This thesis is unpublished and its results are not to be quoted. Problems with data and the identification of my empirical models prevented the attainment of sound results, and the project needs further work. I hope, however, that my theoretical arguments and experiences with the HILDA provide some help to others.

Garima Verma
26th February, 2009

Work-Life Policies and Women's Post-Childbirth Labour Mobility

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Declaration of Originality

I, Garima Madhariya Verma, declare that this thesis is my own work, and that any contributions or materials by other authors have been appropriately acknowledged. This thesis has not been submitted to any other university or institution as a requirement for a degree or other award.

Garima Madhariya Verma

27th October 2008

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Abstract

It is important for women to maintain their attachment to work after having children. Studies have shown that career absences and job mobility result in the depreciation of skills. However, skills depreciation from unavoidable career absences may be mitigated by a reduction in job mobility. Maternity leave is one such career interruption, and studies find smaller wage penalties for women who return to their pre-childbirth job, reflecting the value of job-specific skills. Overseas research suggests that employer-provided policies reduce job mobility and the associated loss of skills. However, Australian policy debates centre on maternity leave, and do not consider women's ability to ease back into work and maintain a work-life balance. This study attempts to address this gap in the literature, by investigating the impact of general work-life policies on women's mobility decisions after childbirth.

Using 6 Waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey, I assemble an unbalanced panel of women who are in work before having a child. A two-part model identifies the effect of work-life policies upon women's return to work decisions, whilst accounting for the endogeneity of access to these policies. My IV Probit models face exogeneity problems, while Bivariate Probit models have difficultly disentangling the effect of unobservables that affect both the probability of returning to work, and the probability of accessing a given work-life policy.

After assuming perfect correlation in unobservables (Sartori, 2003), I find that general work-life policies (such as permanent part-time work, and home-based work) increase the probability of a return to work. This corresponds to theoretical predictions and previous research (McRae, 1994; Desai and Waite, 1991). Maternity policies are found to have a negative impact, which corresponds to studies finding high uptake of such policies (Baxter, 2008; McRae, 1994; Desai and Waite, 1991).

Introduction

An important issue in labour economics is whether work-life balance policies enhance women's attachment to work after maternity leave. This is particularly relevant in an era of skills shortages and an ageing population. This study finds that general work-life policies – those that help women balance work with non-work commitments – positively impact the probability of returning to work after giving birth. Employer-provided maternity policies are found to *reduce* the probability of return, at least in the very short-term, reflecting preferences for longer maternity leave periods (Baxter, 2008).

Work-life policies assist women's labour force attachment, as women unable to ease back into work after maternity leave may change jobs or leave the workforce entirely. This generates private and public costs: in the short-term, women are constrained in their ability to raise children and fulfil career ambitions, while the economy is denied valuable skills and labour. In the long-term, unsupportive work practices will likely affect economic productivity, gender equity, women's financial stability, fertility, and population ageing (Productivity Commission (PC), 2008a).

However, Australia's policy environment discourages women's labour force participation (Council of Australian Governments (COAG), 2006; Whitehouse, 2005). Women's participation rates in Australia are lower than in Canada, the United States and the United Kingdom (Australian Bureau of Statistics (ABS), 2007a), and statistics indicate that 770 000 women out of the labour force actually wish to work (ABS 2007b). This constrained participation under-utilises the economy's skills and creates labour market inefficiencies.

These labour market outcomes have long-term consequences for women's skills. Career absences cause the depreciation of both general skills (like literacy) and job-specific skills, with specific skills further affected by job mobility (Edin and Gustavsson, 2008; Kunze, 2002; Neal, 1995). However, women returning to the same employer suffer a smaller wage penalty after maternity leave compared to those who change jobs (Kunze, 2002).

These findings promote a widening of policy debates beyond maternity leave. Broader consideration of work-life balance may better "stimulate lifetime employment rates of women" and encourage "the normalcy of combining a caring role for children and working" (PC, 2008b p.XIV). While maternity leave has long-term health and economic implications (PC, 2008a; World Health Organisation (WHO), 2008; Baker and Milligan, 2008; Rhum, 2000), short-term labour attachment requires work cultures that help reduce post-childbirth labour mobility.

Overseas research finds that employer-provided policies influence mobility decisions (McRae, 1994; Desai and Waite, 1991; Rhum, 1990). However, Australian research and policy debates centre on maternity leave policies, and neglect the impact of organisational cultures on work attachment. I address this gap by testing the effect of organisational cultures - as proxied by work-life policies - on women's post-childbirth work decisions.

Using the Household, Income and Labour Dynamics in Australia (HILDA) survey, I create an unbalanced panel of 377 women who give birth between 2001 and 2006. HILDA provides work-life policies as a series of binary variables, which I aggregate into both count and binary variables. The binary variables separate maternity-related policies (like paid maternity leave) from general work-life polices (such permanent part-time work). Unpaid Maternity Leave is excluded from these aggregations, as it is a legislative entitlement and does not reflect organisational culture (*Workplace Relations Act, 1996* (Cth)). I use two-part models to estimate the probability of returning to work whilst controlling for the endogeneity of work-life policies.

Work-life policies are assumed to be endogenous because women planning a pregnancy may select into particular jobs. An IV Probit model addresses the count policy variable's endogeneity, however there are problems with the exogeneity of instruments. Models using binary policy variables are estimated with Bivariate Probit. These have difficulty disentangling the effects of unobservables common to both the return to work decision (the outcome equation), and the probability of accessing a given work-life policy (reduced form equation).

Bivariate Probit models report perfect correlation between the errors of outcome and reduced form equations. As I assume pre-childbirth job choices incorporate fertility plans, it is reasonable for the same unobservables to affect both policy access and the return to work decision (Sartori, 2003). I therefore retain these perfect correlations in my models.

Interestingly, the errors are positively correlated in models with maternity policies, but negatively correlated in models with general work-life policies. Positive correlation is considered reasonable for maternity leave policies, which are usually accessible by highly skilled women (Risse, 2007; Gray and Tudball, 2002, Rhum, 1990). High opportunity costs of labour force withdrawal make such women more likely to return to work. There is a negative coefficient on maternity policies, which reflects the actual usage of such policies in the short-term (Baxter, 2008; McRae, 1994).

Negative correlations in models with general policies are similarly intuitive. Studies find that general work-life policies significantly influence women with low work-commitment or low costs of labour force withdrawal (McRae, 1994; Desai and Waite, 1991). This reduces the coefficient estimate because women choosing flexible jobs may be less likely to return to work. A positive coefficient on general work-life policies thus reflects how such policies help women ease back into work after giving birth.

These findings highlight the importance of flexible employment to post-maternity labour attachment. General work-life policies should therefore be offered alongside maternity leave policies to best reduce labour mobility (Baird and Charlesworth, 2007). However, general work-life policies reflect organisational cultures, and should therefore be employer-motivated (Gray and Tudball, 2002; Rhum, 1998)

While the Productivity Commission is proposing universal paid maternity leave (PC, 2008b), a more holistic approach is required to assist women's workforce attachment. If employers are better informed about the benefits of work-life policies, they may be inclined to instigate employee-responsive cultures. Policymakers could help provide such information, and might interact with industry groups to minimise mutually detrimental labour mobility.

Apart from the short-term benefits of reducing unwanted mobility and skills loss, work-life balance policies impact a range of public and private goals. These include gender equity, enhanced economic productivity and welfare, better health outcomes for workers and families, improved community wellbeing, and improved long-run economic growth (Human Rights and Equal Opportunity Commission (HREOC), 2008; Skinner and Pocock, 2008; Baker and Milligan, 2008; Organisation for Economic Cooperation and Development (OECD), 2007; PC, 2006; Berger et al, 2005).

Chapter 1 presents a detailed analysis of these benefits, while Chapter 2 describes the variables utilised from the HILDA survey. Chapter 3 outlines my theoretical model and econometric approach, the results and analysis of which are in Chapter 4. Finally, this paper is concluded in Chapter 5 with a discussion of my study's shortcomings, suggestions for future research, and a discussion of policy implications.

CHAPTER 1: MOTIVATIONS AND LITERATURE

1.1 Women and Work

1.1.1 Trends in Women's Labour Force Participation

Australia is facing a skills shortage and an ageing population, which in turn fuels fears for productivity and future economic growth. Increased workforce participation may alleviate such concerns, however, current policy neglects a crucial segment of the workforce – women of childbearing age (COAG, 2006).

Women have been instrumental to increasing labour participation rates. Between 1990 and 2005, the employment rate of Australian women aged 15-64 years rose from 62 to 68 percent (ABS 2007b). However, Australian women may be less willing and/or able to combine work and motherhood compared with women in similar countries. In 2005, 73 percent of childbearing Australian women were employed, compared with 80 percent in Canada, 76 percent in the United States and 74 percent in the United Kingdom (Abhayaratna and Lattimore, 2006).[1]

These relatively lower rates may stem from Australia's lack of policy support for mothers. Data from the Parental Leave in Australia Survey[2] indicates that, of women who choose to exit the workforce around the time of birth, "30 per cent quit because of an inflexible, stressful or unsupportive work environment" (Whitehouse et al, 2007). Recent labour force policies have focused upon older workers, welfare recipients and migrants while taxation policies and maternity payments *discouraged* women's attachment to work around childbirth (COAG, 2006; Whitehouse, 2005).

[1] These figures are revisions of OECD estimates.
[2] This is a nested study within the Longitudinal Survey of Australian Youth. For more details, see Whitehouse, G., Baird, M., Diamond C. and Hosking, A. (2006) *The Parental Leave in Australia Survey: November 2006 Report.*

Childbirth related career interruptions significantly affect women's long-term employment, and difficulties balancing work with non-work commitments could induce exits from the labour force. Recent statistics show that of 5.5 million Australians over 15 who are not in the labour force, 61% are women (ABS 2007b). Of these women, 23% want to work, meaning that at least 770 000 women are willing but unable to enter the labour market.

1.1.2 Cultural Restraints on Women's Labour Force Participation

Women's labour market disadvantages arise from two main sources: 1) cultural expectations allocating unequal burdens of unpaid work, and 2) organisational cultures that promote the "breadwinner" model of work, and are unresponsive to employees' non-work needs (HREOC, 2008). These factors constrain women's participation in paid work, which in turn may induce economically or socially undesirable work decisions.

1.2 Economic Consequences of Women's Constrained Labour Force Participation: Skill and Wage Depreciation

1.2.1 General and Specific Skills

Women's constrained participation results in the loss of skills through career breaks and job mobility. Skills, or human capital, can be grouped into two forms: 1) general skills, such as literacy and numeracy, which are transferable between occupations, industries and firms; and 2) specific skills that are useful for particular occupations, industries and firms, such as a knowledge of processes, organisational setup, and clients (Kriechel and Pfann, 2005; Rhum, 1998; Neal, 1995).

The evidence suggests that general skills are valuable, and that lengthier absences generate greater losses of such skills (Edin and Gustavsson, 2008). Kunze (2002) finds that skilled women lose 13-18 per cent of wages per year of parental leave, and low-skilled workers suffer proportionately larger losses (Edin and Gustavsson, 2008; Kunze, 2002).

Specific skills are also affected by career absences, however they are additionally influenced by job mobility. Mobility between employers, occupations and industries is often accompanied by wage reductions, particularly when transitions are unwanted (Kunze, 2002; Neal, 1995). Studies find that women who return to their pre-maternity employer suffer a smaller wage penalty than those who change employer. This indicates the value placed on of specific skills (Davies & Pierre, 2005; Baum, 2002; Kunze, 2002, Waldfogel, 1998). Reducing unwanted job mobility thus decreases loss in both general and specific skills.

1.2.2 The Role of Work-life Policies in Reducing Unwanted Mobility and Skill Depreciation

The loss of skills may be minimised by the provision of job-specific work-life policies. This rests upon an argument developed by Rhum (1990): employer and labour market rigidities may encourage workers to switch to “bridge jobs” - flexible and part-time jobs which ease the transition between full time work and other labour market states. As bridge jobs are often in different fields of work, such transitions are sub-optimal because employer, occupation and industry-specific skills may be lost in the process (Rhum, 1990; Neal**,** 1995; PC, 2008b).

The evidence shows that work-life policies significantly influence workers who desire flexibility or reduced hours (Rhum, 1990; McRae, 1994; Desai & Waite, 1991). Rhum (1990) employs US panel data to analyse the transition of older workers from career jobs to full-time retirement. He finds that mobility to bridge jobs is reduced by employer policies (pension plans) and training investments, characteristics associated with the educated and highly paid.

These patterns of policy provision and employee retention are repeated across the literature – work-life balance polices are more likely to be offered to workers with stable employment, greater education, earnings, and job-related training, indicating that employers recognise the value of skilled employees (Risse, 2007; Davis and Kalberg, 2006; Gray and Tudball, 2002; Whitehouse and Zeitlin, 1999; Glass and Estes, 1997; McRae, 1994; Desai and

Waite, 1991; Rhum, 1990). While there is a view that work-life provisions should be employer motivated (Rhum, 1998; Gray & Tudball, 2002), employers and the economy may lose out if the benefits of these policies are not known.

Rather than reflecting job specific skills, which are mostly accumulated through work experience, policy provision is usually tied to formal education (Risse 2007; Gray and Tudball, 2002). Thus employees with lower 'formal' skills are less likely to be offered such policies, likely to be lower-paid, and are more likely to drop out of work as they face a lower opportunity cost of doing so (Glass and Fujimoto, 1995; Desai and Waite, 1991; Rhum 1990). Yet the above evidence (see Section 1.2.1) suggests there are skill-related benefits to retaining *all* employees, regardless of formal training and education.

In summary, limited employment opportunities produce situations of job mobility and undesired time out of work. This detrimentally impacts skills; productivity; workers' earnings, employment, and financial stability; as well individual and community wellbeing. Reducing skills loss among women, particularly around the crucial period of childbirth, can go towards correcting such outcomes.

1.3 Work participation around maternity leave

Women face their most severe employment constraints when they have children. Statistics in Section 1.1.1 suggest that post-maternity workforce decisions have lasting impacts on women's ability to re-enter the workforce. Hence, policies directed to this period are crucial to women's labour force attachment.

1.3.1 The Australian Policy Context and the Effects of Paid Maternity Leave

In Australia, the policy debate surrounding women's workforce attachment focuses on maternity leave. Australian women have a federally mandated right to 12 months unpaid maternity leave following 12 months of regular work (*Workplace Relations Act 1996*). The accompanying "return-to-work guarantee" protects women's jobs, and a one-off maternity benefit ("baby bonus") helps with the costs of newborn children.

The Productivity Commission is proposing a government funded universal paid maternity leave scheme, providing 18 weeks of paid leave at the minimum wage. These payments will replace the "baby bonus" for women who are in work, however women who do not work will continue to receive the bonus.

Federal public sector employees have the right to paid maternity leave (*Maternity Leave (Commonwealth Employees) Act 1973*), state and territory government have implemented a variety of policies, while the remainder of workplaces have autonomy in their policy provision (Risse, 2007; Whitehouse and Zetlin, 1999).[3]

Despite the focus on maternity policies, their labour market impacts are not well established. Although paid maternity leave may reduce women's chances of resigning from work (Productivity Commission, 2008; Whitehouse 2005), maternity-specific policies may *increase* the length of leave. Paid leave is found to *reduce* the likelihood of returning to work in the short term, indicating the value placed by women on spending time with newborn children (Baxter, 2008; McRae, 1994; Desai and Waite, 1991).

Baxter (2008) further finds that *unpaid* maternity leave has a greater influence than paid leave on the timing of return to work. This reflects the importance of job security, which is provided through the return-to-work guarantee (*Workplace Relations Act 1996*). Consequently, the provision of paid maternity leave is likely to *increase* the length of career breaks (Baxter, 2008) and in turn, skills depreciation.

[3] Employer with over 100 employees are subject to equal opportunity provisions, which may influence their provision of paid maternity leave (*Equal Opportunity for Women in the Workplace Act, 1999*).

1.3.2 The Importance of Maternity Leave Periods

As discussed at Section 1.1.3, time out of work and job mobility major causes of skills depreciation. Therefore, one strategy for skills retention is to minimise the length of career breaks. This is the conventional approach, however it may be inappropriate for maternity leaves, especially given the importance of childhood care for children's health (PC, 2008b). For example, the World Health Organization recommends 6 months of exclusive breastfeeding, which provides infants with nutrients that promote sensory, cognitive and immune system development (WHO, 2008). Parental leave policies play an important role in achieving these outcomes, with generous leave benefits shown to increase breastfeeding rates and reduce infant mortality (Baker and Milligan, 2008; Rhum, 2000).

Lengthier leave therefore helps create a healthier and more productive future workforce, whilst allowing mothers to recover from the birth and bond with their children (PC, 2008b, OECD, 2007). The needs of families are therefore not exclusive from the needs of the economy. In this respect, the minimisation of maternity-related career breaks is not the optimal approach for skills retention.

1.3.3 Reducing unwanted mobility: general versus maternity-specific policies

Given the importance of career breaks around childbirth, some skills depreciation is inevitable. However, this may be minimised if women return to their pre-childbirth employers, industries and occupations, as shown by the higher post-maternity wages of women who return to their previous employers (see Section 1.2.1). Attachment to employers is therefore vital when considering work decisions after maternity leave.

However, maternity leave policies may be insufficient in assisting women's ongoing labour force attachment. Rhum (1998) finds unconvincing the argument that parental leave preserves specific skills by reducing women's need to change employers. Likewise, Diamond et al (2007) find that almost 40 per cent of women in a best practice employer left work *after returning* from maternity leave. This suggests that general work-life policies, such as reduced or flexible hours, are required to ease the transition back to work (Diamond et al, 2007; Baird and Charlesworth, 2007).

While general work-life policies may help stagger the return to work, only policies with job security are truly employee-responsive. Job security is vital for women's ongoing work participation, especially as financial stability is the most important influence on fertility decisions (Weston et al, 2004). Baxter (2008) and McRae (1994) find that women's chances of returning to the same employer are improved by access to part/time work, job-sharing, secure employment contracts, and return-to-work guarantees.

The availability of such secure but flexible policies requires employee-responsive work cultures, in which organisations genuinely appreciate and accommodate employees' non-work commitments. However, recent labour market reforms have promoted *employer-responsive* initiatives such as casualisation, which reduce job security and do not help women balance work with childcare (Pocock et al, 2004). Fundamental organisational change is critical to genuine work-life policies. Employers cannot ignore this if they are to be responsive to employees' needs.

1.4 The Crucial Role of Organisational Culture

Employers need to be convinced of the value of organisational change. Businesses and workers can *both* benefit from accommodative work arrangements beyond the period of maternity leave (Gray and Tudball, 2002; Bailyn, Fletcher and Kolb, 1997; Lewis, 1996). However, despite the bottom line advantages of work-life policies (such as increased productivity, and reductions in absenteeism and employee turnover), the 'ideal worker' is typically defined as someone without non-work commitments who can invest long hours into the workplace (HREOC, 2008; Diamond et al, 2007; Yasbek, 2002; Evans, 2001; Lewis, 1997; Marks, 1994).

These outmoded perceptions of the ideal worker are based on strictly gendered divisions between paid and unpaid work. With the prevalence of dual-income families, this construct must be challenged. However, social policy in countries such as Australia, the US and Britain continues to be informed by dated perceptions. Official unwillingness to tackle core social issues leaves a gap in policy guidance, to be filled by employers (Glass and Fujimoto, 1995).

Consequently, many work-life policies do not actually meet the needs of employees (Glass and Fujimoto, 1995). Employer-initiated policies are accused of marginalising part-time workers to jobs without career prospects ("mommy track" jobs – Lewis, 1996), and imposing full-time workloads into part-time hours. Such policies are tokenistic because employees fear career penalties from their use (HREOC, 2008; Whitehouse et al, 2007; Eaton, 2003; Junor, 1998; Lewis, 1997; Lewis, 1996). Even in countries such as Sweden and Norway – where social policy *is* informed by the notion of working mothers – many women (and men) do not take up work-life policies for fear of recrimination (Whitehouse, 2005; Haas and Hwang, 1995; McDonald, Brown and Bradley, 2005; Blair-Loy and Wharton, 2002).

This narrow focus neglects the role of organisational culture on the uptake of policies. Consequently, work structures create work-life conflicts that not only damage workers' health, but also affect their productivity (HREOC, 2008; Skinner and Pocock, 2008). Around 55 percent of people feel over-worked (Skinner and Pocock, 2008) and may change jobs in order to obtain work flexibility, resulting in a significant loss of skills and experience (US National Study of the Changing Workforce, in Glass and Estes, 1997). The Chamber of Commerce and Industry (ABC, 2008) recently highlighted the importance of work-life policies to women's work participation, and such policies are being investigated in the Productivity Commission's Parental Leave Inquiry.

A change in organisational culture is essential to reduce women's labour market disadvantages, and to help the economy retain valuable skills. The business case for employee-centred work-life policies must therefore be developed, especially as policy uptake depends upon supervisor and co-worker cooperation (Gray and Tudball, 2002; Glass and Fujimoto, 1995; Desai and Waite, 1991). As Eaton (2003) points out, "flexibility *formally* offered by the employer is insufficient as an indicator of flexibility available to the employee," and there is urgent need for organisational cultures that *genuinely* accommodate employees' non-work responsibilities.

CHAPTER 2: DATA

There are many potential influences upon women's labour decisions, and I require a rich dataset in order to access these variables. The two main Australian sources are the Parental Leave in Australia Survey (PLiAS),[1] and the Household Income and Labour Dynamics in Australia (HILDA) survey.[2] These are both longitudinal datasets, with confidentialised unit record files that provide a large number of variables.

While both datasets contain variables relevant to my study, HILDA is preferred for its size, sampling, and its lengthier time dimension. The PLiAS only samples women with newborn children (Whitehouse et al, 2006), while HILDA samples households and therefore includes broader population groups to which I can compare my sample.

Variables extracted from HILDA are listed in Appendix 1A, which incorporates descriptions and details on construction. Any missing data is dealt with using the modified zero-order method.[3] The suffix 'b' indicates the period 'before' the birth (t-1), while 'a' indicates 'after' the birth (t+1). A prefix of 'p' denotes partner information.

2.1 The HILDA Survey

The HILDA a longitudinal survey focusing on family, household formation, income and work. It is ideal for my analysis as it includes current and historical information on women and their families, and has proven to be useful in similar studies.[4] Release 6 of HILDA includes six waves of data collected between 2001 and 2006. This structure allows me to

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[1] See Chapter 1, Note 2.
[2] The HILDA is funded by the Department of Families, Housing, Community Services and Indigenous Affairs, and is administered by the Melbourne Institute of Applied Economic and Social Research, at The University of Melbourne.
[3] The modified zero-order method replaces all missing variables with a '0' value, whilst generating a dummy variable indicating whether the data is missing. I give missing data variables the suffix "MISS."
[4] For example, by Hosking (2007), Risse (2006), Edwards (2004). A full list of studies are available at the Melbourne Institute's website: http://www.melbourneinstitute.com/hilda/Biblio/default.html

follow individuals across time periods and compare labour market situations before and after childbirth.

The HILDA's size is also an advantage, with 19 914 individuals followed from Wave 1, and wave-on-wave attrition rates that are comparable to similar surveys (see Watson, 2008 p. 118). Labour market, housing and demographic variables have a similar distribution to external indicators, however attrition patterns mean higher skilled, married English-speaking people are over-represented in later waves (Watson, 2008 p.97 and p.103)

Information about respondents is sourced from a Person Questionnaire (PQ) and a Self-Completion Questionnaire (SCQ), while the Household Questionnaire (HQ) provides family, financial and geographic variables. As the HILDA is a household based survey, I can match information on respondents' partners to help capture the joint nature of work and care decisions.

2.2 Sample Selection

Following Hosking (2007), I create an unbalanced panel dataset in which women are observed for three consecutive time periods. These women are employed in wave 't-1,' have a birth/adoption event "in the last twelve months" at time 't' (the 'birth wave'), and remain in the dataset at time 't+1.'

The data does not distinguish adoption events from births, thus both are included (see Appendix 1B for further discussion). Henceforth, birth/adoption events will be collectively referred to as "births." The birth observations are taken from waves 2-6 (wave 1 did not collect the birth data).

The final sample includes 377 women, and 456 person-time observations (See Appendix 1B for derivation steps). 305 contribute one birth, 66 contribute two, 5 contribute three, and 1 contributes 4 births. The sample response rate of 90.65 percent is similar to the average 91.25 percent rate across all six waves of HILDA (Watson ed., 2008, p122). My sample is therefore broadly in line with the master data.

The final sample includes only person-time observations for which there are employment observations either one or two years before a birth. This captures the effects of pre-childbirth employment, and the two-year limit reflects the diminishing influence of workplace characteristics over time. Furthermore, employment experiences immediately before births are considered most relevant to post-childbirth decisions.

A sub-sample with long-term data is also derived, which captures longer-term mobility decisions (see Appendix 1B). As this requires data two years after a birth, only births occurring in waves 2, 3 and 4 are included. 221 women (237 person-time observations) stay in the sample for this length of time (205 contribute one birth, 32 contribute two births).

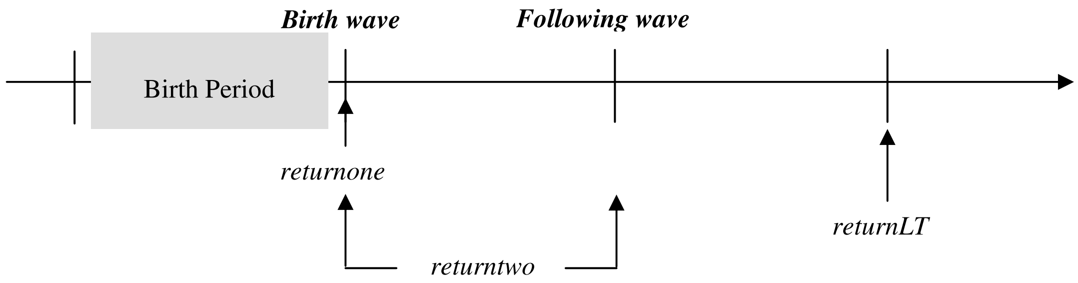
2.3 Dependent Variables

Working is classified as being employed either full-time or part-time, while respondents were not working if unemployed or not in the labour force (NILF). It is considered appropriate for the unemployed to be classed as "not working" (even though they are in the Labour Force) because they do not have employer information relevant to the mobility decision.

Measurement problems arise when I consider the meaning of "working," especially as women may technically be "employed" whilst on maternity leave. However, this definition of "working" is appropriate for this study's focus on work attachment, as it is more important for women to remain connected to their job.

The return to work decision is represented by *returnone, returntwo* and *returnLT. Returnone* and *returntwo* have 456 person-time observations, while *returnLT* has 256 (see Appendix 1B). Figure 3A illustrates the differences.

Figure 2A: Timeframes for Dependent Variables



Returnone is a binary variable of whether the respondent works in the same wave as the birth observation. However, it does not capture all decisions within 12 months of the birth. 107 respondents who have not returned by the birth wave actually return by the following wave (Table 2A).

Table 2A: Comparing Dependent Variables for Short-term Mobility Decisions:
returnone (working in the same wave as the birth is reported) versus *returntwo* (working in either the birth wave or following wave).

	returntwo		
returnone	**0**	**1**	**Total**
0	116	107	223
1	0	233	233
Total	116	340	456

The longer timeframe for *returntwo* captures 107 women who may have returned to work within 12 months, but whose decisions occurred after the HILDA interview.

Returntwo is therefore the preferred measure of short-term decisions, as it captures all women who return within 12 months of giving birth. While longer-term mobility is also of interest, preliminary tests on *returnLT* are highly imprecise (Appendix 2B) and this variable is not pursued. This likely reflects smaller sample size, and diminishing policy effects over the long timeframe. A detailed analysis of *returnLT* is provided in Appendix 1C.

When considering shorter-term decisions (*returnone* and *returntwo*), the timing of birth can be very important. Interestingly, women who give birth closest to the interview (0-3 months beforehand) have the highest rate of return in the birth wave (Appendix 1D). This may count those still on maternity leave, however this is unclear because HILDA does not include a separate variable for whether a woman is on maternity leave, and detailed calendar variables have not been investigated due to time constraints.

Another measurement problem arises from the "return to work guarantee" (*Workplace Relations Act 1996* (Cth)), which protects women's jobs for up to 12 months. The guarantee may bias estimates as it improves the chance of return to the pre-childbirth employer. This reflects broader problems differentiating between short and longer-term mobility. Women who return to work may later leave due to work-family conflict (see Diamond et al, 2007).

Around three-quarters of mothers returned to work for each of the two time periods (Table 2A). However, as *returntwo* extends to the wave *after* the birth wave, it censors observations with a birth in Wave 6. Sensitivity analyses are therefore conducted for a sub-sample of 351 observations from Waves 1-5. Table 2B shows that these women are more likely to return compared to the full sample (Table 2B).

Table 2B: Return to Work in the Short and Longer Terms

		Returned		Did not return	
Variable	**Freq**	**Number**	**%**	**Number**	**%**
returntwo	456	340	75.56	116	25.44
returntwo: Waves 1-5	351	294	83.76	57	16.24
returnLT	237	175	73.84	62	26.16

2.4 Key Explanatory Variables

The SCQ asks respondents about workplace opinions and perceptions. This includes the variables of interest: job-specific work-life policies, which are shown in Figure 2B. As the HILDA is not matched employer-employee data, respondents themselves provide the workplace information.

Figure 2B: The Question on Work-Life Policies, as it appears in the Self-Completion Questionnaire

D3 Following is a list of conditions and entitlements that employers sometimes provide their employees. For each, please indicate whether you, or other employees working at a similar level to you at your workplace, would be able to use these if needed.

(Cross ☒ one box on each line)

		Yes	*No*	*Don't know*
a	Paid maternity leave	☐	☐	☐
b	Unpaid maternity leave	☐	☐	☐
c	Parental leave	☐	☐	☐
d	Special leave for caring for family members	☐	☐	☐
e	Permanent part-time work	☐	☐	☐
f	Home-based work	☐	☐	☐
g	Flexible start and finish times	☐	☐	☐

Note: a question about the availability of employer-provided childcare or childcare subsidy is excluded from the analysis as it is only asked in waves 5 and 6.

However, this is advantageous because of discrepancies between formal policies reported by employers, and their actual availability to employees (Diamond et al, 2007; Budd and Mumford, 2006). Gray and Tudball (2002) find that the within-workplace variation in policy access is consistently larger than between-workplace variation, suggesting heterogenous policy availability. For example, professionals and management have high access to flexible start and finish times, but very little to permanent part-time work. This mirrors concerns raised by Lewis (1996) and Whitehouse (2005) that formal policies do not represent family-friendly organisational cultures, as employees may perceive career disadvantages from the uptake of work-life policies.

That HILDA provides worker's *perceived* access to policies is therefore more suitable for my study, as workers can only respond to policies they know about, rather than formal entitlements of which they may not be aware. Appendix 1E details the treatment of missing data, as well as comparisons of policy distribution in my sample and the broader HILDA sample. Observations in my sample have a higher rate of policy access than a comparable age group in the HILDA, especially regarding to Unpaid Maternity Leave. This indicates potential sample selection effects which are addressed in Chapter 3.

One problem with the SCQ question is the ambiguity of "parental leave." In its common use, parental leave includes maternity, paternity and related leaves. However the inclusion of separate paid and unpaid maternity clouds its definition. Respondents are assumed not to incorporate paid maternity leave into the definition of parental leave (so parental leave may mean paternity or adoption leave). Appendix 1F contains further analysis.

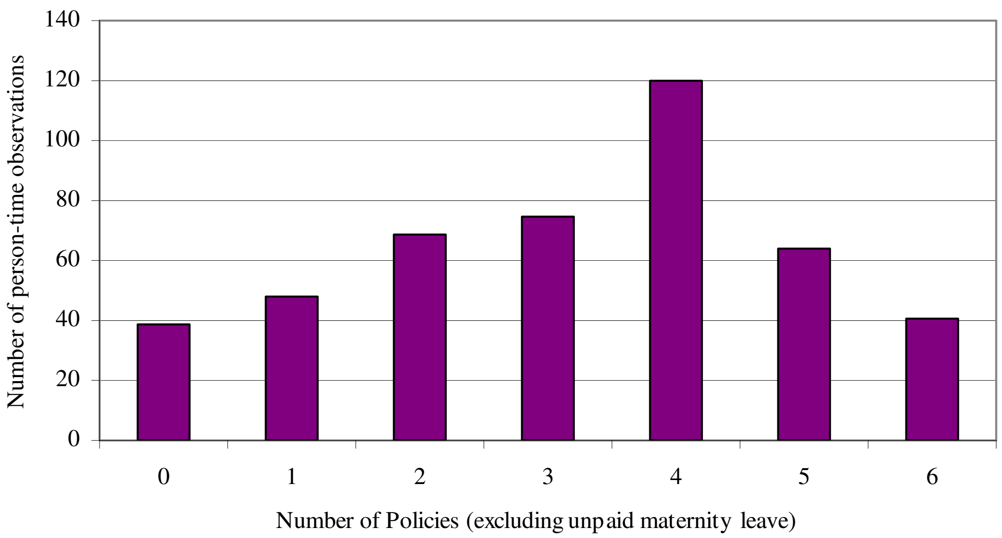
Relationships between different types of leave could stem from either confusion in the definitions, or from collinearity (which may occur as such policies are usually offered as a package of benefits – Gray and Tudball, 2002). Although the correlations between policies are not very large (Appendix 1G), aggregate policy measures are constructed to address these definitional issues, as well as to increase variation in the key explanatory variables.

Following Blair-Loy and Wharton (2002), policy variables are aggregated to separate maternity from general policies. I create the dummy variables: *anyEmaternityb* (paid maternity leave, or parental leave) and *anyEgeneralb* (permanent part-time work, home-based work, flexible start and finish times, special leave to care for family members). As Unpaid Maternity Leave is a legislated entitlement (*Workplace Relations Act, 1996* (Cth)), it is separated from the aggregated variables. The results are not sensitive to the inclusion of Unpaid Maternity Leave within the aggregated variables (results available on request). An interaction term, *bothEpoliciesb* accounts for the inclusion of both policies, while *anyEpolicyb* equals one if the respondent can access any employer-provided policy. As before, the 'b' suffix denotes the pre-childbirth period.

The majority of women can access at least one type of policy (Appendix 1E.2), making it difficult to isolate individual policy effects. The high proportion of respondents with access to employer-provided policies may reflect self-selection and endogeneity problems, as women with access to such policies may be more likely to have children.

However, these aggregated variables do not reflect the degree of employer-responsiveness. To address this, I create a count variable (*totEpoliciesb*) of the number of employer-provided policies. Again, Unpaid Maternity Leave (*unpaidMLb*) is excluded from this functional form. The distribution of *totEpoliciesb* (Figure 3C) shows the most frequent number accessible is 4, though the average is 3.

Figure 2C: Distribution of Employer-Provided Policies



2.5 Control Variables - Employment Related

2.5.1 Respondents' Employment Characteristics

Employment variables are taken from the pre-childbirth job, as this best reflect respondents' preferences and future plans. I capture job-specific effects on work decision with variables for status (*parttimeb, fulltimeb*), job contract (*permanentb, casualb, fixtermb*), and workplace characteristics. Work experience (*experb*) and tenure (*tenureemp*, *tenureoccb*) reflect the accumulation of specific and general skills (see Gray and Tudball, 2002).

As the present study focuses on work-attachment and not labour supply, I do not include the hours of work. However dummy variables (*prefmorehrsb, preflesshrsb, prefsamehrsb*) indicate hours preferences, capturing key issues for work-life balance (Skinner and Pocock, 2008).

Occupation is another important characteristic, particularly as occupational categories reflect skill levels (Risse, 2007; Gray and Tudball, 2002). The 9 Australian Standard Classification of Occupations (ASCO) categories are grouped as *highskilledb, medskilledb, lowskilledb* (Table 2C). To assess sampling problems, sample statistics are compared with the population distribution of occupations[5]

Table 2C: Final sample by Occupation
The sample is compared with the 2001 population distribution for women.

ASCO 1-digit Category	Freq	Sample %	Pop'n %	Generated Variables	Freq	Sample %
Managers and Administrators	22	4.82	5.71			
Professionals	178	39.04	21.20	*High-Skilled*	247	54.17
Associate Professionals	47	10.31	11.45			
Tradespersons and Related Workers	8	1.75	2.99			
Advanced Clerical and Service Workers	30	6.58	7.32			
Intermediate Clerical, Sales and Service Workers	108	23.68	26.03	*Med-Skilled*	150	32.89
Intermediate Production and Transport Workers	4	0.88	2.47			
Elementary Clerical, Sales and Service Workers	37	8.11	13.89	*Low-Skilled*	59	12.94
Labourers and Related Workers	22	4.82	7.05			
Total	456	100	98.11*		456	100

*The remaining categories are "inadequately described" and "not stated"

Professionals are significantly over-represented, while the bottom three occupational categories are under-represented. This reflects attrition patterns in the HILDA (Watson (ed)

[5] The population distribution is available for the Census years of 2001 and 2006, however a change in the 2006 classification codes makes it inconsistent with the HILDA codes. For this reason, the sample is compared to the 2001 Census distribution (ABS 2001a).

2008, p.97), and may indicate selection problems. Professional women may be more likely to have a pre-childbirth job as they are highly skilled and have higher costs of not working.

2.5.2 Employer Characteristics

Employer characteristics affect respondents' access to leave policies, employment opportunities, and a host of other work-life balance issues. The pre-childbirth industry reflects the influence of product markets upon the derived demand for labour. Competitive product markets increase labour demand, which may affect return to work decisions. This is especially so if work-life policies are offered as a retention tool (Glass and Fujimoto, 1991). The generated industry dummy variables (Table 2D) are based on Australian and New Zealand Standard Industry Classification (ANZSIC).[6]

There is an over-sampling of women in Manufacturing; Finance and Insurance; Education; and Health and Community Services. This may reflect selection bias if women choose these occupations because they are deemed family-friendly, and such women are consequently more likely to have children and be in my sample.

Another important influence is sector of work (*governmentb*), for example government jobs tend to provide more policy benefits (Risse, 2007, Gray and Tudball, 2002, also see section 1.4.6, above). The size of employers (*employerU100b, employerO100b)* and workplaces (*workplaceU20b, workplaceO20b*) also matters, especially as there are legislative equal opportunity requirements of large employers (*Equal Opportunity for Women in the Workplace Act, 1999* (Cth)). While large organisations are more likely to offer formal policies, informal benefits that depend upon supervisor cooperation may be more likely in small firms (Glass and Fujimoto, 1995). Therefore workplace size may have a different effect to employer size. Missing data is analysed in Appendix 1H.

[6] As is the case with occupations, the sample industry distribution is compared to the 2001 Census' population distribution (ABS 2001b).

Table 2D: Final sample by Industry
The sample is compared with the Census 2001 population distribution for women.

<table>
<tr><th>ANZSIC 1-digit Category</th><th>Freq</th><th>Sample %</th><th>Pop'n %</th><th>Generated Variables</th><th>Freq</th><th>Sample %</th></tr>
<tr><td>Agriculture</td><td>6</td><td>1.32</td><td>2.67</td><td rowspan="3">Primary Industries</td><td rowspan="3">12</td><td rowspan="3">2.63</td></tr>
<tr><td>Mining</td><td>2</td><td>0.44</td><td>0.27</td></tr>
<tr><td>Electricity, Gas and Water Supply</td><td>4</td><td>0.88</td><td>0.32</td></tr>
<tr><td>Construction</td><td>7</td><td>1.54</td><td>7.16</td><td rowspan="4">Intermediate Industries</td><td rowspan="4">64</td><td rowspan="4">14.04</td></tr>
<tr><td>Manufacturing</td><td>29</td><td>6.36</td><td>1.97</td></tr>
<tr><td>Wholesale Trade</td><td>13</td><td>2.85</td><td>3.76</td></tr>
<tr><td>Transport and Storage</td><td>15</td><td>3.29</td><td>2.43</td></tr>
<tr><td>Retail Trade</td><td>46</td><td>10.09</td><td>16.95</td><td rowspan="3">Retail and Hospitality</td><td rowspan="3">85</td><td rowspan="3">18.64</td></tr>
<tr><td>Personal and other services</td><td>12</td><td>2.63</td><td>6.14</td></tr>
<tr><td>Accommodation, Cafes and Restaurants</td><td>27</td><td>5.92</td><td>3.78</td></tr>
<tr><td>Communication Services</td><td>7</td><td>1.54</td><td>1.35</td><td rowspan="3">Business, Finance and Property</td><td rowspan="3">82</td><td rowspan="3">17.98</td></tr>
<tr><td>Finance and Insurance</td><td>32</td><td>7.02</td><td>4.69</td></tr>
<tr><td>Property and Business Services</td><td>43</td><td>9.43</td><td>11.35</td></tr>
<tr><td>Government Administration and Defence</td><td>19</td><td>4.17</td><td>4.43</td><td rowspan="2">Government Administration, Defence and Education</td><td rowspan="2">98</td><td rowspan="2">21.49</td></tr>
<tr><td>Education</td><td>79</td><td>17.32</td><td>10.90</td></tr>
<tr><td>Health and Community Services</td><td>101</td><td>22.15</td><td>16.86</td><td rowspan="2">Health, Community and Cultural Services</td><td rowspan="2">115</td><td rowspan="2">25.22</td></tr>
<tr><td>Cultural and Recreational Services</td><td>14</td><td>3.07</td><td>2.58</td></tr>
<tr><td>Total</td><td>456</td><td>100</td><td>97.62*</td><td></td><td>456</td><td>100</td></tr>
</table>

*The remaining categories are "non-classifiable economic units" and "not stated"

2.6 Control Variables – Not Employment Related

Some personal, household and situational variables help control for non-employer influences on work decisions. They capture the respondent's opportunity cost of working, family considerations, personal preferences, and situational factors.

2.6.1 Personal Background and Education

Whether the respondent is from a Non-English Speaking Background (*NESB*) is included as it captures personal and cultural influences upon work decisions, as well as reflecting language difficulties that may impede work participation. However, over 95 percent of the sample are from an English-Speaking Background, which may reflect HILDA's attrition patterns (Watson (ed), 2008 p97).

The respondent's *age* and education (*yr12andunder, diplomacert, degreeplus)* control for institutional factors affecting access to work, while family background variables capture influences upon ideals of family size and work-family balance. Parent's work and occupational status proxy unobserved influences upon women's educational and career level before they have children (*motherwk, fatherwk, motherocc, fatherocc*). The number of *siblings* captures fertility preferences (Newman, in Teutsch, 2008).

2.6.2 Income (all values are in 2006 dollars)

The respondent's pre-childbirth wage/salary (*wageb*) represents their direct opportunity cost of not working. It also reflects their levels of human capital, as remuneration tends to be higher for those with greater skills and experience. While HILDA provides other market income (rent, interest and profit), labour income best reflects the value of respondents' time.

Other income includes government transfers and partner's income. Government transfers include Family Tax Benefits A and B (*ftben, ftbena*); the childcare benefit *(ccareben, ccarebena*); and the maternity benefit or "Baby Bonus" (*matben, matbena*). These are sourced from the post-childbirth period, as respondents are presumed to know their eligibility for benefits when making return-to-work decisions.

The partner's pre-childbirth wage/salary (*pwageb*) indicates the financial need for respondents to work. Pre-childbirth information is used because the majority of wages change between pre and post-childbirth waves (see Appendix 1I). While wage variations are expected in these time periods, the change may endogenously relate to the respondents' return to work decision.

2.6.3 Family Formation and the Timing of the Birth

Family variables represent the effects of family size and fertility, and help capture the joint nature of work and childrearing decisions. This includes relationship status (*single*), which is a standard inclusion in the literature. Detailed partner information is in section 2.6.5.

The presence of children is expected to influence initial work status, as well as the return to work decision. I use a variety of variables for this effect, including the number of children under 4 (*children04*), and whether the respondent had parental responsibilities for children under 17 (*parespb*). The latter is more appropriate than total fertility because some children may be stepchildren or adopted. *Newmum* captures the effects of new mothers, who are more likely to have been working full-time and more likely influenced by employer policies (Desai and Waite, 1991). *Multibirths* indicates whether women contributed multiple births in the sample period, accounting for unobserved effects of lengthy work absences, as well as preferences towards childbirth during the sample period.

The timing of the birth is also a crucial influence upon respondent's work decisions. This is included as a series of dummy variables (*birthq1, birthq2, birthq3, birthq4*). It also addresses some measurement problems associated with *returntwo* - women giving birth very soon before the birth wave face a very different decision than those with earlier births.

2.6.4 Household and situational information

Apart from the care of children, women usually face larger burdens of unpaid work, which affect their labour force participation and demand for flexible employment. This is addressed by including the hours spent caring for elderly or disabled dependents (*careb*), and hours doing housework (*houseworkb).* An index of childcare availability is also included (*childcarea*). These variables are sourced from the pre-childbirth period, as the post-childbirth data is potentially endogenous in the return to work model.

Geographical influences are captured by the Australian Bureau of Statistics' 2001 Socio-Economic Indexes for Areas (SEIFA), as socio-economic disadvantage (*SEIFAsocio*), economic resources (*SEIFAecon*), and education and occupation (*SEIFAeduc*). Time spent commuting is also included (*travelb*).

2.6.5 Partner Information

As work and fertility decisions are made jointly, information about the respondents' partners is an important control (McRae, 1994). Partners' household participation is taken from the pre-childbirth period, as this indicates the historical share of unpaid work (*phouseworkb*) during the respondent's wave of pre-childbirth work. This captures the effect of family structures on work decisions. Post-childbirth household participation is not included as it may be endogenous. For example, the partner's share of housework may increase *because* the respondent has returned to work.

The partner's post-childbirth employment information (see Appendix 1A), however, is not considered to be endogenous. This is because household income plays an important role in the decision to have children (Weston et al, 2004) and the data reveals that a small percentage of partners change their employment details (see Appendix 1I). Partner's job status, contract, industry, occupation, and access to work-life policies are included in the estimation, as they affect "other income" and utility from non-market time (see Chapter 3). Note that Appendix 1I amalgamates job contract into the variable *pcontract*.

CHAPTER 3: THEORY AND ECONOMETRIC APPROACH

3.1 A Modified Theory of Time Allocation

This study is based on neoclassical models of time allocation and labour supply, which assume that work decisions depend on market and non-market influences upon individual utility (for a comprehensive explanation, see Becker, 1965; Blau, Ferber and Winkler, 2005; Ehrenberg and Smith, 2006). This approach is applied to the period of maternity leave, during which women do not work but make decisions about workforce re-entry. These decisions are assumed to maximise utility from all aspects of time allocation - market work, non-market work, and leisure. Following Becker (1965) and Blau, Ferber and Winkler (2006), I assume that:

(i) time spent in market work represents the value of market goods and services that can be purchased with the income earned; and

(ii) all non-market and leisure time is spent producing non-market goods and services.

The second assumption arises from difficulty distinguishing between non-market time and leisure time. Whilst generally unrealistic (Apps, 2002; Gronau, 1977), it is appropriate here because mothers of newborn children face large demands and may not have conventional leisure time. Time constraints prevent the use of detailed time-use data that is preferred for such models (Apps and Rees, 2005; Apps, 2002). However this is not problematic because I am investigating mobility and not the quantity of labour supply. Furthermore, Gronau's (1977) assumption that market and home-produced goods are perfectly substitutable is inappropriate in the present situation. The advantages of home-based care of newborns (see section 1.4.2) make it an imperfect substitute for market childcare.

Both market and non-market goods and services are inputs into commodities, and it is from these commodities that individuals derive utility (Becker, 1965). Non-market time is assigned a monetary value because non-market production can substitute market purchases (for example, childcare services). Therefore, the true cost of market work includes foregone non-market production.

The commodities that enter into the utility equation incorporate the inputs of market and non-market production. I will again use the example of childcare as it is particularly relevant in this context. Childcare can be entirely market-based if, say, a nanny is hired; or it can have both market and non-market inputs if parents undertake some care themselves whilst also purchasing childcare services.

One advantage of assuming that utility is derived from commodities, and not directly from the time / goods themselves, is that it allows for substitution between market and non-market time when costs change (Becker, 1965). This is especially important given the changing opportunity cost of work after children are born. Following Becker (1965), the vector of commodities consumed by individual i is expressed as:

$$Z_i = f_i\,(x_{i,}\, T_i^N) \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \qquad (1)$$

where x_i is the value of market time / market purchases, and T_i^N is the amount of time spent in non-market activities. The individual utility function depends upon utility from these commodities:

$$U_i = U\,(Z_i) \;=\; U\,(x_{i;}\, T_i^N) \quad . \quad . \quad . \quad . \quad . \quad . \qquad (2)$$

Individuals maximise this utility subject to their income (I), which consists of their personal income (W_i) and other income (V_i) (Becker, 1965). Personal income consists of wages and salaries earned by the individual, while other income includes financial contributions of partners and other household members, as well as government transfer payments. These affect an individual's consumption of market goods, as well as their need to work. All income is assumed to be spent on market goods and services, therefore the individual's budget constraint is:

$$p_i x_i = I_i = W_i + V_i \quad . \quad . \quad . \quad . \quad . \quad . \quad . \qquad (3)$$

where p_i is the unit price of market goods and services, which is normalised to 1. From assumption (ii), the time spent on market work is equivalent to the value of market goods and services purchased, therefore personal and other incomes can be written as:

$$W_i = x_i^W = w_i T_i^W \text{, and} \quad . \quad . \quad . \quad . \quad . \quad . \qquad (4)$$

$$V_i = x_i^V \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \qquad (5)$$

Here, w_i is the pay rate per time unit of market work, T_i^W is the time spent working, and x_i^W and x_i^V respectively denote goods purchased from personal income from those purchased with other income. The time constraint must also be noted:

$$T_i = T_i^W + T_i^N \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \qquad (6)$$

where T_i represents total time available. The budget constraint can thus be re-written as:

$$I_i = x_i = x_i^W + x_i^V = w_i T_i^W + x_i^V \quad . \quad . \quad . \quad . \quad . \qquad (7)$$

and the utility maximisation condition is now:

$$\max U_i = U(w_i T_i^W + x_i^V, T_i^N)$$

$$\text{subject to: } I_i - w_i T_i^W - x_i^V = 0 \quad . \quad . \quad . \quad . \quad . \qquad (8)$$

Individuals are therefore assumed to choose their hours of work based upon their respective utilities from market and non-market goods and services. They have a choice between time spent working for market-based purchases, and time spent producing non-market goods and services.

The HILDA provides a rich set of controls variables, which correspond to the various elements of the utility function:

- Income per labour unit (w_{i}) enters the utility equation positively, and represents returns to human capital from education, training and work experience; occupational characteristics; and indirect factors such as communication skills and labour demand.
- Utility from time spent working (T_i^W) depends upon similar variables as per-unit labour income (w_{i}), whilst also capturing work-life conflict, the effects of work-life policies, work preferences, and varying demands from different occupations and industries. T_i^W is expected to enter concavely to reflect diminishing marginal utility from excessive work.
- Market goods purchased with other income (x_i^V) are expected to have a negative impact on the utility from work. This is likely key influence on return to work decisions, and is expected to have a negative relationship with hours of work (T_i^W). Therefore, it is important to consider income from partners and government transfers, as well as constraints on work such as childcare costs.
- The division of labour between market time (T_i^W) and non-market time (T_i^N) is also controlled for with family background variables (capturing parental influences on career and family ideals); and household influences including time spent on household chores and caring for dependents. Partner's non-income variables are also important, as having partners in stressful occupations or industries may increase the respondent's utility from non-work time T_i^N, while partners in flexible jobs are better able to share household responsibilities and thus increase utility from T_i^W.

Details about the control variables are available in Chapter 2 and Appendix 1A. Section 3.3.1 illustrates the relationships between the variables and the labour supply / work participation decisions using the example of Other Income.

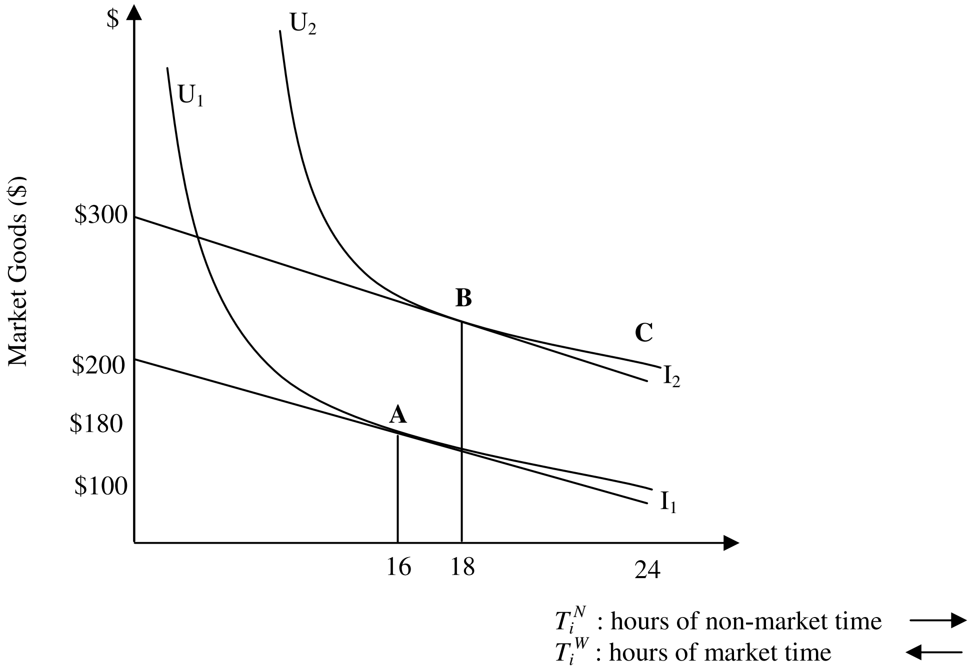
3.1.1 The influence of Non-Labour Income upon work decisions

I use Non-Labour ("Other") Income (V^i or x_i^V) to illustrate the influence of control variables upon the respondent's utility. Figure 3A is based on Blau, Ferber and Winkler (2006, p103) and explain the influences upon the division of time. As market income is spent on market goods (assumption (i)), the vertical axis represents the value of market goods in dollars ($). Hours of market and non-market time are represented by the horizontal axis. The utility function (U_i) is represented by indifference curves, and shows a negative relationship between non-market time and market goods. This is expected as fewer hours of market time reduce the consumption of market goods, while preferences for non-market time (such as spending time with children) reduce the utility from market time. I_i is the budget constraint, incorporating both labour and other income ($I_i = w_i T_i^W + x_i^V$).

To illustrate the impact of Other Income, consider a woman at two different points after the birth of her child. The first is immediately after the birth (Figure 3A), during which she has $100 of non-labour (other) income received when all 24 hours of the day are spent in non-market activities. She maximises utility at point A: when the marginal utility from an extra hour of work equals their marginal utility from an extra hour of non-market time. 16 hours per day are spent on non-market activities (including sleeping, eating and looking after children), and 8 hours are spent at work earning $10 per hour. Total income is thus $180.

However, an increase in other income (for example, a rise in partner's income, or paid maternity leave) means that a higher utility level is reached by substituting market time with non-market time. This is likely to occur immediately after a birth, as mothers prefer to extend maternity leave where possible (Baxter, 2008) and may derive greater utility from spending time with newborn children rather than purchasing childcare services.

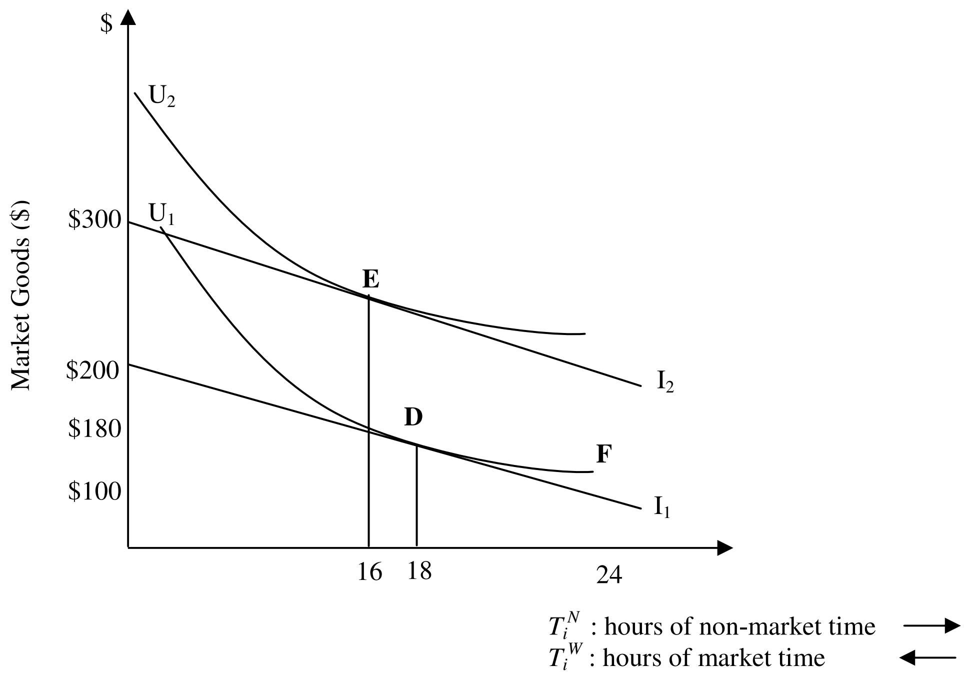
Figure 3A: The Effect of Other Income on Participation – Immediately After Giving Birth



The effect upon work participation depends on women's ability to balance this market and non-market time. If employers allow a reduced workday (to 6 hours), then the individual maximises utility at point B and remains in work. If market time is conceptualised as time spent physically at work, then flexibility provisions such as working from home and flexible hours also help to maintain attachment. However, if employers are inflexible and demand 8 hours a day, the individual is better off at point C and not working at all.

To illustrate the importance of timing, consider the same individual six months after giving birth (Figure 3B). This period reflects a time after which many women seek a return to work (especially given breastfeeding guidelines – WHO, 2008), however other time periods may be substituted. The utility curves are flatter than in Figure 3A, indicating that each hour of market time has higher utility than it did immediately after the birth. This may be because mothers wish to work, and may be more comfortable with purchased childcare. The budget constraints are the same as before.

Figure 3B: The Effect of Other Income on Participation – Six Months After Giving Birth



Assuming Other Income of $100, a mother could return to her previous job if she was able to work 6 hours per day, or alternatively, needed to be physically at work for 6 hours. Inflexible employment might induce women to change to jobs with the preferred conditions. A lack of flexible jobs means utility is maximised at point F, forcing a withdrawal from the workforce.

However, an increase in other income (to I_2) would induce a substitution of non-market time with market time. Extra income may purchase services otherwise produced in non-market time, such as childcare, thus allowing women to work an 8-hour day. This improves their access to jobs and ability to work, as well as increasing utility to U_2.

It can be seen that non-labour income has a very different effect upon work participation depending upon women's preferences. If other income is not available when women wish to re-enter work, then flexible employment conditions are crucial influences upon work status and employer mobility. The same payment (such as paid maternity leave) could play a role in both non-market work (soon after the birth), and market work (for example, six months after the birth).

3.2 Issues of Endogeneity and Selection

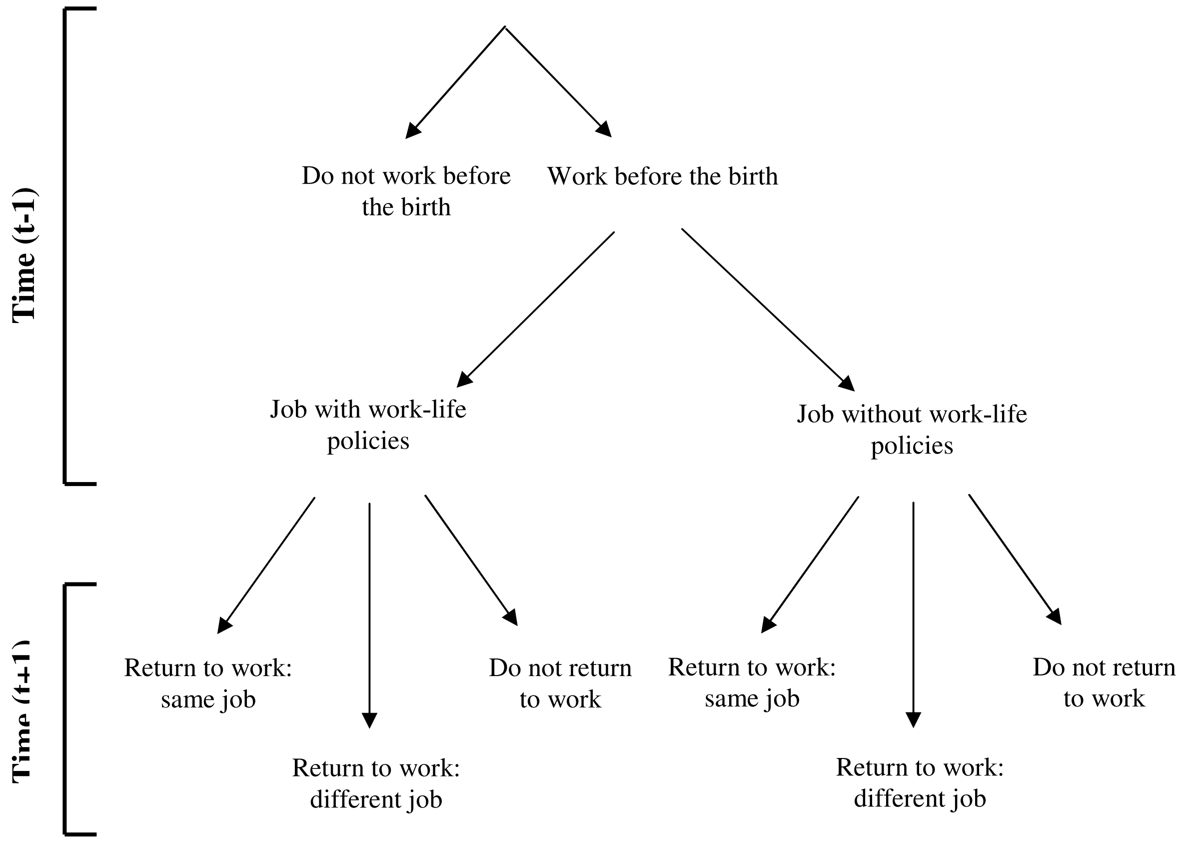
My population involves women who are in the workforce before giving birth, thus work-life policies may be endogenous if the same unobservables affect both the initial choice of job and the return to work decision. Section 2.5 shows that a large percentage of women are in hospitality, education and healthcare – industries that are female-dominated and possibly considered 'family-friendly.' Furthermore this study over-samples women in these industry groups, as well as those in high-skilled occupations.

However, this non-random sampling is addressed with the inclusion of control variables, and should not bias policy estimates. This is also the reason why I do not employ longitudinal sample weights. These weights are based on attrition patterns (such as age, employment status, education and occupation – see Watson, 2008 p.123), many of which I account for with control variables.

Non-random sampling may, however, create endogeneity bias if it relates to the fertility decision itself. Women may choose their pre-childbirth job based upon their fertility plans and preferences, and thus be in jobs with more work-life policies. Unobserved preferences and cultural values may also affect initial job choices and therefore return to work decisions, creating endogeneity bias upon policy estimates.

The decision tree in Figure 3C shows both endogeneity and selection biases. Selection bias occurs in the initial decision to work. Assuming all women have the same fertility intentions, only women in certain industries or occupations may be able to combine work and child rearing, and therefore be working in the first place. As I focus on women who *already* work, I do not model selection bias but instead focus on the second stage of the decision tree - the choice between jobs with or without work-life policies.

Figure 3C: The Decision Making Process for jobs before childbirth [time (t-1)], and after childbirth [time (t+1)].



Note: 'job' denotes employer, occupation or industry. Returning to the same job in (t+1) is not considered to be conditional upon returning to work, because the pre-childbirth job captures the ability to work. Furthermore, the return-to-work guarantee and potential conditions attached to paid maternity leave (discussed in Chapter 2) make a conditional "return to job" decision inappropriate for models of employer mobility.

It is reasonable to focus on the endogeneity of policy variables, because factors affecting endogeneity are also likely to affect selection, especially for women who already have children. If self-selection into pre-childbirth employment depends upon the perceived ability to balance work with fertility, then controlling for the endogeneity of work-life policies captures the selection effect.

Given the similar influences on both types of bias, it is useful to consider studies that address both selection and endogeneity in pre-childbirth jobs. Desai and Waite (1991) use workplace variables (sex composition, proportion of women working part-time, the proportion of women with children under 3 years of age) and a commitment variable (desire to be working at age 35) to control for selection into "family friendly" jobs. They run a Probit model of return to work within 3 months of birth, and find these variables statistically insignificant. Flexibility policies are found to impact women *without* long-run preferences for work, indicating those with lower withdrawal costs need greater incentives to remain in work.

Desai and Waite assume that workplace characteristics determine the availability of policies. However, Gray's and Tudball's (2002) finding of heterogenous policy distribution within workplaces suggests that respondents select into particular *jobs*, and not just employers. Using a Bivariate Probit model, McRae (1994) finds that flexibility features have significant effects upon the return-to-employer decision, however she does not address endogeneity arising from the initial allocation of jobs.

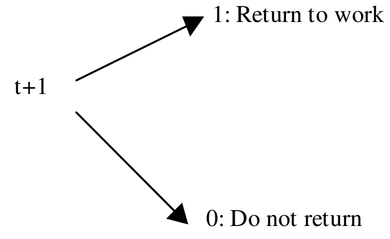
Given the difficulties accounting for endogeneity and selection, I consider it appropriate to avoid a direct model of selection bias. Furthermore, it is simplistic to assume women's reasons for working hinge upon their fertility plans. In an age and year group comparable to my sample, 71 percent of Australian women were in the labour force (ABS, 2006). This large group is likely affected by a myriad of influences, increasing the problems of isolating fertility-related selection bias. The abovementioned indirect treatment of selection bias is therefore considered the best approach.

3.3 Return to work following maternity leave: Econometric Approach

3.3.1 Applying the Theory to Participation Decisions

After maternity leave, women have the choice of whether or not they return to work. This *return to work* decision arises in the post-childbirth period (t+1). It is assumed to be between two alternatives – either a return to work or no return to work – and collapses the first two choices of Figure 3C in time (t+1).

Figure 3D: The Return to Work Decision



While the conventional approach to labour participation assumes that individuals work when their market wage, w, is higher than their reservation wage, w^* (see Blau, Ferber and Winkler, 2005; Ehrenberg and Smith, 2006), the theoretical approach here assumes that non-market time can also be productive. Therefore, the return to work decision is modelled on overall utility, and not just on the wage.

The utility function established in section 3.1 affects two aspects of work decisions: the participation decision, and the amount of labour supplied. This study focuses on the former, and models the unobserved utility from work, U_i^*. Each individual has this inherent preference for work, which is affected by factors relating to time allocation. These factors (w_i T_i^W, x_i^V and T_i^N) are incorporated into the utility function (U_i) so that the work decision is determined by the difference between U_i and U_i^*. Representing this within a random utility framework gives:

$return\ to\ work_i = 1$ if $U_i > U_i^*$, and . . . . (9)

$return\ to\ work_i = 0$ if $U_i \leq U_i^*$ . . . . . (10)

As illustrated in section 3.3.1, work-life policies are expected to positively influence U_i. For example, part-time work may reduce disutility from excess hours, while flexibility provisions may reduce work-life conflict by helping work schedules match household responsibilities. Such policies are therefore expected to increase the probability of a return to work.

3.3.2 Econometric Framework

The econometric framework follows the labour market transitions of women around childbirth, and models the influence of work-life policies upon these transitions. It is based on the work of Rhum (1990), Desai and Waite (1991), McRae (1994), Neal (1995) and Hosking (2007). The focus here is upon 'push' factors affecting mobility, that is, characteristics of the original employer upon the transitions decision.

A latent variable approach is employed, with y_i^* (the return to work outcome variable), being analogous to the utility from work (U_i) in equations (9) and (10):

$return\ to\ work_i = 1$ if $y_i^* > 0 \equiv U_i > U_i^*$ . . . . (11)

$return\ to\ work_i = 0$ if $y_i^* \leq 0 \equiv U_i \leq U_i^*$ . . . . (12)

Both variables *returntwo* and *returnone* are used as the *return to work* dependent variable, and independent variables include the key work-life policies, as well as the controls (See Chapter 2, and Appendix A.2A).

As discussed in Section 3.2, the heterogeneous distribution of policies potentially creates endogeneity. This is addressed using two methods in Stata: Instrumental Variables Probit (IV Probit), and Bivariate Probit. For models with *returntwo,* the 2006 sample is censored because 2006 is the final year of the sample, thus women giving birth in Waves 6 are only tracked in this wave. Sensitivity analysis therefore excludes Wave 6 births.

3.3.3 Probit with Instrumental Variables (IV Probit)

The first model employed is a Probit with a binary outcome (the return to work decision), and continuous endogenous regressor (*totEpoliciesb*). Equation (13) is the reduced form equation, estimating the number of policies accessible, while (14) represent the outcome equation with the endogenous treatment. The unobserved propensity for returning to work (y_2^*) depends upon factors influencing utility ($w_i\, T_i^W$, x_i^V and T_i^N), which are re-arranged to distinguish the key variables of interest. The access to work-life policies also depends upon these variables:

$$y_{i1} = x_{i1}'\beta_1 + v_i \qquad (13)$$

$$y_{i2}^* = \delta y_{i1} + x_{i2}'\beta_2 + u_i \qquad (14)$$

Where:

y_{i1} is the number of work-life policies available in individual 'i's' pre-childbirth job
y_{i2}^* is individual 'i's' unobserved propensity to return to work
x_{i1}' is a vector of influences on the availability of work-life policies
x_{i2}' is a vector of personal, employment, household and environmental characteristics both before and after the birth

$$\begin{pmatrix} v_I \\ u_I \end{pmatrix} \sim BVN\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_V^2 & \rho\sigma_V \\ . & 1 \end{bmatrix}\right]$$

The error terms (u_i and v_i) are correlated by ρ (rho), such that (following the notation of Winkelman and Boes (2006), p117):

$$u_i = \theta v_i + \varepsilon_i \text{ where } \varepsilon_i \sim N(0, 1-\rho^2)$$

therefore the outcome (14) can be re-written as conditional on the error of equation (13):

$$y_{i2}^* = y_{i1} + x_{i2}'\beta_2 + \theta v_i + \varepsilon_i \qquad (15)$$

Stata's *ivprobit* command allows me to predict y_{i1} using OLS, save the residuals (v_i), and then run a Probit regression of Pr ($y_{i2} = 1$) on the regressors and these residuals. This two-step approach of Rivers and Vuong (1988) allows a Wald test of exogeneity, which tests the hypothesis H_0: $\theta = 0$.

It is difficult to find an exogenous variable that affects policy availability but not the return to work decision. This is especially so if pregnancies are planned and women choose jobs with the intention of returning to them after the birth. The choice of instrument relies on the assumption that personal, household and career characteristics before the birth (in period (t-1)) reflect women's preferences about combining work and non-work commitments (Gray and Tudball, 2002; Risse, 2007; McRae, 2007; Desai and Waite, 1991). Consequently, the number of policies is regressed upon history variables (from time t), and a variety of non-employer variables from before the birth (period (t-1)).

Variables in the outcome equation are taken from both the pre-childbirth and post-childbirth periods (see Appendix A.2A for detailed descriptions). *Government benefits* are considered 'income,' but are taken from the post-childbirth period. The reduced form equation is:

$$y_{i1} = f\ (\textit{family background}_{(t)},\ \textit{personal characteristics}_{(t)},\ \textit{employment characteristics}_{(t-1)},\ \textit{family formation}_{(t-1)},\ \textit{situational influences}_{(t-1)},\ \textit{partner's pre-childbirth employment}_{(t-1)}\ ) \quad . \quad . \quad . \quad . \qquad (16)$$

While the outcome equation is:

$$y_{i2}^{*} = f\ (\ y_{i1},\ \textit{personal characteristics}_{(t)},\ \textit{employment characteristics}_{(t-1)},\ \textit{employer characteristics}_{(t-1)},\ \textit{income}_{(t-1)},\ \textit{government benefits}_{(t+1)},\ \textit{family formation}_{(t-1)},\ \textit{household information}_{(t-1)},\ \textit{situational influences}_{(t-1)},\ \textit{partner's pre-childbirth household participation}_{(t-1)},\ \textit{partner's pre-childbirth income}_{(t-1)},\ \textit{partner's post-childbirth employment}_{(t+1)}\ ) \quad . \quad . \quad . \qquad (17)$$

Only *family background* and *partner's pre-childbirth employment* belong exclusively to the reduced form equation. However, partner's employment variables do not change significantly between the pre and post-childbirth periods (see Section 2.6.5 and Appendix 1I), thus they are expected to have a similar impact in both equations. Consequently, the IV Probit relies upon *family background*, which is likely to relate to personal characteristics (such as education) and not be exogenous. It may therefore be difficult to use the count variable (*totEpoliciesb*) as the endogenous regressor. The alternative is to use binary policy variables (see Section 2.4), for which a Bivariate Probit model is more suitable.

3.3.4 Bivariate Probit

Unlike IV Probit, Bivariate Probit does not require the exclusion of instruments for identification. However, it is only appropriate for use with binary endogenous variables when assumptions of normality can be applied to the error terms. The Bivariate Probit performs joint maximum-likelihood estimation of the outcome and reduced form equations, which are similar to equations (13) and (14) in IV Probit, however the endogenous policy variable is now latent (following the notation in Knapp and Seaks, 1998; and Greene, 2003 p710):

$$y_{i1}^{*} = x_{i1}'\beta_1 + v_i \qquad (18)$$

$$y_{i2}^{*} = \delta y_{i1} + x_{i2}'\beta_2 + u_i \qquad (19)$$

Where:

y_{i1}^{*} is individual 'i's' unobserved access to policies
y_{i1} is a binary endogenous work-life policy variable
y_{i2}^{*} is individual 'i's' unobserved propensity to return to work
x_{i1}' is a vector of influences on the availability of work-life policies
x_{i2}' is a vector of personal, employment, household and environmental characteristics both before and after the birth

$$\begin{pmatrix} v_i \\ u_i \end{pmatrix} \sim BVN\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} 1 & \rho \\ . & 1 \end{bmatrix}\right]$$

Rho (ρ) is the correlation between u_i and v_i, and is conditional on x_{i1}' and x_{i2}'. The two latent variables, y_{i1}^{*} and y_{i2}^{*} are modelled simultaneously using Full Information Maximum Likelihood (FIML) (see Greene, 2003 p710) to estimate 4 outcomes:

$P_{11} = Pr(y_1 = 1, y_2 = 1) = \Phi_2 (x_{i1}'\beta_1 , x_{i2}'\beta_2 + \delta, \rho)$

$P_{10} = Pr(y_1 = 1, y_2 = 0) = \Phi_2 (x_{i1}'\beta_1 , -x_{i2}'\beta_2 - \delta, -\rho)$

$P_{01} = Pr(y_1 = 0, y_2 = 1) = \Phi_2 (-x_{i1}'\beta_1 , x_{i2}'\beta_2, -\rho)$

$P_{00} = Pr(y_1 = 0, y_2 = 0) = \Phi_2 (-x_{i1}'\beta_1 , -x_{i2}'\beta_2, \rho)$

Where Φ_2 is the Bivariate normal Cumulative Distribution Function (CDF). The reduced form and outcome equations are exactly the same as equations (16) and (17) in IV Probit, however, the lack of exclusion restrictions means that all variables in the reduced form equation can be used to treat endogeneity.

However, many variables in outcome and reduced form equations are very similar, often being the same variable taken from two different: (t-1) and (t+1). If these variables do not change between periods, there are few variables unique to the reduced form equation that can be used to determine the correlation. Furthermore, similar equations are likely to have similar unobservables, thus the correlations may be quite high. Although these are significant problems, it is otherwise very difficult to control for fixed or random unobservables as the majority of women contribute one birth to my sample.

CHAPTER 4: ESTIMATION RESULTS

4.1 Preliminary Tests

In order to gauge the explanatory power of family-friendly policies, I conduct preliminary tests using binary Probit models of Pr(*returntwo* = 1). Separate models are run with four different functional forms of work-life policies (see Section 2.4 for details on aggregation). As unpaid maternity leave (*unpaidMLb*) is not employer provided, it is excluded from the count and aggregated variables, therefore models with specifications 2, 3 and 4 include unpaid maternity leave as a separate regressor (Appendix 2A):

Functional Form 1: Disaggregated policy variables:

returntwo = f (paidMLb, unpaidMLb, parentalLb, specialLb, permanentptb, wkfromhomeb, flexihrsb)

Functional Form 2: Semi-Aggregated employer policies, with Unpaid Maternity Leave:

returntwo = f (anyEmaternityb, anyEpolicyb, bothEpoliciesb unpaidMLb)

Functional Form 3: Aggregated employer policies, with Unpaid Maternity Leave:

returntwo = f (anyEpolicyb, unpaidMLb)

Functional Form 4: Count of employer policies, with Unpaid Maternity Leave:

returntwo = f (totEpoliciesb, unpaidMLb)

These specifications are first tested without control variables (Appendices 2A – 2C), and only the aggregated (*anyEpolicyb*) and count (*totEpoliciesb*) variables are consistently significant. A parsimonious specification of control variables is then obtained by dropping groups of small and (both individually and jointly) insignificant control variables (Appendix 2B). The removal of unnecessary variables improves statistical significance, and sensitivity to exclusions is checked with Likelihood-Ratio tests, and a comparison of policy coefficients. A similar procedure is not performed for r*eturnone* because the majority of people for whom *returntwo*=1 also have *returnone*=1 (see Table 2B). In the parsimonious model with disaggregated policies, permanent part-time work (*permanentptb*), paid maternity leave (*paidMLb*) and special leave (*specialLb*) are slightly statistically significant (at 10, 12.3 percent and 11 percent, respectively).

The parsimonious specification of control variable is then tested with different functional forms and excluding Wave 6 observations[1] (Appendix 2C). Semi-aggregated variables are statistically insignificant, while *anyEpolicyb* and *totEpoliciesb* are more significant for the Waves 1-5 sub-sample (Appendix 2D).

Tests for the very long-term *returnLT* show that none of the variables are significant (Appendix 2B). Given the small sample size and difficulty obtaining precise estimates, I do not pursue models with *returnLT*, and continue with only models of *returnone* and *returntwo.*

4.2 Controlling for Endogeneity – access to policies

As discussed in Section 3.3, respondents who plan to have a child may self-select into jobs with particular features, creating endogeneity bias upon policy estimates. This is addressed by first analysing the influences of characteristics from before the birth on the number of policies that respondents can access. This forms the "reduced form equation" (equations (11) and (17) from Sections 3.3.3 and 3.3.4, respectively) that is used to treat endogeneity.

An Ordinary Least Squares (OLS) regression helps assess the influence of variables from before the birth (period (t-1)) on the number of accessible polices (*totEpoliciesb*) (Appendix 2E). Employer-specific characteristics (such as "workplace size") are not included as they are endogenous with the fact that respondents are working. Instead, I include variables, such as occupation and experience that can be independent of pre-childbirth employers.

[1] Wave 6 observations for the variable *returntwo* are censored – see Section 2.3.1

Respondents' employment characteristics have large and significant effects on the number of available policies, which is consistent with studies finding high-skilled women are most likely to access work-life policies (see Section 1.2.2). Personal and family backgrounds help capture work and family preferences, while partner's employment variables capture the joint nature of work decisions.

4.3 Estimation using Instrumental Variable Probit (IV Probit)

The endogeneity of work-life policies is first addressed with Stata's *ivprobit* procedure, using the count policy variable (*totEpoliciesb*). The model of Pr (*returntwo* = 1) for the All Waves sample (Table 4A, Model (i) – All Waves) show a small, insignificant and surprisingly negative coefficient on *totEpoliciesb*. All variables are jointly significant (Wald Test of the index p-value = 0), and there is a positive but small correlation between unobservables in the outcome and reduced form equations (ρ = 0.21). Exogeneity is not a problem (Wald Test of Exogeneity p-value = 0.587).

However, the results are sensitive to Wave 6 observations, which are censored and understate the number for whom *returntwo* equals 1. The policy coefficients for Model (i) Waves 1-5 are dramatically magnified. The high *rho* value (0.874) and significance of the Wald Test of Exogeneity (p-value = 0) suggests that common unobservables are affecting both return to work decision and the number of policies available in the pre-childbirth job.

The negative coefficient on *totEpoliciesb* could stem from non-linear effects of lengthy leave periods. The literature in Section 1.2.1 suggests that the degree of human capital depreciation corresponds to the length of career breaks. Thus, the longer a woman's maternity leave, the lower her opportunity cost of staying out of work and the less likely she is to return. As the majority of the sample actually returns by the birth wave (see Section 2.3.1), the long timeframe of *returntwo* (which spans up to two years) could be capturing a non-linear effect of work-life policies, especially as the negative effect is much larger and more significant when the sub-sample of Waves 1-5 observations is used. [2]

Table 4A: IV Probit Results using count policy variable (*totEpoliciesb*)†
P-Values reported in parentheses.

	(i) *returntwo*		(ii) *returnone*
	All Waves	Waves 1-5	All Waves
totEpoliciesb Coefficient	-0.050	-0.512***	0.185
	(0.859)	*(0.000)*	*(0.448)*
Unpaid Maternity Leave Coefficient	0.295	0.637***	0.124
	(0.411)	*(0.000)*	*(0.690)*
constant: outcome equation	0.774	0.704	-0.820
	(0.555)	*(0.566)*	*(0.473)*
constant: reduced form equation	2.250	1.928	2.291
	(0.033)	*(0.103)*	*(0.031)*
Athrho	0.213	1.348***	-0.890
	(0.587)	*(0.000)*	*(0.791)*
Rho	0.210	0.874	-0.089
Wald Test of Exogeneity	0.290	14.000***	0.070
	(0.587)	*(0.000)*	*(0.791)*
Wald Test of the index: chi-2 Statistic	101.05	180.90	87.80
	(0.000)	*(0.000)*	*(0.000)*
Log-Likelihood	-932.86	-660.44	-1010.79
N	456	351	456

* 10% significance, ** 5 % significance, *** 1 % significance

† Control variable omitted, available on request.

The model using the variable *returnone* (Table 4A, model (ii)) shows a positive coefficient on *totEpoliciesb*, which meets a-priori expectations that a greater number of work-life policies help women ease back into work. This supports arguments of non-linear effects in longer time periods.

However, the Waves 1-5 sub-sample has much larger exogeneity and correlation problems compared to the All Waves sample. Both *rho* (0.874) and the Wald Exogeneity Test Statistic (14) are large and highly significant. Given these problems, I instead pursue the aggregated policy variables using a Bivariate Probit approach. Bivariate Probit has different

[2] *Returntwo* is uncensored when the Waves 1-5 sub-sample is used, as all respondents can be tracked for 2 waves. See Section 2.3.1 for more information.

identifying restrictions to IV Probit (see Section 3.3.4), however it may provide more conclusive results.

4.4 Estimation using Bivariate Probit

Following Altonji et al (2005) and Knapp and Seaks (1998), I use a Bivariate Probit approach to control for the endogeneity of binary work-life policies. These are Seemingly Unrelated Regressions (SURs), as most variables in the reduced form equation are not present in the outcome equation (see Appendix 2E). Table 4B shows the models for the Pr(*returntwo* = 1). The variables in all models are jointly significant (Wald Test of the Index p-value = 0 for most models), while Model (iv) has the largest log-likelihoods and thus the best fit.

The constants for both the outcome and reduced form equations are not consistent across all variable specifications. This may be because models are estimated using only one policy variable (for example, Model (i) includes maternity policies, but not general policies). The most significant and largest constant is in Model (vi), for *anyEpolicyb.*

The coefficient on models with maternity policies (Models (i), and (iii)) has different signs for the different samples. *Returntwo* is uncensored in the Waves 1-5 models, and the negative coefficient of policies could have two causes: it reflects the actual usage of policies, or a diminishing opportunity cost of labour force withdrawal for lengthy leave periods. However, the coefficient on *anyEpolicyb* in Model (iv) is negative for both samples, which could stem from a range of factors. These reasons are discussed in Section 4.4.2.

While most results are statistically significant, there are major difficulties disentangling the effect of unobservables. Although the LR Test of *rho* is significant, you can see that *athrho* is insignificant. *Athrho* is the correlation estimated by Stata, and is a modified version of *rho* [$athrho = 1/2^{*} ln[(1+\rho)/(1-\rho)]$]. An insignificant *athrho* value indicates difficulties in identification. The large (unreported) confidence intervals for most *athrho* estimates range from –1 to 1, which are the boundaries of this estimation procedure. *Rho* is either 1 or –1 for all models in Table 4B.

Table 4B: Bivariate Probit Results using binary policy variables
Results for *returntwo* (return to work in either the birth wave or the following wave) †
P-Values reported in parentheses.

	(i)		(ii)		(iii)		(iv)	
	anyEmaternityb		*anyEgeneralb*		*bothEpoliciesb*		*anyEpolicyb*	
	All Waves	Waves1-5	All Waves#	Waves1-5#	All Waves	Waves1-5	All Waves#	Waves1-5
Policy Coefficient	2.284***	-0.646***	2.096***	2.54***	1.809***	-0.673***	-1.539***	-1.010***
	(0.000)	*(0.006)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*
Unpaid Maternity Leave Coefficient	0.135	-0.128	0.177	0.113	0.131	-0.125	0.154	0.028
	(0.413)	*(0.591)*	*(0.340)*	*(0.674)*	*(0.362)*	*(0.557)*	*(0.358)*	*(0.908)*
constant: outcome equation	-0.759	0.232	-1.948*	-2.513	-0.657	0.398	1.686*	0.677
	(0.400)	*(0.856)*	*(0.058)*	*(0.110)*	*(0.461)*	*(0.733)*	*(0.091)*	*(0.623)*
constant: reduced form equation	0.457	0.897**	0.612	0.394	0.358	0.720*	1.397***	1.319***
	(0.175)	*(0.039)*	*(0.175)*	*(0.459)*	*(0.264)*	*(0.058)*	*(0.001)*	*(0.001)*
Athrho	-13.650	14.130	-30.120	-29.653	-14.517	382.029	14.188	12.586
	(0.971)	*(0.975)*	*(0.951)*	*(0.963)*	*(0.968)*	*(0.971)*	*(0.973)*	*(0.968)*
Rho (ρ)	-1.000	1.000	-1.000	-1.000	-1.000	1.000	1.000	1.000
LR Test of Rho: chi-2 Statistic	12.062***	15.49***	7.97***	11.266***	15.097***	15.306***	14.089***	17.071***
	(0.001)	*(0.000)*	*(0.005)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Wald Test of the index: chi-2 Statistic	416.84***	158.40***	446.26***	299.21***	415.87***	162.27***	203.31***	117.06***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*
Log-Likelihood	-414.25	-264.40	-305.86	-189.21	-415.91	-264.72	-292.27	-179.28
N	456	351	456	351	456	351	456	351

* 10% significance, ** 5 % significance, *** 1 % significance

† Control Variables Omitted, available on request.

These models had difficulty converging due to perfect predictability problems, and two missing data indicators (*mworkMISS* and *experbMISS*) are dropped. To avoid further loss of variables, partner's industry variables (government admin and defence, and education) are aggregated in a similar way to the respondent's aggregated industry variables. Results available upon request.

These models use the slightly longer-term timeframe for work decisions (*returntwo*), and show perfect correlation between the unobservables of the outcome and reduced form equations. This correlation is mostly negative in when the censored (All Waves) sample is used, but mostly positive for the Waves 1-5 sub-sample. While the correlations are high, they are very imprecise, suggesting difficulty in disentangling the policy effects from unobservables.

Given these estimation problems, the models are rerun using *returnone* (Table 4C). This is appropriate because most respondents return to work by the birth wave, and these models also check for non-linear effects discussed in Section 4.2.2. When *returnone* is used for the All Waves sample, *rho* falls in magnitude except in the case of *anyEgeneralb* (Model (ii)). The perfect correlation of *rho* in Model (ii) is expected as most respondents have at least one general policy (90.35 percent – Appendix 1E.2), therefore it has little explanatory power. However, none of the *athrho* estimates are significant, indicating the same problems with unobservables that occurred with *returntwo.*

Table 4C: Bivariate Probit Results using binary policy variables
Results using *returnone* (return to work by the birth wave) †
P-Values reported in parentheses.

	(i)		(ii)		(iii)		(iv)	
	anyEmaternityb		*anyEgeneralb*		*bothEpoliciesb*		*anyEpolicyb*	
	All Waves	Waves1-5	All Waves#	Waves1-5	All Waves	Waves1-5	All Waves	Waves1-5
Policy Coefficient	0.714	-1.385***	1.956***	2.053***	0.750	-1.372***	1.235	2.134***
	(0.413)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.445)*	*(0.000)*	*(0.199)*	*(0.000)*
Unpaid Maternity Leave Coefficient	0.242	0.139	0.193	0.206	0.231	0.136	0.245	0.205
	(0.184)	*(0.383)*	*(0.208)*	*(0.250)*	*(0.206)*	*(0.396)*	*(0.168)*	*(0.234)*
constant: outcome equation	-0.797	1.197	-2.056	-1.123	-0.806	1.216	-1.456	-1.324
	(0.479)	*(0.168)*	*0.026***	*(0.282)*	*(0.481)*	*(0.175)*	*(0.292)*	*(0.208)*
constant: reduced form equation	0.912**	0.879**	0.976**	0.554	0.727*	0.693*	1.09**	0.852
	(0.021)	*(0.016)*	*(0.040)*	*(0.303)*	*(0.063)*	*(0.067)*	*(0.048)*	*(0.113)*
Athrho	-0.327	14.337	-18.503	-15.359	-0.332	14.365	-497.000	-210.891
	(0.603)	*(0.969)*	*(0.975)*	*(0.967)*	*(0.641)*	*(0.973)*	*(0.489)*	*(0.554)*
Rho (ρ)	-0.316	1.000	-1.000	-1.000	-0.320	1.000	-0.459	-1.000
LR Test of Rho: chi-2 Statistic	0.256	14.044***	6.000**	12.599***	0.203	15.299***	0.504	14.303***
	(0.613)	*(0.000)*	*(0.014)*	*(0.000)*	*(0.652)*	*(0.000)*	*(0.478)*	*(0.000)*
Wald Test of the index: chi-2 Statistic	172.29***	239.48***	348.68***	280.88***	175.17***	237.76***	134.57***	265.99***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Log-Likelihood	-500.25	-362.32	-384.93	-281.65	-503.22	-361.81	-372.74	-273.87
N	456	351	456	351	456	351	456	351

* 10% significance, ** 5 % significance, *** 1 % significance

† Selected Results reported in Appendix 2G. Other results available on request.

These models had difficulty converging due to perfect predictability problems, and two missing data indicators (*mworkMISS and experbMISS*) are dropped. To avoid further loss of variables, partner's industry variables (government admin and defence, and education) are aggregated in a similar way to the respondent's aggregated industry variables. Results available on request.

Although *returnone* does not create censoring problems for the All Waves sample unlike (*returntwo*), models were also run for the Waves 1-5 sub-sample as a sensitivity check. Both samples indicate difficulty in disentangling the effects of unobservables. The very short time frame of *returnone* reverses the sign of *rho* for Models (i) and (ii), while rho is not significant for Models (i) and (iii). There are perfect correlation between the unobservables, as occurred in Table 4B. This correlation is mostly negative in the All Waves sample, and mixed for the Waves 1-5 sub-sample.

The constant in the outcome equation varies between the models, which probably occurs for the same reasons as for Table 4C. However, the constant of the reduced form equation does not fluctuate as much in size or significance, indicating that this formulation is better suited to models of *returnone* than *returntwo*.

The correlations are generally larger and less significant for the Waves 1-5 sub-sample. Although *returnone* does not face the censoring problems of *returntwo,* models using the Waves 1-5 sub-sample are run as a robustness check. The different correlation results may indicate systematic differences between the two sample groups, or greater estimation problems due to smaller sample size (351 for the sub-sample, versus 456 for All Waves).

4.4.1 Accounting for multiple endogenous regressors

A problem realised late into my project is that only one endogenous policy is treated in each Bivariate Probit model. This creates omitted variable bias in specifications (i), (ii) and (iii), which address only one of 4 possible combinations between maternity policies and general policies.[3] One avenue is to use Multivariate Probit, which is similar to Bivariate Probit, but it uses Simulated Maximum Likelihood estimation and allows the treatment of more than one endogenous binary variable.

Using Stata 10.0's *mvprobit* command, I attempt a Multivariate Probit model using *anyEmaternityb, anyEgeneralb* and *bothEpoliciesb*.[4] However this model does not estimate because my data is unsuitable. These semi-aggregated policy variables are not mutually exclusive, which prevents treatment of the endogenous *bothEpoliciesb* variable. Given these problems, and time constraints that prevent a re-estimation and subsequent analysis of my models, I instead test for bias within the Bivariate models.

[3] The possible policy combinations are to have: 1) only maternity, 2) only general, 3) both maternity *and* general, 4) neither maternity *nor* general policies.
[4] Intercooled Stata 9.1 cannot perform Multivariate Probit.

In order to test for omitted variable bias, I add the untreated work-life policies variables in the Bivariate models (Appendix 2G). The coefficients of treated work-life policies are not sensitive to the inclusion of untreated policies, however they become larger. While this suggests no major omitted variable bias, results should be treated cautiously because each model treats only one of three endogenous policies. It is prudent to pursue the models excluding untreated variables because their policy coefficients are smaller in magnitude, and these models treat all known endogeneity biases.

4.4.2 Econometric reasons for perfectly correlated errors

The perfect correlations indicate that identical unobservables affect both the initial allocation of women across jobs, and also affect their post-childbirth decisions. This was anticipated (as discussed in Section 3.3.4), however not to such a high degree given the extra controls in the reduced form equation. Nonetheless, the majority of variables are unlikely to change between the different waves, which leave little data that is unique to the reduced form equation.

The effect of unobservables is expressed through the coefficient on the endogenous policy variables, and reflects the estimation constraints upon Bivariate Probit. This can be explained with a generic set of outcome and reduced form equations:

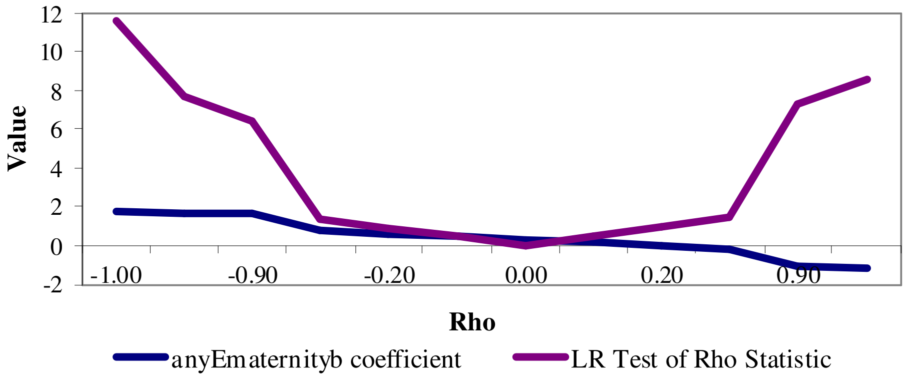
$$y_2^* = f(y_1, x'\beta) + u$$

$$y_1^* = f(z'\alpha, x'\beta) + v$$

$x'\beta$ is relevant for both y_1^* and y_2^*, reflecting the similarity between many variables in (t-1) and (t+1). If the same unobservables affect both equations, then u and v are perfectly correlated (ρ = |1|), thus the estimation Pr ($y_1 = 1$) depends entirely upon $z'\alpha$. Therefore, whether $z'\alpha$ has a positive or negative influence upon Pr ($y_2 = 1$) sets the coefficient upon y_2, and the sign of *rho*. This seems to be occurring in Tables 4B and 4C, and explains why *rho* switches from –1 to 1.

The constraint on *rho* can also be illustrated using Model (i) from Table 4C, which finds a large, positive and significant coefficient for maternity policies. Following Altonji et al (2005), I map the sensitivity of the *anyEmaternityb* coefficient and the LR Test Statistic to changes in *rho*.[5] Figure 4A is obtained by constraining the *rho* to values between –1 and 1.

Figure 2: Bivariate Probit Sensitivity Analysis
***returntwo* with *anyEmaternityb* - All Waves**
Coefficient on *anyEmaternityb* , and the significance of rho.



A gradual change in *rho* from –1 to 1 corresponds to a steady decline in the coefficient. A negative correlation shows through a positive coefficient, and a positive correlation is paired with a negative coefficient. The significance of *rho* tends to 0 as *rho* approaches 0, but increases as *rho* approaches the boundaries.

The presence of strong but imprecise correlations is a key reason why *rho* switches between –1 and 1. These models are expressing the same relationship in two different ways: through a positive correlation and negative coefficient, or vice versa. Perfect correlation in the errors means that the same variables determine both the outcome and reduced form equations. This is not itself problematic, however, the sign of the correlation requires further discussion.

[5] The values for ρ = -1 are taken from Model (i): All Waves. However the model for ρ = 1 does not estimate because $athrho = 1/2^{*}ln[(1+\rho)/(1-\rho)]$, and a perfect correlation constraint implies log(0). Results available on request.

4.4.3 Theoretical reasons for perfectly correlated errors

If, as I have assumed, women make their job choices with fertility plans in mind, it is not surprising for the same variables to affect both access to policies and return to work decisions. Any unobservables in the outcome equation are likely to be present in the reduced form equation; therefore perfect correlation is not an anomaly.

Sartori (2003) argues that some situations require the assumption of perfect correlation. This makes instrumental variables estimation inappropriate, because a "valid exclusion restriction simply does not exist" (2003, p121). She proposes that, where appropriate, a Bivariate Probit model with *rho* set to 1 or –1 results in smaller biases than using Probit or Heckman Selection Models.

This occurs in the present situation, where identical variables seem to govern both the initial choice of job, and the return to that job. While I model access to policies as an endogeneity issue and not a selection issue, the two are closely related (see Section 3.2), and it is reasonable to have perfect correlation between *u* and *v*.

The issue, therefore, is the direction of correlation. Where decisions are similar, a positive correlation between unobservables is expected, and where they are opposites, a negative correlation is expected.

<u>Maternity Policies: negative coefficient and positive correlation</u>

The positive error correlation for models with endogenous maternity policies implies that the same unobservables affect both decisions in the same way. There is consequently an upward endogeneity bias on *anyEmaternityb* which, when removed, results in a negative policy coefficient.

There are two possibilities why maternity variables (*anyEmaternityb, bothEpoliciesb*) have negative coefficients: they indicate the actual usage of maternity policies, or they capture non-linear effects of lengthy leave periods. It is expected that women with access to maternity policies actually make use of them, generating a negative coefficient in the very short-term. This is consistent with findings by Baxter (2008), McRae (1994) and Desai and Waite (1991), and for the Waves 1-5 sub-sample you can see larger negative coefficients on *anyEmaternityb* and *bothEpoliciesb* in models of *returnone* (Table 4C) compared to *returntwo* (Table 4B).[6]

Non-linear effects (as discussed for IV Probit in Section 4.3.2) may also explain negative coefficients, particular in models using *returntwo* (Table 4B). Comparisons will focus upon the Waves 1-5 sub-sample, as it is more appropriate for *returntwo.*[7] Maternity policies are found to have large negative effects upon the probability of return to work (Table 4C, Model (i) Waves 1-5, and (iii) Waves 1-5).

Of the above two explanations, the policy usage one is a more plausible reason because it remains negative for both models of *returnone* and *returntwo.* These dependent variables capture all decisions made within 12 months of giving birth, while non-linear effects are not expected to be felt until after 12 months as this is the limit of job-protected leave. As models of *returnLT* are unsuccessful (see section 4.1.1), it is very difficult to isolate any longer-term non-linear effect.

Given the negative coefficient of maternity policies and the restrictions on Bivariate Probit, it is therefore unsurprising to find a positive correlation in the errors. That ρ = 1 indicates that the same unobservables increase both the probability of accessing maternity leave, and the probability of return to work. This reflects work preferences and costs, as women most likely to access maternity policies are also likely to be highly skilled and educated, thus having higher opportunity costs of leaving work (Risse, 2006; Gray and

[6] Maternity policies have opposite signs for the All Waves and Waves 1-5 sample groups, hinting at systematic differences between these samples. See Appendix 2H for further analysis.
[7] Unlike the All Waves sample, the Waves 1-5 sub-sample is not truncated for models of *returntwo*.

Tudball, 2002). It therefore makes sense to have a positive error correlation, with a negative maternity policy coefficient indicating policy usage.

<u>General Work-life policies: positive coefficient and negative correlation</u>

Unlike maternity policies, general policies suffer a *downward* endogeneity bias. While preliminary Probit regressions revealed a positive coefficient on *anyEgeneralb,* this was muted by the consistently negative impact of special leave to care for family members (*specialLb* – see Appendices 2A to 2C). The treatment of *anyEgeneralb* therefore addresses this variable in particular, resulting in a large positive coefficient.

A positive coefficient on general policies is intuitive, and supports the theoretical predictions in Section 3.1. Compared to those without flexibility policies, women whose pre-childbirth jobs provide home-based work, access to permanent part-time work, or flexible start and finish times, can more easily integrate back into work. This implies a return to pre-childbirth the employer and is consistent with previous findings (McRae, 1994; Desai and Waite, 1991).

The issue then concerns the sign of *rho.* The negative correlation implies that unobserved factors increasing access to general policies make women *less* likely to return to work. This is not intuitive if we assume that women anticipating pregnancy select into jobs with such policies. However, as mentioned in section 3.2, it is simplistic to assume such a strong link between general policies and maternity decisions, especially given the widespread access to at least one of these policies (Appendix 1E.2). Furthermore, it is a ceteris paribus effect of general policies, which assumes no access to maternity policies. For these reasons, the opposite endogeneity bias of general policies may indicate different processes to the endogeneity of maternity policies.

It is possible that women with lower work preferences actively choose jobs with flexible policies. This is particularly so if they choose "mommy track" jobs, part-time work options that are employer-responsive and have little career prospects (see Section 1.3.1 for more literature). This is supported by my regression results for the reduced form equations (Appendix 2F.2) which show that the variables capturing work preferences (siblings, and whether the respondent's mother worked) have a positive correlation with Pr(*anyEgeneralb*) but a negative correlation with Pr(*anyEmaternityb*). Industry variables also have opposite effects, with all sectors except government increasing the probability of access to general policies while decreasing access to paid maternity leave.

These regression results are consistent with earlier findings. Desai and Waite (1991) find flexibility features to have a stronger impact on women *without* a long-run preference to work, and are only significant for return to work decisions within 3 months of giving birth. McRae (1994) finds that permanent part-time work and job-sharing significantly impacts return to employer decisions. Both studies suggest that women who prefer to work, and women with a high opportunity cost of withdrawal, will return to work in any case.

The *downward* endogeneity bias on general policies therefore arises because women allocating into part-time and flexible jobs may have lower attachment to work, and therefore be less likely to return. General policies consequently (and intuitively) have a very large positive relationship with the probability of return to work in the very short-term.

<u>Access to both policy types (*bothEpoliciesb*), and *anyEpolicyb*</u>

Table 4C shows that access to at least one of each policy type makes women *less* likely to return in the very short-term (Model (iii), Waves 1-5). This is expected because access to both policies is indicative of highly responsive workplaces, and it is understandable that the abovementioned policy usage effects dominate in the short-term. The effect of general policies is likely to be felt at the end of leave periods, which my data is unable to pinpoint.

However, having any policy (Table 4C, Model (iv) Waves 1-5) increases the probability of return. The positive effects of general policies are expected to dominate here, as they are more widely accessible than maternity policies (90.35 percent versus 69.08 percent – Appendix 1E.2).

4.4.4 Model Fit

Given the greater precision and intuitive sense of the *returnone* estimates for the Waves 1-5 sub-sample, I focus upon these models for my final results. The models all have highly significant Wald Test statistics, indicating all variables are jointly significant, however measures of fit are difficult to obtain for a Bivariate Probit model.

One commonly used indicator is a Prediction Success Table, which compares predicted outcomes to actual outcomes. The "reference probability" of 0.533 is simply the proportion of people for whom *returnone* equals '1.'[8] This represents the marginal probability of success, Pr(*returnone* = 1), which sum the joint probabilities of success: (Pr(*returnone* = 1, *policy* = 1)) and (Pr(*returnone* = 1, *policy* = 0)), where "policy" denotes any of the binary policy variables (see Appendix 2I for calculations). This reference probability is the proportion of correct predictions in my naïve models - models with only an intercept, that predict all *returnone* values as '1' (Appendix 2J).

The accuracy of my models is measured by comparing their percentage of correct predictions with those from naïve models. Table 4D shows that my models do improve the estimation of Pr(*returnone* = 1). Models (i) and (iii) increase the percentage of correct

[8] Prediction success tables require a probability of success calculated for each observation. This predicted probability, y_i is compared to a reference probability, y^*, such that Pr(outcome = 1) if $y_i >= y^*$. I refer to this "reference probability" as the "sample probability," as my values are taken directly from the data.

predictions by approximately 20 percent; and Models (ii) and (iv) result in an approximately 32 percent improvement. These similar improvements are expected since *anyEmaternityb* dominates in Model (iii), and that *anyEgeneralb* dominates in Model (iv) (see Section 4.4.3).

Table 4D: Percentage of Correct Predictions for models using returnone (return to work by the birth wave), Waves 1-5. Models correspond to Table 4C. *				
Percentage of Correct Predictions				
	(i)	(ii)	(iii)	(iv)
Naïve Models	*anyEmaternityb*	*anyEgeneralb*	*bothEpolciesb*	*anyEpolicyb*
53.28	63.82	70.37	63.25	70.66
* Prediction success tables in Appendix 2J				
All models have higher prediction success rates compared to a naïve model, with the greatest improvement in predictions for models with general policies (Model (ii), and Model (iv) which is dominated by the effect of general policies – see Section 4.4.3). These improve the percentage of correct predictions by approximately 32 percent; while Models (i) and (iii) have a 20 percent improvement.				

4.4.5 Marginal Effects of Work-life Policies

In order to put the coefficient estimates into context, I calculate each policy's marginal effect on the probability of returning to work, Pr(*returnone*=1). More appropriate marginal effects are obtained when the predicted probability of success matches the sample probability. For this purpose, I set some dummy variables to '1.' The predicted probability of return in Model (ii) is slightly overestimated, while it is slightly underestimated in the remaining models.

Table 4E shows that access to any maternity policy reduces the probability of returning to work by 41.3 percentage points; any general policy corresponds to a 41.2 percentage point increase, whilst having both policies reduces the probability of returning to work by 42.8 percentage points. These effects are all slightly understated. Access to any policy increases the probability of return by 48.4 percentage points, which is slightly overstated. The size and direction of these results correspond to patterns in coefficient estimates and the percentage of correct predictions (see Sections 4.4.3 and 4.4.4).

Table 4E: Marginal Effects: Marginal Probabilities for *returnone* (return to work by the birth wave), Waves 1-5. # † P-values in parentheses. Marginal effects are for discrete changes of dummy variables from 0 to 1, other variables calculated at means. Models correspond to Table 4C.				
	(i)	(ii)	(iii)	(iv)
	anyEmaternityb	*anyEgeneralb*	*bothEpoliciesb*	*anyEpolicyb*
Policy Effect	-0.413***	0.412	-0.428***	0.484
	(0.000)	*(0.116)*	*(0.000)*	*(0.106)*
Unpaid Maternity Leave Effect	0.055	0.082	0.054	0.081
	(0.380)	*(0.252)*	*(0.396)*	*(0.228)*
Predicted Pr(*returnone* = 1)	0.494	0.576	0.522	0.500
Dummy Variables Set to 1	*medskilled, businesspropb, newmum, children04*	*emplszU00b, governmentb, multibirths*	*lowskilledb, businessprop, paresp, newmum*	*birthq4, primaryb*
Sample Pr(*returnone* = 1) = 0.533				
* 10% significance, ** 5 % significance, *** 1 % significance				
# Appendix 2K.1 lists the mean values for the reference individual. † Control variables in Appendix 2K.2.				
The marginal probability of success in each model is closely aligned to the sample marginal probability of success, though it is slightly higher in Model (ii). Having any maternity policy reduces the probability of returning to work by 41.3 percentage points; any general policy increases the probability of return by 41.2 percent, whilst having both policies reduces the probability of returning to work by 42.8 percent. These effects are all slightly understated. Access to any policy results in a 48.4 percentage point increase, which is slightly overstated.				

These effects are checked by comparing the differences in joint probabilities of returning to work: Pr(*returnone* = 1, *policy* = 1) and Pr(*returnone* = 1, *policy* = 0). Again, some dummy control variables are set to '1' in order to align the predicted and sample probabilities of return. Models of Pr(returnone = 1, policy = 0) are closely matched (Table 4F), however, the Pr(returnone = 1, policy = 1) predictions are very different to the sample probability.

Models (i) and (iii) see a dramatic increase in the probability of return when the policy is available. This opposes the effects in Table 4E, and likely captures the positive effect of unobservables. Similar patterns for Models (ii) and (iv) are also likely to incorporate the direction of correlation.

Table 4F: Marginal Effects: Changes in Joint Probability for *returnone* (return to work by the birth wave), Waves 1-5. † Marginal effects are for discrete changes of dummy variables from 0 to 1, other variables calculated at means. Models correspond to Table 4C.		
Joint Probability	**Predicted**	**Sample**
(i) *anyEmaternityb*		
Pr (*returnone*=1, *policy*=1)	0.807	0.396
Pr (*returnone*=1, *policy*=0)	0.107	0.137
Policy Effect	0.700	0.259
(ii) *anyEgeneralb #*		
Pr (*returnone*=1, *policy*=1)	0.000	0.504
Pr (*returnone*=1, *policy*=0)	0.054	0.028
Policy Effect	-0.054	0.476
(iii) *bothEpoliciesb*		
Pr (*returnone*=1, *policy*=1)	0.807	0.393
Pr (*returnone*=1, *policy*=0)	0.125	0.140
Policy Effect	0.682	0.253
(iv) *anyEpolicyb ##*		
Pr (*returnone*=1, *policy*=1)	0.043	0.507
Pr (*returnone*=1, *policy*=0)	0.023	0.026
Policy Effect	0.020	0.481
Extra dummy variables set to '1': # newmum ## intermedb = 1		
† Control variables omitted, available on request.		

These results highlight difficulties disentangling policy effects from unobservables. Estimation difficulties for Models (ii) and (iv) are enhanced by the fact that most respondents have general policies (Appendix 1E.2). The effect of *anyEgeneralb* cannot be separately identified from a return to work. Overall, unobservables make interpretation very difficult.

CHAPTER 5: CONCLUSION & POLICY IMPLICATIONS

This study has attempted to test whether work-life policies affect women's labour mobility after childbirth. However, the results in Chapter 4 highlight difficulties in isolating policy effects, especially as unobservables create major endogeneity bias. This bias is addressed with two-step models, which allow for correlations between unobserved factors affecting return to work decisions, and those affecting and access to work-life policies. However, high correlation levels suggest that omitted variables have major effects.

While no dataset captures all relevant variables, my study serves as a warning to others. As I control for a large range of variables, it is likely that unobservables relate to personal preferences that are difficult to measure, but nonetheless affect work decisions. Although HILDA includes some such variables, including work hour preferences and intentions to leave the current employer, these are not used because of their limited variability. Along with the use of detailed calendar variables, these preference variables may capture some currently unobserved effects.

However, I find unobservables create *different* endogeneity biases for different types of work-life policies. Unobservables affecting maternity policies positively influence short-term return to work decisions, while general policies have a negative influence. Future studies should separate these different types of policy variables to enable identification of endogeneity bias.

The transferability of results may also be problematic, especially if future studies use different data. Even within HILDA, models with my Waves 1-5 sub-sample have an opposite correlation sign to models with All Waves of data. While correlations are somewhat more precise in the larger sample, they are nowhere near conventional levels of statistical significance. This insignificance makes it difficult to interpret results from the two groups.

The Bivariate Probit results are also inappropriate when there are multiple endogenous regressors. Whilst the addition of untreated endogenous variables made little difference to coefficients on the included work-life policies, my models cannot simultaneously address the different endogeneity problems associated with different work-life policies. Multivariate Probit estimation is thus the logical extension, and accommodates the different endogeneity biases that arise from different policy types.

Despite the techniques available, it is difficult to completely control for unobservables. Finding good instruments is notoriously difficult, and a panel data approach (see Euwals, 2001) has problems with repetition because most women contribute a single birth. Furthermore, approaches such as fixed effects regression may not be appropriate if control variables do not vary across time.

However, a panel data model of general mobility decisions may be an appropriate avenue. If childbirth is considered an independent variable instead of a criterion for sample selection, then researchers can interact work-life policies with birth indicators to isolate the desired effects. This would significantly increase sample size, and also enables analysis general mobility decisions.

Analyses of both maternity-related and general mobility decisions need to consider employer, occupational and industry mobility. This better address the employer, occupation and industry-specific skills that may depreciate as a result of job mobility. Due to time constraints, I can only address return to work decisions, which are a precursor to these mobility issues. Extending the models to incorporate these decisions is a logical step to take, and such models are more relevant to the impact of mobility on specific skills.

Another logical extension is to analyse a range of population groups. Many respondents to the HILDA answer all questions about work-life policies, and HILDA's sampling structure capture a range of population groups. The literature suggests that work-life policies are beneficial for all workers, not just women with newborn children. Access to work-life policies may therefore be important in the mobility decisions of other population groups, including older workers (Rhum, 1990), and the 55 percent of men and women who feel overworked (Skinner and Pocock, 2008).

A broader change in organisational culture is key to addressing work-life conflict. This requires work-life policies that are genuinely employee responsive, and not tokenistic in the sense that policy uptake curbs careers and invites recrimination. Data restrictions mean that the longer-term labour force retention is not addressed, and neither is the impact of workplace cultures on women's perception of career opportunities. This is an important area to investigate, especially as the longer-term ability of mothers to balance their home and work responsibilities affects gender equity and mobility.

Future studies need to investigate longer-term workforce attachment, as the very policies that ease a return to work may hinder women's careers and induce mobility in the longer term (HREOC, 2008; Diamond et al, 2007; Whitehouse et al, 2007; Eaton, 2003). High employee turnover likely detriments employers, therefore further research might utilise firm-level data (for example, exit surveys) to identify issues with organisational cultures.

Greater employee retention is likely to preserve firm-specific skills, and employers need to recognise these benefits of work-life policies. However, the provision of policies needs to consider all costs and benefits involved. Work-life policies generally reduce the labour supply per employee, which explains employers' preferences for childcare policies over workplace flexibility (Glass and Fujimoto, 1995). However, short-run costs of work-life policies may be outweighed by longer-term benefits of employee retention.

In an era of skills shortages and an ageing population, it is important to maximise the retention of employees and their skills. Researchers need to better quantify these benefits so that firms can make informed policy decisions. Flexibility policies should be employer initiated, as policy mandates cannot accommodate firm-level differences. Furthermore, mutually beneficial policies will likely avoid labour market discrimination that may arise from legislation (Gray and Tudball, 2002; Rhum 1998).

In this respect, there is scope to educate employers about improving organisational cultures. This requires policymakers to work proactively with business, and may necessitate consultations and appraisals with various firms, industry groups and professional associations.

Such initiatives create both private and public benefits, as they promote an efficient use of the economy's skills, enhance productivity, and increase women's financial independence. They also promote social goals such as equity, improved health, and an overall improvement in welfare if employment patterns better match workers' preferences.

APPENDIX 1

Data

APPENDIX 1A

Summary Statistics of All Variables Number of observations = 456 unless indicated otherwise Note: missing data is dealt with using the modified zero-order method. The suffix 'b' indicates the period 'before' the birth (t-1), while 'a' indicates 'after' the birth (t+1). A prefix of 'p' denotes partner information.							
Variable	**Description**	**Specification**	**Mean**	**Standard Deviation**	**Min**	**Max**	**HILDA Codes**
DEPENDENT VARIABLES							
returnone	Work in the year of the birth report	1 = Yes 0= No	0.511	0.5	0	1	esdtl
returntwo	Work in either the year of the birth report, or the following year	1 = Yes 0= No	0.746	0.436	0	1	esdtl
returnLT (N=256)	Work 2 years after the year of the birth report This has 256 observations because an extended time frame is required, thus only births in 2002, 2003 and 2004 are included	1 = Yes 0= No	0.750	0.434	0	1	esdtl
KEY INDEPENDENT VARIABLES							
paidMLb	Paid maternity leave	1 = Yes 0 = No / don't know	0.465	0.499	0	1	jowppml / ajowppmt
unpaidMLb	Unpaid maternity leave	1 = Yes 0 = No / don't know	0.774	0.419	0	1	jowpuml / ajowpumt
parentalLb	Parental leave	1 = Yes 0 = No / don't know	0.612	0.488	0	1	jowppnl / ajowppnt
specialLb	Special leave to care for sick family members	1 = Yes 0 = No / don't know	0.618	0.486	0	1	jowpcr /ajowpcar
permanentptb	Permanent part-time work	1 = Yes 0 = No / don't know	0.763	0.426	0	1	jowpptw / ajowpppt
wkfromhomeb	Home based work	1 = Yes 0 = No / don't know	0.215	0.411	0	1	jowphbw/ ajowphom
flexihrsb	Flexible start/finish times	1 = Yes 0 = No / don't know	0.522	0.500	0	1	jowpfx / ajowpflx
anyEmaternityb	Availability of either employer-provided maternity policies: Paid maternity leave or parental leave	1 = Yes 0= No	0.689	0.463	0	1	-
anyEgeneralb	Availability of employer-provided general policies: either special leave, permanent part-time work, home-based work, or flexible start and finish times.	1 = Yes 0= No	0.897	0.304	0	1	-
bothEpoliciesb	Availability of at least each one employer-provided maternity policy and one general policy..	1 = Yes 0= No	0.679	0.467	0	1	-

totEpoliciesb	Pre-childbirth workplace entitlements: count of the number of employer-provided policies available (excluding Unpaid Maternity Leave)	Number	3.195	1.716	0	6	-
EMPLOYMENT							
Experience and Tenure							
experb	History: total years of paid work at time of pre-childbirth employment	Years	10.899	5.250	0	29.97	ehtjb
experbMISS	Missing data dummy variable	1 = Yes 0= No	0.022	0.147	0	1	-
tenureempb	Tenure with employer in pre-childbirth job	Years	4.053	3.867	0.02	23	jbempt
tenureoccb	Tenure in the pre-childbirth occupation	Years	5.992	4.964	0.02	23	jbocct
Job contract and status							
fulltimeb	Employed full-time in pre-childbirth job	1 = Yes 0= No	0.537	0.499	0	1	esdtl
parttimeb	Employed part-time in pre-childbirth job	1 = Yes 0= No	0.463	0.499	0	1	esdtl
permanentb	Whether permanent contract in pre-childbirth job	1 = Yes 0= No / missing	0.671	0.470	0	1	jbmcnt
casualb	Whether casual contract in pre-childbirth job	1 = Yes 0= No / missing	0.220	0.414	0	1	jbmcnt
fixtermb	Whether fixed-term contract in pre-childbirth job	1 = Yes 0= No / missing	0.110	0.313	0	1	jbmcnt
unionb	Whether employee member of a trade union in pre-childbirth job	1 = Yes 0= No	0.283	0.451	0	1	jbmunio
Work Hours Preferences							
preflesshrsb	Whether respondent preferred fewer hours in the pre-childbirth job One missing observation is for a Manager / Administrator, and is recoded to *prefmorehrsb* to reflect the most common choice in this occupational group.	1 = Yes 0= No / missing	0.305	0.461	0	1	jbhrcpr
prefsamehrsb	Whether respondent was satisfied with hours of work in the pre-childbirth job	1 = Yes 0= No / missing	0.285	0.451	0	1	jbhrcpr
prefmorehrsb	Whether respondent preferred more hours in the pre-childbirth job	1 = Yes 0= No / missing	0.116	0.321	0	1	jbhrcpr
Occupation							
Occupation: highskilledb	ASCO 1 digit occupational classification: Managers and Administrators; Professionals; and Associate Professionals	1 = Yes 0= No	0.542	0.499	0	1	jbmocc1
Occupation: medskilledb	ASCO 1 digit occupational classification: Tradespersons and Related Workers; Advanced Clerical and Service Workers; Intermediate Clerical, Sales and Service Workers; and	1 = Yes 0= No	0.329	0.470	0	1	jbmocc1

	Intermediate Production and Transport Workers						
Occupation: lowskilledb	ASCO 1 digit occupational classification: Elementary Clerical, Sales and Service Workers; and Labourers and Related Workers	1 = Yes 0= No	0.126	0.332	0	1	jbmocc1
Employer Characteristics							
employerO100b	Pre-childbirth employer has over 100 employees across Australia	1 = Yes 0 = No / missing	0.573	0.495	0	1	jbmemsz
employerU100b	Pre-childbirth employer has under 100 employees across Australia	1 = Yes 0 = No / missing	0.108	0.311	0	1	jbmemsz
employerbMISS	Missing data dummy variable	1 = Yes 0= No	0.319	0.467	0	1	-
workplaceO20b	More than 20 people in the pre-childbirth workplace (separate to the total number employed by the pre-childbirth employer).	1 = Yes 0 = No	0.444	0.498	0	1	jbmwps / jbmwpsz
workplaceU20b	Less than 20 people in the pre-childbirth workplace (separate to the total number employed by the pre-childbirth employer).	1 = Yes 0 = No	0.556	0.498	0	1	jbmwps / jbmwpsz
governmentb	Whether private or government sector organisation	1 = government 0= private	0.322	0.468	0	1	jbmmplr / jbmmply
Pre-childbirth Industry: primaryb	ANZSIC 1 digit Industry classification: Agriculture; Electricity, Gas and Water Supply; and Mining	1 = Yes 0= No	0.026	0.160	0	1	jbmind1
Pre-childbirth Industry: intermedb	ANZSIC 1 digit Industry classification: Construction; Manufacturing; Wholesale Trade; and Transport and Storage	1 = Yes 0= No	0.152	0.359	0	1	jbmind1
Pre-childbirth Industry: retailhospb	ANZSIC 1 digit Industry classification: Retail Trade; Personal and Other Services; and Accommodation, Cafes and Restaurants	1 = Yes 0= No	0.186	0.390	0	1	jbmind1
Pre-childbirth Industry: businesspropb	ANZSIC 1 digit Industry classification: Communication Services; Finance and Insurance; and Property and Business Services	1 = Yes 0= No	0.180	0.384	0	1	jbmind1
Pre-childbirth Industry: goveducb	ANZSIC 1 digit Industry classification: Government Administration and Defence; and Education These categories were combined due to perfect predictability problems for Government Administration and Defence Government Administration and Defence is combined with Education due to perfect predictability problems. This aggregation is considered appropriate as the majority of educational institutions are likely to be government run, and this creates a common factor affecting access to work-life policies. These categories are not aggregated for partners.	1 = Yes 0= No	0.215	0.411	0	1	jbmind1
Pre-childbirth Industry: hlthcommb	ANZSIC 1 digit Industry classification: Health and Community Services; Cultural and Recreational Services	1 = Yes 0= No	0.252	0.435	0	1	jbmind1

PERSONAL CHARACTERISTICS AND EDUCATION							
age	Age of respondent at time of birth report	Years	31.471	4.952	19	49	hgage
NESB	Non-English Speaking Background	1 = Yes 0= No	0.090	0.286	0	1	abncob
degreeplus	Highest education level: bachelors degree or higher	1 = Yes 0= No	0.463	0.499	0	1	edhigh
diplomacert	Highest education level: diploma or certificate	1 = Yes 0= No	0.235	0.424	0	1	edhigh
yr12andunder	Highest education level: year 12 or below	1 = Yes 0= No	0.303	0.460	0	1	edhigh
FAMILY BACKGROUND							
siblings	Total number of siblings respondent has	Number (missing=0)	2.362	1.638	0	12	fmnsib
siblingMISS	Missing data dummy variable	1 = Yes 0= No	0.037	0.190	0	1	-
motherwk	Whether mother worked when respondent aged 14	1 = Yes 0= No / missing	0.618	0.486	0	1	fmmemp
mworkMISS	Missing data dummy variable	1 = Yes 0= No	0.020	0.139	0	1	-
motherocc	Mother's occupational status scale	0-100 (higher: higher status occupation)	37.450	27.812	0	100	fmmoccs
moccMISS	Missing data dummy variable	1 = Yes 0= No	0.171	0.377	0	1	-
fatherwk	Whether father worked when respondent aged 14	1 = Yes 0= No / missing	0.015	0.123	0	1	fmfemp
fworkMISS	Missing data dummy variable	1 = Yes 0= No	0.015	0.123	0	1	-
fatherocc	Father's occupational status scale	0-100 (higher: higher status occupation)	44.738	24.555	0	100	fmfoccs
foccMISS	Missing data dummy variable	1 = Yes 0= No	0.039	0.195	0	1	-
INCOME							

wageb	Financial year gross wages / salary of respondent in year of pre-childbirth job. 18 respondents without pre-childbirth wage observations are represented by *wagebMISS*, however 15 others list '0.' This is an anomaly, given these respondents are employees at the time (3 fix-term, 9 casual and 3 permanent). As the marginal effects are calculated at the mean wage, these 15 respondents are also coded as having wages 'missing.' This removes the effect of downward bias on the income figures. A total of 33 observations have *wageb*=0, the mean *wageb* value used in marginal effects (37.62 for the All Waves sample, 38.48 for the Waves 1-5 sub-sample) excludes these '0' values. Excluding the two outliers of $155 036 and $161 580 changes the All Waves mean to 37.04, which is not sensitive, therefore these outliers are included in the sample.	$'2006 (000s)	34.897	25.485	0	160.58	wsfg
wagebMISS	Missing data dummy variable	1 = Yes 0= No	0.072	0.259	0	1	-
ftben	Family Tax Benefit received from the government in post-childbirth financial year - corresponds to *returnone* timeframe	$'2006 (000s)	3.139	3.461	0	22.341	hifftb
ftbena	Family Tax Benefit received from the government in post-childbirth financial year - corresponds to *returntwo* timeframe	$'2006 (000s)	3.855	3.660	0	22.34	hifftb
ccareben	Childcare benefit amount received from the government in post-childbirth financial year - corresponds to *returnone* timeframe	$'2006 (000s)	0.313	1.032	0	8.303	hifccb
ccarebena	Childcare benefit amount received from the government in post-childbirth financial year - corresponds to *returntwo* timeframe	$'2006 (000s)	0.432	1.107	0	7.84	hifccb
matben	Maternity allowance: amount received from the government in post-childbirth financial year - corresponds to *returnone* timeframe	$'2006 (000s)	1.014	1.143	0.000	6.288	hifmat
matbena	Maternity allowance: amount received from the government in post-childbirth financial year - corresponds to *returntwo* timeframe	$'2006 (000s)	1.213	1.409	0	6.33	hifmat
-							
FAMILY FORMATION AND THE TIMING OF THE BIRTH							
couple	Whether respondent in a couple relationship during the birth wave (married or de-facto)	1 = Yes 0= No	0.940	0.238	0	1	mrcurr
single	Whether respondent is single during the birth wave	1 = Yes 0= No	0.060	0.238	0	1	-

children04	Total resident children from 0-4 years old in household Note: 12 respondents who reported a birth and reported 0 children from 0-4 were recoded as '1' child. There is an anomaly as 12 person-time observations in the final sample report 0 children between 0 and 4 (tcr04=0). This is amended by recoding these observations to '1' so it reflects the birth event being reported.	Number	1.370	0.529	1	3	tcr04
children04b	Total resident children from 0-4 years old in household during pre-childbirth period of employment	Number	0.442	0.611	0	3	tcr04
paresp	Parental responsibility for children under 17 during birth wave	1 = Yes 0= No	0.456	0.499	0	1	paresp
parespb	Parental responsibility for children under 17 during pre-childbirth period of employment	1 = Yes 0= No	0.453	0.498	0	1	paresp
newmum	Whether the reported birth is the respondent's first child.	1 = Yes 0= No	0.557	0.496	0	1	lebth, tchad
multibirths	Whether respondent contributed more than one birth to the final sample	1 = Yes 0= No	0.331	0.471	0	1	lebth
birthq1	Whether the reported birth occurred 9-12 months before the interview	1 = Yes 0= No	0.311	0.464	0	1	lebthQ1
birthq2	Whether the reported birth occurred 6-9 months before the interview	1 = Yes 0= No	0.265	0.442	0	1	lebthQ2
birthq3	Whether the reported birth occurred 3-6 months before the interview	1 = Yes 0= No	0.230	0.421	0	1	lebthQ3
birthq4	Whether the reported birth occurred 0-3 months before the interview	1 = Yes 0= No	0.165	0.371	0	1	lebthQ4
HOUSEHOLD INFORMATION							
houseworkb	Hours per week spent doing housework and household errands in pre-childbirth work period. There is a large range of values for this variable, however the median value (12) is not very different to the mean of 13.317. Therefore, the ten percent of observations with hours of housework over 30 hours a week are included.	Hours	13.317	11.691	0	60	lshrerr, lsmnerr, lshrhw, lsmnhw
houseworkbMISS	Missing data dummy variable. As data provided from Wave 2 onwards, (*houseworkbMISS* captures both the Wave 1 data and non-responses.	1 = Yes 0= No	0.007	0.081	0	1	-
careb	Hours per week spent caring for elderly/disabled dependents. This variable combines the separately recorded hours and minutes data in HILDA. Hours of care information is provided from wave 2 onwards, so the missing data dummy variable (*carebMISS*) represents both actual missing information as well as the Wave 1 information.	Hours	0.106	1.665	0	35	lshrcar, lsmncar

carebMISS	Missing data dummy variable	1 = Yes 0= No	0.252	0.435	0	1	-
SITUATIONAL INFLUENCES ON THE ABILITY TO WORK							
childcare	Index of the difficulty finding childcare in post-childbirth period, matching the timeframe of *returnone*. HILDA asks a series of questions (11 questions in Waves 1-4, 12 in Waves 5 and 6) in which respondents provide a rank between 1 and 10 of various aspects of childcare (including affordability, convenience, and quality). These are combined into an index and weighted to sum to 100. Although the indices for Waves 5 and 6 are slightly different, it is not anticipated to cause a problem as the 11 questions in Waves 1-4 could be capturing the effects of the extra question in waves 5 and 6. Furthermore, this 12th question contributes a maximum of 10 percent of the value of Wave 5 and 6 indices, which is not a large influence.	0-100 (higher --> greater difficulty)	13.251	19.12	0	89.167	ccdifgq, ccdifrp, ccdifhr, ccdifsc, ccdifdh, ccdifcs, ccdifjm, ccdifds, ccdifcc, ccdifrl, ccdifch, ccdifsn (waves 5-6 only)
childcarea	Index of the difficulty finding childcare in post-childbirth period, matching the timeframe of *returntwo*.	0-100 (higher --> greater difficulty)	15.520	19.857	0	89.17	see above
travelb	Total hours per week spent travelling to and from work in pre-childbirth work period	Hours	2.758	3.720	0	40	lsmncom, lshrcom
travelbMISS	Missing data dummy variable		0.202	0.402	0	1	
SEIFAsocio	ABS 2001 Census' socioeconomic indicator: SEIFA deciles of relative socioeconomic disadvantage: reflects access to facilities, education, unemployment levels and other geographical influences upon household decisions	1-10 (higher: less disadvantage)	5.985	2.754	1	10	hhda10
SEIFAsociob	SEIFA Decile Index of Socioeconomic disadvantage in the period of pre-childbirth employment	1-10 (higher: less disadvantage)	5.908	2.760	1	10	hhda10
SEIFAecon	ABS 2001 Census' socioeconomic indicator: SEIFA deciles of relative economic resources (income, expenditure, assets of households). Reflects social trends in the respondent's geographic area.	1-10 (higher: less disadvantage)	5.833	2.688	1	10	hhec10
SEIFAeconb	SEIFA Decile Index of economic resources in the period of pre-childbirth employment	1-10 (higher: less disadvantage)	5.963	2.813	1	10	hhec10
SEIFAeduc	ABS 2001 Census' socioeconomic indicator: SEIFA deciles of education and occupation, index takes into account variables like the proportion of people with a higher qualification or employed in a skilled occupation in the geographic area.	1-10 (higher: less disadvantage)	5.958	2.730	1	10	hhed10
SEIFAeducb	SEIFA Decile Index of education and occupation in the period of pre-childbirth employment	1-10 (higher: less disadvantage)	5.752	2.699	1	10	hhed10

PARTNER INFORMATION							
Partner's pre-childbirth income, employment and household participation							
pnotwkb	Partner is not employed in the pre-childbirth period		0.033	0.179	0	1	esdtl
pwageb	Financial year gross wages / salary of partner in year of respondent's pre-childbirth job 63 missing *pwageb* observations, are recoded as *pwagebMISS*. Another 36 have *pwageb* equal to 0. As there is no requirement that partner's be working, a zero wage is. Zero and missing values are excluded from the means for marginal effects (50.26 for the All Waves sample, 53.25 for the Waves 1-5 sub-sample). The mean value excluding two outliers (greater than $200 000) falls to 49.16. Though the regression results are not sensitive to these outliers, they are excluded from the mean *pwageb* value for marginal effects.	$'2006 (000s)	43.315	35.857	0	280	wsfg
pwagebMISS	Missing data dummy variable	1 = Yes 0= No	0.138	0.345	0	1	-
plowskilledb	Partner's ASCO 1 digit occupational classification: Managers and Administrators; Professionals; and Associate Professionals	1 = Yes 0= No / missing	0.092	0.290	0	1	jbmocc1
pmedskilledb	Partner's ASCO 1 digit occupational classification: Tradespersons and Related Workers; Advanced Clerical and Service Workers; Intermediate Clerical, Sales and Service Workers; and Intermediate Production and Transport Workers	1 = Yes 0= No / missing	0.338	0.473	0	1	jbmocc1
phighskilledb	Partner's ASCO 1 digit occupational classification: Elementary Clerical, Sales and Service Workers; and Labourers and Related Workers	1 = Yes 0= No / missing	0.412	0.493	0	1	jbmocc1
pprimaryb	Partner's ANZSIC 1 digit Industry classification: Agriculture; Electricity, Gas and Water Supply; and Mining	1 = Yes 0= No / missing	0.072	0.259	0	1	jbmind1
pintermedb	Partner's ANZSIC 1 digit Industry classification: Construction; Manufacturing; Wholesale Trade; and Transport and Storage	1 = Yes 0= No / missing	0.298	0.458	0	1	jbmind1
pretailhospb	Partner's ANZSIC 1 digit Industry classification: Retail Trade; Personal and Other Services; and Accommodation, Cafes and Restaurants	1 = Yes 0= No / missing	0.129	0.336	0	1	jbmind1
pbusinesspropb	Partner's ANZSIC 1 digit Industry classification: Communication Services; Finance and Insurance; Property and Business Services	1 = Yes 0= No / missing	0.145	0.352	0	1	jbmind1
peducationb	Partner's ANZSIC 1 digit Industry classification: Education	1 = Yes 0= No / missing	0.053	0.224	0	1	jbmind1
pgovtndefenceb	Partner's ANZSIC 1 digit Industry classification: Government Administration and Defence	1 = Yes 0= No / missing	0.050	0.219	0	1	jbmind1
phlthcommb	Partner's ANZSIC 1 digit Industry classification: Health and	1 = Yes	0.092	0.289	0	1	jbmind1

	Community Services; Cultural and Recreational Services	0= No / missing					
pemplbMISS	Missing data dummy variable	1 = Yes 0 = No	0.160	.367	0	1	-
phouseworkb	Partner's hours per week spent doing housework and household errands in pre-childbirth work period	Hours	6.559	7.850	0	50	lshrerr, lsmnerr, lshrhw, lsmnhw
ptravelb	Partner's total hours per week spent travelling to and from work in pre-childbirth work period	Hours	2.947	3.595	0	15	lsmncom, lshrcom
ptravelbMISS	Partner's total hours per week spent travelling to and from work in pre-childbirth work period	1 = Yes 0 = No	0.333	0.412	0	1	-
Partner's post-childbirth employment							
pnotwka	Partner is not employed in the post-childbirth period	1 = does not work 0 = works / missing	0.114	0.318	0	1	esdtl
pfulltimea	Partner works full-time in post-childbirth period	1 = Yes 0= No / missing	0.798	0.402	0	1	esdtl
pparttimea	Partner works part-time in post-childbirth period	1 = Yes 0= No / missing	0.061	0.240	0	1	esdtl
pselfempla	Partner self-employed in post-childbirth period	1 = Yes 0= No / missing	0.149	0.357	0	1	es
ppermanenta	Partner employee: permanent contract in post-childbirth period	1 = Yes 0= No / missing	0.590	0.492	0	1	jbmcnt
pfixterma	Partner employee: fixed term contract in post-childbirth period	1 = Yes 0= No / missing	0.070	0.256	0	1	jbmcnt
pcasuala	Partner employee: casual contract in post-childbirth period	1 = Yes 0= No / missing	0.053	0.224	0	1	jbmcnt
plowskilleda	ASCO 1 digit occupational classification: Managers and Administrators; Professionals; and Associate Professionals	1 = Yes 0= No / missing	0.127	0.334	0	1	jbmocc1
pmedskilleda	ASCO 1 digit occupational classification: Elementary Clerical, Sales and Service Workers; and Labourers and Related Workers	1 = Yes 0= No / missing	0.320	0.467	0	1	jbmocc1
phighskilleda	ASCO 1 digit occupational classification: Tradespersons and Related Workers; Advanced Clerical and Service Workers; Intermediate Clerical, Sales and Service Workers; Intermediate Production and Transport Workers	1 = Yes 0= No / missing	0.456	0.499	0	1	jbmocc1
pgovernmenta	Whether private or government sector organisation	1 = government 0= private	0.184	0.388	0	1	jbmmplr / jbmmply
pprimarya	Partner's ANZSIC 1 digit Industry classification: Agriculture; Electricity, Gas and Water Supply; and Mining	1 = Yes 0= No / missing	0.072	0.259	0	1	jbmind1
pintermeda	Partner's ANZSIC 1 digit Industry classification: Construction; Manufacturing; Wholesale Trade; and	1 = Yes 0= No / missing	0.250	0.433	0	1	jbmind1

	Transport and Storage						
pretailhospa	Partner's ANZSIC 1 digit Industry classification: Retail Trade; Personal and Other Services; and Accommodation, Cafes and Restaurants	1 = Yes 0= No / missing	0.129	0.336	0	1	jbmind1
pbusinesspropa	Partner's ANZSIC 1 digit Industry classification: Communication Services; Finance and Insurance; Property and Business Services	1 = Yes 0= No / missing	0.147	0.354	0	1	jbmind1
peducationa	Partner's ANZSIC 1 digit Industry classification: Government Administration and Defence	1 = Yes 0= No / missing	0.044	0.205	0	1	jbmind1
pgovtndefencea	Partner's ANZSIC 1 digit Industry classification: Education	1 = Yes 0= No / missing	0.064	0.244	0	1	jbmind1
phlthcomma	Partner's ANZSIC 1 digit Industry classification: Health and Community Services; and Cultural and Recreational Services	1 = Yes 0= No / missing	0.086	0.280	0	1	jbmind1
pemplaMISS	Missing data dummy variable for whether post-childbirth work participation, contract, sector, industry or occupation is missing (missing information is perfectly correlated)	1 = Yes 0= No	0.241	0.428	0	1	
Partner's Post-childbirth access to policies							
ppaidMLa	Partner's post-childbirth workplace entitlements: availability of paid maternity leave	1 = Yes 0= No / missing	0.311	0.464	0	1	jowppml / ajowppmt
punpaidMLa	Partner's post-childbirth workplace entitlements: availability of unpaid maternity leave	1 = Yes 0= No / missing	0.467	0.499	0	1	jowpuml / ajowpumt
pparentalLa	Partner's post-childbirth workplace entitlements: availability of parental leave	1 = Yes 0= No / missing	0.513	0.500	0	1	jowppnl / ajowppnt
pspecialLa	Partner's post-childbirth workplace entitlements: availability of special leave to care for sick family members	1 = Yes 0= No / missing	0.500	0.501	0	1	jowpcr /ajowpcar
ppermanentpta	Partner's post-childbirth workplace entitlements: availability of permanent part-time work	1 = Yes 0= No / missing	0.439	0.497	0	1	jowpptw / ajowpppt
pwkfromhomea	Partner's post-childbirth workplace entitlements: availability of home based work	1 = Yes 0= No / missing	0.213	0.410	0	1	jowphbw ajowphom
pflexihrsa	Partner's post-childbirth workplace entitlements: availability of flexible start/finish times	1 = Yes 0= No / missing	0.436	0.496	0	1	jowpfx / ajowpflx
ppolicyaMISS	Missing data dummy variable: equals to 1 if any of the policy variables are missing	1 = Yes 0= No	0.211	0.408	0	1	

APPENDIX 1B

Derivation of the final sample		
Description	*Person Observations*	*Person-time Observations*
Total Sample of women aged 18 +	5487	25322
Women responding to the SCQ	5362	22955
Women with at least one birth in the 6 year period	780	3901
Women with a work observation up to 2 years before a birth	473	584
Answered the Workplace Entitlement questions in the pre-childbirth employment wave (dropped "not asked" and "not applicable")	431	530
Remained in the survey after a birth	412	510
Women who are employees (drops self-employed, employers and contractors)*	389	475
Answered question on parental responsibility**	387	473
Answered questions about pre-childbirth industry (dropping one observation with missing industry information)	386	472
Included information about employment contract	377	456
Final Sample	**377**	**456**
Sub-sample with long-term data Surveyed 2 years after the birth (using wave 2, 3, and 4 births only)	**221**	**237**

*This exclusion only affects the magnitude of one key variable (*parental leave*), but not the magnitudes or statistical significance of the other key variables. Results available upon request.
**The results are not sensitive to this exclusion. Results available on request.

Women who give birth are identified by *birth*, a dummy variable equal to one if there was a birth/adoption in the past 12 months. Though Hosking (2007) also uses "changes in the number of children in the household between waves" and "the presence of at least one resident child aged one year or less," these variables may indicate the presence of children from a partner's relationship or other sources (e.g. the child of a relative in a combined household). For these reasons, the birth/adoption variable is considered most precise.

While adoptions are not births per se, they are not entirely incongruous either. Adoptions also create employment disruptions, though arguably to a lesser extent than biological births. Furthermore, the varying lengths of time after childbirth in which women return to work (see Baxter, 2008 for a comprehensive study) makes it unlikely that adoption events will have a systematic impact on the timing of return to work.

Women who are under 18 when giving birth are excluded (following Hosking 2007), as such pregnancies are unlikely to affect work decisions to the same extent as for older women. As it is an unbalanced panel in which many join the sample, 18 years of age is the lower bound for *each wave,* that is, respondents who are 18 in any wave are included, even if they are under 18 in earlier waves.

APPENDIX 1C

Of the 199 who returned within two years (i.e. person-time observations with *returntwo*=1), there are 35 observations in which respondents are not working in the longer-term (this number is understated because *returnLT* does not include whether women with births in waves 5 and 6 later dropped out). 27 women ended up rejoining work a few years after the birth, which is a large percentage of those in the given sample. Although the sample is too small (and potentially too biased) to represent the entire population of women, it indicates that some women may later drop out of the workforce if they cannot balance work and non-work responsibilities.

Longer-term work status (*returnLT*)					
		Working in long-term		**Not working in long-term**	
***returntwo* Status**	**Freq with *returnLT* observation**	**Number**	**%**	**Number**	**%**
Returned	199	164	82.41	35	17.59
Did not return	38	27	71.05	11	28.95

APPENDIX 1D

Timing of the birth and return to work patterns								
Number of months before the interview	Full Sample		returned in birth wave (*returnone=1*)		returned in wave after birth wave (*returnone*=0 & *returntwo*=1)		Total returned	
	Freq	% of sample	Freq	% of births in that period	Freq	% of births in that period	Freq	% of births in that period
9-12 months	142	31.14	64	45.07	31	21.83	95	66.90
6-9 months	121	26.54	58	47.93	34	28.10	92	76.03
3-6 months	105	23.03	51	48.57	30	28.57	81	77.14
0-3 months	75	16.45	54	72.00	9	12.00	63	84.00
Not stated	13	2.85	6	46.15	3	23.08	9	69.23
Total	456	100.00	233		107		340	

APPENDIX 1E: Key Policy Variables

The final sample excludes 19 women (54 person-time observations) who answered "not applicable" or for reasons unknown were "not asked" about these policies. As the final sample includes those who were working in the year that the policies are recoded, it is unlikely that "not applicable" refers to work status. It may be hat the respondent does not qualify for these policies (thus focussing on the first part of the question asked – "whether *you*…would be able to use these if needed"). Overall, the uncertainties surrounding this "not applicable" answer necessitate the safe option of dropping these 19 observations.

Any "don't know" responses are coded as '0' for not available, as people who don't know about the variables are unlikely to use them, and their employment decisions are presumably based on the unavailability of such entitlements. While this reasoning concords with Edwards (2004), unlike Edwards I do not delete these observations. Following Risse (2007), this study keeps the effects of respondents unaware about policies.

Respondents who returned by the birth wave (*returnone*=1) are more likely to have each policy compared to those who return the following wave (*returnone*=0 *and returntwo*=1). This is particularly so for paid and unpaid maternity leaves, and flexible start and finish times. The final column records all respondents who remain attached to work, a slight majority of whom had unpaid maternity leave and permanent part-time work in their pre-childbirth jobs. These percentages cannot be directly compared to the first two columns because only 11 respondents who had not returned within the first two waves (that is, for whom *returnone*=0 and *returntwo*=0) return in the very long term (*returnLT*=1). The *returnLT* information therefore retains all those who had returned earlier.

1E.1 Policy availability by those who returned to work Note: sample size for *returnone* and *returntwo* = 456; sample size for *returnLT* = 237						
	returnone=1		**returntwo=1**		**returnLT=1**	
	Freq	**% of those who returned**	**Freq**	**% of those who returned**	**Freq**	**% of those who returned**
Paid Maternity Leave	127	54.51	45	42.06	86	36.29
Unpaid Maternity Leave	195	83.69	81	75.70	139	58.65
Parental Leave	154	66.09	69	64.49	106	44.73
Special Leave to care for family members	155	66.52	65	60.75	106	44.73
Permanent Part-time work	190	81.55	84	78.50	138	58.23
Home Based work	60	25.75	23	21.50	42	17.72
Flexible start and finish times	130	55.79	52	48.60	85	35.86
Total Retuned	233		107		237	

Compared to the HILDA sample, my sample reports higher levels of access to most policies, particularly unpaid maternity leave.

1E.2 Comparing policy availability with the broader HILDA sample.							
Policy	**Sample Freq**	**Sample %**	**HILDA %**	**Generated Variables**	**Sample Freq**	**Sample %**	**HILDA %**
Unpaid Maternity Leave	353	77.41	59.76				
Paid Maternity Leave	212	46.49	38.88	*anyEmaternityb* feature	315	69.08	57.64
Parental Leave	279	61.18	50.29				
Special Leave to care for family members	282	61.84	55.96	*anyEgeneralb* feature	412	90.35	88.09
Permanent Part-time work	348	76.32	71.77				
Home Based work	98	21.49	20.77				
Flexible start and finish times	238	52.19	51.26				
				bothEpoliciesb	310	67.98	56.24
				anyEpolicyb	417	91.45	89.49
The comparable HILDA sample has 12867 person-time observations from 3879 women aged 19-49 (matching the age range of my sample).							

APPENDIX 1F: The definition of "parental leave"

Of people who had parental leave, 63 percent report access to paid maternity leave, while 92 percent report access to unpaid maternity leave. Given that a large number of people with parental leave do not have paid maternity leave, it is unlikely that respondents are confusing these definitions. The high figure for unpaid maternity leave is also not definitive, because unpaid maternity leave is a statutory entitlement (*Workplace Relations Act, 1996*) and thus is unlikely to be confused with employer-provided leave. However, there is no way of knowing respondents' interpretation of these terms.

Cross-Tabulation of maternity policies when Parental Leave = 1		
	Freq	%
Paid Maternity Leave = 1	176	63.08
Unpaid Maternity Leave = 1	257	92.11

APPENDIX 1G

Correlations between the policy variables							
Policy	*paidMLb*	*unpaidMLb*	*parentalLb*	*specialLb*	*permanentptb*	*wkfromhomeb*	*flexihrsb*
paidMLb	1.00						
unpaidMLb	0.20	1.00					
parentalLb	**0.42**	**0.44**	1.00				
specialLb	**0.46**	0.33	**0.57**	1.00			
permanentptb	0.24	0.25	0.32	0.26	1.00		
wkfromhomeb	0.08	0.12	0.19	0.18	0.09	1.00	
flexihrsb	-0.01	0.12	0.15	0.15	0.12	**0.43**	1.00

APPENDIX 1H

Almost half of the employer size variable is missing. Of those who return to work in the short-term, the largest proportion work for large employers in large workplaces. These missing observations are dealt with by the modified zero-order method, creating the dummy variable *employerbMISS.*

Employer size and workplace size			
	Workplace Size		*Total*
Employer Size	Over 20	Under 20	
Over 100	159	94	253
Under 100	5	42	47
Missing	58	98	156
Total	222	234	456

APPENDIX 1I

Whether partner information changes between the pre-childbirth and post-childbirth waves (matching the timeframe of *returntwo*)			
	Observations with a change in data values		
Variable	**Freq**	**Number**	**%**
Partner's employment status and situational information			
p labour force status	421	45	10.69
p employment status (employee, self-employed, employer, contributing family member)	446	67	15.02
p union	419	69	16.47
p contract	399	67	16.79
p occupation	421	138	32.78
p industry	417	115	27.58
p wage	406	335	82.51
p hours travelling	260	226	86.92
Partner's perceived access to policies			
p paidML	288	68	23.61
p unpaidML	287	53	18.47
p parentalL	319	65	20.38
p wkfromhome	352	73	20.74
pspecialL	315	59	18.73
ppermanentpt	330	79	23.94
pflexihrs	357	80	22.41
Note: Partner information may be missing because the respondent is a single mother; the partner did not respond to the entire Self-Completion Questionnaire (SCQ), or the partner did not responds to particular SCQ questions.			

APPENDIX 2

Results

APPENDIX 2A: Return to work in the short-term, models without control variables

Probability of returning to work in the birth or following wave (returntwo): Probit without control variables P-values are reported in parentheses. Marginal effects are for discrete changes of dummy variables from 0 to 1.		
	(i)	
	coefficient	marginal effect
Disaggregated Key Variables		
paidMLb	0.244	0.096
	(0.11)	*(0.103)*
unpaidMLb	0.273	0.107
	(0.104)	*(0.101)*
parentalLb	0.145	0.057
	(0.418)	*(0.413)*
specialLb	-0.129	-0.051
	(0.458)	*(0.457)*
permanentptb	0.356**	0.138**
	(0.022)	*(0.021)*
wkfromhomeb	0.394**	0.152**
	(0.035)	*(0.026)*
flexihrsb	-0.060	-0.024
	(0.672)	*(0.672)*
constant	0.038	-
	(0.810)	-
Base Probability of success	-	0.515
N	456	456
Log-likelihood	-244.724	-
Pseudo R-squared	0.054	-
* 10% significance, ** 5 % significance, *** 1 % significance		
N = 456		

The availability of permanent part-time work increases the probability return by 13.8 percent, which is significant at the 5 percent level, while the ability to work from home has an even larger effect (15.2 percent) and is as precisely estimated. As over three-quarters of the sample reported access to permanent part-time work, the large marginal effect is somewhat expected. However, the magnitude of *wkfromhomeb* is far greater than expected, as only one quarter of respondents could access it. The large effects of both these variables suggest that job-security and work-life balance are important influences upon short-term mobility decisions (Baxter, 2008).

These coefficient may also reflect endogeneity biases. The effect of working from home could, for example, reflect that the majority of the sample are professionals (38%) who may be able to work remotely, while other major occupational group are clerical workers who are likely able to work part-time (Gray and Tudball, 2002).

The table continue below, and shows aggregated policy forms are slightly more significant (below).

Probability of returning to work in the birth or following wave (returntwo): Probit without control variables (cont.)						
P-values are reported in parentheses. Marginal effects are for discrete changes of dummy variables from 0 to 1, other variables calculated at means (rounded to the nearest whole figure).						
	(ii)		(iii)		(iv)	
	coefficient	marginal effect	coefficient	marginal effect	coefficient	marginal effect
Semi-Aggregated Key Variables						
anyEmaternityb	0.110	0.044	-	-	-	-
	(0.855)	*(0.855)*	-	-	-	-
anyEgeneralb	0.271	0.107	-	-	-	-
	(0.258)	*(0.258)*	-	-	-	-
bothEpoliciesbb	0.253	0.100	-	-	-	-
	(0.684)	*(0.677)*	-	-	-	-
unpaidMLb	0.255	0.101	-	-	-	-
	(0.118)	*(0.115)*	-	-	-	-
Aggregated Key Variables						
anyEpolicyb	-	-	0.48**	0.187***	-	-
	-	-	*(0.029)*	*(0.010)*	-	-
unpaidMLb	-	-	0.384**	0.151**	-	-
	-	-	*(0.011)*	*(0.030)*	-	-
Count Variable						
totEpoliciesb	-	-	-	-	0.133***	.048***
	-	-	-	-	*(0.001)*	*(0.001)*
unpaidMLb	-	-	-	-	0.257	0.086
	-	-	-	-	*(0.112)*	*(0.124)*
constant	-0.007	-	-0.060	-	0.064	-
	(0.972)	-	*(0.776)*	-	*(0.662)*	-
Base Probability of success	-	0.497	-	0.476	-	0.678
N	456	456	456	456	456	456
Log-likelihood	-248.393	-	-251.133	-	-248.314	-
* 10% significance, ** 5 % significance, *** 1 % significance						
N = 456						

APPENDIX 2B: Deriving the parsimonious specification for returntwo

Probability of returning to work in the birth or following wave (returntwo): Probit with control variables†

P-Values are reported in parentheses. Marginal effects for dummy variables are for changes from 0 to 1, other variables at means. Likelihood-Ratio Test Statistics are calculated with reference to Model (i)

	Un-restricted	Variables Dropped Cumulatively						
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
paidMLb	0.310	0.298	0.32	0.317	0.305	0.350	0.349	0.349
	(0.219)	*(0.243)*	*(0.195)*	*(0.195)*	*(0.210)*	*(0.143)*	*(0.141)*	*(0.123)*
unpaidMLb	0.198	0.161	0.228	0.222	0.202	0.269	0.270	0.169
	(0.446)	*(0.530)*	*(0.354)*	*(0.364)*	*(0.406)*	*(0.259)*	*(0.257)*	*(0.453)*
parentalLb	0.172	0.193	0.184	0.188	0.221	0.217	0.209	0.199
	(0.504)	*(0.447)*	*(0.457)*	*(0.445)*	*(0.364)*	*(0.369)*	*(0.383)*	*(0.397)*
specialLb	-0.392	-0.382	-0.366	-0.363	-0.371	-0.388	-0.374	-0.364
	(0.127)	*(0.133)*	*(0.138)*	*(0.136)*	*(0.125)*	*(0.103)*	*(0.113)*	*(0.110)*
permanentptb	0.340	0.339	0.314	0.314	0.31	0.274	0.282	0.355*
	(0.139)	*(0.138)*	*(0.161)*	*(0.161)*	*(0.164)*	*(0.210)*	*(0.196)*	*(0.085)*
wkfromhomeb	0.074	0.060	0.08	0.082	0.092	0.107	0.103	0.222
	(0.792)	*(0.830)*	*(0.768)*	*(0.758)*	*(0.732)*	*(0.685)*	*(0.695)*	*(0.380)*
flexihrsb	0.101	0.083	0.069	0.087	0.068	0.038	0.034	0.053
	(0.626)	*(0.685)*	*(0.730)*	*(0.660)*	*(0.728)*	*(0.845)*	*(0.859)*	*(0.773)*
constant	0.883	0.964	0.835	0.713	0.523	0.448	0.477	0.478
	(0.592)	*(0.537)*	*(0.562)*	*(0.617)*	*(0.708)*	*(0.743)*	*(0.719)*	*(0.704)*
Log-likelihood	-165.437	-165.754	-167.713	-167.953	-168.617	171.520	-171.760	-175.980
Pseudo R-squared	0.360	0.036	0.352	0.351	0.348	0.337	0.336	0.320
LR Test Statistic	-	0.630	4.550	5.030	6.360	12.170	12.650	21.090
	-	*(0.889)*	*(0.984)*	*(0.996)*	*(0.995)*	*(0.985)*	*(0.994)*	*(0.999)*

* 10% significance, ** 5 % significance, *** 1 % significance

N=456. † Control variables omitted, results available on request.

This table shows the sensitivity of key variables to exclusions. Small and insignificant variables are dropped by category (see Appendix A.4B for details. (i) Unrestricted Model - all control variables included.
The excluded variables are: (ii) Some Personal Background Variables; (iii) All Family Background Variables; (iv) Some Employment Characteristics; (v) Some Income Variables; (vi) Some Household and situational influences; (vii) Some Pre-childbirth Partner Variables; (viii) Some Post-childbirth Partner Variables
Model (vii) forms the final parsimonious specification. There is not a large difference between Model (viii) and Model (i) in terms of coefficients and fit, however the key variables are generally more significant.

The final model (viii) is obtained as follows:

(i) Unrestricted model: The base dummy variables aim to represent the 'average' individual in the sample. Therefore, where possible, the most common category in each variable group is set as the base:
- Personal background and education: English-speaking background, educated with a bachelor's degree or higher
- Family background: no siblings, neither parent worked when respondent was 14
- Employment characteristics: permanent, full-time contract, high-skilled occupation, satisfied with the number of hours worked.
- Employer characteristics: over 100 employees; under 20 employees in workplace; non-unionised, private sector, industry: health and community services.
- Family Formation and birth timing: couple relationship, responsible for a child under 17, but no children aged 0-4; contributes a single birth 9-12 months before the interview.
- Partner's post-childbirth information: high-skilled, full-time, permanent private sector employee; working in an intermediate industry.

Variables are excluded as follows:

(ii) Excluding some Personal background variables: *NESB, degreeplus, diplomacert.*
UnpaidMLb becomes smaller and less significant, other variables not sensitive.

(iii) Excluding all family background variables: siblings, siblingMISS, motherwk, *mworkMISS, motherocc, moccMISS, fatherwk, fworkMISS, fatherocc, foccMISS*

(iv) No dramatic impact of excluding family background variables. *PaidMLb* and *unpaidMLb* increase in size and significance. LR Test p-value is also very large, justifying the dropping of these variables.

(v) Excluding some employment characteristics: *prefmorehrsb, preflesshrsb, unionb.*
No large change in other coefficients or model fit. LR Test p-value very large.

(vi) Excluding some income variables: *wagepercentb, ftbena.*
PaidMLb, unpaidMLb and the constant decrease in size and significance, no other major changes.

(vii) Household and situational influences: *careb, carebMISS, travelb, travelbMISS, SEIFAsocio, SEIFAecon, SEIFAeduc.*
PaidMLb and *UnpaidMLb* increase in size and significance. The LR Test p-value is large but insignificant.

(viii) Excluding some partner pre-childbirth variables: *phouseworkb, ptravelb, ptravelbMISS*
No large change.

(ix) Excluding some partner post-childbirth variables: *pselfempla, pparttimea, pfixterma, pcasuala,* all partner industry variables (*pprimarya, pretailhospa, pbusinesspropa, peducationa, pgovtndefencea, phlthcomma*), most policy variables (*punpaidMLa, pparentalLa, pspecialLa, ppermanentpta, pwkfromhomea, pflexihrsa*).
PaidMLb, permanentptb and *wkfromhomeb* become larger and more significant. There is a large but insignificant LR Test statistic, and the Pseudo R-squared is 0.32, compared to 0.36 for the unrestricted model, which is not a large change in explanatory power over a base model with just an intercept.

APPENDIX 2C

2C.1 Returntwo– Probit with control variables for disaggregated and semi-aggregated policies †
P-values are reported in parentheses. Marginal effects are for discrete changes of dummy variables from 0 to 1, other variables calculated at means.

	(i) All Waves		(i) Waves 1-5		(ii) All Waves		(ii) Waves 1-5	
	coef.	marg. effect	coef.	marg. effect	coef.	marg. effect	coef.	marg. effect
Disaggregated Key Variables								
paidMLb	0.349	0.119	0.749**	0.079	-	-	-	-
	(0.123)	*(0.169)*	*(0.038)*	*(0.581)*	-	-	-	-
unpaidMLb	0.169	0.060	0.065	0.011	-	-	-	-
	(0.453)	*(0.475)*	*(0.838)*	*(0.849)*	-	-	-	-
parentalLb	0.199	0.070	0.466	0.060	-	-	-	-
	(0.397)	*(0.408)*	*(0.187)*	*(0.578)*	-	-	-	-
specialLb	-0.364	-0.141	-0.224	-0.045	-	-	-	-
	(0.110)	*(0.119)*	*(0.523)*	*(0.647)*	-	-	-	-
permanentptb	0.355*	0.120	0.098	0.016	-	-	-	-
	(0.085)	*(0.156)*	*(0.755)*	*(0.768)*	-	-	-	-
wkfromhomeb	0.222	0.078	0.360	0.050	-	-	-	-
	(0.380)	*(0.372)*	*(0.344)*	*(0.593)*	-	-	-	-
flexihrsb	0.053	0.194	0.275	0.041	-	-	-	-
	(0.773)	*(0.771)*	*(0.331)*	*(0.567)*				
Semi-Aggregated Key Variables								
anyEmaternity	-	-	-	-	0.302	0.111	0.980	0.110
	-	-	-	-	*(0.729)*	*(0.715)*	*(0.466)*	*(0.582)*
anyEgeneral	-	-	-	-	0.158	0.060	0.545	0.081
	-	-	-	-	*(0.593)*	*(0.598)*	*(0.174)*	*(0.541)*
bothEpoliciesb	-	-	-	-	0.065	0.025	-0.194	-0.045
	-	-	-	-	*(0.941)*	*(0.941)*	*(0.887)*	*(0.899)*
unpaidMLb	-	-	-	-	0.107	0.041	-0.067	-0.014
	-	-	-	-	*(0.623)*	*(0.629)*	*(0.833)*	*(0.832)*
constant	0.478	-	-0.202	-	0.494	-		
	(0.704)	-	*(0.914)*	-	*(0.690)*	-		-
Base Probability of success	-	0.650	-	0.899	-	0.601	-	0.873
Log-likelihood	-175.98	-	-89.35	-	-178.72	-	-90.34	-
Pseudo R-squared	0.320	-	0.426	-	0.309	-	0.420	-
N	456		351		456		351	

* 10% significance, ** 5 % significance, *** 1 % significance

† Control variables omitted, results available on request.

2C.2 Returntwo – Probit with control variables for aggregated and count policies† P-values are reported in parentheses. Marginal effects are for discrete changes of dummy variables from 0 to 1, other variables calculated at means.								
	(iii) All Waves		(iii) Waves 1-5		(iv) All Waves		(iv) Waves 1-5	
	coef.	marg. effect	coef.	marg. effect	coef.	marg. effect	coef.	marg. effect
Aggregated Key Variables								
anyEpolicyb	0.318	0.118	0.826**	0.078	-	-	-	-
	(0.252)	*(0.286)*	*(0.028)*	*(0.588)*	-	-	-	-
unpaidMLb	0.198	0.075	0.108	0.017	-	-	-	-
	(0.345)	*(0.374)*	*(0.718)*	*(0.766)*	-	-	-	-
Count Variable								
totEpoliciesb	-	-	-	-	0.105*	0.036	0.252***	0.012
	-	-	-	-	*(0.084)*	*(0.155)*	*(0.001)*	*(0.624)*
unpaidMLb	-	-	-	-	0.131	0.043	-0.010	0.010
	-	-	-	-	*(0.544)*	*(0.580)*	*(0.974)*	*(0.720)*
constant	0.459	-	-0.185	-	0.495	-	-0.144	-
	(0.710)	-	*(0.918)*	-	*(0.688)*	-	*(0.936)*	-
Base Probability of success	-	0.587	-	0.906		0.71		0.980
Log-likelihood	-179.97	-	-92.74	-	-179.11	-	-91.241	-
Pseudo R-squared	0.304	-	0.404	-	0.307	-	0.414	-
N	456		351		456		351	
* 10% significance, ** 5 % significance, *** 1 % significance								
† Control variables omitted, results available on request.								
Aggregating policy variables improves their overall precision. The higher variability in the count variable (*totEpoliciesb*) makes it more significant than the simple aggregated variable (*anyEpolicyb*). The key results are sensitive to the inclusion of Wave 6 birth observations, which are censored because the timeframe for returntwo includes both the birth and following waves, and our sample only goes to Wave 6. The exclusion of Wave 6 births increases the size of policy variables. Wave 6 marginal effects are calculated for the means of the Wave 1-5 sub-sample Marginal effects for the full sample / sub-sample from Waves 1-5 are calculated for the "average" person: all dummy variables are set at 0, while the following continuous variables are set at their means: age (31.47 / 31.5 years); total years in paid work (11.37 / 11.65 years); tenure with pre-childbirth employer (6 / 6.23 years); childcare benefit ($432 / $467); maternity benefit ($1 210 / $855); hours of housework per week (13.58 / 12.62); partner's hours of housework per week (6.56 / 6); difficulty finding childcare index score (15.12 / 17.07 out of 100). The wage and salary means exclude all '0' values: pre-childbirth wage ($ 37 620 / $38 470); pre-childbirth percentage contribution to household wages and salaries (47.89% / 49.5%), while the partner's pre-childbirth wage is sensitive to outliers and thus its mean is exclusive of these ($43 315 / $53 246). The base probability for the sub-sample is higher than the percentage of those in Waves 1-5 who returned (83.76%). This may be because different base dummy variable categories representing the 'average' person in the sub-sample as compared to the full sample.								

The high base probability of success for the Waves 1-5 sub-sample (0.98) is likely to be overstated, as the only 84 percent had returned to work (Table 2A). The base dummy variables are the most common categories, which represents the “average” person in the sample.

APPENDIX 2D

Probability of being in work 2 years after the birth wave (*returnLT*): Probit without control variables

P-values are reported in parentheses. Marginal effects are for discrete changes of dummy variables from 0 to 1, other variables calculated at means (rounded to the nearest whole figure).

	(i)		(ii)		(iii)		(iv)	
	coefficients	marginal effects	coefficients	marginal effects	coefficients	marginal effects	coefficients	marginal effects
Disaggregated Key Variables								
paidMLb	0.000	0.000	-	-	-	-	-	-
	(1.000)	*(1.000)*	-	-	-	-	-	-
unpaidMLb	0.157	0.058	-	-	-	-	-	-
	(0.498)	*(0.496)*	-	-	-	-	-	-
parentalLb	0.288	0.103	-	-	-	-	-	-
	(0.241)	*(0.204)*	-	-	-	-	-	-
specialLb	-0.218	-0.085	-	-	-	-	-	-
	(0.358)	*(0.365)*	-	-	-	-	-	-
permanentptb	0.268	0.097	-	-	-	-	-	-
	(0.219)	*(0.216)*	-	-	-	-	-	-
wkfromhomeb	-0.039	-0.016	-	-	-	-	-	-
	(0.872)	*(0.873)*	-	-	-	-	-	-
flexihrsb	-0.009	-0.004	-	-	-	-	-	-
	(0.964)	*(0.964)*	-	-	-	-	-	-
Semi-Aggregated Key Variables								
anyEmaternity	-	-	0.505	0.188	-	-	-	-
	-	-	*(0.493)*	*(0.456)*	-	-	-	-
anyEgeneral	-	-	0.463	0.174	-	-	-	-
	-	-	*(0.151)*	*(0.154)*	-	-	-	-
anyEmaternity*anyEgeneral	-	-	-0.511	-0.199	-	-	-	-
	-	-	*(0.507)*	*(0.475)*	-	-	-	-
unpaidMLb	-	-	0.181	0.071	-	-	-	-
	-	-	*(0.425)*	*(0.423)*	-	-	-	-
Aggregated Key Variables								
anyEpolicyb	-	-	-	-	0.461	0.070	-	-
	-	-	-	-	*(0.114)*	*(0.404)*	-	-
unpaid maternity leave	-	-	-	-	0.177	0.173	-	-
	-	-	-	-	*(0.407)*	*(0.121)*	-	-
Count Variable								
totEpoliciesb	-	-	-	-	-	-	0.044	0.157
	-	-	-	-	-	-	*(0.416)*	*(0.404)*
unpaidMLb	-	-	-	-	-	-	0.195	0.653
	-	-	-	-	-	-	*(0.389)*	*(0.402)*
constant	0.306	-	0.093	-	0.094	-	0.355	-
	(0.158)	-	*(0.738)*	-	*(0.733)*	-	*(0.074)*	-
Base Probability of success	-	0.620	-	0.537	-	0.537	-	0.687
Log-likelihood	-133.438	-	-248.393	-	-134.068	-	-134.981	-
Pseudo R-squared	0.020	-	0.016	-	0.016	-	0.009	-
* 10% significance, ** 5 % significance, *** 1 % significance								
N = 237								

APPENDIX 2E

OLS Regression of the determinants of work-life policies, using a count of policies (*totEpoliciesb*)
P-values are reported in parentheses.

Personal and Family Background		*Family Formation and Situational Influences*	
NESB	-0.297	parespb	-0.126
	(0.284)		*(0.600)*
siblings	-0.087*	children04b	0.141
	(0.088)		*(0.471)*
siblingMISS	-0.384	SEIFAsociob	0.159***
	(0.351)		*(0.006)*
motherwk	-0.189	SEIFAeconb	-0.016
	(0.303)		*(0.746)*
mworkMISS	0.436	SEIFAeducb	-0.135**
	(0.449)		*(0.012)*
motherocc	0.003		
	(0.435)	*Partner's Pre-childbirth Variables*	
moccMISS	-0.405	pemplbMISS	-.478*
	(0.142)		*(0.085)*
		pprimaryb	0.263
Employment Characteristics			*(0.409)*
experb	0.051***	pretailhospb	-0.167
	(0.001)		*(0.501)*
experbMISS	1.229**	pbusinesspropb	-0.469*
	(0.025)		*(0.066)*
medskilledb	-0.619***	pgovtndefenceb	0.537
	(0.001)		*(0.139)*
lowskilledb	-0.882***	peducationb	0.165
	(0.002)		*(0.650)*
		phlthcommb	-0.726**
primaryb	-0.138		*(0.012)*
	(0.776)	plowskilledb	-0.376
intermedb	0.028		*(0.186)*
	(0.916)	pmedskilledb	-0.326*
retailhospb	-0.529**		*(0.089)*
	(0.036)		
businesspropb	0.483**	constant	3.507***
	(0.040)		*(0.000)*
goveducb	0.148	R-squared	0.254
	(0.508)	Adjusted R-Squared	0.201
* 10% significance, ** 5 % significance, *** 1 % significance			
N = 456			
A range of factors influence the number of policies available, particularly the respondent's employment characteristics. Fertility variables (*parespb, children04b*) are not individually or jointly significant, however this is possibly due to small variability. They are included as their size is relatively large, and because the presence of dependants is highly likely to affect the choice of pre-childbirth job.			

APPENDIX 2F

2F.1 Outcome Equation for *returnone* Waves 1-5. Coefficient Estimates. Models correspond to Table 4C.									
	(i)	(ii)	(iii)	(iv)		(i)	(ii)	(iii)	(iv)
Variable	*anyE maternityb*	*anyE generalb*	*bothE policiesb*	*anyE policyb*	**Variable**	*anyE maternityb*	*anyE generalb*	*bothE policiesb*	*anyE policyb*
policy	-1.385***	2.053***	-1.372***	2.136***	ccareben	0.411**	0.427***	0.406**	0.435***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*		*(0.011)*	*(0.003)*	*(0.013)*	*(0.003)*
unpaidMLb	0.139	0.206	0.136	0.205	matben	-0.121**	-0.145**	-0.125**	-0.137**
	(0.383)	*(0.250)*	*(0.396)*	*(0.234)*		*(0.047)*	*(0.037)*	*(0.046)*	*(0.050)*
age	-0.010	-0.012	-0.012	-0.006	single	0.070	0.127	0.186	0.042
	(0.639)	*(0.681)*	*(0.593)*	*(0.829)*		*(0.864)*	*(0.770)*	*(0.619)*	*(0.922)*
experb	0.016	-0.015	0.020	-0.015	paresp	-0.185	-0.168	-0.200	-0.189
	(0.456)	*(0.588)*	*(0.400)*	*(0.588)*		*(0.658)*	*(0.732)*	*(0.634)*	*(0.713)*
experbMISS	0.069	-0.061	0.011	-0.077	newmum	-0.257	-0.506*	-0.279	-0.537**
	(0.942)	*(0.931)*	*(0.991)*	*(0.935)*		*(0.224)*	*(0.062)*	*(0.183)*	*(0.049)*
tenureempb	-0.010	-0.004	-0.011	-0.002	children04	0.008	-0.249	0.012	-0.258
	(0.627)	*(0.847)*	*(0.587)*	*(0.927)*		*(0.964)*	*(0.284)*	*(0.950)*	*(0.270)*
tenureoccb	-0.011	-0.010	-0.011	-0.012	multibirths	0.230*	0.438***	0.240*	0.431***
	(0.473)	*(0.585)*	*(0.482)*	*(0.517)*		*(0.060)*	*(0.003)*	*(0.052)*	*(0.005)*
parttimeb	-0.067	-0.077	-0.060	-0.101	birthq2	-0.128	-0.093	-0.125	-0.112
	(0.657)	*(0.688)*	*(0.696)*	*(0.598)*		*(0.316)*	*(0.594)*	*(0.374)*	*(0.526)*
fixtermb	0.312	0.307	0.287	0.362	birthq3	-0.165	-0.162	-0.172	-0.166
	(0.153)	*(0.295)*	*(0.238)*	*(0.222)*		*(0.280)*	*(0.357)*	*(0.250)*	*(0.357)*
casualb	0.034	-0.062	0.027	0.019	birthq4	0.359**	0.471**	0.361**	0.466**
	(0.837)	*(0.748)*	*(0.869)*	*(0.922)*		*(0.037)*	*(0.039)*	*(0.042)*	*(0.036)*
medskilledb	-0.380***	0.059	-0.379**	0.059	houseworkb	0.0123**	0.011*	0.013**	0.011
	(0.034)	*(0.773)*	*(0.041)*	*(0.775)*		*(0.018)*	*(0.088)*	*(0.018)*	*(0.108)*
lowskilledb	-0.375	0.101	-0.462*	0.012	houseworkbMISS	0.061	-0.293	0.091	-0.369
	(0.150)	*(0.728)*	*(0.081)*	*(0.968)*		*(0.930)*	*(0.724)*	*(0.899)*	*(0.660)*
workplszO20b	-0.074	0.006	-0.072	-0.002	childcare	0.003	0.003	0.002	0.004
	(0.538)	*(0.967)*	*(0.560)*	*(0.990)*		*(0.392)*	*(0.454)*	*(0.463)*	*(0.393)*
emplszU100b	0.308	0.413*	0.327*	0.397*	pwageb	-0.002	0.000	-0.001	0.000
	(0.116)	*(0.088)*	*(0.096)*	*(0.091)*		*(0.446)*	*(0.959)*	*(0.505)*	*(0.961)*
emplszbMISS	0.287**	0.368**	0.306**	0.395**	pwagebMISS	-0.310	-0.388	-0.320	-0.329
	(0.050)	*(0.030)*	*(0.028)*	*(0.023)*		*(0.164)*	*(0.133)*	*(0.157)*	*(0.252)*
governmentb	0.309**	0.438**	0.304*	0.445**	pnotwk	0.026	-0.009	0.013	0.076
	(0.041)	*(0.017)*	*(0.073)*	*(0.017)*		*(0.931)*	*(0.981)*	*(0.968)*	*(0.840)*
primaryb	0.186	0.637	0.232	0.660	pemplMISS	0.014	-0.095	0.024	-0.104
	(0.655)	*(0.182)*	*(0.581)*	*(0.172)*		*(0.922)*	*(0.635)*	*(0.875)*	*(0.617)*
intermedb	-0.295	-0.289	-0.346	-0.383	pgovernment	-0.240	-0.528**	-0.224	-0.502**
	(0.232)	*(0.293)*	*(0.169)*	*(0.170)*		*(0.213)*	*(0.021)*	*(0.240)*	*(0.030)*
retailhospb	-0.433*	-0.108	-0.415	-0.143	plowskilled	0.169	0.178	0.139	0.229
	(0.068)	*(0.696)*	*(0.107)*	*(0.607)*		*(0.507)*	*(0.513)*	*(0.576)*	*(0.420)*
businesspropb	-0.466**	-0.646**	-0.496**	-0.661**	pmedskilled	-0.205	-0.292	-0.209	-0.282
	(0.044)	*(0.013)*	*(0.032)*	*(0.011)*		*(0.194)*	*(0.106)*	*(0.204)*	*(0.126)*
goveducb	0.154	-0.190	0.157	-0.198	ppaidML	0.227	0.381**	0.240*	0.365**
	(0.473)	*(0.415)*	*(0.467)*	*(0.396)*		*(0.113)*	*(0.037)*	*(0.098)*	*(0.050)*
wageb	0.008***	0.008**	0.009***	0.008*	ppolicyMISS	0.134	0.252	0.148	0.257
	(0.009)	*(0.047)*	*(0.009)*	*(0.057)*		*(0.490)*	*(0.340)*	*(0.516)*	*(0.342)*
wagebMISS	0.179	0.278	0.231	0.211	Constant	1.197	-1.123	1.216	-1.324
	(0.493)	*(0.331)*	*(0.351)*	*(0.495)*		*(0.168)*	*(0.282)*	*(0.175)*	*(0.208)*
* 10% significance, ** 5 % significance, *** 1 % significance									
N = 351									

2F.2 Reduced Form Equation for *returnone* Waves 1-5.
Coefficient Estimates. Models correspond to Table 4C.

Variable	(i) *anyE maternityb*	(ii) *anyE generalb #*	(iii) *bothE policiesb*	(iv) *anyE policyb #*	Variable	(i) *anyE maternityb*	(ii) *anyE generalb*	(iii) *bothE policiesb*	(iv) *anyE policyb*
NESB	-0.229	-0.198	-0.240	-0.245	goveducb	0.533	0.110	0.530	0.072
	(0.243)	*(0.517)*	*(0.317)*	*(0.425)*		*(0.044)*	*(0.725)*	*(0.045)*	*(0.822)*
siblings	-0.011	0.073	-0.007	0.071	parespb	-0.176	0.028	-0.171	0.033
	(0.829)	*(0.248)*	*(0.894)*	*(0.248)*		*(0.458)*	*(0.934)*	*(0.465)*	*(0.919)*
siblingMISS	-0.536	0.763	-0.481	0.633	children04b	0.152	-0.054	0.165	-0.111
	(0.098)	*(0.094)*	*(0.145)*	*(0.181)*		*(0.383)*	*(0.846)*	*(0.360)*	*(0.691)*
motherwk	-0.092	0.165	-0.059	0.161	SEIFAsociob	0.062	0.179	0.059	0.185
	(0.523)	*(0.407)*	*(0.719)*	*(0.431)*		*(0.167)*	*(0.008)*	*(0.196)*	*(0.007)*
mworkMISS	0.640	-	0.659	-	SEIFAeconb	-0.047	-0.125	-0.051	-0.121
	(0.154)	-	*(0.159)*	-		*(0.218)*	*(0.043)*	*(0.200)*	*(0.055)*
motherocc	0.000	0.007	0.000	0.007	SEIFAeducb	-0.046	-0.057	-0.037	-0.055
	(0.913)	*(0.088)*	*(0.870)*	*(0.144)*		*(0.300)*	*(0.340)*	*(0.432)*	*(0.377)*
moccMISS	-0.198	0.232	-0.138	0.206	pemplbMISS	0.080	-0.281	0.166	-0.527
	(0.381)	*(0.477)*	*(0.559)*	*(0.532)*		*(0.770)*	*(0.374)*	*(0.543)*	*(0.109)*
experb	0.031	0.023	0.035	0.013	plowskilledb	0.172	0.231	0.110	0.162
	(0.053)	*(0.229)*	*(0.030)*	*(0.479)*		*(0.539)*	*(0.495)*	*(0.689)*	*(0.636)*
experbMISS	-0.267	-	-0.173	-	pmedskilledb	0.081	0.259	0.134	0.086
	(0.754)	-	*(0.840)*	-		*(0.612)*	*(0.272)*	*(0.436)*	*(0.752)*
medskilledb	-0.568	-0.454	-0.584	-0.440	pprimaryb	-0.347	-0.055	-0.285	-0.250
	(0.002)	*(0.059)*	*(0.001)*	*(0.079)*		*(0.083)*	*(0.885)*	*(0.175)*	*(0.523)*
lowskilledb	-0.435	-0.908	-0.550	-0.818	pretailhospb	-0.654	0.229	-0.643	0.180
	(0.107)	*(0.004)*	*(0.049)*	*(0.013)*		*(0.001)*	*(0.423)*	*(0.002)*	*(0.546)*
primaryb	-0.083	0.105	-0.025	0.089	pbusinessprob	-0.079	0.017	-0.029	-0.194
	(0.847)	*(0.845)*	*(0.953)*	*(0.873)*		*(0.675)*	*(0.958)*	*(0.880)*	*(0.545)*
intermedb	-0.241	0.213	-0.271	0.349	pgoveducb	0.307	0.941	0.404	0.776
	(0.335)	*(0.509)*	*(0.284)*	*(0.322)*		*(0.327)*	*(0.054)*	*(0.151)*	*(0.116)*
retailhospb	-0.626	0.198	-0.613	0.172	phlthcommb	-0.269	0.214	-0.208	0.092
	(0.012)	*(0.523)*	*(0.018)*	*(0.582)*		*(0.192)*	*(0.579)*	*(0.310)*	*(0.816)*
businesspropb	-0.001	0.088	-0.020	0.226	Constant	0.879	0.554	0.693	0.852
	(0.996)	*(0.779)*	*(0.931)*	*(0.472)*		*(0.016)*	*(0.303)*	*(0.067)*	*(0.113)*

* 10% significance, ** 5 % significance, *** 1 % significance

N = 351

The variables *mworkMISS*and *experbMISS* hindered convergence in these models, and were therefore excluded.

APPENDIX 2G

2G.1 Bivariate Probit Results including untreated endogenous policy variables - returnone in the All Waves sub-sample. †

Models excluding untreated policies are taken from Table 4B.

	(i)		(ii)		(iii)	
Treated Policy:	*anyEmaternityb*		*anyEgeneralb*		*bothEpoliciesb*	
	excl. untreated policies	incl. untreated policies	excl. untreated policies	incl. untreated policies	excl. untreated policies	incl. untreated policies
anyEmaternityb	0.714	0.447	-	0.073	-	-0.143
	(0.413)	*(0.685)*	-	*(0.885)*	-	*(0.847)*
anyEgeneralb	-	0.360	1.956***	1.900***	-	0.357
	-	*(0.181)*	*(0.000)*	*(0.000)*	-	*(0.183)*
bothEpoliciesb	-	0.243	-	0.043	0.750	0.901
	-	*(0.749)*	-	*(0.933)*	*(0.445)*	*(0.446)*
Unpaid Maternity Leave	0.242	0.218	0.193	0.167	0.231	0.214
	(0.184)	*(0.231)*	*(0.208)*	*(0.292)*	*(0.206)*	*(0.236)*
constant: outcome equation	-0.797	-1.028	-2.056**	-2.064**	-0.806	-1.055
	(0.479)	*(0.353)*	*(0.026)*	*(0.026)*	*(0.481)*	*(0.340)*
constant: reduced form equation	0.912**	0.913**	0.976**	0.979**	0.727*	0.723*
	(0.021)	*(0.020)*	*(0.040)*	*(0.041)*	*(0.063)*	*(0.062)*
Athrho	-0.327	-0.368	-18.503	-13.594	-0.332	-0.421
	(0.603)	*(0.538)*	*(0.975)*	*(0.976)*	*(0.641)*	*(0.531)*
Rho (ρ)	-0.316	-0.352	-1.000	-1.000	-0.320	-0.398
LR Test of Rho: chi-2 Statistic	0.256	0.364	6.000**	5.855	0.203	0.374
	(0.613)	*(0.546)*	*(0.014)*	*(0.016)*	*(0.652)*	*(0.541)*
Wald Test of the index: chi-2 Statistic	172.29***	177.81***	348.68***	348.00***	175.17***	185.56***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Log-Likelihood	-500.25	-498.950	-384.93	-384.695	-503.22	-502.12

* 10% significance, ** 5 % significance, *** 1 % significance

N = 456

† Control Variables omitted, available on request

2G.2 Bivariate Probit Results including untreated endogenous policy variables - returnone in the Waves 1-5 sub-sample. †

Models excluding untreated policies are taken from Table 4C.

	(i)		(ii)		(iii)	
Treated Policy:	*anyEmaternityb*		*anyEgeneralb*		*bothEpoliciesb*	
	excl. untreated policies	incl. untreated policies	excl. untreated policies	incl. untreated policies	excl. untreated policies	incl. untreated policies
anyEmaternityb	-1.385***	-1.177**	-	0.388	-	0.191
	(0.000)	*(0.036)*	-	*(0.469)*	-	*(0.727)*
anyEgeneralb	-	0.436**	2.053***	2.147***	-	0.434**
	-	*(0.016)*	*(0.000)*	*(0.000)*	-	*(0.012)*
bothEpoliciesb	-	-0.315	-	-0.478	-1.372***	-1.678***
	-	*(0.591)*	-	*(0.389)*	*(0.000)*	*(0.002)*
Unpaid Maternity Leave	0.139	0.094	0.206	0.231	0.136	0.092
	(0.383)	*(0.548)*	*(0.250)*	*(0.211)*	*(0.396)*	*(0.541)*
constant: outcome equation	1.197	0.968	-1.123	-1.164	1.216	1.074
	(0.168)	*(0.294)*	*(0.282)*	*(0.266)*	*(0.175)*	*(0.252)*
constant: reduced form equation	0.879**	0.810**	0.554	0.528	0.693*	0.628
	(0.016)	*(0.050)*	*(0.303)*	*(0.352)*	*(0.067)*	*(0.118)*
Athrho	14.337	12.150	-15.359	-16.071	14.365	14.210
	(0.969)	*(0.974)*	*(0.967)*	*(0.965)*	*(0.973)*	*(0.978)*
Rho (ρ)	1.000	1.000	-1.000	-1.000	1.000	1.000
LR Test of Rho: chi-2 Statistic	14.044***	14.360***	12.599***	12.925***	15.299***	15.39***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Wald Test of the index: chi-2 Statistic	239.48***	239.79***	280.88***	270.43***	237.76***	237.82***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Log-Likelihood	-362.32	-359.497	-281.65	-281.296	-361.81	-359.14

* 10% significance, ** 5 % significance, *** 1 % significance

N = 351

† Control Variables omitted, available on request.

APPENDIX 2H

The differing effect of *anyEmaternityb* in the two sample groups hints at systematic sample differences. However, this variable is similarly distributed in both groups and work statuses, so it is difficult to know why this policy has opposite signs for the different samples.

Cross-tabulations of access to maternity policies by return to work status in the very short-term (*returntwo*)

All Waves

	returnone=1	%	returnone=0	%	Total
anyEmaternityb = 1	175	75.11	140	62.78	315
anyEmaternityb=0	58	24.89	83	37.22	141
Total	233		223		456

Waves 1-5

	returnone=1	%	returnone=0	%	Total
anyEmaternityb = 1	139	74.33	103	62.80	242
anyEmaternityb=0	48	25.67	61	37.20	109
Total	187		164		351

APPENDIX 2I

Predicting the marginal probability of success (Pr(returnone=1)) incorporates two joint probabilities of success: Pr(policy =1, returnone=1) and Pr(policy=0, returnone=1). In my sample, these joint probabilities sum to 0.533, which is the mean of *returnone* in the Waves 1-5 sub-sample.

2I.1 Sample Probabilities: returnone, Waves 1-5
Model (i): anyEmaternityb

		anyEmaternityb 0	anyEmaternityb 1	*Total*	Joint Probability returnone=1	
returnone	**0**	61	103	164	*anyEmaternityb*= 1	0.396
	1	48	139	187	*anyEmaternityb*= 0	0.137
	Total	109	242	351	Marginal probability	0.533

2I.2 Sample Probabilities: returnone, Waves 1-5
Model (ii): anyEgeneralb

		anyEgeneralb 0	anyEgeneralb 1	*Total*	Joint Probability returnone=1	
returnone	**0**	26	138	164	*anyEgeneralb*= 1	0.504
	1	10	177	187	*anyEgeneralb*= 0	0.028
	Total	36	315	351	Marginal probability	0.533

2I.3 Sample Probabilities: returnone, Waves 1-5
Model (iii): bothEpoliciesb

		bothEpoliciesb			Joint Probability returnone=1	
		0	**1**	*Total*		
returnone	**0**	64	100	164	*bothEpoliciesb*= 1	0.393
	1	49	138	187	*bothEpoliciesb*= 0	0.140
	Total	113	238	351	Marginal probability	0.533

2I.4 Sample Probabilities: returnone, Waves 1-5
Model (iv): anyEpolicyb

		anyEmaternityb			Joint Probability returnone=1	
		0	**1**	*Total*		
returnone	**0**	23	141	164	*anyEmaternityb*= 1	0.507
	1	9	178	187	*anyEmaternityb*= 0	0.026
	Total	32	319	351	Marginal probability	0.533

APPENDIX 2J

Prediction Success Tables: Pr(*returnone* = 1) Waves 1-5

Prediction success tables are obtained by first predicting the marginal probability of success for each observation (y_i), then comparing this to the sample marginal probability of success ($y^* = 0.533$). Observations for which $y_i > 0.533$ are predicted as '1,' while others are predicted to be '0.' The tables indicate how many '1' and '0' values are correctly predicted (the top-left and bottom-right boxes), and how many are incorrectly predicted (the top-right and bottom-left boxes).

Naïve Models

		Actual 0	Actual 1	*Total*
Predicted	**0**	0	0	
	1	164	187	351
	Total	164	187	351

Percentage correct: 46.72

Model (i): *anyEpolicyb*

		Actual 0	Actual 1	*Total*
Predicted	**0**	86	52	138
	1	78	135	213
	Total	164	187	351

Percentage correct: 62.96

Model (ii): *anyEgeneralb*

		Actual 0	Actual 1	*Total*
Predicted	**0**	132	68	200
	1	32	119	151
	Total	164	187	351

Percentage correct: 71.51

Model (iii): *bothEpoliciesb*

		Actual 0	Actual 1	*Total*
Predicted	**0**	120	91	211
	1	44	96	140
	Total	164	187	351

Percentage correct: 61.54

Model (iv): *anyEpolicyb*

		Actual 0	Actual 1	*Total*
Predicted	**0**	129	66	195
	1	35	121	156
	Total	164	187	351

Percentage correct: 71.23

APPENDIX 2K

2K.1 The reference individual for marginal effects

Variable	Mean / Base Value	Variable	Mean / Base Value
unpaidMLb*	1	childcare	13.25
age	31.5	pwageb	53.24
experb	11.17	siblings	2
tenureempb	4.13	motherwk*	1
tenureoccb	6.22	motherocc	38.37
wageb	38.47	SEIFAsociob	6.02
ccareben	0.313	SEIFAeconb	5.809
matben	1.34	SEIFAeducb	6.05
houseworkb	12.63		

* Dummy Variable

These values are used to calculate the marginal effects for all models in the Waves 1-5 sub-sample. The means are slightly different to those reported in Appendix 1A, as that uses the entire (All Waves) sample group.

2K.2 Marginal Effects for the marginal probability of return (Pr(returnone = 1), *returnone* Waves 1-5.
Models correspond to Table 4C.

	(i)	(ii)	(iii)	(iv)		(i)	(ii)	(iii)	(iv)
Variable	*anyE maternityb*	*anyE generalb*	*bothE policiesb*	*anyE policyb*	**Variable**	*anyE maternityb*	*anyE generalb*	*bothE policiesb*	*anyE policyb*
policy	-0.413***	0.412	-0.428***	0.484	ccareben	0.164**	0.167***	0.162**	0.174***
	(0.000)	*(0.116)*	*(0.000)*	*(0.106)*		*(0.011)*	*(0.003)*	*(0.013)*	*(0.003)*
unpaidMLb	0.055	0.082	0.054	0.081	matben	-0.048**	-0.057*	-0.050**	-0.055**
	(0.380)	*(0.252)*	*(0.396)*	*(0.228)*		*(0.047)*	*(0.057)*	*(0.047)*	*(0.050)*
age	-0.004	-0.005	-0.005	-0.003	single	0.028	0.049	0.073	0.017
	(0.639)	*(0.680)*	*(0.592)*	*(0.829)*		*(0.864)*	*(0.768)*	*(0.613)*	*(0.922)*
experb	0.006	-0.006	0.008	-0.006	paresp	-0.073	-0.067	-0.079	-0.075
	(0.456)	*(0.588)*	*(0.399)*	*(0.588)*		*(0.655)*	*(0.729)*	*(0.628)*	*(0.714)*
experbMISS	0.028	-0.024	0.004	-0.031	newmum	-0.102	-0.199*	-0.109	-0.204*
	(0.942)	*(0.932)*	*(0.991)*	*(0.935)*		*(0.223)*	*(0.061)*	*(0.169)*	*(0.087)*
tenureempb	-0.004	-0.002	-0.004	-0.001	children04	0.003	-0.097	0.005	-0.103
	(0.627)	*(0.847)*	*(0.587)*	*(0.927)*		*(0.964)*	*(0.250)*	*(0.950)*	*(0.269)*
tenureoccb	-0.004	-0.004	-0.004	-0.005	multibirths	0.091*	0.173***	0.094*	0.167***
	(0.473)	*(0.586)*	*(0.484)*	*(0.517)*		*(0.058)*	*(0.003)*	*(0.051)*	*(0.008)*
parttimeb	-0.027	-0.030	-0.024	-0.040	birthq2	-0.051	-0.037	-0.050	-0.045
	(0.656)	*(0.691)*	*(0.696)*	*(0.597)*		*(0.314)*	*(0.594)*	*(0.373)*	*(0.523)*
fixtermb	0.123	0.115	0.112	0.141	birthq3	-0.065	-0.064	-0.069	-0.066
	(0.140)	*(0.292)*	*(0.220)*	*(0.217)*		*(0.277)*	*(0.361)*	*(0.248)*	*(0.350)*
casualb	0.014	-0.024	0.011	0.008	birthq4	0.140**	0.170*	0.1340**	0.179*
	(0.837)	*(0.748)*	*(0.869)*	*(0.922)*		*(0.036)*	*(0.059)*	*(0.042)*	*(0.061)*
medskilledb	-0.148**	0.023	-0.149**	0.023	houseworkb	0.005**	0.004	0.005**	0.004
	(0.033)	*(0.772)*	*(0.035)*	*(0.775)*		*(0.018)*	*(0.109)*	*(0.017)*	*(0.108)*
lowskilledb	-0.146	0.039	-0.178*	0.005	houseworkbMISS	0.024	-0.116	0.036	-0.144
	(0.127)	*(0.725)*	*(0.091)*	*(0.968)*		*(0.930)*	*(0.723)*	*(0.898)*	*(0.645)*
workplszO20b	-0.030	0.003	-0.029	-0.001	childcare	0.001	0.001	0.001	0.001
	(0.538)	*(0.967)*	*(0.560)*	*(0.990)*		*(0.393)*	*(0.456)*	*(0.462)*	*(0.393)*
emplszU100b	0.121	0.164*	0.127*	0.154*	pwageb	-0.001	0.000	-0.001	0.000
	(0.115)	*(0.084)*	*(0.094)*	*(0.093)*		*(0.446)*	*(0.959)*	*(0.505)*	*(0.961)*
emplszbMISS	0.113**	0.136**	0.119**	0.153**	pwagebMISS	-0.121	-0.154	-0.127	-0.129
	(0.050)	*(0.044)*	*(0.031)*	*(0.028)*		*(0.149)*	*(0.128)*	*(0.149)*	*(0.245)*
governmentb	0.122**	0.173**	0.118*	0.172**	pnotwk	0.011	-0.004	0.005	0.030
	(0.038)	*(0.016)*	*(0.067)*	*(0.024)*		*(0.931)*	*(0.981)*	*(0.968)*	*(0.840)*
primaryb	0.074	0.220	0.091	0.245	pemplMISS	0.006	-0.038	0.010	-0.041
	(0.652)	*(0.168)*	*(0.574)*	*(0.211)*		*(0.922)*	*(0.637)*	*(0.875)*	*(0.615)*
intermedb	-0.116	-0.115	-0.136	-0.149	pgovernment	-0.095	-0.208**	-0.089	-0.192**
	(0.218)	*(0.290)*	*(0.161)*	*(0.165)*		*(0.215)*	*(0.018)*	*(0.237)*	*(0.037)*
retailhospb	-0.167*	-0.043	-0.163	-0.057	plowskilled	0.067	0.068	0.055	0.091
	(0.055)	*(0.697)*	*(0.103)*	*(0.605)*		*(0.505)*	*(0.505)*	*(0.575)*	*(0.412)*
businesspropb	-0.180**	-0.251**	-0.187**	-0.246**	pmedskilled	-0.081	-0.116	-0.083	-0.111
	(0.041)	*(0.013)*	*(0.028)*	*(0.026)*		*(0.188)*	*(0.104)*	*(0.203)*	*(0.123)*
goveducb	0.061	-0.075	0.062	-0.079	ppaidML	0.090	0.141**	0.094*	0.142**
	(0.470)	*(0.412)*	*(0.462)*	*(0.394)*		*(0.115)*	*(0.043)*	*(0.097)*	*(0.047)*
wageb	0.003***	0.003*	0.003***	0.003*	ppolicyMISS	0.053	0.095	0.059	0.102
	(0.009)	*(0.054)*	*(0.010)*	*(0.057)*		*(0.488)*	*(0.323)*	*(0.515)*	*(0.336)*
wagebMISS	0.071	0.105	0.091	0.083					
	(0.489)	*(0.313)*	*(0.346)*	*(0.491)*					

* 10% significance, ** 5 % significance, *** 1 % significance

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