Binder and Krause, 2003; e.g. Korenman and Neumark, 1992; Waldfogel, 1997). While it has been argued that job characteristics may be outcomes of motherhood status and should not be controlled for when estimating the size of the motherhood wage penalty (Waldfogel, 1998b), they have been included in most studies to estimate the direct effect of children, and gauge the contribution of job characteristics to the motherhood penalty (e.g. Anderson, Binder and Krause, 2002; Anderson, Binder and Krause, 2003; Budig and England, 2001). In addition, most studies control for marital status, and some also include age, race, region and household resources (see Table 3.1). Controlling for job characteristics and demographics, the model becomes:

$$\ln(w_{it}) = \eta + \beta Mother_{it} + \gamma_1 HC_{it} + \gamma_2 JC_{it} + \gamma_3 Dem_{it} + u_{it}$$

where JC_{it} is a vector of variables relating to job characteristics such as part-time status, occupation, industry, firm size and union status and Dem_{it} is a vector of demographics, such as marital status, race, age, region and household resources.

[23] Another study by Budig and England (2001) also controlled for the number of career interruptions to account for any negative signalling effects from frequently changing jobs.

4.2 Empirical Issues

4.2.1 Selection into Employment

The Nature of the Problem

An issue that arises in estimation of women's wage equations is that wages are not observed for non-working women. While the aim is to estimate the effect of motherhood on the wage received, omitting from the sample women who are unemployed or out of the labour force may introduce selection bias (Wooldridge, 2002, p.552). If those women who would face the greatest motherhood penalty are also those most likely to be not employed, then estimating the motherhood penalty with a sample of employed women only will understate the true population value (Budig and England, 2001, p.213).

Testing for and Dealing with Selection into Employment

In order to generalise the results to all women, not just those employed at the time of the survey, it is necessary to account for the selection of women into employment (Wooldridge, 2002, p.561). This has typically been done by using a Heckman-type correction (Amuedo-Dorantes and Kimmel, 2005; Baum, 2002; Edwards, 2006; Gupta and Smith, 2002; Joshi, Paci and Waldfogel, 1999; Krepp, 2007; Waldfogel, 1995).[24] The Heckman correction involves estimating an equation for selection into

[24] Korenman and Neumark (1992) test for selection of high wage earners into employment following the birth of a child by estimating a cross-sectional regression with women without children. They include dummy variables indicating whether a woman gave birth and was subsequently working. If those women who give birth and subsequently return to work earn higher pre-birth wages than

employment and a wage equation using either a two-step or maximum likelihood procedure (see Section 5.1 for greater detail). The maximum likelihood procedure is more efficient than the two-step procedure under the assumption of joint normality of the selection and wage equation error terms (Wooldridge, 2002, p.566).

It is possible to achieve identification of the Heckman model with the same set of regressors in the selection and wage equations, however more convincing estimates may be obtained by finding a valid exclusion restriction (Cameron and Trivedi, 2009, p.546). In the current context, a valid exclusion restriction is a variable which has a substantial impact on the probability of being employed, but is uncorrelated with the wage equation error.[25] Such a variable will be included in the selection equation, but omitted from the wage function.

A variety of exclusion restrictions have been used in the literature (Table 4.1). A number of studies have used non-labour income (Baum, 2002; Edwards, 2006; Gupta and Smith, 2002; Joshi, Paci and Waldfogel, 1999; Korenman and Neumark, 1992; Krepp, 2007) or associated variables such as marital status, the presence of a partner, husbands' employment, household wealth and housing ownership and tenure (Gupta and Smith, 2002; Joshi, Paci and Waldfogel, 1999; Korenman and Neumark,

women who do not return after birth, this is taken as evidence of selection of high wage earners into post-birth employment. While this method provides a way of testing for selectivity, it does not correct for it, as is the case with the Heckman model.

[25] That is, the exclusion restriction must not have any effect on the wage besides that working indirectly through variables controlled for in the wage equation.

1992; Waldfogel, 1995). Women's attitudes towards women's involvement in the work force at present (Baum, 2002; Chapman *et al.*, 2001) and in the past (Joshi, Paci and Waldfogel, 1999) have also be used. Moreover, others have used factors related to attitudes such as characteristics of a woman's household when she was younger (Baum, 2002), whether a woman lived with her parents by age 18 and the highest education completed by her parents (Amuedo-Dorantes and Kimmel, 2005).

The use of non-labour income and attitudes towards work as exclusion restrictions is in accordance with labour supply theory's proposition that a woman's decision to enter the labour force is dependant on the wage rate, non-labour income and preferences (Hyclak, Johnes and Thornton, 2005, p.79). Moreover, there is qualitative evidence that variables measuring attitudes about combining work and family are strongly related to the probability of employment but unrelated to women's earnings (Duncan and Rosalind, 1999). Similarly, after controlling for observable characteristics (and time invariant unobserved factors in first-difference and fixed effects models), non-labour income is unlikely to have a direct effect on wages.

Table 4.1. Exclusion Restrictions Used in the Motherhood Penalty Literature

Study	Country (Data)	Exclusion Restrictions
Amuedo-Dorantes and Kimmel (2005)	USA (NLSY79)	▪ Highest education grade completed by a woman's parents ▪ Whether the woman lived with her parents by age 18
Baum (2002)	USA (NLSY79)	▪ Non-labour income ▪ Characteristics of the woman's household when she was younger ▪ Woman's attitudes towards women's involvement in the work force at present
Chapman *et al.* (2001)	Australia (NLCS)	▪ Attitudes towards combining work and family
Edwards (2006)	Australia (HILDA)	▪ Non-labour income
Gupta and Smith (2002)	Denmark (0.5% of Population Panel)	▪ Household wealth ▪ Non-labour income ▪ Dwelling ownership
Joshi, Paci and Waldfogel (1999)	Britain (NCDS, MRC)	▪ Woman's attitudes at age 16 ▪ Mother's family building history ▪ Presence of a partner and his characteristics ▪ Non-labour income ▪ Housing tenure
Korenman and Neumark (1992)	USA (NLSYW)	▪ Non-labour income ▪ Weeks of husband's unemployment
Krepp (2007)	Australia (HILDA)	▪ Welfare benefits ▪ Investment income
Waldfogel (1995)	Britain (NCDS)	▪ Marital status ▪ Partner's income

Key: NLCS: Negotiating the Life Course Survey, NLSY/YW: National Longitudinal Survey of Youth/ Young Women, HILDA: Household, Income and Labour Dynamics in Australia, NCDS: National Child Development Study, MRC: Medical Research Council's National Survey of Health and Development.

In a cross-sectional model, the Heckman correction must be employed to take account of self-selection into employment. If however panel data are available, selection bias may be removed through fixed effects or first-difference estimation provided the unobserved factors correlated with the choice to enter the labour force are time invariant.

Evidence of Selection Bias

The evidence of selection bias in the motherhood penalty literature is mixed. No selection bias was detected by Waldfogel (1995) in her study of a young British cohort, or by Edwards (2006), Chapman *et al.* (2001) and Krepp (2007) for Australia.[26] In contrast, Amuedo-Dorantes and Kimmel (2005) found evidence of sample selection bias in their pooled cross-sectional model.[27] However, when accounting for individual level heterogeneity by including fixed effects, the coefficient of the sample selection term was substantially reduced. This suggests "that controlling for unobserved individual heterogeneity captures much of the individual unobservable characteristics correlated with being employed" (Amuedo-Dorantes and Kimmel, 2005, p.33).

Similarly, in their cross sectional model (n=1181), Korenman and Neumark (1992) found some evidence of selection bias with the inverse Mill's ratio significant at the ten percent level. However, using a similar correction in their first-difference model (n=888), the inverse Mill's ratio terms were insignificant and the coefficient estimates with and without the correction were virtually the same. Their result

[26] Waldfogel used a two-step Heckman procedure with 2,722 wage earners and an additional 2,735 non-working women and found the inverse Mill's ratio to be insignificant. She concluded that the high level of female LFP among the young British cohort has resulted in the sample of young working women being representative of the whole female population. Similarly, Edwards (using 1,927 working and 2,213 non-working women) and Chapman *et al.* (using 697 working and 385 non-working women) used a two-step Heckman procedure and found the inverse Mill's ratio to be insignificant. Krepp, using a total sample of 11,382 woman-year observations, found the inverse Mill's ratio to be significant in a regression with few controls, but it became insignificant when controls for human capital and job characteristics were added.

[27] The inverse Mill's ratio was significant at the one percent level and the motherhood penalty estimates halved from 6.5 percent to 3.5 percent when accounting for sample selection.

therefore also suggests that controlling for time invariant unobserved heterogeneity accounts for the factors causing selection into employment.[28]

4.2.2 Reverse Causality

The Nature of the Problem

In addition to selection into employment, reverse causality between the wage rate and motherhood status may also introduce bias.[29] In the above wage equations it is assumed that causality runs from motherhood to the wage rate. However it is also possible that changes in the wage may affect women's fertility decisions. Such reverse causality will cause the estimated effect of motherhood on wages to be biased. Since foregone wages are one component of the opportunity cost of having children, it is conceivable that those women with lower current or future wages are more likely to become mothers (Lundberg and Rose, 2000, p.692). If this is the case, the OLS motherhood penalty estimate will be overstated as the lower wages of women entering motherhood will confound the causal effect of motherhood on wages.

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[28] Baum (2002) found evidence of sample selection bias with the inverse Mill's ratio significantly different from zero. However the effect on the coefficients is unclear as the uncorrected results are not provided for comparison.

[29] A related issue is the endogeneity of experience and tenure as labour supply is expected to respond to changes in the wage (Hyclack, Johnes and Thornton, 2005; Korenman and Neumark, 1992; Waldfogel, 1995). While it is recognised as a possible source of endogeneity, this issue is not pursued in this thesis.

Dealing with Reverse Causality

In general, there are two ways to mitigate the bias caused by reverse causality. The first is to conduct a randomised controlled experiment (or a quasi-experiment) so that the "treatment" is randomly (or "as if" randomly) assigned and thus uncorrelated with the error term. Randomly assigning motherhood status however is not possible, and finding an "as-if" random assignment would be very unlikely.[30]

In the absence of random assignment, consistent estimators may be obtained through instrumental variables methods. To use these methods, there must exist a valid instrument (z), that is, a variable which is correlated with the endogenous regressor but uncorrelated with the wage equation error term ($E(\mu_{it} | z_{it}) = 0$). Moreover, the instrument must be relevant; after controlling for the exogenous regressors, the instrument must account for significant variation in the endogenous variable (Cameron and Trivedi, 2009, p.175). Use of an instrument which is only marginally related to the endogenous regressor (a weak instrument) will result in lost precision and misleading asymptotic critical values in finite samples (Cameron and Trivedi, 2009, p.175-176).

If one or more valid instrument does exist, two stage least squares (TSLS) can be used whereby the endogenous variable is regressed on the instruments and

[30] Scenarios of a contraceptive pill manufacturer accidently randomly distributing ineffective medications or a country's governance randomly assigning fertility rights are very unlikely.

exogenous variables. The fitted values are obtained and are used in the place of the endogenous variable in the structural equation. Provided the conditions for a valid instrument are satisfied, the TSLS estimates obtained are consistent.

Few studies have attempted to account for the endogeneity of motherhood in the motherhood penalty literature (see Table 4.2 for exceptions). Two exceptions are Korenman and Neumark (1992) and Amuedo-Dorrantes and Kimmel (2005) who used TSLS with the father's and mother's education and whether the woman lived with her parents in adolescence as instruments. In addition, Korenman and Neumark also included the parent's educational goals for the woman, whether the woman's mother worked at age 14 and the number of siblings.

Joshi, Paci and Waldfogel (1999) also account for the endogeneity of motherhood using a Heckman type procedure which allows for the simultaneous determination of employment status. To identify their model, the authors used the woman's past attitudes, her mother's family building history and other variables which have been used to identify employment-selection models.

Table 4.2. Fertility Instruments Used in the Motherhood Penalty and Related Literature

Study	Country (Data)	Instrument
The Effect of Motherhood on Wages		
Amuedo-Dorantes and Kimmel (2005)	USA (NLSY79)	▪ Highest education grade completed by women's parents ▪ Whether the woman lived with her parents by age 18
Joshi, Paci and Waldfogel (1999)	USA (NCDS, MRC)	▪ Woman's attitudes at age 16 ▪ Mother's family building history ▪ Presence of a partner and his characteristics ▪ Non-labour income ▪ Housing tenure
Korenman and Neumark (1992) and Neumark and Korenman (1994)	USA (NLSYW)	▪ Father and mother's education ▪ Parents educational goals for the woman at age 14 ▪ Number of siblings ▪ Whether the woman's mother worked at age 14 ▪ Whether the woman lived with both parents at age 14
Simonsen and Skipper (2006)	Denmark (Statistics Denmark Data)	▪ Number of siblings
The Effect of Motherhood on Labour Supply or Other Outcomes		
Angrist and Evans (1998)	USA (PUMS)	▪ Sex-mix of the first two children born
Hotz, Williams McElroy and Sanders (2005)	USA (NLSY79)	▪ Miscarriage
Klepinger, Lundberg and Plotnick (1999)	USA (NLSY79 & Other Sources)	▪ Age of first menstrual period ▪ The age at which consent for abortion and contraception use is not needed in each state ▪ The presence of restrictive abortion provisions in each state ▪ Indications of state policies on abortion and family planning funding ▪ County-level variables on abortion rates and services

Key: NCDS: National Child Development Study; NLSY/YW: National Longitudinal Survey of Youth/Young Women; NLCS: Negotiating the Life Course Survey; PUMS: Census Public Use Micro Samples.

These studies using family background variables have argued that family background is unlikely to affect wages other than through education and ability (Amuedo-Dorantes and Kimmel, 2005; Neumark and Korenman, 1994).[31] In studies using instrumental variables fixed effects methods, (time invariant) ability is controlled for in the wage equation, and thus correlation between family background and ability should not bias the results.[32] However in models without fixed effects (or an accurate ability control), family background variables may not be valid instruments.

The related literature on the effect of motherhood on labour supply and other maternal outcomes provides additional instruments for motherhood. Klepinger, Lundberg and Plotnick (1999) used state and county indicators of the cost of fertility control, laws on pregnancy termination and related variables in studying the effect of teenage childbearing on a variety of outcomes. Also looking at teenage mothers, Hotz, Williams McElory and Sanders (2005) used the naturally occurring event of miscarriages to construct an instrumental variables estimate. Finally, Angrist and Evans (1998) exploited parents' preference for a mixed sibling-sex composition to construct an instrument for further fertility using the sex-mix of the first two children born.

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[31] Similarly, the number of siblings is argued to affect fertility, but have no effect on wages other than through education (Simonsen and Skipper, 2006).

[32] Amuedo-Dorantes and Kimmel (2005) and Neumark and Korenman (1994) used instrumental variables fixed effects models which allow them to account for unobserved heterogeneity and reverse causality.

Evidence of Reverse Causality

The evidence of endogeneity bias from reverse causality is unclear. On the one hand, Korenman and Neumark (1992) do not reject the exogeneity of motherhood finding no statistical evidence that motherhood is correlated with the wage equation error. On the other hand, Amuedo-Dorrantes and Kimmel (2005) report that motherhood is endogenous, however it is unclear whether motherhood continues to be correlated with the wage equation error when fixed effects are included.

4.2.3 Unobserved Heterogeneity

The Nature of the Problem

Another issue which arises in estimating the causal effect of motherhood on wages is unobserved heterogeneity. Since motherhood is a choice, women may select into motherhood status based on observable and unobservable characteristics. If selection into motherhood status is made on observables only (e.g. level of education or work experience) OLS estimation is consistent as long as these factors are controlled for in the model. However, if selection is made on unobservable (or unmeasurable) characteristics, OLS estimates will suffer from heterogeneity bias (Wooldridge, 2002, p.63).

It is conceivable that unobserved factors such as career orientation, ability and motivation are both positively correlated with the market wage and negatively correlated with the desire for children. If this is the case, and these factors are omitted from the model, the negative effect of motherhood on wages will be overestimated. On the contrary, if those with wage enhancing unobserved factors are more likely to become mothers, the estimated effect of motherhood on wages will be positively biased.

Dealing with Unobserved Heterogeneity- Fixed and Random Effects

As with reverse causality, it is possible to control for unobserved heterogeneity by using a randomised controlled experiment or instrumental variables methods (as discussed in Section 4.2.2). However instead, most studies in the motherhood penalty literature have made use of panel data estimating fixed effects (or first-difference) or random effects models which account for time invariant unobserved heterogeneity (see Table 3.1).

Both fixed and random effects models are based on the following equation:

$$\ln(w_{it}) = \eta + \beta Mother_{it} + \gamma_1 HC_{it} + \gamma_2 JC_{it} + \gamma_3 Dem_{it} + \phi_i + u_{it}$$

where ϕ_i is a time invariant individual-specific effect which can be viewed as part of the model's error, $\varepsilon_{it} = \phi_i + u_{it}$. The key difference between the fixed and random-effects models is the assumption made about the correlation between ϕ_i and the regressors.

The fixed effects model allows regressors to be correlated with the time invariant, individual specific component of the error, ϕ_i (Cameron and Trivedi, 2009, p.251).

The fixed effects model is estimated by running OLS on 'de-meaned' data, that is, the average value from the multiple time observations for each person is subtracted from their observations at each point in time t ($\forall i = 1,2,...,T$). Therefore the model estimated is:

$$\begin{aligned}\ln(w_{it}) - \overline{\ln(w_i)} &= \beta\left(Mother_{it} - \overline{Mother_i}\right) + \gamma_1\left(HC_{it} - \overline{HC_i}\right) \\ &+\gamma_2\left(JC_{it} - \overline{JC_i}\right) + \gamma_3\left(Dem_{it} - \overline{Dem_i}\right) + \left(u_{it} - \overline{u_i}\right)\end{aligned}$$

The estimation removes time invariant unobserved heterogeneity (ϕ_i) and thus the fixed effects estimators ($\beta, \gamma_1, \gamma_2, \gamma_3$) are consistent even if the unobserved factors are correlated with one or more of the regressors (Cameron and Trivedi, 2009, p.251). Nevertheless, if the regressors are correlated with the time-varying component u_{it}, heterogeneity bias will remain.

In contrast, the random effects estimator is only consistent if ϕ_i is uncorrelated with the regressors (Cameron and Trivedi, 2009, p.261). The random effects model assumes that $\phi_i \sim (\phi, \sigma_\phi^2)$ and $u_{it} \sim (0, \sigma_u^2)$ resulting in the combined error $\varepsilon_{it} = \phi_i + u_{it}$ being serially correlated. To take account of this, the random effects model is estimated by feasible generalised least squares (FGLS), which is given by OLS on the following model:

$$\begin{aligned}\ln(w_{it}) - \widehat{\omega_i}\overline{\ln(w_i)} &= \left(1-\widehat{\omega_i}\right)\eta + \beta\left(Mother_{it} - \widehat{\omega_i}\overline{Mother_i}\right) + \gamma_1\left(HC_{it} - \widehat{\omega_i}\overline{HC_i}\right) \\ &+\gamma_2\left(JC_{it} - \widehat{\omega_i}\overline{JC_i}\right) + \gamma_3\left(Dem_{it} - \widehat{\omega_i}\overline{Dem_i}\right) + \left\{\left(1-\widehat{\omega_i}\right)\phi_i + \left(u_{it} - \widehat{\omega_i}\overline{u_i}\right)\right\}\end{aligned}$$

where $\widehat{\omega_i}$ is a consistent estimate of $\omega_i = 1 - \sqrt{\sigma_u^2 / \left(T_i \sigma_\phi^2 + \sigma_u^2\right)}$. If the individual effect, ϕ_i, is in fact distributed independently of the regressors, the random effects model is more efficient as it makes use of variation 'within' and 'across' individuals, whereas fixed effects only utilises within variation. If however ϕ_i is correlated with the regressors, the random effects estimators will not be consistent, and a fixed effects model should be used.

A disadvantage of the fixed effects model is that the coefficients of any time invariant variables cannot be identified and the estimates will be relatively imprecise for variables with little variation over time (Cameron and Trivedi, 2009, p.251). In contrast, the random effects model allows the coefficients of time invariant regressors be identified, but relies on a stronger assumption about ϕ_i (Cameron and Trivedi, 2009, p.232).

To choose between the competing models, the Hausman test may be used. The Hausman test compares the fixed effects and random effects estimates under the null hypothesis (H_0) of no correlation between the regressors and ϕ_i. Under H_0, both estimators are consistent; however the random effects estimator is more efficient. If the two models produce different results, H_0 is rejected and fixed effects are used, however if the results are sufficiently similar, the more efficient random effects are preferred (Cameron and Trivedi, 2009, p.412).

Evidence of Heterogeneity Bias

The presence of heterogeneity bias has been tested in the motherhood penalty literature by comparing the motherhood penalty estimates with and without fixed or random effects. The evidence of heterogeneity bias is mixed with some studies finding the results change when unobserved heterogeneity is accounted for (Anderson, Binder and Krause, 2002; Anderson, Binder and Krause, 2003; Korenman and Neumark, 1992), and others finding only a minor or no effect (Budig and England, 2001; Neumark and Korenman, 1994; Waldfogel, 1995; Waldfogel, 1997).

5 Empirical Approach

This chapter describes the econometric models to be estimated. The first section describes Models I-III which mirror the specifications conventionally used in the literature to estimate the effect of children on women's wages. The second section describes Models IV-V which move beyond the conventional estimates to examine the effect of children on both wage levels *and* wage growth. The third section discusses the choice of control variables while the fourth section discusses potential sources of bias. Finally, the last section discusses the use of an unbalanced panel.

5.1 Conventional Estimates of the Motherhood Wage Penalty

The first model is a single time period cross-sectional model:

$$\begin{aligned} \ln W_i = \eta + \beta_1 Child1_i + \beta_2 Child2_i \\ + \gamma_1 HC_i + \gamma_2 JC_i + \gamma_3 MS_i + \phi_i + u_i \end{aligned} \qquad \text{(Model I)}$$

Here $\ln W_i$ is the natural logarithm of the hourly wage (in 2007 dollars) of woman i ($\forall i = 1,2,...,N$); $Child1_i$ and $Child2_i$ are dummy variables equal to one if the woman has one or more children (and has a valid wage rate), and two or more children respectively; HC_i is a vector of human capital variables, namely, work experience, experience squared, education and tenure with the current employer; JC_i is a vector of job characteristics, namely, part-time and casual employment status, industry, occupation, sector, firm size and union membership; MS_i is a vector of dummy variables representing marital status, namely, partnered (which includes married and de-facto) and separated (which includes separated, divorced and widowed); ϕ_i is an individual specific intercept; and u_i is a random error term.

The coefficient β_1 gives the expected log wage differential between mothers and non-mothers net of differences in human capital, job characteristics and marital status.[33] A significantly negative (positive) β_1 indicates that there is a motherhood wage penalty (premium). Since $Child1_i$ and $Child2_i$ are equal to one if the woman has one or more children and two or more children respectively, the coefficient β_2 gives the incremental effect of a second child.

In Model I, only one cross-sectional year is used in the estimation. To increase the sample size and hence precision of the estimates, multiple years of data are combined to create a pooled cross-sectional sample. In combining several cross-sectional waves the model becomes:

$$\begin{aligned} \ln W_{it} &= \eta + \beta_1 Child1_{it} + \beta_2 Child2_{it} \\ &\quad + \gamma_1 HC_{it} + \gamma_2 JC_{it} + \gamma_3 MS_{it} + \gamma_4 Year_t + \phi_i + u_{it} \end{aligned} \qquad \text{(Model II)}$$

where $Year_t$, a vector of year dummies, is included to account for year specific effects on wages and should capture wage inflation above increases in the general price level. All other variables are interpreted in the same way as Model I except that each individual i ($\forall i = 1,2,...,N$) may be observed in multiple years

[33] With the dependant variable in natural log form, the coefficients of Child1 and Child2 approximate the percentage wage differential between mothers and non-mothers.

t ($\forall t = 1,2,...,T$). To account for correlation between observations from the same individuals over time, cluster-robust standard errors are calculated.[34]

In Models I and II, sample selectivity will exist if those women who are employed (and wage earners) are different in unobservable ways to women who are not employed (see Section 4.2.1.). To investigate whether selection into employment is independent of the wage determination process, a Heckman selection model will be estimated using the pooled cross-section sample used in Model II.[35]

The Heckman-corrected model allows for dependence between the employment and wage processes (Cameron and Trivedi, 2009, p.542-543). It is assumed that Model II represents the wage determination process and each woman's employment status in each period t is determined according to the following equation:

$$\begin{aligned} h_{it}^* = \eta + \pi_1 NLInc_{it} + \pi_2 Child1_{it} + \pi_3 Child2_{it} \\ + \pi_4 HC_{it} + \pi_5 MS_{it} + \pi_6 Year_t + u_{it} \end{aligned} \qquad \text{(Model II')}$$

where

$$h_{it} = \begin{cases} 1 \text{ if } h_{it}^* > 0 \\ 0 \text{ if } h_{it}^* \leq 0 \end{cases}$$

34 The usual OLS standard errors assume that the regression errors are independent and identically distributed (i.i.d) and are thus underestimated when individuals are observed multiple times (Cameron and Trivedi, 2009, p.327). The cluster-robust standard errors are also robust to heteroscedasticity (Cameron and Trivedi, 2009, p.83)

35 Self-employed women are excluded from the sample as their wages are not determined in the same way as employees. As such, the selection correction accounts for selection into being an employee rather than employment in general.

Here h_{it}* is a latent variable representing the propensity to be employed and h_{it} is a binary variable equal to one if the woman is employed and zero otherwise. The system of equations II and II' is estimated using maximum likelihood where the likelihood function is:

$$L = \prod_{i=1,t=1}^{N,T} \left\{ \Pr\left(h_{it}^* \leq 0\right) \right\}^{1-h_{it}} \left\{ f\left(w_{it} \middle| h_{it}^* > 0\right) \times \Pr\left(h_{it}^* > 0\right) \right\}^{h_{it}}$$

The first term is the contribution if individual i (in time t) is not employed and the second term is the contribution if he or she is employed and hence, earning a wage.

While it is possible to estimate the Heckman model without an exclusion restriction, identification may be fragile if the non-linearity of the employment equation is slight (Cameron and Trivedi, 2009, p.542). To obtain more convincing estimates, a variable which has a non-trivial impact on the probability of employment, but does not have a direct effect on the wage should be included in the employment equation. Since labour supply theory posits that non-labour income is a key determinant of labour force participation (Hyclak, Johnes and Thornton, 2005, p.75), but is unlikely to have an independent effect on wages after controlling for other observable characteristics, non-labour income is used as an exclusion restriction. This follows many studies in the motherhood penalty literature which have used measures of non-labour income (see Table 4.1).

Even in the absence of selectivity bias, the coefficients of $Child1_i$ and $Child2_i$ will be biased if there are individual specific unobserved factors ϕ_i which are correlated with both motherhood status and the wage rate (see Section 4.2.3).[36] The unobserved factors can be controlled for, and the bias removed, by de-meaning Model II to obtain the following fixed effects model:

$$\begin{aligned}\ln W_{it} - \overline{\ln W_i} = {} & \beta_1\left(Child1_{it} - \overline{Child1_i}\right) + \beta_2\left(Child2_{it} - \overline{Child2_i}\right) \\ & +\gamma_1\left(HC_{it} - \overline{HC_i}\right) + \gamma_2\left(JC_{it} - \overline{JC_i}\right) \qquad \text{(Model III)} \\ & +\gamma_3\left(MS_{it} - \overline{MS_i}\right) + \gamma_4\left(Year_t - \overline{Year_t}\right) + \varepsilon_{it}\end{aligned}$$

where $\varepsilon_{it} = u_{it} - \bar{u}_i$; $\overline{\ln W_i}$ is the average log wage for individual i calculated over the T years in which they are observed, $\overline{Child1_i}$ is the average value of the dummy variable $Child1_{it}$ over the sample period; and so forth for the remaining variables. ϕ_i is absent from Model III as it is 'netted out' through de-meaning.

So long as the unobserved factors which are correlated with the regressors are time invariant, the fixed effects estimates will not suffer from heterogeneity bias. Moreover, since the unobserved factors which cause a woman to enter (or not enter) employment are controlled for, the fixed effects estimates should not suffer from selectivity bias either. Nevertheless, if the unobserved factors correlated with the regressors or the probability of employment are not constant over time, heterogeneity and selectivity bias will remain.

---

[36] Similarly, coefficients γ_{1-4} will be biased if unobserved factors are correlated with the associated regressors.

5.2 The Effect of Children on Wage Levels and Wage Growth

The above Models I-III provide estimates of the motherhood wage differential, however further analysis is necessary to understand whether this arises immediately after birth or develops over time through wage growth. To estimate the immediate effect of children on wage levels and the effect on subsequent wage growth, the methodology of Loughran and Zissimopoulos (2009, pp.331-333) is adopted.

First consider the following pooled cross-sectional model:

$$\ln W_{it} = \eta + \beta_1 Child1_{it} + \beta_2 Child2_{it} + \beta_3 YChild1_{it} + \beta_4 YChild2_{it}$$
$$+\gamma_1 HC_{it} + \gamma_2 JC_{it} + \gamma_3 MS_{it} + \gamma_4 Year_t + \gamma_5 Gap_{it} + \alpha_i Exp_{it} + \vartheta Exp_{it}^{\ 2} + \phi_i + u_{it}$$

Here, HC_{it} represents education and tenure with experience (Exp_{it}) and the quadratic in experience (Exp_{it}^2) included separately. In addition to $Child1_{it}$ and $Child2_{it}$, two variables $YChild1_{it}$ and $YChild2_{it}$ are now included which count the number of years since returning to the workforce after giving birth to the first and second child respectively (equal to one in the first year of return to work after birth).[37] Moreover, Gap_{it} is included which measures the number of years not in the labour force around the first and second births. Gap_{it} is equal to zero in years before the birth and remains equal to zero for women who gave birth but returned to work in the same year.[38] For women who gave birth and had an employment break, Gap_{it} is set equal to the number of waves not working, and remains at this value in the

[37] Note that although the same notation is used, β_1 and β_2 do not hold the same interpretation in Models 1-III as in Models IV-V.

[38] For women who don't give birth in the sample period, *Gap* remains equal to zero.

years thereafter.[39] The coefficient γ_5 gives the average effect of a year out of the workforce around birth and is constrained to be the same for first and second children.

In this specification, motherhood is allowed to affect both wage levels and wage growth. The immediate effect on the wage level in the first year of work after giving birth is given by $\beta_1 + \beta_3 + \gamma_5 \times \overline{Gap}^{1st}$ for the first child and the incremental effect of a second child is given by $\beta_2 + \beta_4 + \gamma_5 \times \overline{Gap}^{2nd}$. The effect of the birth on subsequent annual wage growth is given by β_3 for a first child while β_4 gives the incremental effect on growth of an additional child.

In addition to allowing the wage equation to have separate intercepts (ϕ_i) the above model also allows different slopes in experience (α_i) for each individual. Thus individual specific unobserved factors may affect both wage levels and wage growth.

By taking first-differences of each variable and assuming that experience increases by one every year, Model IV is obtained:

$$\begin{aligned}\Delta \ln W_{it} &= \beta_1 \Delta Child1_{it} + \beta_2 \Delta Child2_{it} + \beta_3 Child1_{it} + \beta_4 Child2_{it} \\ &+ \gamma_1 \Delta HC_{it} + \gamma_2 \Delta JC_{it} + \gamma_3 \Delta MS_{it} + \gamma_4 \Delta Year_t + \gamma_5 \Delta Gap_{it} + \alpha_i + \delta Exp_{it} + \Delta u_{it}\end{aligned} \quad \text{(Model IV)}$$

[39] *Gap* is not separated into the gap around the first and second births as in first-difference form only one variable ΔGap is required.

where $\delta = 2\vartheta$ and $\Delta Exp_{it} = 1$ has dropped out. Here, $\Delta Child1_{it}$ and $\Delta Child2_{it}$ are equal to one in the first year working after the first and second births respectively, and equal to zero in all other years, while $Child1_{it}$ and $Child2_{it}$ are equal to one in the first year working after the birth and remain equal to one every year thereafter. Similarly, the first-difference ΔGap_{it} is equal to the break in employment in the first year of return after birth and is equal to zero in all other years.

Taking first-differences removes the time invariant ϕ_i, however the effect of unobserved heterogeneity on wage growth, α_i, remains. This allows for the possibility that wages have different growth rates over time for different individuals. If unobserved productivity traits such as career motivation are positively correlated with wage growth and also induce women to delay or forego childbearing, coefficients β_{1-4} will be negatively biased. Similarly, if there are unobserved factors which increase wage growth and induce women to become mothers β_{1-4} will be positively biased.

To eliminate this source of bias, Model IV is demeaned to remove the time invariant individual specific effect α_i:

$$
\begin{aligned}
\Delta \ln W_{it} - \overline{\Delta \ln W_i} = {} & \beta_1 \left(\Delta Child1_{it} - \overline{\Delta Child1_i} \right) + \beta_2 \left(\Delta Child2_{it} - \overline{\Delta Child2_i} \right) \\
& + \beta_3 \left(Child1_{it} - \overline{Child1_i} \right) + \beta_4 \left(Child2_{it} - \overline{Child2_i} \right) \\
& + \gamma_1 \left(\Delta HC_{it} - \overline{\Delta HC_i} \right) + \gamma_2 \left(\Delta JC_{it} - \overline{\Delta JC_i} \right) \qquad \text{(Model V)} \\
& + \gamma_3 \left(\Delta MS_{it} - \overline{\Delta MS_i} \right) + \gamma_4 (\Delta Year_t - \overline{\Delta Year_t}) \\
& + \gamma_5 (\Delta Gap_{it} - \overline{\Delta Gap_i}) + \delta \left(Exp_{it} - \overline{Exp_{it}} \right) + \left(\Delta u_{it} - \overline{\Delta u_{it}} \right)
\end{aligned}
$$

Model V is a fixed effects model where the mean first-difference value for the sample period is subtracted from the current period's value for each variable. For example, $\Delta \ln W_{it} - \overline{\Delta \ln W_i}$ is the wage growth in period t for person i minus the mean wage growth for person i.

In the panel used by Loughran and Zissimopolous, individuals are not observed every year so experience does not necessarily increase by one between observations, as is required to obtain Model V. To account for this, Loughran and Zissimopoulos re-introduce the square of experience in Models IV and V and divide the change in the log wage, experience and experience squared by the time elapsed between the respondent's interviews. Instead of diverging from the specifications, the sample and experience measure used in this thesis to estimate Models IV and V will be constructed in such a way to ensure that experience increases by one between wage observations (see Section 6.4). In doing so, it is not necessary to include any additional variables in Models IV and V, or to divide any variables by the time between interviews.

5.3 Control Variables

While most studies control for differences in human capital, job characteristics and marital status in their wage equations, other authors have only controlled for human capital variables arguing that characteristics such as part-time employment are outcomes of child bearing and thus should not be held constant (Waldfogel, 1998b), or out of concern for the endogeneity of the covariates (Loughran and Zissimopoulos, 2009). Instead of taking one stance, the controls will be progressively added to Models I-V and all results reported.

The control variables chosen are derived from labour market theory and empirical work which posits that wages are function of human capital, job characteristics and demographics. The standard variables of the Mincer wage equation of experience, experience squared and education are included to represent general human capital, while tenure with the current employer is included to account for firm-specific knowledge (Sandell and Shapiro, 1978). The inclusion of experience squared allows the returns to experience to display a non-linear path which is expected to be concave.

A control for part-time employment is also included. Since mothers are more likely to work part-time, any wage penalty or premium part-time jobs attract will affect the motherhood wage differential. Moreover, since not all part-time jobs are casual, a separate control for casual work status is included to account for the hourly pay loading Australian casual workers generally receive as compensation for not receiving paid holiday and sick leave.

Occupation and industry controls are also included to account for the effect on wages of differences in occupation and industries between mothers and non-mothers. Similarly, sector of employment, union status and firm size are controlled for following studies in Australia that have found union members (Cai and Waddoups, 2008) and individuals employed in the public sector (Siminski, 2008) or in large firms (Miller and Mulvey, 1996) receive higher wages.

Finally, controls are included for marital status to identify the effect of motherhood on wages, independent of the wage effects associated with marriage.

5.4 Potential Sources of Bias

The above models address a number of sources of bias which threaten validity; Model II accounts for selectivity bias in the cross-sectional model while Models III-V account for all sources of time invariant unobserved heterogeneity. However, one potential source of bias which is not accounted for is reverse causality. While it is possible to address this source of endogeneity with instrumental variables, a variable which is highly correlated with motherhood status and uncorrelated with the wage rate is required. Motherhood instruments used in other studies (see Table 4.2) however are either not available in Australia or not possible given the sample size.[40] As such, reverse causality is not addressed in the analysis and this limitation should be kept in mind when interpreting the results.

5.5 Unbalanced Panel

Models II-V will be estimated using an unbalanced panel of employed women as a balanced panel is deemed to be too restrictive for the current study. To be included in a balanced panel, each woman must have a wage observation (and thus must be working) in every wave. However since child bearing is associated with time away from the workforce, too few women who have given birth during the sample period are observed working every year. Consequently, using a balanced panel would result in very few births being observed in the panel and thus limit the capacity for coefficients β_1 and β_2 to be identified in Models III-V.

Moreover, the chance of selection bias is arguably lower in an unbalanced panel relative to a balanced sample. Only workers with continuous attachment to the labour force are included in the balanced panel, whereas anyone with at least one wage observation will be observed in the unbalanced alternative. If continuous

[40] The use of state-wide indicators of the cost of fertility or fertility control are unlikely to provide enough variation in Australia where fertility and fertility control policies vary little across the few eight states and territories. The use of the sex-mix of the first two children would restrict the sample to women with two or more children already. Data on other variables used such as miscarriage are only available in limited years in HILDA. Information on the number of siblings is available in HILDA and the use of this variable as an instrument in the Australian context may be pursued in future research.

workers differ from intermittent workers on unobservable productivity traits, selectivity bias should be lower in an unbalanced panel, all else equal.

6 Data

This chapter describes the data used in the analysis. The first section introduces the HILDA survey while Section 6.2 discusses the use of sampling weights. Section 6.3 describes the sample construction and provides descriptive statistics for the sample used to obtain conventional estimates of the motherhood wage differential. The construction of the key variables is also outlined. Finally, Section 6.4 describes the additional sample restrictions and variables required to estimate the effect of children on wage levels and wage growth.

6.1 HILDA

This thesis uses unit-record data from the first seven waves (2001-2007) of the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HILDA survey is funded by the Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is conducted by the Melbourne Institute of Applied Economic and Social Research at the University of Melbourne. The HILDA survey began in 2001 with a national probability sample of 7,682 privately occupied Australian households consisting of 19,914 individuals. All members of the households providing at least one interview in Wave 1 are pursued each wave thereafter. The sample has gradually increased over time as the composition of the original households have changed and new household members have been added to the panel (Watson, 2009, p.2).

6.2 Weights

The first wave of the HILDA survey was broadly representative of the Australian population residing in private dwellings, with the exception of some remote communities in the Northern territory (Watson, 2009). However, cross-sectional sampling weights may be applied to adjust for the probability that each household was selected into the original Wave 1 sample and "ensure that the weighted person estimates match several known person–level benchmarks" (Watson, 2009, p.64). From Wave 2 onwards, the cross-sectional weights make each sample representative of the population at the time the data was collected and account for the non-random selection of new members of responding households.

In addition to cross-sectional weights, longitudinal weights are also available but may only be applied to a balanced panel. Longitudinal weights make the sample representative of a base-year (the first wave of the panel) and account for attrition after the first wave (Watson, 2009, p.65). However in an unbalanced panel where individuals may enter and leave the sample in any year, there is no 'natural' base year to act as a benchmark. Accordingly, longitudinal weights are not appropriate for an unbalanced panel and therefore not used in this thesis. Unfortunately, no alternative weights suitable for an unbalanced panel are available.

Since longitudinal weights are not applied, the regression models are not adjusted for attrition. However, some evidence suggests that attrition in HILDA may not pose a large problem. Attrition is of most concern when it's causes are non-random; if the likelihood of response in any one wave is dependant on individual specific unobserved factors or the models error term, standard estimates will suffer from attrition bias (Verbeek, 2008, p. 401). However, in estimating an econometric model predicting attrition over the first four waves of HILDA, Watson and Wooden (2006) found that "there is a very large random component to non-response" (Wooden and Watson, 2007, 217) which suggests that attrition (over the first four waves at least) may not be a large concern for this thesis. Nevertheless, the limitation remains that if attrition is in fact non-random, the estimates obtained may be biased.

In estimating the single year cross-sectional Model I and the pooled cross-sectional Model II responding person cross-sectional weights will be applied, and the sensitivity of the results to weighting reported. Although Model II uses an unbalanced panel sample, the longitudinal nature of the data is not used; the seven cross-sections are simply 'stacked' together and thus cross-sectional weights are appropriate. For the remaining Models (III-V) the repeated observations on individuals are used in taking first-differences and applying fixed effects and therefore cross-sectional weights are inappropriate. As no suitable weights are available, Models III-V are not weighted.

6.3 Conventional Estimates of the Motherhood Wage Penalty

This section details the sample construction process, provides descriptive statistics and outlines how the variables were constructed for Models I-III which give conventional estimates of the motherhood wage differential.[41]

6.3.1 Sample Construction

The unbalanced panel sample includes observations from Waves 1 to 7 of the HILDA survey. A number of sample restrictions have been applied which are detailed in Table 6.1.

Table 6.1. Sample Construction: Unbalanced Panel A (Waves 1-7)

Remaining Woman-Year Observations	
Women	47 727
Aged between 21 and 52	26 849
Employed	19 529
Employees (not self-employed)	17 131
Not studying full time	16 550
Not missing wage data	16 412
Not an outlying wage	16 272
Not inconsistent child data	16 195
No deceased children	15 953
Not missing human capital data	15 478
Not missing job characteristic data	14 975
Not missing marital status	14 972

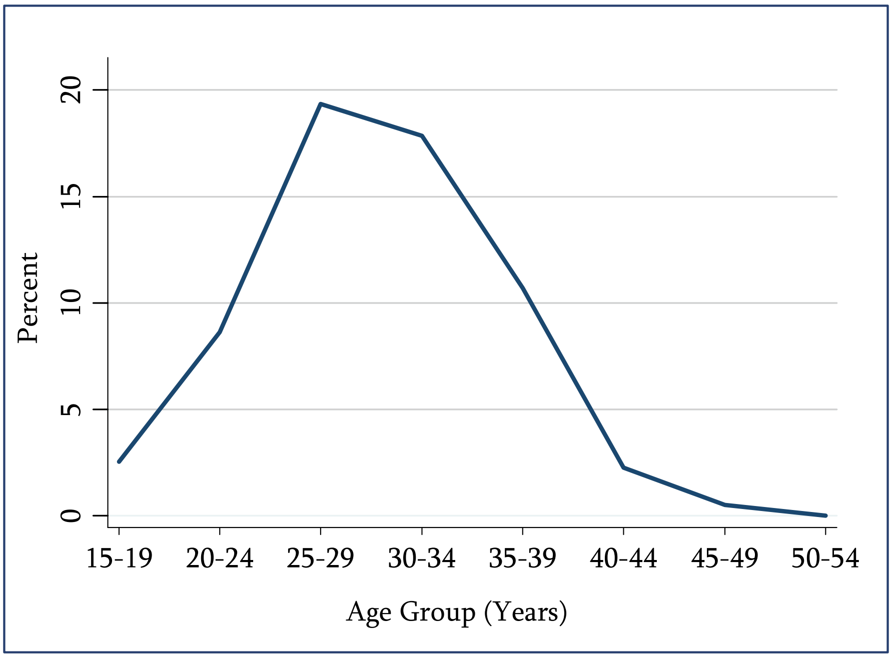
Source: HILDA, Waves 1-7

Over the seven waves of HILDA, a total of 9,792 women were surveyed resulting in 47,727 woman-year observations. 1,215 aged 21 years or less were excluded as wage

[41] Note that Model I uses a single wave subset of the unbalanced panel selected for Models II and III.

rates of young workers are generally determined by junior pay rate scales and as such, do not reflect individual worker productivity. A further 2,549 women older than the usual childbearing age-range were also dropped. Inspection of the HILDA data shows that pregnancy rates fall greatly beyond the age of 45 (Figure 6.1). However to allow a woman aged close to 45 to have a child in the first of HILDA and be included in the sample in the waves that follow, only women aged 52 years or older were excluded.

Figure 6.1. Share of Women Pregnant in the Last 12 Months by Age Group



Source: HILDA, Wave 7

Since each woman-year observation must have a valid wage rate, 7,320 observations in which a woman was unemployed or out of the labour force were dropped. The self-employed were also excluded as their wages are not determined in the same way as employees. These exclusions lead to a greater proportion of prime-age mothers being dropped relative to non-mothers; a greater proportion of mothers (33 percent) are not employed relative to non-mothers (13 percent), and of those working, a larger portion of mothers are self employed (15 percent compared to seven percent). The impact of these sample restrictions will be tested in Section 7.1 with a Heckman selection model.

Full-time students were also excluded from the sample as their decisions about occupations and wage contracts are likely to differ from individual's no longer in full-time education. Furthermore, women with missing salary or hours data required to construct wages were also excluded and outlying wage observations in the top or bottom 0.5 percent of the remaining sample were dropped.[42]

A further 77 observations were excluded due to inconsistent child data in which the total number of children the woman currently has exceeded the total number of children ever given birth to or adopted.[43] Women with deceased children were also dropped as they may have wage effects stemming from childbearing and rearing in the past and therefore differ to women who have never had children.

Finally, observations with missing data on human capital: specifically, experience (463), education (1) and tenure (11); job characteristics, specifically, industry (38), casual status (3), sector (19), union status (4) and firm size (439); and marital status (3) were excluded. After applying all restrictions, a final sample of 4,255 women

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[42] The wage cut-offs were 3.48 and 87.00 in 2007 dollars.

[43] This should not occur as step and foster children are not counted in children currently have.

(2,596 with one or more children, 1,998 with two or more children) making 14,972 woman-year observations was obtained.

The same sample restrictions were applied in constructing the Wave 1 sample (Table 6.2). The percentages displayed at the bottom of Table 6.2 represent the proportion of the sample remaining after missing, inconsistent and outlying observations were removed. It can be seen that the proportion of mothers and non-mothers excluded are equal suggesting that the tendency for observations to be missing is not systematically related to motherhood status.

Table 6.2. Sample Construction: Single Year Cross-Section (Wave 1)

Remaining Observations	Mothers	Non-Mothers	Total
Women	5 227	2 108	7 335
Aged between 21 and 52	3 063	1 228	4 291
Employed	1 924	1 054	2 978
Employees (not self-employed)	1 605	980	2 585
Not studying full time	1 597	917	2 514
Not missing wage data	1 590	916	2 506
Not an outlying wage	1 571	904	2 475
Not inconsistent child data	1 568	904	2 472
No deceased children	1 532	900	2 432
Not missing human capital data	1 531	899	2 430
Not missing job characteristic data	1 507	884	2 391
Not missing marital status	1 506	883	2 389
Percentage of employees aged 21 to 52 not studying full-time and without deceased children retained:	97%	97%	97%

Source: HILDA, Wave 1

6.3.2 Descriptive Statistics

Descriptive statistics for the unbalanced panel sample are provided in Table 6.3. Comparisons of the mean wages show that mothers earn around one percent less than non-mothers, however the difference is not statistically significant. Mothers are on average older than non-mothers and have accumulated more years of work experience and tenure. Non-mothers have achieved higher levels of education than mothers on average with a significantly larger portion of non-mothers holding a bachelor degree or diploma and a significantly smaller proportion having Year 11 or below as their highest educational attainment. Although the differences in educational attainment may reflect a tendency for mothers to invest less in education, it may also reflect generational differences in educational investments given the age profile of mothers in the sample.

In accordance with higher levels of education, non-mothers are more likely to be in a professional or trade occupation and less likely to hold a community and personal services, machinery or labouring position. Motherhood status also appears to be systematically related to the type of industry chosen. Mothers are more likely to be employed in public administration, education and training or health care, while non-mothers are more likely to be employed in information, media and telecommunications, arts and recreation, financial and real estate or science and technology industries. Similarly, the sector of employment varies with non-mothers more likely to work in the private for-profit sector and mothers more likely to work in a Government job. Mothers are also slightly more likely to be a union member.

Table 6.3. Descriptive Statistics for Unbalanced Panel A

	Mother	Non-Mother			Mother	Non-Mother	
Hourly wage	22.22	22.36		*Industry Continued*			
Log-hourly wage	3.03	3.04		Construction	0.04	0.04	
Age (years)	40.62	30.29	***	Retail/Hospitality	0.20	0.19	
Experience (years)	18.20	11.08	***	Transport	0.02	0.02	
Tenure (years)	6.03	4.29	***	Culture	0.03	0.06	***
Education				Finance/Science	0.11	0.21	***
Post-Graduate	0.10	0.13	***	Education/Health	0.49	0.37	***
Bachelor Degree	0.17	0.30	***	Other (Omitted)	0.03	0.03	
Diploma	0.10	0.13	***	*Sector*			
Certificate	0.17	0.12	***	Private Sector	0.56	0.62	***
Year 12	0.16	0.19	***	Public Sector	0.33	0.28	***
Year 11 (Omitted)	0.30	0.12	***	Other (Omitted)	0.11	0.10	
Occupation				*Firm Size*			
Manager	0.07	0.08		Small	0.24	0.22	**
Professional	0.26	0.36	***	Medium (Omitted)	0.13	0.14	
Trade	0.04	0.05	**	Large	0.62	0.64	
Community	0.16	0.09	***	*Other Job Characteristics*			
Clerical	0.27	0.27		Part-time Worker	0.54	0.18	***
Sales	0.10	0.09		Casual Worker	0.27	0.17	***
Machinery	0.02	0.01	*	Union member	0.30	0.27	***
Labourer (Omitted)	0.09	0.05	***	*Marital Status*			
Industry				Partnered	0.80	0.49	***
Primary	0.01	0.00	**	Separated	0.15	0.03	***
Utilities/Mining	0.00	0.01	***	Never Married	0.04	0.48	***
Manufacturing	0.06	0.07		(Omitted)			

Source: HILDA, Waves 1-7
Notes: *,**,** means mothers and non-mothers are statistically different at the 5%, 1% and 0.1% levels of significance. Means are weighted by cross-sectional probability weights

One of the largest differences between mothers and non-mothers is the proportions employed in part-time jobs; just over half of mothers are employed part-time compared to only 18 percent of non-mothers. Mothers are also much more likely to be married or de-facto, or to have been partnered in the past with almost half of non-mothers never being married.

6.3.3 Construction of Key Variables

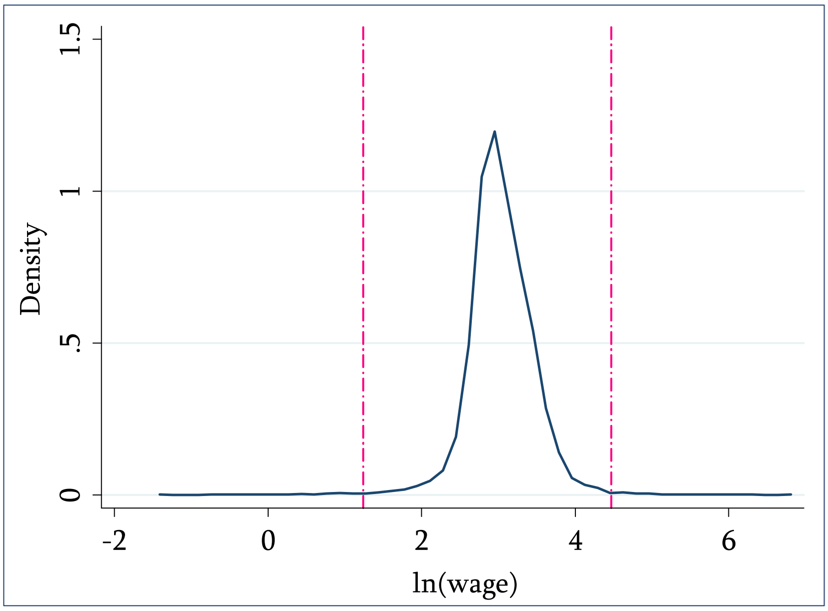
The construction of the hourly wage, motherhood status, experience and non-labour income are outlined in detail below. Details of the remaining variables are provided in Appendix A.

Hourly Wage

The hourly wage is constructed by dividing the usual weekly gross wages and salary in the main job by the hours per week usually worked in the main job. Having access to usual hours and earnings rather than those of the week prior to the interview is an advantage of HILDA as the week prior to the interview may be atypical. The nominal wages are converted to 2007 dollars using the consumer price index (CPI).[44] A Kernel density plot of the natural log of the hourly wage is provided in Figure 6.2 with the reference lines indicating the upper and lower wage cut offs. It can be seen that the cropped log wage is roughly normally distributed with the influence of outlying observations removed.

[44] The annual CPI, which is provided quarterly, is averaged over the financial year to correspond with each HILDA interview period.

Figure 6.2. Kernel Density Plot of the Natural Log of the Hourly Wage



Source: HILDA, Waves 1-7
Note: Reference lines at ln(wage) cut offs 1.24 and 4.47.

Child Variables

In this thesis, a mother is defined as a woman with one or more natural or adopted, resident or non-resident living children of any age. Children who have since died, foster children and step children are not counted when constructing the variables $Child1$ and $Child2$, which were defined in Section 5.1.

The exclusion of foster and step children accords with the theoretical arguments that the effects of children on women's wages accumulate over time and begin to accrue during or in anticipation of pregnancy. Since responsibility for foster and step children may have begun many years after the child was born, their wage impact is likely to differ from the effects of biological children.[45] Accordingly, throughout this thesis the term child excludes foster and step children.

It may equally be argued that the effect of adopted children on their mother's labour market experiences also differs from natural children as the mother does not endure the pregnancy and may begin caring for the child years after it is born. It is however, common for children to be adopted in their infancy (AIHW, 2002) and for extended periods of leave be taken from work after the adoption.[46] Thus, following the adoption, the labour market experiences of a mother adopting a child may not differ to a mother who gave birth. In any case however, it is not possible to distinguish between natural and adopted children in HILDA and including adopted children is unlikely to affect the results as the number of adoptions is very small relative to the number of births.[47]

A number of questions in the HILDA survey provide information which may be used to construct $Child1$ and $Child2$ (Table 6.4). The first variable (TCHAVE) counts the total number of children each woman currently has, and as such, represents the appropriate measure to construct $Child1$ and $Child2$. However TCHAVE is not provided in Waves 1 and 5; instead, respondents are asked to

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[45] In the HILDA survey questions relating to motherhood status, respondents are asked to exclude both foster and step children in their response.

[46] This is supported by comparable maternity leave entitlements for new mothers of natural and adopted infants (*Workplace Relations Act 1996,* s.300).

[47] The number of adoptions represented only 0.1 percent of the number of births in 2001 (AIHW, 2002; ABS, 2008)

identify how many children they have ever given birth to or adopted (TCHAD) which includes children who are no longer alive. The total number of children who had since died (TCDIED) is also recorded for Waves 1 and 5, however it is only recorded in Wave 1 if the information is volunteered by the respondent while it is explicitly asked in Wave 5. Although it would be possible to calculate the TCHAVE values for Waves 1 and 5 by subtracting TCDIED from TCHAD, the value for Wave 1 may be inaccurate if TCDIED was not volunteered by all women who have deceased children. Thus to avoid measuring $Child1$ and $Child2$ with error in Wave 1, and to maintain consistency in the way these variables are constructed across waves, an alternate set of variables are used.

Table 6.4. Motherhood Variables Available in HILDA

Variable Name	Survey Question	Waves Provided
TCHAVE	How many children do you have?	▪ Asked in waves 2,3,4,6 & 7
TCHAD	How many children in total have you ever had? That is, ever given birth to or adopted?	▪ Asked in waves 1 & 5 ▪ Derived for all waves
TCDIED	Wave 1: Number of children who have since died. (Only recorded if information is volunteered) Wave 5: Have you had any children who have since died? If yes, how many? (Question asked explicitly)	▪ Recorded if volunteered in wave 1 ▪ Asked in wave 5 ▪ Derived for all waves
RCAGE1-11	Age of resident children	▪ Asked in all waves
NCAGE1-13	Age of non-resident children	▪ Asked in all waves

Source: HILDA 2009 Cross Wave Index, Melbourne Institute for Applied Economic and Social Research

In every wave, respondents are asked to list the ages of their currently living children whom they gave birth to or adopted in the resident and non-resident child grids. The ages of the resident and non-resident children listed in each grid are recorded in the variables RCAGE1-11 and NCAGE1-13 respectively. Since these variables are available for all waves and relate to children currently living, they are the best variables available to construct $Child1$ and $Child2$. For those women who have listed at least one child's age, $Child1$ is equal to one, and for those women who have listed two or more child's ages $Child2$ is equal to one.[48]

Experience

The measure of experience used in Models I-III is the HILDA variable for work experience which is calculated as time spent in paid work in all jobs, part-time or full-time, since finishing full-time education for the first time. The first time they are interviewed, respondents are asked how many years and months they have spent working since finishing school. Any additional experience gained subsequent to the first interview is recorded using the calendar which breaks down the time between July of the previous year and the current interview date into the start, middle and end of each month. The experience variable is updated each wave by adding the portion of the year spent in employment since the last interview to the previous total.

[48] To determine which women have deceased children for the purpose of the sample restrictions the count taken of all resident and non-resident children's ages and the HILDA variable TCHAD are used. It is assumed that a child is deceased when the difference between TCHAD and the number of children a woman currently has is greater than zero. To improve accuracy, the values for TCDIED collected in Wave 5 when respondents were asked to identify the number of deceased children are used. If the respondent said that they have had zero children die, it was assumed there were no deceased children in all waves up to an including Wave 5.

Having access to a measure of actual experience is an advantage of the HILDA data. It is particularly valuable in this thesis as the intermittent work histories of mothers means that potential experience would act as a poor proxy for the actual time spent working. However one limitation of the HILDA experience variable is that time spent in paid leave (including paid maternity leave) is counted as time in employment and thus is included in experience. Since during maternity leave mothers are not accumulating work experience, the estimated effects of experience on wages may be biased downward.

Non-Labour Income

Non-labour income, which is used in the Heckman-corrected pooled cross-section, is constructed by subtracting the woman's financial year wages and salary from the household financial year income (excluding windfall gains). To obtain a measure of the non-labour income available to the woman, the result was divided by the number of adult equivalents in the household, measured in accordance with the modified OECD equivalence scale.[49] This method assumes that the other household members income is unaffected by the woman's employment decision and that household income is fully shared.

[49] The modified OECD equivalence scale assigns a value of 1 to the household head, 0.5 to each additional adult and 0.3 to each child (under the age of 15).

6.4 The Effect of Children on Wage Levels and Wage Growth

This section outlines the sample used to estimate Models IV-V which provide estimates of the immediate effect of children on wage levels and the effect on subsequent wage growth. The construction of additional variables is also described.

6.4.1 Sample Construction

In addition to the sample restrictions outlined in Table 6.1, women without the necessary wage data to estimate Models IV and V were excluded (Table 6.5).

Table 6.5. Sample Construction: Unbalanced Panel B (Waves 1-7)

Remaining Woman-Year Observations	
Unbalanced Panel A- each woman employed in at least one wave	14 972
Part of a valid block encompassing 3 or more wages	11 683
Dropping the first observation from each block in making first-differences	9 365
Ratio of consecutive wages no more than 1.5	7 989

Source: HILDA, Waves 1-7

In order to estimate Models IV and V, the change in each variable between the years a woman is working must be constructed. However, to ensure that experience changes by (around) one year between consecutive wage observations (as required to obtain Model V) first-differences are not taken over non-responding years. Instead, 'blocks' of consecutive years were identified where a woman was working and had a valid wage observation *or* was not employed. This method should ensure that for the women in the sample, experience does not increase in the years no wage is observed.

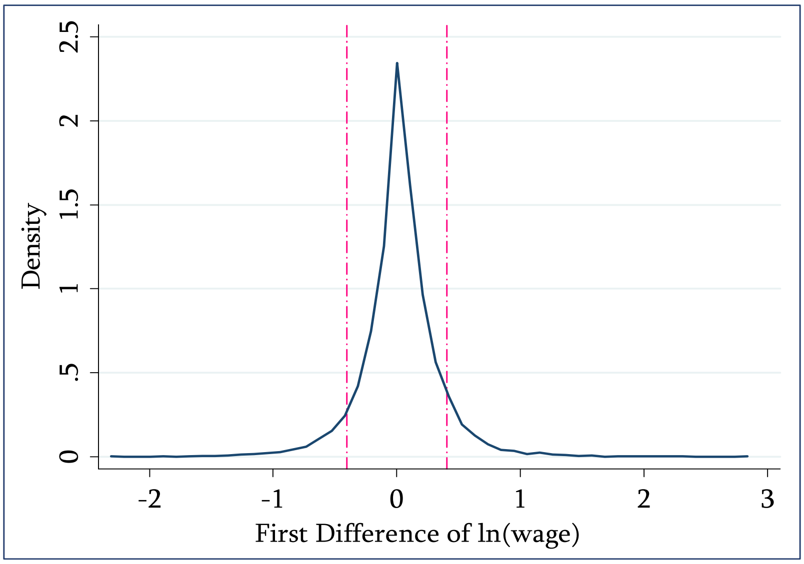
To be included in the sample, each woman must have a valid block of responding years encompassing at least three wage observations to allow first-differences to be constructed, and the first-difference with fixed effects model to be estimated.[50] Altogether, 3,289 woman-year observations without a valid block were excluded, leaving a sample of 11,683. After losing the first observation in taking first-differences, a total of 9,365 woman-year observations were retained.

Finally, any observations where the ratio of consecutive wages exceeded a factor of 1.5 were excluded to remove the influence of outlying wage changes.[51] The sensitivity of the result to this cut-off will be discussed in Section 7.2.3. The kernel density plot of the first-difference of the natural log of the hourly wage before exclusions is shown in Figure 6.3.

[50] To make full use of the data, additional second blocks were identified. 82 women have 2 valid blocks (Waves 1-3 and Waves 5-7). First-differences are only taken within each block, that is, *not* across waves 5 and 3.

[51] That is, any wage which increased by more than 50 percent or decreased by more than one third was excluded. This corresponds to a change in the natural log of the hourly wage of ± 0.405.

Figure 6.3. Kernel Density Plot of the First-Difference of the Natural Log of the Hourly Wage



Source: HILDA, Waves 1-7
Note: Reference lines at $\Delta \ln(wage) = \pm 0.405$

After excluding outlying wage changes, a final sample of 2,247 women making 7,989 woman-year observations remained of which 1,460 had one or more children and 1,137 had two or more children. In this sample, a total of 132 first births and 96 second births were observed.

6.4.2 Construction of Key Variables

In addition to first-differences of the variables in Models I-III, Models IV and V include first-differences of the number of years with one or more (*YChild1*) and two or more children (*YChild2*) and the variable showing the number of years not employed after childbirth (*Gap*). Moreover, a constructed experience variable which increases by one each year replaces the HILDA experience variable.

Child Variables

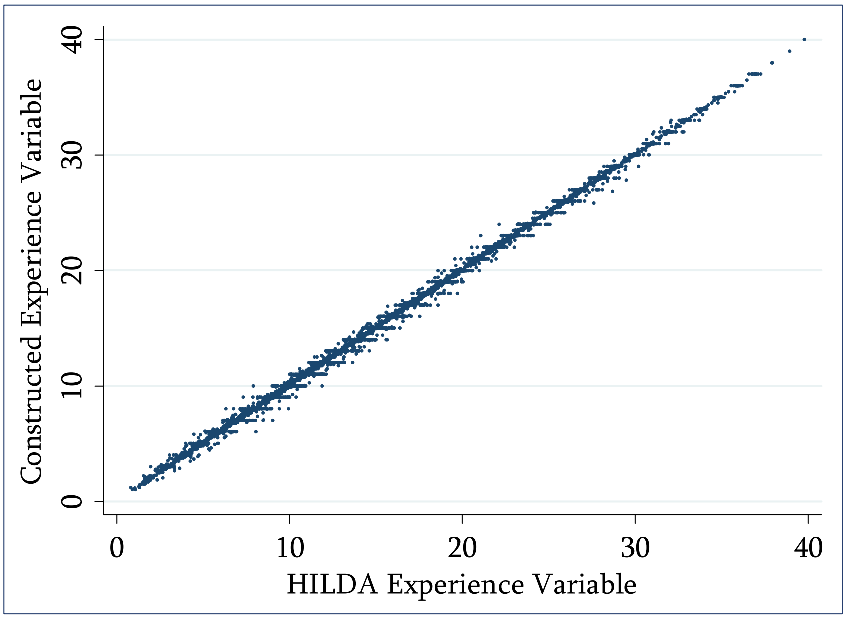
Instead of constructing first-differences of *YChild1* and *YChild2* and dividing by the number of years between interviews, this thesis follows Loughran and Zissimopoulos (2009) in using the conceptually equivalent *Child1* and *Child2* variables instead. *Child1* and *Child2* are the more reliable measure as the information required to construct *YChild1* and *YChild2* is not available in the general release HILDA data.[52]

Experience

In the way the sample is constructed, actual experience increases by approximately one year between wage observations. However due to differences in the interview dates, and incomplete work years, most changes in experience are slightly more or less than one. Since the econometric specification requires that experience increases by exactly one each year to obtain Model V (see Section 5.2), an experience measure has been constructed which equals actual experience in the first year, and increases by one each working year thereafter. The scatter graph of the constructed and HILDA experience measures illustrates the strong positive correlation ($\rho = 0.999$) between the two variables (Figure 6.4).

[52] The year of birth of each child is not provided in the general release responding person files of HILDA and the year in which a woman returned to work after birth is unknown for children born outside of the sample period. While it is possible to obtain a proxy for the year of birth of the first and second children by using the ages of the eldest and second eldest child, *YChild1* and *YChild2* will be inaccurate for women who return to work after the year of birth.

Figure 6.4. Comparison of the Constructed and HILDA Experience Variables



Source: HILDA, Waves 1-7

Gap Variable

The first-difference of *Gap* equals the number of years a women was not observed working after the birth of her first or second child in the first year of returning to work, and is equal to zero in all other years. For women who returned to work in the (interview) year they gave birth, the change in *Gap* is equal to zero, whereas for women who did not return to work in the year of birth, the change in *Gap* equals the number of waves the woman was not employed.

The interpretation of *Gap* is complicated by the treatment of paid leave in HILDA. Since periods of paid maternity leave are classified as employment, many of those women who are recorded as employed in the year of birth may not actually be at work. However, without a means to distinguish paid leave from work time, *Gap* remains defined as the number of years not in employment after birth.[53]

Examination of the sample data reveals that just over half of the women who had a first or second child returned to work within the interview year of birth (Table 6.6). However these sample proportions are likely to overstate the proportion of women returning to work quickly as women who did not return to work within the sample period are not represented.

Table 6.6. Tabulations of the Gap Variable

Gap	First Birth (%)	Second Birth (%)
0	54	56
1	36	38
2	7	3
3	2	3
4	1	0

Source: HILDA, Waves 1-7

[53] Respondents are asked how many days in total they spent in maternity, parental, long service, bereavement and carers leave, but the days spent in each type isn't recorded.

7 Empirical Results

This chapter presents the empirical results. Section 7.1 reports conventional estimates of the motherhood wage differential for Australia (Models I-III) and assesses the interaction between motherhood and professional occupation, part-time employment and martial status. In Section 7.2, estimates of Models IV and V which give the immediate effect of motherhood on wage levels and the subsequent effect on wage growth are presented.

Only the main coefficient estimates are presented in this chapter, complete results tables can be found in Appendix B. In all Models I-V, the following sets of controls have been progressively added (Table 7.1):

Table 7.1. Control Variables

A	No Controls
B	Experience
B'	*Gap*
C	Education, Tenure + Above
D	Part-time, Casual Status + Above
E	Industry, Occupation + Above
F	Sector, Firm Size, Union Status + Above
G	Marital Status + Above

Note: Gap is only included in models IV and V. Year dummies are included in all panel models.

7.1 Conventional Estimates of the Motherhood Wage Penalty

7.1.1 Wave 1 Cross-Section *(Model I)*

The weighted and unweighted Wave 1 cross-section results are presented in Table 7.2. With no controls, mothers earn about five percent less than non-mothers on average, with no additional penalty for second or higher order children. As mothers in the sample are older, and consequently have more years of experience than non-mothers (see Section 6.3.2), controlling for experience causes the wage penalty to increase to 11 percent. However, controlling for education and tenure reduces the penalty by around half as the lower wages of mothers are partly explained by fewer years of tenure (when experience is held constant) and lower educational attainment.

Contrary to prior American and British studies (Budig and England, 2001; Joshi, Paci and Waldfogel, 1999; Waldfogel, 1997), controlling for part-time and casual employment has only a small and negative impact on the child coefficients. The contrasting results may be explained by differences in part-time wages between Australia and these countries. The results in Appendix B (Tables A.1 and A.2) show that when industry and occupation are held constant, part-time employment attracts a pay premium in Australia in-line with prior Australian research (Booth and Wood, 2008).

Table 7.2. Motherhood Wage Differential, Wave 1 Cross-Section, Model I

N = 2379	Weighted						
	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.049*	-0.115***	-0.064**	-0.068**	-0.058*	-0.058*	-0.064*
	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)	(0.024)	(0.025)
Child2	0.026	0.014	0.028	0.029	0.023	0.024	0.020
	(0.023)	(0.024)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
R^2	0.002	0.036	0.189	0.192	0.273	0.287	0.289
F	2.120	19.903***	57.481***	49.157***	31.987***	30.386***	28.955***
N = 2389	Unweighted						
	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.052*	-0.112***	-0.057*	-0.060*	-0.053*	-0.050*	-0.057*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)	(0.023)
Child2	0.024	0.010	0.026	0.026	0.020	0.020	0.015
	(0.023)	(0.023)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
R^2	0.002	0.037	0.196	0.200	0.275	0.288	0.291
F	2.705	23.431***	62.293***	53.016***	34.588***	32.334***	31.207***

Source: HILDA, Wave 1

Notes: Robust standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable is the natural log of the hourly wage in constant 2007 dollars. All regressions correspond to Model I. Full results reported in Tables A.1 and A.2, Appendix B. *Child1* is the estimated effect of motherhood on log wages of the first child;*Child2* gives the incremental effect of a second child. Weighted regressions are weighted by responding person cross-sectional weights.

Altogether, controlling for job characteristics has little effect on the motherhood coefficients which suggests that the propensity for mothers to choose certain jobs does not contribute to the raw wage penalty in Australia.

Finally, controlling for marital status has a small impact on the motherhood penalty, causing it to increase by 0.6-0.7 percentage points. With motherhood status and other observable factors held constant, partnered women on average earn wages four percent higher than single women. This finding is consistent with a household production model where living in a partnership is easier than living alone which allows each member to be more productive. However, this is also consistent with a selection model in which those with desirable unobserved traits are more likely to succeed in both the marriage and labour markets (Waldfogel, 1997, p.211).

7.1.2 Pooled Cross-Section *(Model II)*

Table 7.3 presents the pooled cross-section OLS regressions. The weighted and unweighted results reveal no significant raw wage differential between mothers and non-mothers, however a significant eight percent penalty arises when controlling for experience.

Table 7.3. Motherhood Wage Differential, Pooled Cross-Section, Model II

Unbalanced Panel A

N = 14915 (4242)	Weighted						
	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.012	-0.082***	-0.032*	-0.033	-0.024	-0.025	-0.040**
	(0.019)	(0.020)	(0.016)	(0.017)	(0.016)	(0.015)	(0.015)
Child2	-0.003	-0.022	-0.003	-0.003	-0.010	-0.009	-0.014
	(0.019)	(0.019)	(0.016)	(0.016)	(0.014)	(0.014)	(0.014)
R^2	0.011	0.054	0.230	0.233	0.304	0.317	0.320
F	14.868***	35.166***	103.034***	96.997***	79.338***	74.790***	72.722***
N = 14972 (4255)	Unweighted						
	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.007	-0.075***	-0.022	-0.022	-0.013	-0.014	-0.027*
	(0.016)	(0.016)	(0.014)	(0.015)	(0.013)	(0.013)	(0.013)
Child2	-0.006	-0.026	-0.009	-0.009	-0.020	-0.018	-0.023
	(0.016)	(0.016)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)
R^2	0.009	0.054	0.231	0.235	0.300	0.311	0.313
F	17.721***	45.854***	114.438***	106.573***	87.553***	82.867***	82.338***

Source: HILDA, Waves 1-7

Notes: Robust clustered standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable is the natural log of the hourly wage in constant 2007 dollars. All regressions correspond to Model II. Full results reported in Tables A.3 and A.4, Appendix B. *Child1* is the estimated effect of motherhood on log wages of the first child;*Child2* gives the incremental effect of a second child. Weighted regressions are weighted by responding person cross-sectional weights.

In contrast to the single cross-section results, the motherhood penalty becomes small (two to three percent) and insignificant when controlling for education and tenure in the unweighted regression, and part-time and casual status in the weighted model. There continues to be no significant difference between mothers' and non-mothers' wages until controls are included for marital status. With all controls included, there remains a significant residual wage differential of 2.7 percent in the unweighted model and four percent with weights applied. These estimates are less negative and more precise than the single wave point estimates. A comparison of Tables 7.2 and 7.3 shows that standard errors in the pooled model are 30 to 40 percent smaller than the single wave cross-section.

7.1.3 Heckman-Corrected Pooled Cross-Section

To account for selection bias caused by excluding non-working and self-employed women from the wage equation, Model II is re-estimated using a Heckman Maximum Likelihood procedure. In addition to the 14,972 wage observations, 8,347 observations from women not working (or self-employed) were included in estimating a probit model for the probability of employment. Table 7.4 shows the coefficients for each variable in the employment equation.

In accordance with *a priori* expectations, motherhood has a significantly negative effect on the probability of employment. Moreover, women who are more educated, are not partnered and have more years of work experience are more likely to be working and not self-employed. In addition, non-labour income, which is used as the exclusion restriction, has a highly significant and negative effect on employment.

Table 7.4. Coefficients of Employment Equation, Model II'

From Probit Model, Unbalanced Panel A

	Weighted	Unweighted
Child1	-0.813***	-0.780***
	(0.038)	(0.030)
Child2	-0.101*	-0.118***
	(0.030)	(0.026)
Exp	0.104***	0.096***
	(0.005)	(0.004)
Exp^2/100	-0.171***	-0.155***
	(0.015)	(0.013)
Post Grad	0.458***	0.525***
	(0.041)	(0.035)
Bachelor	0.488***	0.535***
	(0.034)	(0.028)
Diploma	0.286***	0.308***
	(0.037)	(0.033)
Certificate	0.224***	0.232***
	(0.032)	(0.028)
Year 12	0.212***	0.251***
	(0.032)	(0.028)
Partnered	-0.241***	-0.110***
	(0.035)	(0.030)
Separated	-0.224***	-0.121**
	(0.047)	(0.040)
Non-Labour Income	-0.004***	-0.004***
	(0.000)	(0.000)
Constant	0.055*	0.019
	(0.045)	(0.040)
χ^2	2317.44***	4273.60***
Psuedo-R^2	0.147	0.141
N (Total)	23216	23319

Source: HILDA, Waves 1-7

Notes: Robust clustered standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Dependant variable is employment (=1 if employed and not self-employed, 0 otherwise). Results correspond to Model II'. *Child1* is the estimated effect of motherhood on the probability of employment; *Child2* gives the incremental effect of a second child. Weighted regression is weighted by scaled responding person cross-sectional weights. Regressions include year dummies.

The Heckman-corrected wage equation results (Table 7.5) show significant evidence of selection into employment on unobservable characteristics with a Wald test failing to reject the null hypothesis of zero correlation between the employment and wage equation error terms (p=0.000). The results also reveal the child coefficients are biased by self-selection with the Heckman-corrected motherhood penalty estimates larger (by around 2.6 percentage points) than the pooled OLS results. Moreover, there is evidence of a significant three percent additional penalty for mothers with two or more children in the unweighted model. These results suggest that mothers most likely to suffer a wage penalty are less likely to be employed, and therefore failure to account for selection into employment will understate the true motherhood wage penalty.

Table 7.5. Motherhood Wage Differential, Heckman-Corrected Pooled Cross-Section
Unbalanced Panel A

	Weighted	Unweighted
Child1	-0.068***	-0.054***
	(0.016)	(0.015)
Child2	-0.017	-0.027*
	(0.014)	(0.012)
Log L	-15665.36***	-17104.69***
λ	0.078	0.080
ρ	0.243	0.248
Wald χ^2	19.74***	16.84***
N (Censored)	8301 (1322)	8347 (1327)
N (Uncensored)	14915 (4242)	14972 (4255)

Source: HILDA, Waves 1-7
Notes: Robust clustered standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results correspond to the Heckman-corrected Model II with non-labour income included in the selection equation and omitted from the wage equation. Full controls are included in the wage equation. Full results reported in Table A.5, Appendix B. Model is estimated with Maximum likelihood. *Log L* is the log pseudolikelihood. λ is the estimated inverse Mill's ratio. ρ is the estimated correlation between the wage and employment equation error terms. χ^2 is the chi squared value from a Wald test of independence of the wage and selection equations ($H_0 : \rho = 0$). The dependant variable is the natural log of the hourly wage in constant 2007 dollars. *Child1* is the estimated effect of motherhood on log wages of the first child; *Child2* gives the incremental effect of a second child. Weighted regression is weighted by responding person cross-sectional weights.

Sensitivity to Weighting

A comparison of the weighted and unweighted results thus far reveals that applying weights generally produces larger estimates of the motherhood wage penalty. As such, the unweighted estimates which follow may be interpreted as conservative estimates of the effect of motherhood on wages.

7.1.4 Fixed Effects *(Model III)*

Although the Heckman-corrected model accounts for selection into employment, the estimates may be biased if there are unobserved factors which affect motherhood and the wage received. To account for this, a fixed effects model has been estimated.[54] As long as the unobserved factors correlated with motherhood and employment are time invariant, the motherhood penalty estimates will be robust to both heterogeneity and selection bias.

Table 7.6 presents the fixed effects estimates of the motherhood wage differential. No significant motherhood penalty exists in Columns A to C controlling for human capital variables. However when part-time and casual status are included, a significant five percent penalty appears. Moreover, the four percent penalty for two or more children becomes significant at the ten percent level. The increase in the wage penalty when part-time status is included reflects the large premium to part-

[54] The results of a Hausman test (Table A.7, Appendix B) comparing random effects and fixed effects estimates rejected the null hypothesis that the estimates were consistent under both models. As such, only fixed effects results are presented and discussed.

time employment. The part-time premium of ten percent found in the fixed effects model is almost twice the size of the pooled and Wave 1 coefficient suggesting that those with wage decreasing unobserved characteristics are more inclined to work in part-time jobs.

Including controls for other job characteristics and marital status has an immaterial effect on the motherhood coefficient. It appears that the effect of marital status on the motherhood penalty in Models I and II was capturing omitted unobserved factors. In the fixed effects model the marriage premium is one percentage point less than the cross-sectional estimate suggesting that the marriage premium is partially explained by a selection effect.

With all controls included, the fixed effects results show mothers with one child receive a five percent penalty while mothers of two or more children earn around nine percent less than non-mothers on average, even after controlling for observable and unobservable differences. These penalties are similar to the unweighted Heckman-corrected pooled estimates providing some evidence that selection into employment may be accounted for by fixed effects. The similarity of results also implies that mothers do not differ from non-mothers on unobservable productivity traits other than those which affect selection into employment.

Table 7.6. Motherhood Wage Differential, Fixed Effects, Model III

Unbalanced Panel A

N = 14972 (4255)	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	0.013	0.010	0.010	-0.051*	-0.049*	-0.049*	-0.049*
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)
Child2	-0.041	-0.033	-0.032	-0.042	-0.041	-0.040	-0.039
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
R^2	0.042	0.048	0.048	0.065	0.073	0.076	0.076
F	46.600***	42.155***	27.352***	32.588***	19.783***	17.957***	17.166***

Source: HILDA, Waves 1-7

Notes: Robust clustered standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable is the natural log of the hourly wage in constant 2007 dollars. All regressions correspond to Model III. Full results reported in Table A.6, Appendix B. *Child1* is the estimated effect of motherhood on log wages of the first child;*Child2* gives the incremental effect of a second child. All regressions are unweighted.

The residual wage penalty may exist because mothers are less productive than non-mothers due to factors not held constant. Following Becker's work effort hypothesis, it is possible that the residual penalty reflects a 'tired mother' effect whereby mothers have less energy to devote to work. Alternatively, the residual penalty may exist because employers pay mothers less than non-mothers with equal productivity. This is consistent with employers 'taste' discriminating against mothers, or holding an (inaccurate) perception that mothers are less productive.

The motherhood penalties obtained are similar to some estimates in the United States (Lundberg and Rose, 2000; Waldfogel, 1997; Waldfogel, 1998b) however are larger than estimates for Denmark (Gupta and Smith, 2002) and other American results (Anderson, Binder and Krause, 2002; Anderson, Binder and Krause, 2003; Budig and England, 2001), and smaller than results for Britain (Waldfogel, 1995; Waldfogel, 1998b).

This result stands in contrast to prior Australian studies which found no significant residual motherhood wage penalty (Edwards, 2006; Krepp, 2007; Whitehouse, 2002). The difference does not appear to be due to unobserved heterogeneity as a significant motherhood wage penalty was also found in the cross-sectional models shown above. As such, the contrasting results are likely to be due to differences in the way mothers are defined, sample composition, the time periods covered and the controls included in the models (see Section 3.3).

Heterogeneity between Mothers

To investigate whether women in professional occupations, who are partnered, or employed part-time receive a different motherhood wage penalty to other women, a fixed effects model with interactions was estimated (Table 7.7). None of the interaction terms however are significant suggesting that the motherhood penalty is not statistically different across marital, part-time work and professional occupation status.

Table 7.7. Motherhood Wage Differential, Fixed Effects with Interaction Terms
Unbalanced Panel A, All Controls

N= 14972 (4255)					
Professional Occupation		Part-time Employment		Marital Status	
Child1	-0.062**	*Child1*	-0.055*	*Child1*	-0.081*
	(0.022)		(0.024)		(0.041)
*Child1*Prof*	0.033	*Child1*PT*	0.014	*Child1*Partnered*	0.033
	(0.026)		(0.029)		(0.035)
Child2	-0.026	*Child2*	-0.034	*Child2*	-0.028
	(0.026)		(0.029)		(0.037)
*Child2*Prof*	-0.037	*Child2*PT*	-0.008	*Child2*Partnered*	-0.013
	(0.029)		(0.027)		(0.031)
R^2	0.077	R^2	0.076	R^2	0.076
F	16.406***	*F*	16.462***	*F*	16.410***

Source: HILDA, Waves 1-7
Notes: Robust clustered standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable is the natural log of the hourly wage in constant 2007 dollars. All regressions correspond to Model III, with additional interaction terms. Full results reported in Table A.8, Appendix B. *Child1* is the estimated effect of motherhood on log wages of a first child for women not in a professional occupation; *Child1*Prof* gives the differential effect of a first child on the wages of women in a professional occupation; *Child2* gives the incremental effect of a second child for a woman not in a professional occupation; *Child2*Prof* gives the incremental differential effect of a second child for a women in a professional occupation. The corresponding coefficients for partnered and part-time employment are interpreted in the same way. All regressions are unweighted.

7.1.5 Sensitivity of Results to the Wage Cut-off

Table 7.8 shows the sensitivity of Model I-III results (with full controls) to the wage cut-off used. The weighted and unweighted regressions show the same degree of sensitivity, and therefore only the unweighted results are presented. The results for Models I-III where one percent (top and bottom 0.5 percent) of the wage distribution was excluded are reproduced in Column 3.

Table 7.8 shows the results are generally insensitive to the wage cut-off chosen. The largest change occurs in the fixed effects model where relaxing the sample restriction to 0.25 percent of wages reduces the coefficient of one or more children by about two percentage points and causes it to become insignificant. Apart from this, changing the wage cut-off has little effect on the conclusions drawn.

Table 7.8. Sensitivity of Conventional Results to Wage Cut-off

	Proportion of Sample Dropped				
	0.25%	0.5%	1%	2%	4%
Single Wave CS					
Child1	-0.062*	-0.060*	-0.057*	-0.049*	-0.044*
Child2	0.027	0.020	0.015	0.007	0.005
Pooled CS					
Child1	-0.026	-0.027*	-0.027*	-0.026*	-0.025*
Child2	-0.018	-0.019	-0.023	-0.024*	-0.018
Heckman-Pooled CS					
Child1	-0.046**	-0.050***	-0.053***	-0.056***	-0.057***
Child2	-0.021	-0.023	-0.027*	-0.029*	-0.023*
Fixed Effects					
Child1	-0.027	-0.039	-0.049*	-0.056**	-0.051**
Child2	-0.037	-0.039	-0.039	-0.022	-0.022

Source: HILDA, Waves 1-7
Notes: Robust clustered standard errors are used; standard errors not shown, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable is the natural log of the hourly wage in constant 2007 dollars. All regressions include full controls and are unweighted.

7.2 The Effect of Children on Wage Levels and Wage Growth

The conventional estimates reported above show that motherhood has a significantly negative effect on wages levels. Holding observable and unobservable characteristics constant, women with one child receive a five percent penalty while women with two or more children earn around nine percent less than non-mothers on average. To determine whether this wage differential arises immediately after the birth of a child, or reflects the effect of motherhood on wage growth, Models IV and V have been estimated.

The average immediate effect of motherhood on wage levels is given by the sum of the coefficients of *Child1*, *YChild1* and *Gap* evaluated at the average number of waves not working after the first birth ($\beta_1 + \beta_3 + \gamma_5 \times \overline{Gap}^{1st}$). Similarly, the sum of *Child2*, *YChild2* and *Gap* evaluated at the average number of waves not working after the second birth ($\beta_2 + \beta_4 + \gamma_5 \times \overline{Gap}^{2nd}$) gives the incremental effect of a second child. In the tables which follow, the sum of these coefficients and the corresponding standard error are presented in addition to the individual coefficients. The coefficients of *YChild1* (β_3) and *YChild2* (β_4) give the effect of motherhood on wage growth.[55]

[55] Note that although the results are discussed in terms of the level form equation, the models were estimated with the variables in first-difference form as specified in Section 5.2.

7.2.1 First-Difference *(Model IV)*

The first-difference results reveal that having a first or second child has no immediate effect on the wage level (Table 7.9). Across all sets of control variables, the average effect of having a child in the first year of return to work is close to zero and not statistically significant. Contrary to prior expectations of a negative effect, the coefficient of *Gap* is not statistically different from zero.

In contrast, the coefficient of *YChild1* shows that having a first child significantly reduces wage growth. After the birth of a first child, annual wage growth is reduced by one percentage point ($p<0.05$). The coefficient of *YChild2* shows an offsetting positive effect of a second child on wage growth, however is not significant at conventional levels.

Altogether, the first-difference results suggests that the wage differential between mothers and non-mothers has come about through a reduction in wage growth, rather than an immediate fall in the wage level after birth.

Table 7.9. Wages and Wage Growth, First-Difference, Model IV

Unbalanced Panel B

$N = 7989$ (2247)	(A)	(B)	(B')	(C)	(D)	(E)	(F)	(G)
Child1 (β_1)	0.036*	0.034	0.018	0.018	-0.004	-0.005	-0.005	-0.005
	(0.018)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Child2 (β_2)	-0.019	-0.021	-0.034	-0.033	-0.034	-0.033	-0.033	-0.033
	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Gap (γ_5)	-	-	0.038	0.039	0.031	0.033	0.033	0.033
			(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Effect of Motherhood on Wage Growth								
YChild1 (β_3)	-0.014**	-0.012*	-0.012*	-0.012*	-0.010*	-0.010	-0.010	-0.010*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
YChild2 (β_4)	0.006	0.006	0.006	0.006	0.007	0.007	0.007	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Immediate Effect of Motherhood:								
First Child: $\beta_1 + \beta_3 + \gamma_5 \times \overline{Gap}^{1st}$	0.0218	0.022	0.030	0.031	0.005	0.006	0.007	0.006
	(0.017)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.020)
Second Child: $\beta_2 + \beta_4 + \gamma_5 \times \overline{Gap}^{2nd}$	-0.013	-0.015	0.030	-0.004	-0.008	-0.007	-0.006	-0.007
	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
R^2	0.003	0.003	0.003	0.005	0.018	0.024	0.024	0.024
F	2.212*	2.261**	2.260**	2.142**	5.984***	4.322***	3.823***	3.743***

Source: HILDA, Waves 1-7

Notes: Robust clustered standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable, the natural log of the hourly wage, and all regressors, are in first-difference form as specified in Model IV. Full results reported in Table A.9, Appendix B. $\beta_1 + \beta_3 + \gamma_5 \times \overline{Gap}^{1st}$ gives the estimated average effect of motherhood on log wages in the year of returning to work after the birth of the first child where $\overline{Gap}^{1st}$ is equal to 0.63; *YChild1* gives the estimated effect of a first child on subsequent annual wage growth. $\beta_2 + \beta_4 + \gamma_5 \times \overline{Gap}^{2nd}$ and *YChild2* give the incremental effect of a second child on wage levels and wage growth where $\overline{Gap}^{2nd}$ is equal to 0.59. In regressions A and B where *Gap* is not controlled for, the immediate effects for a first and second child are $\beta_1 + \beta_3$ and $\beta_2 + \beta_4$ respectively. All regressions are unweighted.

7.2.2 First-Difference with Fixed Effects *(Model V)*

To account for the effect of unobserved heterogeneity on wage growth, a fixed effects model was estimated using the first-differenced variables (Table 7.10). The immediate effects of a first and second child on the wage level remain generally the same. The effect of a first child continues to be close to zero and not statistically significant while the effect of a second child has become positive, but remains statistically insignificant.

In contrast, allowing for individual slopes in experience has a large impact on the effect of motherhood on wage growth. The point estimates show having a first child reduces wages by 3.5 percent per year and having a second child *increases* annual wage growth by around 4.5 percentage points. Nevertheless, the standard errors are much larger in Model V rendering the effect of a first child insignificant, and the effect of a second child only significant at the ten percent level.

The dissimilarity of the Model IV and V point estimates may be due to the effect of unobserved heterogeneity on wage growth, which is only controlled for in the latter model. A comparison of the coefficients suggests that those women with wage-growth enhancing unobserved traits are more likely to have a first child, but less likely to have a second. However, since these effects are only marginally significant at best, there may be no systematic effect on wage growth when unobserved factors are taken into account. It may also be that the first-difference with fixed effects specification is too demanding for seven waves of data and requires a longer panel to obtain precise results.

Altogether, the estimates of Models IV and V imply that the wages mothers receive in the first year of work are the same as the wage earned before birth. However in subsequent years, annual wage growth is reduced by one (in Model IV) to 3.5 (in Model V) percentage points. Loughran and Zissimopoulos found the opposite result for the United States finding motherhood reduces wages by two percent in the year of birth, and has no significant effect on subsequent wage growth.

Given the Australian maternity leave legislation, it is not surprising that there is no immediate wage effect. Under the *Workplace Relations Act 1996* (Cwlth), Australian employees (permanent and casual) are entitled to 12 months of job protected unpaid maternity leave, and have the right to return to the same position at their pre-birth employer.[56] As such, mothers' remuneration is unlikely to change immediately, even if productivity has declined.

However, in subsequent periods when new wage contracts are signed, mothers' wages may not increase at the pre-birth rate if the presence of children has reduced work effort or imposed constraints which limit a woman's chance of promotion.

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[56] All employees must have had 12 months continuous service with their employer to be eligible. Casual employees must also be employed on a regular and systematic basis for at least 12 months prior to the birth and expect to return to their employer following leave. As of the 1st of January 2010, women will have will have the right to request an additional 12 months of unpaid leave under the New Employment Standards (NES) (Productivity Commision, 2009).

Table 7.10. Wages and Wage Growth, First-Difference with Fixed Effects, Model V
Unbalanced Panel B

$N = 7989$ (2247)	(A)	(B)	(B')	(C)	(D)	(E)	(F)	(G)
Child1 (β_1)	0.055*	0.054*	0.039	0.039	0.018	0.019	0.019	0.020
	(0.026)	(0.026)	(0.028)	(0.028)	(0.026)	(0.026)	(0.026)	(0.026)
Child2 (β_2)	-0.033	-0.033	-0.045	-0.044	-0.045	-0.045	-0.045	-0.045
	(0.026)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Gap (γ_5)	-	-	0.039	0.039	0.032	0.034	0.033	0.034
			(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Effect of Motherhood on Wage Growth								
YChild1 (β_3)	-0.037	-0.036	-0.034	-0.035	-0.032	-0.034	-0.033	-0.035
	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
YChild2 (β_4)	0.048	0.049	0.048	0.047	0.048	0.045	0.045	0.045
	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)
Immediate Effect of Motherhood								
First Child: $\beta_1 + \beta_3 + \gamma_5 \times \overline{Gap}^{1st}$	0.018	0.018	0.030	0.029	0.007	0.006	0.007	0.006
	(0.015)	(0.023)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Second Child: $\beta_2 + \beta_4 + \gamma_5 \times \overline{Gap}^{2nd}$	0.015	0.015	0.026	0.026	0.022	0.020	0.020	0.020
	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.030)	(0.028)
R^2	0.003	0.003	0.003	0.004	0.017	0.023	0.023	0.023
F	1.569	1.442	1.408	1.244	4.445***	3.269***	2.919***	2.853***

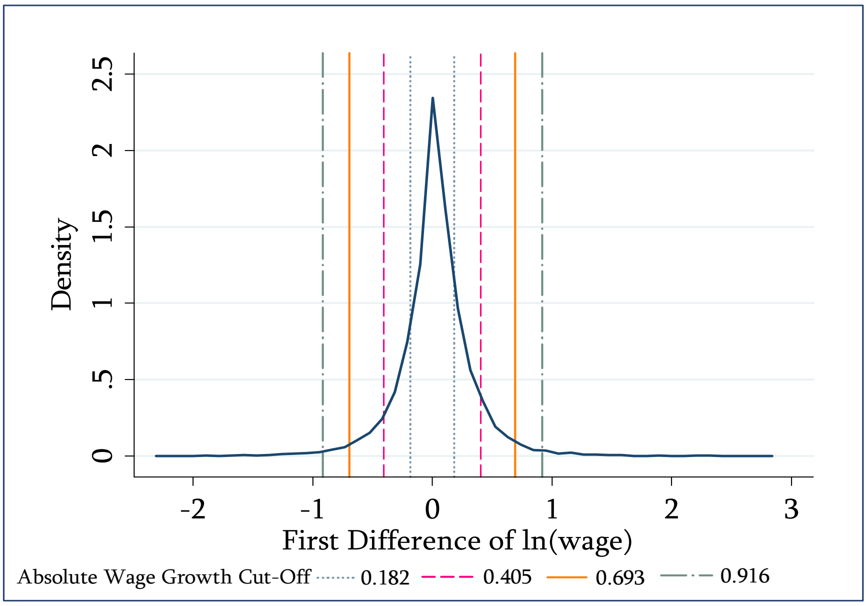
Source: HILDA, Waves 1-7
Notes: Robust clustered standard errors are used; standard errors are in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependant variable, the natural log of the hourly wage, and all regressors, are in first-difference form as specified in Model V. Full results reported in Table A.10, Appendix B. $\beta_1 + \beta_3 + \gamma_5 \times \overline{Gap}^{1st}$ gives the estimated average effect of motherhood on log wages in the year of returning to work after the birth of the first child where $\overline{Gap}^{1st}$ is equal to 0.63; *YChild1* gives the estimated effect of a first child on subsequent annual wage growth. $\beta_2 + \beta_4 + \gamma_5 \times \overline{Gap}^{2nd}$ and *YChild2* give the incremental effect of a second child on wage levels and wage growth where $\overline{Gap}^{2nd}$ is equal to 0.59. In regressions A and B where *Gap* is not controlled for, the immediate effects for a first and second child are $\beta_1 + \beta_3$ and $\beta_2 + \beta_4$ respectively. All regressions are unweighted.

Since it is common for Australian mothers to change to part-time hours after childbirth (Hosking, 2007), the wage growth decline may also reflect characteristics of part-time jobs. Although part-time work attracts an hourly wage premium in Australia, it is still possible that part-time workers' wage profiles are less steep if the there are fewer opportunities for promotion in part-time jobs.

7.2.3 Sensitivity of Results to the Wage-Growth Cut-off

In the analysis presented above, observations were excluded where the wage growth exceeded 0.405 in absolute terms. To investigate the sensitivity of the results to the cut-off chosen, Models IV and V were re-estimated using the cut-offs depicted in Figure 7.1. Table 7.11 shows the average immediate effect of motherhood on wages and the effect motherhood on wage growth for each cut-off (above results reproduced in Column 2).

Figure 7.1. Kernel Density Plot of Wage Growth with Cut-offs



Source: HILDA, Waves 1-7
Notes: Reference lines indicate the four wage-cut offs considered. Restricting the sample to observations where wage growth is less than 0.182 corresponds to excluding observations where the ratio of consecutive wages exceeds 1.2. Similarly, 0.405 corresponds to a factor of 1.5, 0.693 corresponds to a factor of 2 and 0.916 corresponds to a factor of 2.5.

The first-difference (Model IV) estimates do vary with the wage-growth cut-off, however it remains that a first or second child has no significant immediate effect on wages, and a second child has no significant effect of wage growth. The effect of the first child on wage growth is sensitive to a stricter sample restriction (Column 1); however the point estimates prove to be insensitive to the inclusion of large wage changes.

Table 7.11. Sensitivity of Results to Wage-Growth Cut-off

	Wage Growth Cut-off *Observations with wage growth in excess of this were dropped*			
	0.182	0.405	0.693	0.916
First-Difference (Model IV)				
Child1+YChild1+Gap	-0.014	0.006	-0.022	-0.027
	(0.013)	(0.020)	(0.025)	(0.027)
YChild1	-0.001	-0.010*	-0.010	-0.008
	(0.004)	(0.005)	(0.006)	(0.007)
Child2+YChild2+Gap	-0.018	-0.007	0.027	0.026
	(0.013)	(0.020)	(0.029)	(0.033)
YChild2	-0.000	0.006	0.008	0.002
	(0.004)	(0.005)	(0.006)	(0.006)
First-Difference with Fixed effects (Model V)				
Child1+YChild1+Gap	-0.009	0.006	-0.059	-0.055
	(0.018)	(0.025)	(0.033)	(0.036)
YChild1	-0.030	-0.035	-0.085*	-0.080*
	(0.019)	(0.023)	(0.033)	(0.035)
Child2+YChild2+Gap	0.012	0.020	0.065	0.094
	(0.019)	(0.028)	(0.014)	(0.048)
YChild2	0.030	0.045	0.079*	0.099**
	(0.021)	(0.027)	(0.035)	(0.037)
N (Total Observations)	5553	7989	8948	9159
N (First Births)	76	132	162	167
N (Second Births)	66	96	119	126

Source: HILDA, Waves 1-7. *Notes:* Robust clustered standard errors are used; standard errors in parentheses, *p<0.05, **p<0.01, ***p<0.001. The dependant variable, the natural log of the hourly wage, and all regressors, are in first-difference form as specified in Models IV and V. All regressions include full controls and are unweighted.

The effect of sample changes on Model V is more pronounced. When larger wage changes are included in the sample, the negative effect of a first birth on annual wage growth increases to around eight percentage points ($p<0.05$). Moreover, the *positive* effect of a second child on annual wage growth increases to eight to ten percentage points. The immediate effects of a first and second birth on the wage levels also change in the same directions; however the large standard errors mean the effects remain insignificant.

These very large and opposing impacts of a first and second child on wage growth are inconsistent with the conventional estimates of the effect of motherhood on wages. Models I-III found a motherhood wage penalty in the range of five percent for one child, with a further three to four percent penalty for a second. However the unrestricted Model V results suggest a first child reduces wages by around eight percent per year, and a second child has an offsetting wage increase. Even over a period of a few years, these estimates imply a much larger and opposing long-run wage effects beyond the range consistent with the conventional estimates.

The sample sizes reported in Table 7.11 show that a large portion of women have large year-to-year wage changes.[57] The source of these large changes is unclear, however given the sensitivity of the results, they are presumably not explained by the variables included in the model.

[57] It can also be seen that a similar proportion of mothers and non-mothers have outlying wage changes.

Overall, it appears that the first-difference (Model IV) specification is relatively robust; however the first-difference with fixed effects (Model V) specification is sensitive to outlying wage changes. In estimating the latter model for the United States however, Loughran and Zissimopoulos (2009) reported no such sensitivity. This may be due to the much longer (and larger) National Longitudinal Survey (NLS) data sets used in their analysis. Perhaps as more waves of HILDA become available, the first-difference with fixed effects specification may be more robust.

8 Summary and Conclusions

While a large body of literature exists for other developed countries, the effect of motherhood on women's wages has received little attention in Australia. Until now, no study has estimated the motherhood wage differential with unobserved factors held constant, or examined the effect of children on wage growth.

Given the importance of this issue to current Australian policy on female LFP and birth rates, and the study of gender wage equality, the first objective of this thesis was to determine whether mothers, on average, earn lower wages than non-mothers. Following this, the second objective was to study the effect of motherhood on wage growth to understand how a motherhood wage differential emerges.

Holding observable and unobservable differences constant, fixed effects estimates reveal mothers with one child earn around five percent less than non-mothers on average, with a further four percent penalty for a second child. This residual wage penalty may be due to actual productivity differences if responsibility for children leaves mothers with less energy to exert at work. Alternatively, mothers may be paid less than non-mothers because employers perceive mothers to be less productive or have a 'taste' for discriminating against them.

Contrary to prior studies overseas, part-time employment did not explain a large portion of the motherhood wage penalty. Across the different specifications, part-time work was consistently found to attract higher wages (of five to ten percent) and controlling for part-time and casual status generally increased the motherhood penalty. Similarly, the propensity of mothers to work in certain occupations, industries and sectors explains little of the gap. Controlling for marital status increased the motherhood penalty slightly; however the fixed effects results show marriage was acting as a proxy for unobserved factors.

Estimating a Heckman selection model revealed that those women most likely to suffer a motherhood wage penalty are less likely to be employed. Consequently, models not accounting for selection underestimated the motherhood penalty. The similarity of the Heckman and fixed effects results suggests that mothers do not differ to non-mothers on unobservable productivity traits other than those which affect selection into employment.

The effect of motherhood on wages and wage growth was examined using the methodology of Loughran and Zissimopoulos (2009). The first-difference results (Model IV) reveal a first or second child has no immediate effect on wages in the first year of returning to work, but a first child reduces subsequent annual wage growth by one percentage point. Sensitivity tests showed these results are relatively robust to large wage changes.

The first difference with fixed-effects (Model V) results however proved much more sensitive to outliers. Nevertheless, with large wage changes excluded, the results show that allowing for individual slopes in experience increases the negative effect of a first child on annual wage growth to 3.5 percentage points, and reveals an offsetting *positive* effect of a second child on wage growth. However, both the first and second child coefficients have large standard errors and only the latter is (marginally) significant.

Overall, the wage growth analysis suggests that the motherhood wage penalty emerges through reduced wage growth, rather than an immediate wage decline after birth. This is consistent with Australian maternity leave legislation which entitles most women to return to their prior position with their pre-birth employer and thus wages may be unaffected in the short-term. However subsequent wage growth may be reduced if the presence of children reduces mothers' actual or perceived productivity, or if employers have a taste for discrimination. Moreover, a reduction in wage growth is also consistent with flatter wage profiles for part-time workers.

As such, policies which make combining work and motherhood easier are likely to improve Australian mothers' wages and wage growth relative to non-mothers'. Greater access to childcare services, particularly in the workplace, may improve women's ability, and employer's perception of their ability, to balance family and work. Moreover, practices which improve career advancement of part-time workers are likely to increase mothers' wage growth.

Limitations and Further Areas of Research

One limitation of the empirical analysis is that reverse causality between motherhood and wages was not addressed. To determine the impact of this source of endogeneity, future research may estimate the motherhood penalty using instrumental variables techniques, provided a valid instrument is available. As more waves of data become available in HILDA, instruments used overseas such as sibling sex-mix may be feasible.

Another limitation is the small number of first and second births observed over the seven waves of HILDA. As further waves of data are collected, more first and second children will be born and a number of mothers not yet back in the labour force in Wave 7 will subsequently return. Including such observations will increase the precision of the motherhood coefficients and enable the effect of longer leave durations to be examined. Moreover, a longer panel may render the first-difference with fixed effects specification more robust.

Given the sensitivity of the wage growth results and the large proportion of women with large year-to-year wage changes, further investigation into the source of outlying wage trajectories is warranted. Moreover, a comparison of mothers with and without maternity leave coverage around birth will shed further light on the ability of job-protected maternity leave to mitigate an immediate wage decline. Further investigation into part-time workers wage trajectories' may also shed light on the effect of part-time work on mothers' wage growth.

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Appendix A- Variable Descriptions

Please see Section 6.3 for details on the hourly wage, child variables, experience and non-labour income.

Education

The highest education level achieved (EDHIGH) is used to construct six education categories:

Post Grad	= Doctorate, Masters, Graduated Diploma or Graduate Certificate
Bachelor	= Bachelor Degree
Diploma	= Diploma or Advanced Diploma
Certificate	= Certificate I, II, III, IV or undefined certificate level
Yr 12	= Year 12
Yr 11	= Year 11 or below

Tenure

The tenure variable (JBEMPT) measures the time (expressed in years) spent working with the current employer.

Part-time Status

The detailed employment status variable (ESDTL) is used to identify those working part-time.

Casual Status

The derived casual status variable (JBCASAB) which uses the ABS definition of a causal worker as one receiving no paid holiday or pay sick leave is used to identify casual workers.

Industry

The Australian and New Zealand Standard Industrial Classification (ANZSIC) 1 digit industry variable (JBMI61) is used to define 10 industry categories:

Primary	= Agriculture, Forestry and Fishing
Util/Mining	= Electricity, Gas, Water, Waste Services and Mining
Manufacture	= Manufacturing
Construction	= Construction and Wholesale Trade
Ret/Hosp	= Retail Trade, Accommodation, Food Services and Administration
Transport	= Transport, Postal and Warehousing
Culture	= Information, Media, Telecommunications, Arts and Recreation
Fin/Science	= Financial, Insurance, Rental, Hiring, Real Estate, Professional, Scientific and Technical Services
Educ/Health	= Public Administration and Safety, Education and Training, Health Care and Social Assistance
Other	= Other Services

Occupation

The Australia and New Zealand Standard Classification of Occupations (ANZSCO) 1 digit occupations variable (JBMO61) is used to define eight occupation categories:

Managers = Managers
Professionals = Professionals
Trade = Technicians and Trade Workers
Community = Community and Personal Services Work
Clerical = Clerical and Administrative Workers
Sales = Sales Workers
Machinery = Machinery Operators and Drivers
Labourers = Labourers

Sector

The variables which describe employment sector (JBMMPL, JBMMPLY, JBMMPLR) are used to classify sector type:

Private = Private for Profit Organisation
Public = Government Enterprise or Organisation
Other = Private not-for-profit Organisation, Other Commercial, Other Non-Commercial

Firm Size

The number of people employed by the respondent's employer at locations throughout Australia (JBMEMSZ) is used as the measure of firm size. If respondent's indicated that their firm only operated from their workplace, the number of employees at their place of work was used (JBMWPS). These variables were used to form three firm size classifications:

Small = < 20 employees
Medium = 20-99 employees, including those who responded "don't know but more than 20" to the question of number of employees at place of work, and those who responded "don't know but less than 100" to the question of number of employees in locations around Australia.
Large = >100 employees

Union Status

Union membership is determined with the variable JBMUABS.

Marital Status

The variable MRCURR was used to construct marital status categories:

Partnered = Married and De facto
Separated = Divorced, Separated or Widowed
Never = Never Married and not De-facto

Appendix B- Complete Empirical Results

Table A.1. Motherhood Wage Differential, Weighted Wave 1 Cross-Section, Model I

Wave 1 (N=2379)

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.049*	-0.115***	-0.064**	-0.068**	-0.058*	-0.058*	-0.064*
Child2	0.026	0.014	0.028	0.029	0.023	0.024	0.020
Exp		0.028***	0.025***	0.024***	0.020***	0.020***	0.019***
Exp^2/100		-0.061***	-0.057***	-0.057***	-0.047***	-0.047***	-0.045***
Post Grad			0.385***	0.379***	0.212***	0.209***	0.211***
Bachelor			0.291***	0.284***	0.126***	0.127***	0.130***
Diploma			0.155***	0.149***	0.063*	0.062*	0.066**
Certificate			0.009	0.005	-0.002	-0.006	-0.004
Year 12			0.073**	0.070**	0.040	0.038	0.039
Tenure			0.008***	0.008***	0.006***	0.005***	0.005***
Part-time				0.030	0.054**	0.060***	0.055**
Casual				-0.060**	-0.015	-0.000	0.002
Primary					0.008	-0.010	-0.019
Util/Mining					0.156*	0.115	0.106
Manufacturing					0.086	0.056	0.050
Construction					0.122*	0.098*	0.091
Ret/Hosp					-0.015	-0.041	-0.045
Transport					0.189**	0.142*	0.133*
Culture					0.112*	0.068	0.068
Fin/Science					0.152***	0.124**	0.118*
Educ/Health					0.079	0.039	0.034
Manager					0.326***	0.339***	0.332***
Professional					0.322***	0.330***	0.326***
Trade					0.076	0.096*	0.090*
Community					0.084*	0.104**	0.104**
Clerical					0.143***	0.152***	0.150***
Sales					0.138***	0.142***	0.141***
Machinery					0.012	0.021	0.020
Private						0.063*	0.062*
Public						0.072**	0.072**
Small						-0.028	-0.027
Large						0.056**	0.057**
Union						0.011	0.012
Partnered							0.041*
Separated							-0.010
Constant	3.009***	2.812***	2.641***	2.654***	2.484***	2.418***	2.409***
R^2	0.002	0.036	0.189	0.192	0.273	0.287	0.289
F	2.120	19.903***	57.481***	49.157***	31.987***	30.386***	28.955***

Table A.2. Motherhood Wage Differential, Unweighted Wave 1 Cross-Section, Model I

Wave 1 (N=2389)

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.052*	-0.112***	-0.057*	-0.060*	-0.053*	-0.050*	-0.057*
Child2	0.024	0.010	0.026	0.026	0.020	0.020	0.015
Exp		0.030***	0.026***	0.025***	0.020***	0.020***	0.020***
Exp²/100		-0.068***	-0.062***	-0.061***	-0.050***	-0.049***	-0.048***
Post Grad			0.391***	0.383***	0.216***	0.216***	0.217***
Bachelor			0.303***	0.294***	0.133***	0.135***	0.138***
Diploma			0.147***	0.140***	0.055*	0.057*	0.060*
Certificate			0.012	0.009	0.002	-0.002	0.000
Year 12			0.072**	0.069**	0.037	0.037	0.038
Tenure			0.008***	0.008***	0.006***	0.005***	0.005***
Part-time				0.032	0.057***	0.062***	0.058***
Casual				-0.062**	-0.020	-0.007	-0.005
Primary					0.020	-0.005	-0.017
Util/Mining					0.157	0.110	0.100
Manufacturing					0.096	0.059	0.052
Construction					0.126*	0.096	0.089
Ret/Hosp					-0.001	-0.032	-0.036
Transport					0.195**	0.145*	0.137*
Culture					0.116*	0.071	0.072
Fin/Science					0.166***	0.133**	0.127*
Educ/Health					0.095*	0.059	0.054
Manager					0.318***	0.330***	0.324***
Professional					0.314***	0.321***	0.317***
Trade					0.073	0.090*	0.085*
Community					0.074*	0.093**	0.092**
Clerical					0.143***	0.151***	0.149***
Sales					0.137***	0.137***	0.138***
Machinery					0.013	0.018	0.016
Private						0.078**	0.078**
Public						0.067**	0.066**
Small						-0.032	-0.032
Large						0.050*	0.052*
Union						0.022	0.023
Partnered							0.043*
Separated							-0.005
Constant	3.019***	2.802***	2.634***	2.648***	2.474***	2.404***	2.391***
R^2	0.002	0.037	0.196	0.200	0.275	0.288	0.291
F	2.705	23.431***	62.293***	53.016***	34.588***	32.334***	31.207***

Table A.3. Motherhood Wage Differential, Weighted Pooled Cross-Section, Model II

Unbalanced Panel A (N=14915)

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.012	-0.082***	-0.032*	-0.033	-0.024	-0.025	-0.040**
Child2	-0.003	-0.022	-0.003	-0.003	-0.010	-0.009	-0.014
Exp		0.029***	0.026***	0.025***	0.022***	0.022***	0.020***
Exp^2/100		-0.062***	-0.058***	-0.056***	-0.049***	-0.048***	-0.044***
Post Grad			0.402***	0.396***	0.231***	0.227***	0.227***
Bachelor			0.333***	0.328***	0.181***	0.176***	0.178***
Diploma			0.161***	0.158***	0.086***	0.085***	0.090***
Certificate			0.045**	0.042**	0.032*	0.029*	0.031*
Year 12			0.062***	0.060***	0.028	0.027	0.029*
Tenure			0.008***	0.007***	0.006***	0.005***	0.005***
Part-time				0.022*	0.050***	0.056***	0.054***
Casual				-0.056***	-0.008	0.008	0.010
Primary					-0.016	-0.030	-0.036
Util/Mining					0.226***	0.174***	0.173***
Manufacturing					0.107***	0.070*	0.067*
Construction					0.074*	0.044	0.039
Ret/Hosp					-0.023	-0.060*	-0.061*
Transport					0.084	0.040	0.037
Culture					0.117***	0.066*	0.066*
Fin/Science					0.118***	0.086***	0.083**
Educ/Health					0.081**	0.034	0.033
Manager					0.277***	0.288***	0.286***
Professional					0.275***	0.282***	0.281***
Trade					0.046	0.062*	0.064**
Community					0.037	0.054**	0.055**
Clerical					0.120***	0.130***	0.131***
Sales					0.074***	0.077***	0.080***
Machinery					-0.035	-0.028	-0.026
Private						0.070***	0.069***
Public						0.081***	0.078***
Small						-0.033*	-0.034*
Large						0.048***	0.048***
Union						0.016	0.017
Partnered							0.058***
Separated							0.026
W2	-0.005	-0.006	-0.008	-0.008	-0.010	-0.009	-0.010
W3	0.012	0.013	0.004	0.004	0.008	0.006	0.006
W4	0.027**	0.029**	0.020*	0.020*	0.020*	0.019*	0.018
W5	0.059***	0.058***	0.043***	0.041***	0.039***	0.036***	0.035***
W6	0.081***	0.082***	0.063***	0.062***	0.061***	0.057***	0.056***
W7	0.102***	0.102***	0.081***	0.080***	0.082***	0.079***	0.078***
Constant	3.000***	2.789***	2.603***	2.620***	2.484***	2.427***	2.409***
R^2	0.011	0.054	0.230	0.233	0.304	0.317	0.320
F	14.868***	35.166***	103.034***	96.997***	79.338***	74.790***	72.722***

Table A.4. Motherhood Wage Differential, Unweighted Pooled Cross-Section, Model II

Unbalanced Panel A (N=14972)

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	-0.007	-0.075***	-0.022	-0.022	-0.013	-0.014	-0.027*
Child2	-0.006	-0.026	-0.009	-0.009	-0.020	-0.018	-0.023
Exp		0.031***	0.025***	0.024***	0.021***	0.020***	0.019***
Exp^2/100		-0.064***	-0.056***	-0.054***	-0.046***	-0.045***	-0.042***
Post Grad			0.407***	0.396***	0.234***	0.231***	0.231***
Bachelor			0.328***	0.319***	0.174***	0.172***	0.174***
Diploma			0.157***	0.151***	0.078***	0.080***	0.083***
Certificate			0.040**	0.036**	0.022	0.022	0.023
Year 12			0.066***	0.061***	0.027*	0.027*	0.028*
Tenure			0.008***	0.007***	0.006***	0.005***	0.005***
Part-time				0.025*	0.052***	0.058***	0.057***
Casual				-0.068***	-0.018	-0.006	-0.003
Primary					-0.007	-0.024	-0.028
Util/Mining					0.242***	0.195***	0.194***
Manufacturing					0.090**	0.057*	0.056*
Construction					0.071*	0.044	0.041
Ret/Hosp					-0.022	-0.054*	-0.055*
Transport					0.100**	0.054	0.052
Culture					0.110***	0.067*	0.067*
Fin/Science					0.113***	0.085***	0.083***
Educ/Health					0.076**	0.032	0.031
Manager					0.278***	0.288***	0.286***
Professional					0.280***	0.286***	0.284***
Trade					0.061**	0.073***	0.073***
Community					0.047**	0.064***	0.063***
Clerical					0.127***	0.135***	0.135***
Sales					0.078***	0.080***	0.080***
Machinery					0.024	0.032	0.034
Private						0.065***	0.064***
Public						0.078***	0.077***
Small						-0.029*	-0.029*
Large						0.043***	0.044***
Union						0.009	0.010
Partnered							0.055***
Separated							0.032*
W2	0.003	-0.000	-0.006	-0.006	-0.008	-0.007	-0.008
W3	0.026**	0.022**	0.011	0.010	0.012	0.010	0.010
W4	0.036***	0.035***	0.019*	0.018*	0.019*	0.018*	0.017
W5	0.056***	0.056***	0.036***	0.035***	0.036***	0.032***	0.032***
W6	0.079***	0.081***	0.061***	0.060***	0.063***	0.059***	0.058***
W7	0.105***	0.106***	0.086***	0.085***	0.087***	0.083***	0.082***
Constant	3.005***	2.781***	2.611***	2.633***	2.494***	2.441***	2.417***
R^2	0.009	0.054	0.231	0.235	0.300	0.311	0.313
F	17.721***	45.854***	114.438***	106.573***	87.553***	82.867***	82.338***

Table A.5. Motherhood Wage Differential, Heckman-Corrected Pooled Cross-Section

Unbalanced Panel A

	Weighted	Unweighted
Child1	-0.067***	-0.053***
Child2	-0.017	-0.027*
Exp	0.024***	0.023***
Exp^2/100	-0.050***	-0.048***
Post Grad	0.242***	0.250***
Bachelor	0.195***	0.196***
Diploma	0.100***	0.096***
Certificate	0.040**	0.035**
Year 12	0.038*	0.040**
Tenure	0.005***	0.005***
Part-time	0.054***	0.056***
Casual	0.008	-0.005
Primary	-0.035	-0.027
Util/Mining	0.172***	0.196***
Manufacturing	0.068*	0.057*
Construction	0.041	0.042
Ret/Hosp	-0.059*	-0.053*
Transport	0.039	0.052
Culture	0.067*	0.067*
Fin/Science	0.084	0.083**
Educ/Health	0.034	0.032
Manager	0.286***	0.285***
Professional	0.283***	0.285***
Trade	0.066**	0.074***
Community	0.056**	0.063***
Clerical	0.132***	0.135***
Sales	0.081***	0.081***
Machinery	-0.026	0.035
Private	0.068***	0.064***
Public	0.077***	0.077***
Small	-0.033*	-0.029*
Large	0.048***	0.044***
Union	0.017	0.011
Partnered	0.048***	0.050***
Separated	0.020	0.030
W2	-0.010	-0.008
W3	0.006	0.010
W4	0.018	0.016
W5	0.035**	0.031**
W6	0.055***	0.057***
W7	0.077***	0.081***
Constant	2.345***	2.348***
Log L	-15665.36***	-17104.69***
λ	0.078	0.080
ρ	0.243	0.248
Wald χ^2	19.74***	16.84***
N (Censored)	8301 (1322)	8347 (1327)
N (Uncensored)	14915 (4242)	14972 (4255)

Table A.6. Motherhood Wage Differential, Fixed Effects, Model III

Unbalanced Panel A (N=14972)

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Child1	0.013	0.010	0.010	-0.051*	-0.049*	-0.049*	-0.049*
Child2	-0.041	-0.033	-0.032	-0.042	-0.041	-0.040	-0.039
Exp		0.067***	0.068***	0.073***	0.069***	0.069***	0.068***
Exp^2/100		-0.050***	-0.050***	-0.053***	-0.046***	-0.046***	-0.043***
Post Grad			0.096	0.127*	0.103*	0.101*	0.096
Bachelor			0.046	0.077	0.053	0.052	0.050
Diploma			0.036	0.043	0.039	0.034	0.035
Certificate			0.023	0.028	0.018	0.018	0.019
Year 12			0.059	0.052	0.046	0.045	0.046
Tenure			-0.000	-0.000	-0.000	-0.000	-0.000
Part-time				0.100***	0.106***	0.107***	0.107***
Casual				0.024*	0.028*	0.032**	0.032**
Primary					0.045	0.048	0.048
Util/Mining					0.133**	0.127**	0.127**
Manufacturing					0.013	0.014	0.014
Construction					0.037	0.038	0.037
Ret/Hosp					-0.008	-0.009	-0.010
Transport					0.006	0.002	0.000
Culture					0.046	0.039	0.038
Fin/Science					0.025	0.026	0.026
Educ/Health					0.065*	0.052*	0.052*
Manager					0.057*	0.058*	0.059*
Professional					0.068**	0.068**	0.069**
Trade					0.021	0.025	0.025
Community					0.006	0.008	0.008
Clerical					0.023	0.024	0.025
Sales					-0.014	-0.014	-0.014
Machinery					0.026	0.027	0.028
Private						-0.013	-0.013
Public						0.009	0.009
Small						-0.021	-0.021
Large						0.023*	0.023*
Union						-0.004	-0.004
Partnered							0.028*
Separated							0.044*
Constant	2.993***	2.234***	2.186***	2.104***	2.074***	2.079***	2.063***
R^2	0.042	0.048	0.048	0.065	0.073	0.076	0.076
F	46.600***	42.155***	27.352***	32.588***	19.783***	17.957***	17.166***

Table A.7. Hausman Test: Fixed and Random Effects

Unbalanced Panel A (N=14972)

	Fixed Effects	Random Effects	Difference	S.E.
Child1	-0.049	-0.039	-0.010	0.013
Child2	-0.039	-0.033	-0.006	0.015
Exp	0.068	0.020	0.048	0.009
Exp²/100	-0.043	-0.040	-0.003	0.007
Post Grad	0.000	0.004	-0.004	0.001
Bachelor	0.096	0.265	-0.169	0.045
Diploma	0.050	0.202	-0.152	0.042
Certificate	0.035	0.106	-0.071	0.041
Year 12	0.019	0.025	-0.006	0.023
Tenure	0.046	0.050	-0.003	0.036
Part-time	0.107	0.081	0.026	0.004
Casual	0.032	0.009	0.023	0.005
Primary	0.048	0.026	0.022	0.025
Util/Mining	0.127	0.175	-0.048	0.025
Manufacturing	0.014	0.036	-0.023	0.016
Construction	0.037	0.052	-0.015	0.015
Ret/Hosp	-0.010	-0.027	0.017	0.014
Transport	0.000	0.033	-0.032	0.022
Culture	0.038	0.048	-0.010	0.016
Fin/Science	0.026	0.064	-0.038	0.014
Educ/Health	0.052	0.042	0.010	0.013
Manager	0.059	0.176	-0.117	0.013
Professional	0.069	0.196	-0.128	0.013
Trade	0.025	0.064	-0.039	0.015
Community	0.008	0.043	-0.035	0.012
Clerical	0.025	0.108	-0.083	0.013
Sales	-0.014	0.049	-0.063	0.013
Machinery	0.028	0.055	-0.027	0.019
Private	-0.013	0.014	-0.027	0.007
Public	0.009	0.038	-0.029	0.007
Small	-0.021	-0.026	0.005	0.005
Large	0.023	0.039	-0.016	0.005
Union	-0.004	0.006	-0.010	0.005
Partnered	0.028	0.042	-0.015	0.010
Separated	0.044	0.024	0.019	0.015
W2	-0.051	-0.009	-0.042	0.009
W3	-0.070	0.010	-0.080	0.016
W4	-0.099	0.020	-0.119	0.024
W5	-0.122	0.037	-0.158	0.032
W6	-0.133	0.062	-0.195	0.040
W7	-0.143	0.088	-0.232	0.048

H_0: Difference in coefficients is not systematic

$\chi^2 = 447.24^{***}$

Table A.8. Motherhood Wage Differential, Fixed Effects with Interactions, Model III

Unbalanced Panel A (N=14972)

Professional Occupation		Marital Status		Part-time Employment	
Child1	-0.062**	*Child1*	-0.081*	*Child1*	-0.055*
*Child1*Prof*	0.033	*Child1*Partnered*	0.033	*Child1*PT*	0.014
Child2	-0.026	*Child2*	-0.028	*Child2*	-0.034
*Child2*Prof*	-0.037	*Child2*Partnered*	-0.013	*Child2*PT*	-0.008
Exp	0.068***	*Exp*	0.068***	*Exp*	0.068***
$Exp^2/100$	-0.043***	$Exp^2/100$	-0.043***	$Exp^2/100$	-0.043***
Post Grad	-0.000	*Post Grad*	-0.000	*Post Grad*	-0.000
Bachelor	0.097	*Bachelor*	0.097	*Bachelor*	0.095
Diploma	0.050	*Diploma*	0.050	*Diploma*	0.049
Certificate	0.034	*Certificate*	0.034	*Certificate*	0.035
Year 12	0.019	*Year 12*	0.018	*Year 12*	0.019
Tenure	0.047	*Tenure*	0.046	*Tenure*	0.047
Part-time	0.107***	*Part-time*	0.107***	*Part-time*	0.101***
Casual	0.032**	*Casual*	0.032**	*Casual*	0.032**
Primary	0.049	*Primary*	0.048	*Primary*	0.048
Util/Mining	0.126**	*Util/Mining*	0.126**	*Util/Mining*	0.127**
Manufacturing	0.013	*Manufacturing*	0.014	*Manufacturing*	0.013
Construction	0.036	*Construction*	0.037	*Construction*	0.037
Ret/Hosp	-0.010	*Ret/Hosp*	-0.010	*Ret/Hosp*	-0.010
Transport	-0.001	*Transport*	0.001	*Transport*	0.000
Culture	0.038	*Culture*	0.038	*Culture*	0.038
Fin/Science	0.025	*Fin/Science*	0.026	*Fin/Science*	0.025
Educ/Health	0.051*	*Educ/Health*	0.051*	*Educ/Health*	0.052*
Manager	0.059*	*Manager*	0.060*	*Manager*	0.059*
Professional	0.065*	*Professional*	0.069**	*Professional*	0.069**
Trade	0.025	*Trade*	0.024	*Trade*	0.025
Community	0.008	*Community*	0.008	*Community*	0.008
Clerical	0.024	*Clerical*	0.025	*Clerical*	0.025
Sales	-0.014	*Sales*	-0.014	*Sales*	-0.014
Machinery	0.029	*Machinery*	0.028	*Machinery*	0.029
Private	-0.013	*Private*	-0.013	*Private*	-0.013
Public	0.009	*Public*	0.009	*Public*	0.009
Small	-0.021	*Small*	-0.021	*Small*	-0.021
Large	0.023*	*Large*	0.023*	*Large*	0.023*
Union	-0.004	*Union*	-0.004	*Union*	-0.004
Partnered	0.028*	*Partnered*	0.023	*Partnered*	0.028*
Separated	0.043*	*Separated*	0.058*	*Separated*	0.044*
W2	-0.051***	*W2*	-0.051***	*W2*	-0.051***
W3	-0.070**	*W3*	-0.069**	*W3*	-0.070**
W4	-0.099**	*W4*	-0.098**	*W4*	-0.099**
W5	-0.122**	*W5*	-0.120**	*W5*	-0.122**
W6	-0.134*	*W6*	-0.132*	*W6*	-0.134*
W7	-0.144*	*W7*	-0.142*	*W7*	-0.143*
Constant	2.065***	*Constant*	2.071***	*Constant*	2.064***
R^2	0.077	R^2	14972	R^2	0.076
F	16.406	F	0.076	F	16.462

Table A.9. Wages and Wage Growth, First-Difference, Model IV

Unbalanced Panel B (N=7989)

	(A)	(B)	(B')	(C)	(D)	(E)	(F)	(G)
Child1	0.036*	0.034	0.018	0.018	-0.004	-0.005	-0.005	-0.005
YChild1	-0.014**	-0.012*	-0.012*	-0.012*	-0.010*	-0.010	-0.010	-0.010*
Child2	-0.019	-0.021	-0.034	-0.033	-0.034	-0.033	-0.033	-0.033
YChild2	0.006	0.006	0.006	0.006	0.007	0.007	0.007	0.006
Exp^2/100		-0.035	-0.036	-0.037	-0.040*	-0.040*	-0.040*	-0.040*
Gap			0.038	0.039	0.031	0.033	0.033	0.033
Post Grad				0.100*	0.110*	0.105*	0.105*	0.105*
Bachelor				0.082	0.093*	0.088*	0.087*	0.087*
Diploma				0.034	0.034	0.033	0.033	0.033
Certificate				0.013	0.013	0.010	0.010	0.010
Year 12				0.057	0.050	0.051	0.052	0.052
Tenure				0.001	0.001	0.001	0.001	0.001
Part-time					0.048***	0.048***	0.048***	0.048***
Casual					0.033***	0.034***	0.034***	0.034***
Primary						-0.011	-0.009	-0.010
Util/Mining						0.029	0.029	0.029
Manufacturing						-0.000	0.001	0.001
Construction						0.010	0.011	0.011
Ret/Hosp						0.020	0.020	0.020
Transport						0.029	0.030	0.030
Culture						0.010	0.010	0.010
Fin/Science						0.019	0.020	0.020
Educ/Health						0.043*	0.042*	0.042*
Manager						0.010	0.010	0.011
Professional						0.011	0.011	0.011
Trade						-0.001	-0.000	0.000
Community						0.012	0.011	0.011
Clerical						-0.011	-0.011	-0.011
Sales						-0.029	-0.028	-0.028
Machinery						0.005	0.005	0.005
Private							-0.009	-0.009
Public							-0.001	-0.001
Small							-0.004	-0.004
Large							-0.001	-0.001
Union							0.001	0.001
Partnered								-0.007
Separated								0.004
W2	-0.028*	-0.029*	-0.041**	-0.043**	-0.044**	-0.045**	-0.045**	-0.044**
W3	-0.056*	-0.057*	-0.082**	-0.086**	-0.086**	-0.087**	-0.088**	-0.087**
W4	-0.080*	-0.082*	-0.118**	-0.125**	-0.126**	-0.128**	-0.128**	-0.126**
W5	-0.100*	-0.102*	-0.151**	-0.160**	-0.159**	-0.163**	-0.163**	-0.161**
W6	-0.122*	-0.125*	-0.185*	-0.196**	-0.196**	-0.200**	-0.200**	-0.197**
W7	-0.140*	-0.143*	-0.215*	-0.228**	-0.227**	-0.232**	-0.232**	-0.229**
Constant	0.050***	0.055***	0.067***	0.069***	0.071***	0.070***	0.070***	0.070***
R^2	0.003	0.003	0.003	0.005	0.018	0.024	0.024	0.024
F	2.212*	2.261**	2.260**	2.142**	5.984***	4.322***	3.823***	3.743***

Table A.10. Wages and Wage Growth, First-Difference with Fixed Effects, Model V

Unbalanced Panel B (N=7989)

	(A)	(B)	(B')	(C)	(D)	(E)	(F)	(G)
Child1	0.055*	0.054*	0.039	0.039	0.018	0.019	0.019	0.020
YChild1	-0.037	-0.036	-0.034	-0.035	-0.032	-0.034	-0.033	-0.035
Child2	-0.033	-0.033	-0.045	-0.044	-0.045	-0.045	-0.045	-0.045
YChild2	0.048	0.049	0.048	0.047	0.048	0.045	0.045	0.045
$Exp^2/100$		0.168	0.094	0.060	0.065	-0.005	-0.062	-0.074
Gap			0.039	0.039	0.032	0.034	0.033	0.034
Post Grad				0.059	0.066	0.067	0.067	0.068
Bachelor				0.049	0.056	0.055	0.055	0.055
Diploma				0.035	0.034	0.035	0.036	0.036
Certificate				0.023	0.024	0.022	0.022	0.022
Year 12				0.062	0.051	0.052	0.051	0.051
Tenure				0.001	0.001	0.001	0.001	0.001
Part-time					0.044***	0.044***	0.044***	0.044***
Casual					0.034***	0.035***	0.035***	0.035***
Primary						-0.017	-0.017	-0.017
Util/Mining						0.020	0.020	0.019
Manufacturing						-0.015	-0.015	-0.015
Construction						0.003	0.003	0.003
Ret/Hosp						0.016	0.016	0.016
Transport						0.033	0.033	0.034
Culture						0.011	0.011	0.011
Fin/Science						0.014	0.014	0.014
Educ/Health						0.033	0.033	0.033
Manager						0.010	0.011	0.011
Professional						0.009	0.009	0.009
Trade						-0.004	-0.003	-0.003
Community						0.013	0.013	0.013
Clerical						-0.010	-0.009	-0.009
Sales						-0.032	-0.032	-0.031
Machinery						0.009	0.009	0.010
Private							-0.005	-0.005
Public							-0.005	-0.005
Small							(0.011)	(0.011)
Large							-0.000	-0.000
Union							-0.003	-0.003
Partnered							0.005	0.005
Separated								-0.016
W2	-0.035*	-0.031	-0.046	-0.047*	-0.048*	-0.051*	-0.051*	-0.051*
W3	-0.069*	-0.064	-0.092*	-0.095*	-0.096*	-0.099*	-0.099*	-0.098*
W4	-0.097*	-0.092	-0.133*	-0.136*	-0.140*	-0.143*	-0.142*	-0.142*
W5	-0.124*	-0.120*	-0.174*	-0.178*	-0.182*	-0.185**	-0.184*	-0.183*
W6	-0.152*	-0.150*	-0.215*	-0.220*	-0.226*	-0.227**	-0.225*	-0.224*
W7	-0.174*	-0.177*	-0.253*	-0.257*	-0.266*	-0.263*	-0.260*	-0.258*
Constant	0.049*	0.019	0.044	0.051	0.051	0.073	0.075	0.077
R^2	0.003	0.003	0.003	0.004	0.017	0.023	0.023	0.023
F	1.569	1.442	1.408	1.244	4.445***	3.269***	2.919***	2.853***