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Honours Thesis

Let's Talk About Sex, Baby

Investigating Sex Specific Differences in the Impact of Unemployment on Fertility

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Declaration

I declare that this thesis is my own work and that, to the best of my knowledge, it contains no material which has been written by another person or persons, except where acknowledgement has been made. This thesis has not been submitted for the award of any degree or diploma at the University of New South Wales Sydney, or at any other institute of higher education.

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Patrick Parrish
22nd November, 2019

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

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Contents

Abstract

This paper examines differences in the impacts of female and male unemployment on the likelihood of having a child among heterosexual couples in Australia. Using propensity score matching, I find female unemployment tends to decrease the likelihood of having a child but male unemployment does not. This result is unexpected under the assumptions of a traditional household model, where male unemployment causes a large income effect and female unemployment causes a large substitution effect. I investigate other factors which could explain sex specific differences in the impact of unemployment on fertility, including heterogeneity in psychological distress following unemployment, labour force attachment and division of household labour. I also examine the influence of the Baby Bonus and Paid Parental Leave on the impacts of unemployment on fertility and their corresponding welfare implications.

Chapter 1
Introduction

In 2017 the total fertility rate in Australia fell to a historic low of 1.74 births per woman (ABS 2018). Despite government policies intended to accommodate childbearing, such as the Baby Bonus and Paid Parental Leave, the total fertility rate has consistently failed to reach replacement levels. Historically low fertility risks trapping Australia in the same crises currently afflicting Japan and South Korea: a shrinking workforce burdened with an ever-growing ageing population. Australian couples typically want more children than they have, but 32% of couples report delaying childbearing due to financial insecurity (Hammarberg and Clarke 2005). The importance of economic instability in the fertility decision motivates my investigation into the impact of unemployment on childbearing Australia.

The literature is divided about the impact of unemployment on fertility. Unemployment causes an income shock and decreases firm specific human capital makes couples less likely to have a child. However, unemployment also decreases the opportunity costs of childbearing which makes couples more likely to have a child. We may expect these impacts depend on which partner becomes unemployed. Under a traditional model of the household (e.g. Becker 1960), when the male 'breadwinner' loses his job the family experiences a larger income effect relative to female unemployment. Meanwhile, when the female 'caregiver' loses her job there is a larger substitution effect relative to male unemployment.

In this paper I demonstrate the empirical findings are exactly opposite to these predictions: female unemployment decreases the likelihood of having a child more than male unemployment. The traditional household model fails to explain fertility decision-making in the real world because it does not consider heterogeneity in division of labour and the behavioural impacts of unemployment. By investigating sex specific differences in the impacts of unemployment on fertility empirically, I can test for departures from the traditional household model to better understand how this relationship operates in reality.

I use propensity matching to identify the sex specific differences in the impacts of unemployment on the likelihood of having a child. Propensity matching adjusts for selection driven bias by comparing individuals who are similar in their likelihood of unemployment but differ in actual employment status. I demonstrate my results are robust to different matching specifications, departures from the unconfoundedness assumption and different choice of outcome variable. As an additional robustness check, I provide an instrumental variable analysis using involuntary redundancy as exogenous variation in unemployment.

I demonstrate that while female unemployment decreases the likelihood of a couple having a child by 3.7 percentage points, male unemployment has no statistically or economically significant impact on the likelihood of having a child. These impacts can vary by heterogeneity in household division of labour. Female breadwinners are less likely to reduce fertility when unemployed compared to female non-breadwinners due to higher likelihood and quantity of redundancy pay, hours of work and stress from work. In comparison, male breadwinners and non-breadwinners do not display significant differences in impacts of unemployment on likelihood of having a child.

I also examine the role of the Baby Bonus and Paid Parental Leave on the impacts of unemployment on fertility for women. The Baby Bonus increased the likelihood of unemployed women having a child, delaying the mother's return to the workforce. I find less educated women are more likely to have a child than more educated women during the period of the Baby Bonus, indicating that by lengthening the gap in human capital accumulation for unemployed mothers the Baby Bonus may also increase inequality between poor and rich households in Australia. Meanwhile, Paid Parental Leave made women less likely to have a child while unemployed, although a more generous Paid Parental Leave program would provide a stronger incentive for unemployed women to return to work.

This paper is intended to make four key contributions to the literature. The first contribution is to fill the gap in the literature on the sex specific differences of unemployment in Australia. The second contribution is to use the unique responses from the Household Labour Dynamics in Australia survey to identify behavioural factors driving sex specific differences, an area of study lacking in previous literature. The third contribution is to improve our understanding of the mechanisms through which economic instability contributes to family formation and gendered division of household work. The fourth contribution is to give policy-makers guidance on the effects of different policies on the impacts of female and male unemployment, as well as the welfare implications of these policies.

Chapter 2
Literature Review

2.1 Theoretical Perspectives

The income shock from unemployment predicts a decrease fertility. Becker (1960) employs an economic framework in which children are a good, so decreases in household income should decrease the quantity of children demanded. Easterlin (1961) approaches the income effect somewhat differently, arguing it is changes in income relative to an individual's material standards of living during childhood that drive changes in fertility. When income is relatively high compared to one's material aspirations, parents are more willing to have children because that child can enjoy similar standards of living to what the parent experienced. In this case, an unemployment shock decreases relative income, therefore decreasing demand for children. Unemployment is also accompanied by a loss of firm specific human capital (Becker 1962) meaning future earnings may be also expected to decrease, compounding the income effect.

Meanwhile, the substitution effect from unemployment predicts an increase fertility. Butz and Ward (1979) use a household utility maximising model where the inputs are work, leisure and childcare. They argue decreases in female wages decrease the opportunity cost of childbearing and thus increase or hasten fertility. Ermisch (1980) directly critiques Easterlin (1961) in favour of the 'new home economics' model where the household decision-making focuses on family division of labour. Under this model, it is relative changes in mens and womens' earnings capacities that influence time spent in labour and time spent producing household commodities. The decision to have a child may occur during periods of unemployment because one partner can now be allocated to a childcare role.

Unemployment may also lead to behavioural effects such as uncertainty and stress which may in turn affect fertility. Friedman, Hechter, and Kanazawa (1994) introduce a model based on uncertainty reduction to explain fertility behaviour. Under this framework, a mother who faces uncertainty in her work career may choose to pursue a more stable 'career' as a mother based on her expected value of parenthood. Early labour market instability, such as unemployment, would increase family formation particularly among young women. Conversely, someone who becomes unemployed may experience additional stress and pressure on mental health (Darity and Goldsmith 1996) and the mental health of their partner (Strom 2003) making it difficult to establish and maintain a healthy environment to raise a child. While income and substitution effects are important, in this paper I will also emphasise behavioural factors in understanding sex specific differences in the impacts of unemployment on fertility.

2.2 Empirical Findings

Evidence for the impact of unemployment on fertility at the aggregate level is mixed. Early research found aggregate fertility was countercyclical, falling during economic upswings and rising during downswings (Ermisch 1988; Butz and Ward 1979). However, more recent studies have suggested fertility is procyclical, with economic slowdowns decreasing fertility (Orsal and Goldstein 2010; Hondroyiannis 2009; Adsera 2004; Macunovich 1996) or increasing postponement of childbearing (Adsera 2011). However, these effects can also vary by country: unemployment accelerates fertility for women in Norway (Kravdal 2002), Sweden (Andersson 2000), Finland, Germany and the UK (Schmitt 2008) whereas it delays it in France (Schmitt 2008; Meron and Widmer 2002) and amongst highly educated women in Germany (Kreyenfeld 2005). In Australia, Martin (2003) examines aggregate trends and finds the total fertility rate falls below trend during economic declines. However, these papers typically take a descriptive trend-based approach to the data and fail to identify a causal relationship between unemployment and fertility.

Individual level studies typically find evidence male unemployment delays childbearing while female unemployment does not. In Germany, Kurz, Steinhage, and Golsch (2001) find the impact of unemployment on likelihood of having a child is negative for men but positive for women. Similarly, Liefbroer and Corijn (1999) examine young Dutch couples and find unemployment slows family formation for men but accelerates it for women. In Italy, Cazzola, Pasquini, and Angeli (2016) find both male and female unemployment decrease fertility, although the effect is more negative for men. However, some studies find women who become unemployed decrease fertility, including Kravdal (2002) for higher order births and Vikat (2004) for women over 30. However, these papers fail to identify the effects of unemployment may be driven by selection bias.

Bono, Weber, and Winter-Ebmer (2015) use redundancy from firm closures as exogenous variation in employment to estimate the causal effect of unemployment on fertility. They find unemployment has no significant causal impact on fertility among white collar women in Austria, although the event of job displacement does. To account for the endogeneity of unemployment the authors use job loss from firm closure as an exogenous form of variation in unemployment. Using this identification strategy, the results indicate job displacement decreases the number of children born by 0.2 over 3 years and 0.4 over 6 years but the period of unemployment does not lead to a statistically significant change in this effect. Although this causal estimate is a useful contribution to the literature, the use of firm closure as an instrument restricts the authors to a certain subgroup of women and may not be predictive of other groups such as blue collar women.

Matysiak and Vignoli (2013) conduct a comparative study of Poland and Italy, which are similar in country specific obstacles to work and levels of fertility but vary by attitudes towards female labour supply. Although they acknowledge their estimates may not be causal, they argue use of typical instrumental variables for unemployment would restrict their analysis to small, specific subgroups. Over the sample period, labour force participation remains at around 65% for women aged 25-49 in Italy but rises as high as 80% in Poland. The proportion of people who believe both men and women should contribute to the household budget is 25% in Italy and 42% in Poland. The authors find in Italy, employed women are less likely to have a first or second child compared to unemployed women, but no difference for Polish women. Matysiak and Vignoli (2013) attribute the difference in fertility to culturally rooted behaviour patterns and attitudes, indicating institutional and social factors may also play a role in sex specific differences in the impact of unemployment on fertility.

While the literature does predict the existence of sex specific differences in the impacts of unemployment on fertility, the magnitude of the difference appears to be dependent on country specific effects including institutional support, historical attitudes towards female labour supply and the perceived value of female income contributions to the household budget. However, to the best of my knowledge, there is currently no literature estimating sex specific differences in the impact of unemployment on fertility at the individual level in Australia.

Chapter 3
Data

3.1 Sample Selection

I use data from the Household Income and Labour Dynamics in Australia (HILDA) survey, a longitudinal survey of Australian households conducted by the Melbourne Institute. HILDA is an annual survey on economic and personal well-being, labour market dynamics and family life for a nationally representative sample of households and their descendants. The original sample consisted of 13,969 individuals which was topped up with an additional 5,477 individuals in 2011. For this study I use the waves from 2002-2017. I exclude the first wave from 2001 because it does not provide all of the variables used in this study.

I restrict my sample to working men and women who are aged 15 to 45 for which there are no missing data (n=99,600). Since I am interested in the behaviour of couples I also restrict my sample to cohabitating heterosexual couples (n=50,896) to create a sample that is representative of two partner households in Australia. I remove casual and self-employed workers from the sample as they are not granted the same unemployment protections as part time or full time employees such as guaranteed hours of work, annual leave or redundancy entitlements. For unemployed individuals I match their work characteristics from their last reported job. Therefore this sample captures individuals engaged in full time or part time work (n=36,497).

I make an adjustment to unemployment status for individuals who transition from employment to not in labour force (NILF) via job displacement. If I only include employed or unemployed individuals then my sample will drop individuals classified as NILF. However, individuals who are made unemployed may misclassify themselves as NILF for the purposes of the survey. Therefore I make an adjustment to unemployment status such that if a NILF individual is fired in a given year but was employed in the previous two years I classify them as unemployed. This adjustment ensures individuals who transition from employment to NILF via job displacement are captured in the sample.

3.2 Variable Construction

To construct the measure of fertility I use the life events section of the HILDA survey where fertility equals one if that person has had a child in the past year and zero otherwise. This measure of fertility captures the short term effects of unemployment rather than long term effects. I construct the unemployment variable using employment status such that unemployment equals one if an individual is unemployed in a given year and zero otherwise.

I use a range of variables provided by HILDA, including demographic controls, labour market characteristics and education. I match individuals with their partner's HILDA survey responses to capture partner's education, employment status and age. Additionally, HILDA asks respondents to answer attitudinal questions. I use a section on how often individuals have felt different forms of emotional distress recently on a scale from one (all of the time) to five (none of the time). I also use a section on to what degree individuals agree with a series of questions on stress at work on a scale from one (strongly disagree) to seven (strongly agree). Further detail on these variables can be found in Appendix A.1.

3.3 Attrition Bias

Selective attrition may pose a threat to the experimental design if unemployment is likely to cause attrition. HILDA does not continue to track partners if a couple separates. As a result, couples who separate are dropped from the sample and will not be captured in my estimation. In order to determine whether attrition bias is likely to be a concern for this sample, I run a regression of likelihood of separation against unemployment to determine whether unemployment is likely to increase the likelihood of separation.

Unemployed individuals are more likely to separate and therefore be dropped from the sample. From Table 3.1, unemployment increases the likelihood of separation by 2.7 percentage points. Assuming individuals that separate are less likely to have a child as they do not have a partner, the true treatment effect should be more negative than estimated. However, attrition bias should be small since relatively few couples are separating following unemployment. I revisit the issue of upward bias in Chapter 6 in my post estimation robustness checks.

Table 3.1: Likelihood of Separation as a Result of Unemployment

	Likelihood of Separation	
	(1)	(2)
Unemployment	0.0355^{***}	0.0268^{***}
	(0.00089)	(0.00438)
Number of Observations	36497	36497
Controls	No	Yes

Notes. This table reports the OLS regression of likelihood of separation on unemployment for the full sample. Controls include age, personal characteristics, partner's characteristics and year fixed effects. Robust standard errors are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 4
Method

4.1 Causal Framework

The Rubin causal framework (Rubin 1974) is a statistical approach to causality based on potential outcomes. The estimation of treatment is based on a counterfactual framework in which inferences must be made about the outcomes for treated individuals had they not been treated. To describe this framework with relevance to the impact of unemployment on fertility denote lagged unemployment as U_i and fertility as F_i.

U_i is equal to one if an individual was unemployed in the previous year and equal to zero otherwise. F_i is equal to one if an individual has a child in a given year and equal to zero otherwise. Unemployment is lagged by one year because the pregnancy period creates a gap between the fertility decision and observed childbirth. For each individual, there are two potential outcomes:

$$\text{Potential Outcome} = \begin{cases} F_{1i} \text{ if } U_i = 1 \\ F_{0i} \text{ if } U_i = 0 \end{cases} \tag{4.1}$$

Potential outcomes capture the two counterfactual levels of fertility given individual i is either employed or unemployed. F_{1i} is the fertility status of an individual who has become unemployed, while F_{0i} is the fertility status of that same individual who has not become unemployed. The difference between F_{1i} and F_{0i} is the causal effect of unemployment on fertility for individual i.

The fundamental problem of examining causality arises because it is impossible to observe both potential outcomes for one person. To make inferences about the counterfactual cases, researchers produce two main parameters of interest. The first is the average treatment effect (ATE): the difference between average fertility of individuals who were and were not made unemployed. This parameter tells us what the expected effect of unemployment is on fertility if individuals in the population were randomly assigned unemployment (Caliendo and Kopeinig 2008).

$$ATE = E[F_{1i} - F_{0i}] \tag{4.2}$$

However, the ATE is not of primary interest because it includes the effect of unemployment on individuals who were never 'at risk' of unemployment (Heckman, Lalonde, and Smith 1999). Therefore, I turn to the second parameter of interest: the average treatment effect on the treated (ATT). The ATT is the difference in expected fertility between the two potential outcomes for individuals who actually became unemployed.

$$ATT = E[F_{1i}|U_i = 1] - E[F_{1i}|U_i = 0] \tag{4.3}$$

The problem with estimating the ATT is I cannot observe the expected fertility of an unemployed individual given they did not become unemployed. However, choosing a proper substitute is difficult. Using the expected fertility for individuals who did not become unemployed may lead to selection bias if unemployment is not independent of potential outcomes.

$$\begin{aligned} \underbrace{E[F_i|U_i = 1] - E[F_i|U_i = 0]}_{\text{Observed difference in average fertility}} &= \underbrace{E[F_{1i}|U_i = 1] - E[F_{0i}|U_i = 1]}_{\text{True } ATT} \\ &+ \underbrace{E[F_{0i}|U_i = 1] - E[F_{0i}|U_i = 0]}_{\text{Selection bias}} \end{aligned} \tag{4.4}$$

4.2 Evidence of Selection Bias

It is unrealistic to treat unemployment as randomly assigned. Examining Table 4.1 reveals there are substantial observable differences between individuals who are unemployed and individuals who are employed. Simply taking the difference in expected fertility for unemployed and employed groups would result in selection bias because of underlying differences between individuals who do and do not become unemployed. This selection bias motivates the need for an identification strategy to accurately estimate the causal impacts of unemployment on likelihood of having a child.

Table 4.1: Balance of Covariates

Variable	Employed	Unemployed	Difference
Sex	0.477	0.428	-0.049***
	(0.499)	(0.495)	(0.006)
Age	34.265	33.143	-1.122***
	(6.965)	(7.108)	(0.088)
Immigrant Status	0.179	0.188	0.009*
	(0.383)	(0.391)	(0.005)
University Educated	0.400	0.275	-0.126***
	(0.490)	(0.446)	(0.006)
Married	0.688	0.629	-0.060***
	(0.463)	(0.483)	(0.006)
Defacto	0.312	0.371	0.060***
	(0.463)	(0.483)	(0.006)
Ever had a child	0.631	0.643	0.013**
	(0.483)	(0.479)	(0.006)
Partner's Age	34.712	33.591	-1.122***
	(8.033)	(8.004)	(0.100)
Partner Employed	0.854	0.765	-0.088***
	(0.353)	(0.424)	(0.005)
Partner Unemployed	0.019	0.047	0.027***
	(0.138)	(0.211)	(0.002)
Partner NILF	0.127	0.188	0.061***
	(0.332)	(0.390)	(0.004)
Observations	23,519	1,055	24,574

Notes. This table reports the means and standard deviations of each variable for the employed and unemployed groups. The difference between groups is computed by regressing the variable on unemployment and computing the difference and associated standard error between employed and unemployed subgroups.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3 Propensity Score Matching

Propensity score matching (PSM) is a statistical method in which observations are matched based on their predicted likelihood of becoming unemployed conditional on covariates (propensity scores). I report the logit model used to calculate propensity scores as estimated for the pooled, female and male subsamples in Appendix A.2. By comparing matched individuals who have similar propensity scores but have different potential outcomes I can adjust for selection driven bias. Causal interpretation of the ATT from PSM requires two assumptions: unconfoundedness and overlap.

The first identifying assumption is unconfoundedness or 'selection on observables': conditional on covariates the likelihood of unemployment is independent of potential outcomes. This assumption requires all variables that influence treatment are observed. Although this assumption cannot be proven, I argue the rich set of covariates I use satisfy the unconfoundedness assumption. In Section 6.1, I test the robustness of the results to departures from the unconfoundedness assumption.

The second identifying assumption is the overlap assumption: individuals from the unemployed group have corresponding individuals from the employed group with a similar propensity score. ATT is only defined in the region of common support where the employed group can be matched to the unemployed group. The region of common support is depicted in Figure 4.1. In order to ensure common support, I trim the sample by deleting observations outside the region of common support.

Given unconfoundedness holds and there is common support between the unemployed and employed groups, the generic PSM estimator for the ATT is the mean difference between outcomes over the region of common support appropriately weighted by the propensity score.

$$ATT^{PSM} = E_{P(X)|U=1}\{E[F_{1i}|U=1, P(X)] - E[F_{0i}|U=0, P(X)]\} \tag{4.5}$$

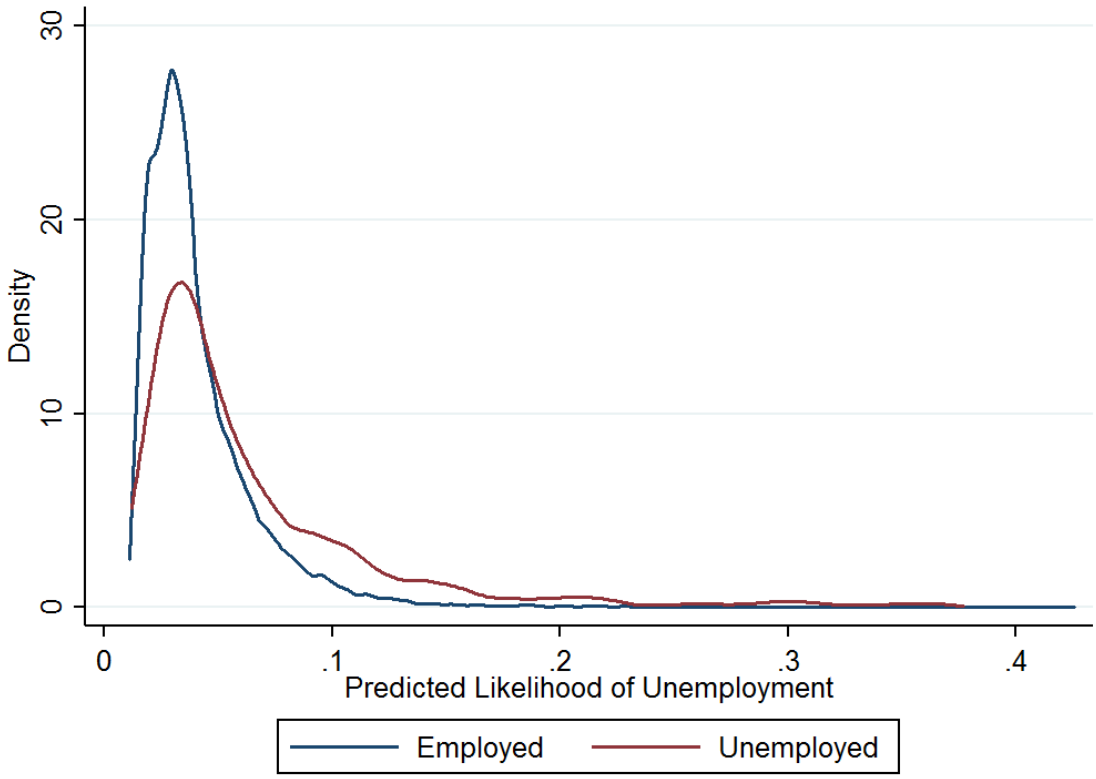


Figure 4.1: Region of Common Support

Notes. This figure depicts the kernel density plot approximating the distribution of propensity scores for employed and unemployed groups.

4.4 Selection of Covariates

Selection of variables is based on satisfying the unconfoundedness assumption. Although adding too many variables will not increase bias, Bryson, Dorsett, and Purdon (2002) note adding unnecessary variables can make matching more difficult and increase variance of estimates. Therefore I choose a parsimonious set of variables that simultaneously influence likelihood of unemployment and likelihood of having a child.

These include personal characteristics such as age, age squared, immigrant status, marital status, whether they have had a previous child, whether they live in a rural area and gender. In addition, occupational characteristics including industry, managerial or occupational category and education are controlled for. I also control for partner's employment status, age and education under the assumption that an individual's labour force attachment and their fertility choice may depend on the characteristics of their partner. Year fixed effects are included to account for time trends.

4.5 Selection of Matching Method

The matching algorithm I use is nearest neighbour matching, where individuals from the employed group are selected as comparison units for an individual who was made unemployed. The nearest neighbour matching estimate of the ATT can be written as the expectation of the difference between the fertility for unemployed individuals ($i \in U$) and the weighted sum of the fertility of their employed nearest neighbours ($j \in E$).

$$ATT^{NN} = \frac{1}{N^T}\left[\sum_{i \in U} F_{1i} - \sum_{j \in E} w_{ij} F_{0j}\right] \tag{4.6}$$

Asymptotically different PSM estimators should reach the same results and selection of method involves a trade-off between bias and variance (Caliendo and Kopeinig 2008). For this study, I find the results are not sensitive to number of nearest matches (see Appendix A.3) and choose to use equal weights over 5 nearest neighbours.

Chapter 5
Results

5.1 Pooled Estimation

When male and female unemployment are pooled into one estimation, unemployment has no significant impact on fertility. I report the estimates for the ATT of unemployment on fertility for the full sample in Table 5.1. The coefficient on lagged unemployment can be interpreted as the change in expected likelihood of a couple having a child given an individual is unemployed relative to the employed group. The unmatched estimate is a naive ordinary least squares regression of lagged unemployment on the likelihood of having a child while the matched estimate is the propensity matched estimate. Neither the matched or unmatched estimates give a statistically or economically significant impact of unemployment on likelihood of having a child. However, the pooled estimation may be hiding the heterogeneous impacts of female and male unemployment.

Table 5.1: Full Sample Estimation

	Likelihood of Couple Having a Child	
	(1)	(2)
	Unmatched	Matched
Lagged Unemployment	-0.00809	-0.00449
	(0.00918)	(0.00948)
Observations	24574	24574
Mean of Dependent Variable	0.094	0.094

Notes. This table reports the ATT of unemployment on fertility for the full sample. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Matched estimates are constructed with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Sex Specific Estimation

Allowing for heterogeneous impacts of female and male unemployment reveals female unemployment decreases the likelihood of the couple having a child while male unemployment does not. I report the estimates for the ATT of female and male unemployment on fertility in Table 5.2. The matched estimates indicate the impact of female unemployment is a decrease in the likelihood of having a child by 3.7 percentage points. In comparison, the matched estimates indicate the impact of male unemployment is an increase in the likelihood of having a child by 0.7 percentage points. The impact of male unemployment is not statistically significant. These results provide surprising evidence on the sex specific impacts of unemployment: there is a negative gap of 4 percentage points between the impacts of female and male unemployment.

Table 5.2: Sex Specific Estimation

	Likelihood of Couple Having a Child			
	Female		Male	
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched
Lagged Unemployment	-0.0335**	-0.0368***	0.00724	0.00682
	(0.0119)	(0.0104)	(0.0133)	(0.0139)
Observations	10949	10949	13625	13625
Mean of Dependent Variable	0.065	0.065	0.117	0.117

Notes. This table reports the ATT of male and female unemployment on fertility. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Columns (1) to (2) report the impacts of female unemployment and columns (3) to (4) report the impacts of male unemployment. Matched estimates are constructed with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

One factor the traditional household model fails to account for that may explain sex specific differences in the impacts of unemployment on fertility is stress resulting from unemployment. HILDA asks respondents to rank the degree to which they feel different forms of psychological distress on a scale from one to five. Women who experienced job displacement reported feeling on average 6.1% more "hopeless", 5.4% more "depressed" and 6.7% more "tired out for no good reasons" relative to women who were not displaced. In comparison, men who experienced job displacement reported feeling on average 4.1% more "hopeless", 3.6% more "depressed" and 0.9% more "tired out for no good reasons" relative to men who were not displaced. If female unemployment tends to have larger impacts on stress, then the impacts for that woman's mental health and their relationship may be a factor in sex specific differences in the impact of unemployment on fertility.

To check whether stress is driving the sex specific differences of unemployment on having a child I rerun the estimation controlling for self-reported feelings of sadness, depression and tiredness. Since these questions are only asked every 2 to 3 years, sample size is significantly reduced. With this specific sample the unmatched estimates are slightly different to the full sample, although similar. If unemployment is operating through the channel of distress then since distress is positively correlated with unemployment and negatively correlated with fertility, the estimates controlling for stress should be more positive than when stress is not controlled. From Table 5.3, distress appears to be an important channel for female unemployment but not for male unemployment. Although imprecisely estimated, these results provide supporting evidence that stress may be one of the key channels driving sex specific differences in the impacts of unemployment on fertility.

Table 5.3: Sex Specific Estimation Controlling for Emotional Distress

	Likelihood of Couple Having a Child			
	Female		Male	
	(1)	(2)	(3)	(4)
Lagged Unemployment	-0.0253	-0.0205	0.0164	0.0182
	(0.0168)	(0.0157)	(0.0215)	(0.0211)
Distress Controls	No	Yes	No	Yes
Observations	3886	3886	4795	4795
Mean of Dependent Variable	0.070	0.070	0.118	0.118

Notes. This table reports the matched ATT of male and female unemployment on fertility. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, emotional distress, partner's characteristics and year fixed effects. Columns (1) to (2) report the impacts of female unemployment and columns (3) to (4) report the impacts of male unemployment. Distress controls add additional controls for self-reported tiredness, depression and hopelessness. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 Estimation by Breadwinner

The impacts of unemployment on fertility depend on which member of the household is the breadwinner. I define an individual as a breadwinner if their annual income is higher than their partner's annual income. I report the estimates for the ATT of female and male unemployment on fertility by breadwinner in Table 5.4. For female breadwinners the impact of unemployment is a decrease in the likelihood of having a child by 1.7 percentage points. For female non-breadwinners the impact of unemployment is a decrease in likelihood of having a child by 2.8 percentage points. Meanwhile the impacts of male breadwinner and male non-breadwinner unemployment on likelihood of having a child are both statistically insignificant, although are more negative for male breadwinners.

The estimates for female breadwinner compared to female non-breadwinner are surprising; if female breadwinners are responsible for the primary income of the household their unemployment may be expected to cause a larger income shock. However, this income shock may be mediated by redundancy pay. For this sample, female breadwinners are twice as likely to receive redundancy pay when they become unemployed compared to female non-breadwinners. Furthermore, female breadwinners received twice as much redundancy pay, on average about $1,900 more over the financial year relative to female non-breadwinners. Since redundancy pay lessens the income shock, female breadwinners may be less likely to delay fertility as a result of unemployment.

The difference between female breadwinner and non-breadwinner estimates may also be attributable to substitution effects. Because women bear most of the time costs from fertility, women in higher occupational positions face higher opportunity costs from childbearing (Kalwij 2010). Female breadwinners from this sample are on average engaged in six hours more work per week than female non-breadwinners. In addition, when asked to agree on a scale from one to seven whether individuals find their job "more stressful than [they] had ever imagined", "fear the amount of stress in their job will make [them] physically ill" or "have to work very intensely in [their] job" the mean score for female breadwinners were .15, .16 and .24 standard deviations higher relative to female non-breadwinners. If female breadwinners have larger time and stress commitments due to working in higher responsibility positions, the heterogeneity in the impacts of female unemployment may be attributable to the fact that unemployed female breadwinners have a larger decrease in the opportunity costs of childbearing.

In contrast, male breadwinners and non-breadwinners do not appear to have a significant difference in income shocks following unemployment. On average, male breadwinners earn about \$10 000 more annually than male non-breadwinners. However, once accounting for redundancy pay the difference in income shocks decreases significantly: male breadwinners are about 70% more likely to receive redundancy pay and receive on average \$3000 more over the financial year relative to male non-breadwinners. In addition, male breadwinners and non-breadwinners who are employed typically work similar hours - breadwinners only work on average 1.5 hours more than non-breadwinners - indicating that even if not the breadwinner, men consider their primary role is to work.

The differences in impacts of male breadwinners and non-breadwinners also may be due to substitution effects. Families that have a female breadwinner are more likely to have more equal division of household labour relative to families with a male breadwinner (Drago, Black, and Wooden 2004). If male non-breadwinners have greater willingness to take on household work, then their unemployment may provide a good opportunity to have a child. For individuals in my sample, male breadwinners who become unemployed on average take on an additional 2 hours of childcare and 1 hour of housework, while male non-breadwinners on average take on an additional 6 hours of childcare and 2 hours of housework. The differences in contributions to household labour are relatively small, providing further evidence that even when male non-breadwinners become unemployed they are still not expected to take on the primary childbearing role.

If female breadwinners are less likely to decrease fertility following unemployment relative to female non-breadwinners then it may indicate to policymakers female breadwinners cannot pursue a career and motherhood simultaneously. Using the most recent wave from the HILDA survey, Cowie and Grieve (2019) find female breadwinners on average spend 24.1 hours on housework and 19.3 hours on childcare, while their male partners spent 15.3 hours on housework and 10.9 hours on childcare. Similarly, for my sample I find female breadwinners on average spend 15.3 hours on housework and 21.7 hours on childcare while their male partners spent 8.5 hours on housework and 12.6 hours on childcare. Even when the female partner is responsible for the primary household income, she is still also primarily responsible for household labour. To improve work opportunities for mothers it is valuable to investigate how institutional policies have influenced the impact of female unemployment on likelihood of having a child.

Table 5.4: Breadwinner Estimation

	Likelihood of Couple Having a Child							
	Female				Male			
	Breadwinner		Non-Breadwinner		Breadwinner		Non-Breadwinner	
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) Unmatched	(6) Matched	(7) Unmatched	(8) Matched
Lagged Unemployment	-0.0349	-0.0174	-0.0322*	-0.0275**	0.00864	0.00914	0.000435	0.0217
	(0.0239)	(0.0187)	(0.0137)	(0.0102)	(0.0150)	(0.0162)	(0.0289)	(0.0217)
Number of Observations	3762	3762	7187	7187	11540	11540	2085	2085
Mean of Dependent Variable	0.069	0.069	0.063	0.063	0.117	0.117	0.123	0.123

Notes. This table reports the ATT of male and female unemployment on fertility for breadwinner and non-breadwinner subgroups. An individual is classified as a breadwinner when they earn more than their partner. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Columns (1) to (4) report the impacts of female unemployment and columns (5) to (8) report the impacts of male unemployment. Matched estimates are derived by matching on propensity score with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4 The Role of the Baby Bonus and Paid Parental Leave

To understand why I observe differences in the impacts of female breadwinner and non-breadwinner unemployment on fertility it is important to consider policies affecting work and childbearing over the sample period. Since 1979, female employees have been entitled to 52 weeks of unpaid parental leave conditional on being employed. Prior to the introduction of Paid Parental Leave access to paid parental leave was uncommon and varied in length and payment. According to Baird (2004) about 60% of women in Australia did not have access to paid maternity leave. Using HILDA survey responses, I find 49% of women did not have access to paid maternity leave prior to 2004.

In 2004 the Australian government introduced the Baby Bonus, then called the Maternity Payment, which provided a universal $3000 to any family who gives birth to combat low birth rates and ageing population concerns (Drago, Sawyer, Shreffler, Warren, and Wooden, 2009). The Baby Bonus did not carry obligations for either parent to be at work or take time off work to receive the payment, although an income threshold was applied in 2009. Over time, the amount of the Baby Bonus periodically increased reaching $5000 by 2011.

In 2011 the Australian government introduced the Paid Parental Leave policy was introduced to provide eligible working parents with up to 18 weeks of government funded paid leave at the national minimum wage after the birth of a child. In 99.5% of cases Paid Parental Leave is taken by the mother (OECD 2013) and at its inception 84% of working mothers were expected to be eligible (PC 2009). Before the abolition of the Baby Bonus in 2014, families who were eligible for both the Baby Bonus and Paid Parental Leave had to choose between the two payments.

To examine how each policy affects the impact of female unemployment on likelihood of having a child I divide the sample up into three periods: pre-Baby Bonus (2002-2003), Baby Bonus (2004-2010) and Paid Parental Leave (2011-2016). I estimate the impact of female unemployment on fertility for each of these periods in Table 5.5. Compared to before the introduction of the Baby Bonus, the Baby Bonus decreased the impact of female unemployment on fertility. When Paid Parental Leave was introduced, the negative impact of female unemployment on fertility returned.

Table 5.5: Effect of Female Unemployment on Fertility During Different Policy Periods

	Likelihood of Couple Having a Child					
	Pre-Baby Bonus		Baby Bonus		Paid Parental Leave	
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) Unmatched	(6) Matched
Lagged Unemployment	-0.0536	-0.0428***	-0.0175	-0.0145	-0.0409*	-0.0448**
	(-0.0291)	(-0.013)	(-0.0181)	(-0.0172)	(-0.0185)	(-0.0166)
Observations	1795	1795	3902	3902	5252	5252
Mean of Dependent Variable	0.054	0.054	0.057	0.057	0.074	0.074

Notes. This table reports the ATT of female unemployment on fertility during different policy periods. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Columns (1) and (2) report the unmatched and matched estimates for women for the period prior to the introduction of the baby bonus (2002-2003). Columns (3) and (4) report the unmatched and matched estimates for women after the introduction of the baby bonus and prior to the introduction of paid parental leave (2004-2010). Columns (5) and (6) report the unmatched and matched estimates for women after the introduction of paid parental leave (2011-2017). Matched estimates are derived by matching on propensity score with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The Baby Bonus may have had the unintended consequence of making unemployed women less likely to rejoin the labour force. During the Baby Bonus period, a couple is 2.8 percentage points more likely to have a child following female unemployment relative to before the Baby Bonus was introduced. However, incentivising childbearing for unemployed women may increase the period spent away from work, particularly for women with weak employment prospects. Drago et al. (2009) finds that changes in fertility behaviour due to the Baby Bonus was concentrated amongst low education and low income women, meaning the Baby Bonus may disproportionately discourage poor women from returning to work. Similarly, I find women without university education are more likely to have a child during the Baby Bonus period relative to women with university education (Appendix A.4). However, if childbearing increases the period of unemployment, it may also increase household specialisation of labour and decrease the accumulation of human capital for unemployed mothers. Since this impact is concentrated among low income or low education women, this may disproportionately discourage these women from returning to the labour force, limiting the earning potential of the household and potentially entrenching the socioeconomic gap between poor and rich households in Australia.

Meanwhile, the introduction of Paid Parental Leave encouraged women to return to work before having a child but not more so than prior to the Baby Bonus. During the Paid Parental Leave period, a couple is 3 percentage points less likely to have a child following female unemployment relative to the Baby Bonus period. As unemployed mothers are not eligible for Paid Parental Leave, childbearing carries larger opportunity costs for unemployed women. This change in incentives is also true for the period where both policies were active, since the total value of Paid Parental Leave was about $10 000 or twice as much as the Baby Bonus (DSS 2014). Although Paid Parental Leave increased labour supply of mothers, conflicts between motherhood and work in Australia are still greater than other OECD countries (OECD 2017). This may explain why the impacts of female unemployment are similar to the estimate before either policy was introduced: Paid Parental Leave is not generous enough to completely disincentivise unemployed mothers from having a child. A more generous scheme may incentivise women to return to work before having a child, helping achieve the goal of facilitating women in Australia to pursue motherhood and a career simultaneously.

These estimations cannot be interpreted as the causal impacts of the policies on the relationship between unemployment and fertility if they are confounded by other cyclical trends or events. For example, from 2004 Australia experienced the mining boom and from 2007 the global financial crisis. Although I control for year dummies we may be concerned this estimation is capturing cyclical effects. In order to examine the trends over time, I plot the results of an event study on the impacts of female unemployment on fertility in Figure 5.1 and provide the impacts of male unemployment for comparison. The years the Baby Bonus and Paid Parental Leave are introduced are indicated by dashed lines. The methodology used to construct this event study is available in Appendix A.5.

The results of this event study do not evidence a strong cyclical trend. The impact of female unemployment on fertility consistently displays more positive impacts during the Baby Bonus period, which included both strong economic growth during the mining boom and weak economic growth during the global financial crisis. After the introduction of Paid Parental Leave, the impacts of female unemployment become more negative again, although appear to rise towards the end of the sample period. Meanwhile, the impact of male unemployment on fertility is consistently insignificant, showing no cyclical trend or policy impacts. Although only preliminary, this event study indicates the Baby Bonus and Paid Parental Leave played an important role in determining the impact of female unemployment on fertility but did not influence the impact of male unemployment on fertility.

5.5 Additional Experiments

I investigate three other sources of heterogeneity in impacts of unemployment on likelihood of having a child. I have excluded these estimations from the main results because they do not directly contribute to explaining sex specific differences in the impact of unemployment on fertility. The first finding, reported in Appendix B.1, is longer term unemployment spells have less negative impacts on fertility compared to shorter term unemployment spells. The second finding, reported in Appendix B.2, is unemployment is likely to delay first and second child, but less likely to delay third child. The third finding, reported in Appendix B.3, is when both female and male partners are simultaneously unemployed the negative impact on likelihood of having a child is significantly greater than when one partner becomes unemployed.

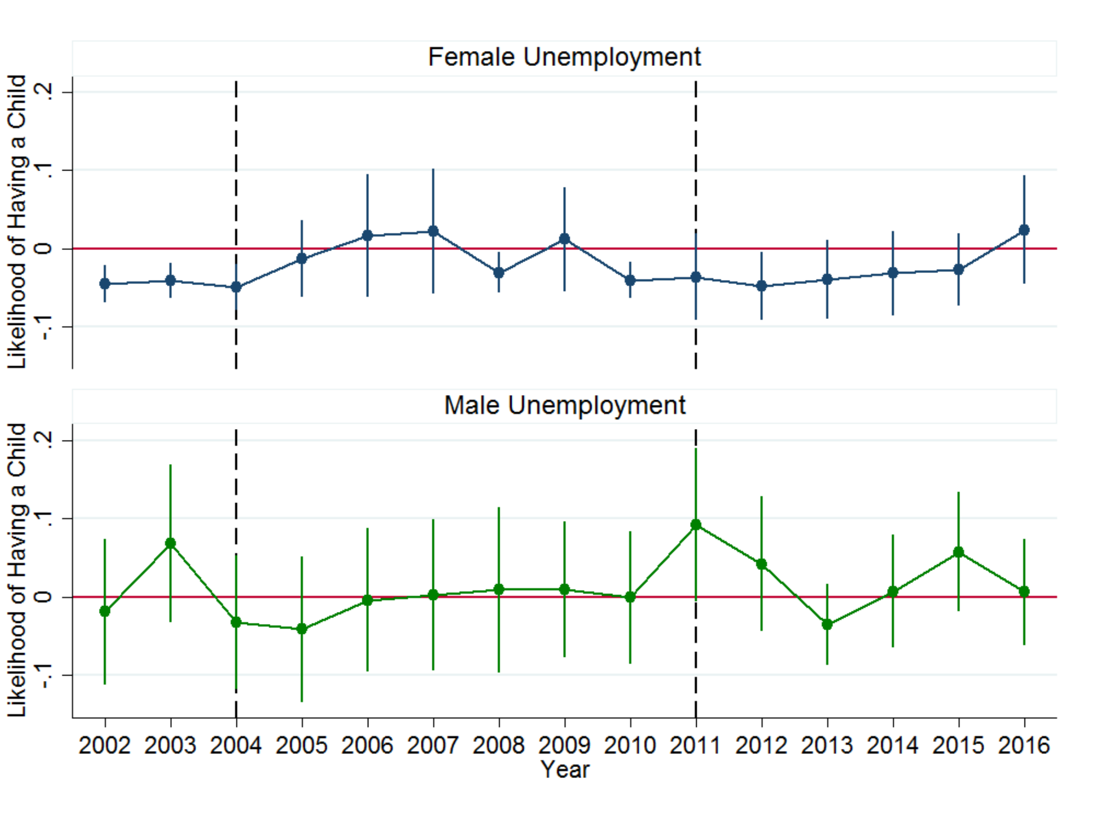


Figure 5.1: Event Study of Female and Male Unemployment on Likelihood that Couple has a Child

Notes. This event study is constructed using an OLS regression of year specific lagged unemployment dummies on likelihood of having a child. Controls include age, personal characteristics, partner's characteristics and year fixed effects. 95% confidence intervals are depicted. The estimation for this event study is available in Appendix A.5.

Chapter 6
Robustness

6.1 Sensitivity Analysis for Hidden Bias

If there are hidden variables that violate the unconfoundedness assumption, then bias may arise to which matching estimators are not robust. Becker and Caliendo (2007) recommend a bounding approach to examine how hidden variables may confound the results of propensity matching analysis. The Mantel-Haeznel test statistic establishes bounds for the ATT given departures from the assumption that the matching estimate is free from unobserved bias. I report the Mantel-Haeznel bounds for the the impacts of female unemployment and male unemployment on likelihood of having a child in Tables 6.1 and 6.2.

The Mantel-Haeznel bounds tell us at what degree of unobserved positive or negative selection the ATT becomes significant or insignificant. $Q+_{mh}$ corresponds to the case of positive hidden selection bias when individuals most likely to become unemployed tend to have higher fertility in the absence of unemployment. $Q-_{mh}$ corresponds to the case of negative hidden selection bias when individuals most likely to become unemployed tend to have lower fertility in the absence of unemployment.

According to the Mantel-Haeznel bounds, the impact of female unemployment becomes insignificant at the 10% level when there is negative hidden selection bias if the likelihood of unemployment differed between treatment and control groups by more than 40%. The impact of male unemployment becomes statistically significant at the 10% level when there is positive hidden bias that causes likelihood of unemployment to differ by more than 30% or negative hidden bias that causes the likelihood of unemployment to differ by more than 10%. These results indicate that the results are relatively robust from small departures from the assumption of no hidden bias, although it is important to consider hidden factors that may be affecting the results.

Table 6.1: Mantel-Haeznel Bounds for ATT of Female Unemployment in the Presence of Hidden Bias

Γ	$Q_{mh}+$	$Q_{mh}-$	$p_{mh}+$	$p_{mh}-$
1	2.62	2.62	0.00	0.00
1.1	2.98	2.26	0.00	0.01
1.2	3.31	1.94	0.00	0.03
1.3	3.62	1.65	0.00	0.05
1.4	3.91	1.39	0.00	0.08
1.5	4.19	1.14	0.00	0.13
1.6	4.45	0.91	0.00	0.18
1.7	4.70	0.69	0.00	0.24
1.8	4.94	0.49	0.00	0.31
1.9	5.17	0.30	0.00	0.38
2	5.39	0.12	0.00	0.45

Table 6.2: Mantel-Haeznel Bounds for ATT of Male Unemployment in the Presence of Hidden Bias

Γ	$Q_{mh}+$	$Q_{mh}-$	$p_{mh}+$	$p_{mh}-$
1	0.52	0.52	0.30	0.30
1.1	0.40	1.21	0.48	0.11
1.2	0.67	1.85	0.25	0.03
1.3	1.26	2.44	0.10	0.01
1.4	1.81	2.98	0.04	0.00
1.5	2.31	3.49	0.01	0.00
1.6	2.79	3.98	0.00	0.00
1.7	3.24	4.43	0.00	0.00
1.8	3.67	4.87	0.00	0.00
1.9	4.07	5.28	0.00	0.00
2	4.46	5.68	0.00	0.00

Notes. These tables report the Mantel-Haeznel bounds for the ATT of female and male unemployment on likelihood of having a child. Γ is the odds of differential assignment due to hidden bias. $Q_{mh}+$ is the Mantel-Haeznel bound in the presence of positive hidden bias and $p_{mh}+$ is its corresponding p-value. $Q_{mh}-$ is the Mantel-Haeznel bound in the presence of negative hidden bias and $p_{mh}-$ is its corresponding p-value.

6.1.1 Bias from Unobservable Work Effort

Work effort is an important source of hidden bias that may affect the sex specific impacts of unemployment. Using a time and energy constrained framework, Becker (1985) suggests individuals who devote more time to household work may reduce use of energy at work. If a couple is pregnant or planning on having a child, they may have less time for work or place lower priority on work. Because lower work effort is likely to lead to a higher likelihood of unemployment, the ATT estimates would then be positively biased.

If women are socially expected to care for children or cannot maintain work effort while pregnant then they may more likely to change work behaviour as a result of unemployment. Changes in work effort may therefore explain some of the gap in the sex specific impacts of unemployment on fertility. However, there is literature contrary to the work effort hypothesis, finding work effort is not a significant factor in the motherhood penalty (Dechter 2014, Anderson, Binder, and Waldfogel 2003, Waldfogel 1997). This evidence suggests work effort may not be dependent on fertility decisions, in which case work effort would not bias the results.

6.1.2 Attrition Bias from Separation

Another source of hidden bias that may affect the sex specific impacts of unemployment is selective attrition. If individuals are dropped from the sample because unemployment causes them to separate and these individuals are less likely to have children due to separating, then the ATT estimates of the impact of unemployment on fertility are likely to be positively biased. In Table 6.3 I show attrition is positively correlated with unemployment for both women and men by similar magnitudes. Female unemployment is slightly more likely to lead to separation, which implies, if anything, the sex specific difference in impacts of unemployment on fertility should be even larger.

Table 6.3: Likelihood of Separation as a Result of Female and Male Unemployment

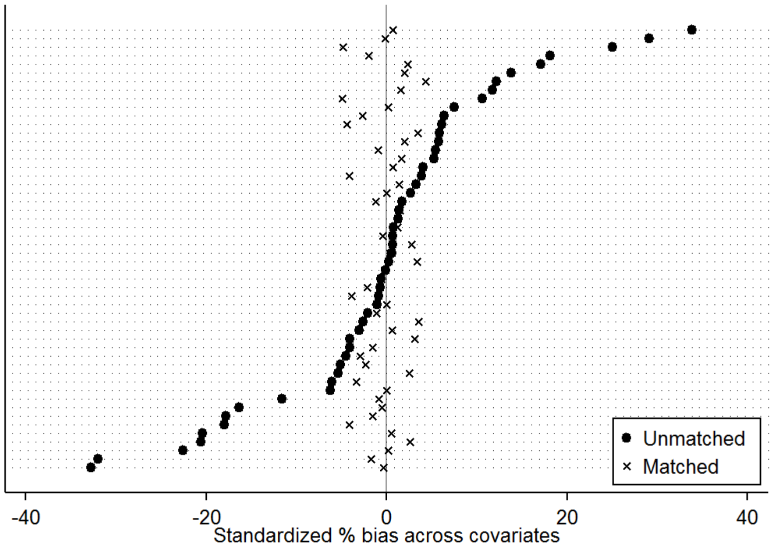
	Likelihood of Separation	
	Female	Male
	(1)	(2)
Unemployment	0.0293***	0.0231***
	(0.00607)	(0.00638)
Number of Observations	17006	19491

Notes. This table reports linear regression of likelihood of separation on unemployment for the female and male subsamples. Controls include age, personal characteristics, partner's characteristics and year fixed effects. Robust standard errors are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

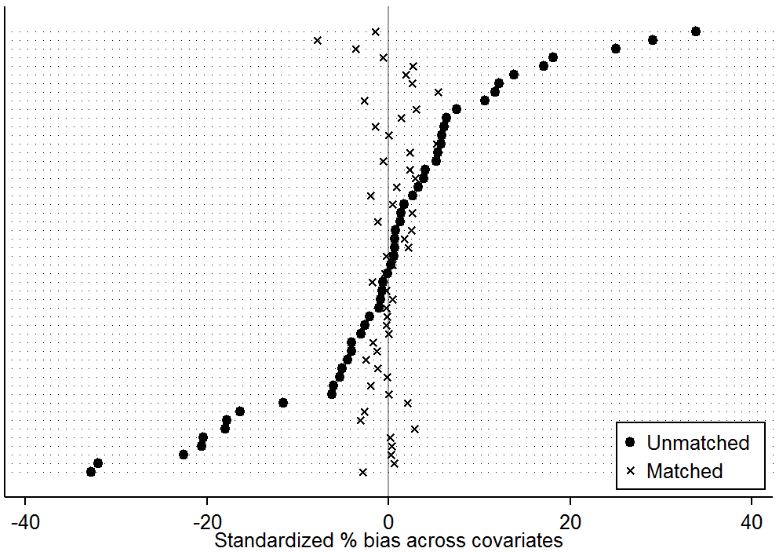
6.2 Assessing Matching Quality on Observables

To assess the match quality I use two measures: standardised bias and pseudo-R^2. Standardised bias assesses the difference in sample means between treated and control groups as a percentage of the square root of the average sample variances in both groups. Effective matching should reduce standardised bias and balance covariates between treatment and control groups. Sianesi (2004) suggests additionally comparing pseudo-R^2 to check well the control variables explain probability of unemployment before and after matching. If after matching there are no systematic differences between the two groups then the control variables should have low explanatory power.

To check matching quality I examine the estimations of male and female unemployment on likelihood of having a child. Standardised bias for the female subsample is plotted in Figure 6.1 (a) and for the male subsample in Figure 6.1 (b). Both estimations indicate substantial improvements in standardised bias. For women, the pseudo-R^2 before matching is 0.085 and after matching is 0.006. For men, the pseudo-R^2 before matching is 0.085 and after matching is 0.004. In both cases, the observable variables have very low explanatory power in predicting likelihood of unemployment after matching indicating PSM was effective in removing observable systematic differences between unemployed and employed individuals.



(a) Impact of Female Unemployment



(b) Impact of Male Unemployment

Figure 6.1: Standardised Bias Before and After Matching

6.3 Using Pregnancy as an Outcome Variable

To check the robustness of choice of dependent variable I rerun the sex specific estimation using pregnancy as an outcome variable rather than birth. Pregnancy is self reported in the Life Events section of the HILDA survey similarly to birth. Table 6.4 indicates female unemployment has a 3.4 percentage point more negative impact on likelihood of couple being pregnant relative to male unemployment. Although this difference is similar in magnitude to using birth as the dependent variable, both the male and female estimates are more positive. The different estimates may be occurring as pregnancy is a less precise measurement of fertility, relying on the reporting partner being aware they or their partner are pregnant. Additionally, not all pregnancies result in births.

Table 6.4: Impacts of Male and Female Unemployment on Pregnancy

	Likelihood of Couple being Pregnant			
	Female		Male	
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched
Lagged Unemployment	-0.0214	-0.0172	0.0190	0.0166
	(0.0166)	(0.0162)	(0.0170)	(0.0173)
Observations	10949	10949	13625	13625
Mean of Dependent Variable	0.128	0.128	0.148	0.148

Notes. This table reports the ATT of male and female unemployment on pregnancy. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Columns (1) to (2) report the impacts of female unemployment and columns (3) to (4) report the impacts of male unemployment. Matched estimates are constructed with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of being pregnant for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.4 Instrumental Variable Approach

As an additional robustness check I use involuntary redundancy as an exogenous source of variation of unemployment, available in Appendix C. The instrumental variable estimates are similar to the propensity matched estimates, but because I was unable to perfectly capture involuntary redundancy I chose to exclude them from the main results.

Chapter 7
Implications, Limitations and Conclusion

7.1 Policy Implications

Government policy can have significant consequences for the impacts of unemployment on fertility. By incentivising fertility, the Baby Bonus increased the likelihood of unemployed women having a child. However, having a child may increase the length of career interruption, causing a longer gap in human capital accumulation and lead to worse future employment prospects. In contrast, Paid Parental Leave incentivises returning to the workforce before having a child. Since Paid Parental Leave is paid at the same rate for all takers, the benefits of the program are likely to be largest for low income, working mothers. Although not primary directives of the policies, the government should be aware of these potential welfare implications.

I would not argue closing the gap in the sex specific differences in the impact on unemployment on fertility should be a policy directive: ultimately it is the factors underlying these differences that should direct policy. If female unemployment decreases the willingness of couples to have a child, then this is an indication that women do want to both work and have children. To alleviate concerns about the ageing population, the government could encourage population growth by supporting the labour supply of mothers. In addition, given the importance of economic instability and job security in the fertility decision the government may want to examine how the fertility implications of other uncertainty inducing labour market institutions such as temporary contracts and casual work.

7.2 Limitations and Future Research

The main limitation of this thesis is that in the presence of unobservables, the propensity matched estimates may underestimate the causal impacts of unemployment on fertility. Although my results provide useful guidance on the gap between impacts of female and male unemployment, future researchers may want to search for sources of exogenous variation in employment to identify the magnitude of the causal effects. In Appendix C.5 I detail two other instrumental variable approaches which could be used to identify causal effects of unemployment in Australia, but were unavailable to myself at the time of writing.

Another limitation of this thesis is casual and self employed workers were excluded from my analysis. Because casual and self employed workers do not share the same entitlements as full and part time workers, they may display different fertility behaviour in response to unemployment. Less stable work conditions may mean casual and self employed workers have fewer assets or job alternatives to fall back on if unemployed. However, because casual and self employed workers are subject to less job stability they may anticipate and prepare for unemployment and therefore be more likely to have a child if unemployed. In addition, because Paid Parental Leave is paid at the same rate for all workers it may be an even more important factor affecting sex specific differences in the impact of unemployment on fertility for casual and self employed women.

This thesis focused on the impacts of unemployment, but I did not investigate other sources of job instability. There are significant differences in job stability across industries and occupations which are likely to also impact the likelihood of having a child. Perceived job stability is likely to also affect fertility but may not necessarily result in unemployment. Future researchers may want to use the survey responses from HILDA on self-assessed job instability to examine the impacts of economic instability, although it is likely this measure may be endogenous. Industry level employment shocks could be one source of variation in job stability which would be plausibly exogenous to the couple's decision to have a child.

7.3 Conclusion

I find among Australian couples, female unemployment decreases the likelihood of having a child by 3.7 percentage points while male unemployment has no significant effect. The discrepancy between theoretical predictions and empirical findings can be attributed to several factors. Firstly, I provide evidence male unemployment tends to have weaker effects on stress and anxiety than female unemployment, which may in turn contribute to willingness to have a child. Secondly, I show the negative effects of female unemployment are concentrated amongst female non-breadwinners due to a combination of differences in redundancy pay, hours of work and intensity of work. Finally, I demonstrate that while cash transfers during the Baby Bonus period incentivised fertility for unemployed women, the increased opportunity costs of having a child while unemployed during the Paid Parental Leave period disincentivised fertility for unemployed women.

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Appendix A
Supplementary Materials

A.1 Variable Definitions

Table A.1: Variable Definitions

Variable	Description
Birth	=1 if mother gives birth in given year =0 otherwise
Unemployment	=1 Unemployed in given year =0 otherwise
Age	Age at last interview
University Educated	=1 if possess at least a bachelors degree =0 otherwise
Immigrant	=1 born overseas =0 otherwise
Rural	=1 if living in a rural area =0 otherwise
Ever Had a Child	=1 has any children =0 otherwise
Defacto	=1 if in a defacto relationship =0 if married
Partner's Age	Age of partner at last interview
Partner University Educated	=1 if partner possesses at least a bachelors degree =0 otherwise
Partner's Employment Status	=1 if partner employed =2 if partner unemployed =3 if partner NILF
Occupation	(1) Managers (2) Professionals (3) Technicians and Trades Workers (4) Community and Personal Service Workers (5) Clerical and Administrative Workers (6) Sales Workers (7) Machinery Operators and Drivers (8) Labourers

Table A.1: Variable Definitions

Variable	Description
Industry	(1) Agriculture, Forestry and Fishing (2) Mining (3) Manufacturing (4) Electricity, Gas, Water and Waste Services (5) Construction (6) Wholesale Trade (7) Retail Trade (8) Accommodation and Food Services (9) Transport, Postal and Warehousing (10) Information Media and Telecommunications (11) Financial and Insurance Services (12) Rental, Hiring and Real Estate Services (13) Professional, Scientific and Technical Services (14) Administrative and Support Services (15) Public Administration and Safety (16) Education and Training (17) Health Care and Social Assistance (18) Arts and Recreation Services (19) Other Services
Year	Set of dummies for year interview was conducted in
Emotional Distress	Scale from 1 (all of the time) to 5 (none of the time) to which respondents feel "hopeless", "depressed" or "tired out for no good reasons"
Views on Work	Scale from 1 (strongly disagree) to 7 (strongly agree) to which respondents find their job "more stressful than [they] ever imagined", "fear the amount of stress in [their] job will make them physically ill" or "have to work very intensely in [their] job"
Breadwinner	=1 if earns more than partner on annual basis =0 otherwise

A.2 Estimation of Propensity Scores

Table A.2: Logit Estimation of Propensity Scores

	Likelihood of Unemployment		
	(1)	(2)	(3)
	Pooled	Female	Male
Sex	0.425***		
	(0.0627)		
Age	-0.270***	-0.312***	-0.229***
	(0.0285)	(0.0411)	(0.0394)
Age Squared	0.00374***	0.00389***	0.00355***
	(0.000421)	(0.000605)	(0.000591)
University Educated	-0.515***	-0.658***	-0.388***
	(0.0724)	(0.102)	(0.104)
Immigrant	0.352***	0.461***	0.207**
	(0.0565)	(0.0859)	(0.0784)
Rural	-0.0770	-0.0850	-0.00389
	(0.0689)	(0.104)	(0.0938)
Ever Had a Child	0.410***	0.778***	0.135
	(0.0621)	(0.0936)	(0.0812)
Defacto	0.457***	0.270***	0.592***
	(0.0525)	(0.0815)	(0.0704)
Partner's Age	-0.00683	0.00560	-0.0209*
	(0.00557)	(0.00737)	(0.00820)
Partner University Educated	-0.00895	-0.0737	-0.0273
	(0.0552)	(0.0859)	(0.0760)
Partner Unemployed	1.340***	1.478***	1.227***
	(0.0845)	(0.132)	(0.113)
Partner NILF	0.613***	0.879***	0.620***
	(0.0597)	(0.128)	(0.0686)
Constant	0.968	2.985***	0.447
	(0.500)	(0.713)	(0.687)
N	36497	17006	19491

This table reports the estimation of propensity scores of unemployment conditional on observable characteristics. The results are estimated using a logit model with robust standard errors. Year, occupation and industry fixed effects are excluded from the regression results for brevity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.3 Robustness to Different Numbers of Matches

Table A.3: Impact of Unemployment with 2, 5 and 10 Nearest Neighbour Propensity Matching

	Likelihood of Couple Having a Child					
	Female Unemployment			Male Unemployment		
	(1) 2 Neighbours	(2) 5 Neighbours	(3) 10 Neighbours	(4) 2 Neighbours	(5) 5 Neighbours	(6) 10 Neighbours
Lagged Unemployment	-0.0387**	-0.0368*	-0.0287**	-0.00244	-0.00682	-0.00754
	(-0.0137)	(-0.0104)	(-0.00898)	(-0.0155)	(-0.0139)	(-0.0131)
Observations	13625	13625	13625	10949	10949	10949
Mean of Dependent Variable	0.065	0.065	0.065	0.117	0.117	0.117

This table reports the ATT of female and male unemployment on likelihood of couple having a child with 2, 5 and 10 nearest neighbours. Propensity for unemployment is estimated using a logit model conditional on age, personal characteristics, partner's characteristics and year fixed effects. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.4 Heterogeneous Impacts of Female Unemployment by Education during the Baby Bonus period

Table A.4 reports the impacts of female unemployment on likelihood of couple having a child for two separate subgroups - low education (not university educated) and high education (university educated) - during the Baby Bonus policy period. The results indicate that the impacts of unemployment are more negative for university educated women than non university educated women. This indicates that the incentives for an unemployed woman to have a child were stronger for less educated women.

Table A.4: Impacts of Female Unemployment on Fertility for University and non-University Educated Women during the Baby Bonus period

	Likelihood of Couple Having a Child	
	(1)	(2)
	Not University Educated	University Educated
Lagged Unemployment	-0.0120	-0.0152
	(0.0177)	(0.0325)
Observations	2188	1714
Mean of Dependent Variable	0.062	0.051

This table reports the estimation for the ATT of female unemployment during the Baby Bonus period (2004-2010). Column (1) reports the matched estimate for non-university educated women and column (2) reports the matched estimate for university educated women. Propensity for unemployment is estimated using a logit model conditional on age, personal characteristics, partner's characteristics and year fixed effects. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.5 Event Study Construction

To construct the event study of the impacts of female and male unemployment on likelihood of having a child I estimate the following model using ordinary least squares.

$$F_{it+1} = \alpha_0 + \sum_{j=2002}^{2016} \beta_j U_{ij} + \alpha_1 \mathbf{X_{it}} + \gamma_t + u_{it}$$

F_{it+1} is a dummy variable equal to one if the couple has a child next period. U_{ij} are a series of dummy variables equal to one if an individual became unemployed in a given period. $\mathbf{X_{it}}$ are a series of individual control variables and γ_t are year fixed effects. u_{it} is the error term which represents unobserved variables which may be affecting likelihood of having a child. I provide the results of this estimation in Table A.5.

Table A.5: Event Study Results

	Female	Male
	(1)	(2)
Unemployed_{2002}	-0.0453**	-0.0192
	(0.0146)	(0.0562)
Unemployed_{2003}	-0.0409**	0.0680
	(0.0139)	(0.0609)
Unemployed_{2004}	-0.0493**	-0.0322
	(0.0176)	(0.0519)
Unemployed_{2005}	-0.0130	-0.0414
	(0.0301)	(0.0566)
Unemployed_{2006}	0.0163	-0.00393
	(0.0477)	(0.0559)
Unemployed_{2007}	0.0225	0.00250
	(0.0483)	(0.0586)
Unemployed_{2008}	-0.0307*	0.00916
	(0.0156)	(0.0640)
Unemployed_{2009}	0.0119	0.00922
	(0.0401)	(0.0528)
Unemployed_{2010}	-0.0403**	-0.000918
	(0.0140)	(0.0515)
Unemployed_{2011}	-0.0360	0.0915
	(0.0333)	(0.0596)

Unemployed_{2012}	-0.0478	0.0417
	(0.0263)	(0.0522)
Unemployed_{2013}	-0.0394	-0.0356
	(0.0304)	(0.0316)
Unemployed_{2014}	-0.0317	0.00731
	(0.0327)	(0.0439)
Unemployed_{2015}	-0.0269	0.0576
	(0.0284)	(0.0461)
Unemployed_{2016}	0.0239	0.00638
	(0.0421)	(0.0411)
Age	0.0405***	0.0396***
	(0.00365)	(0.00477)
Age Squared	-0.000665***	-0.000628***
	(0.0000514)	(0.0000682)
University Educated	0.00383	-0.000905
	(0.00675)	(0.00810)
Immigrant	-0.00248	-0.00679
	(0.00638)	(0.00733)
Ever Had a Child	-0.0105	-0.0110
	(0.00723)	(0.00733)
Defacto	-0.0533***	-0.0849***
	(0.00705)	(0.00786)
Partner's Age	-0.00164**	-0.00701***
	(0.000517)	(0.000801)
Partner University Educated	-0.00589	0.0290***
	(0.00578)	(0.00631)
Rural	0.00233	0.0204*
	(0.00827)	(0.00917)
Constant	-0.472***	-0.232**
	(0.0629)	(0.0836)
Number of Observations	10949	13625

This table reports the estimation of the event study on the impact of unemployment on likelihood of having a child. The results are estimated using OLS with robust standard errors. Year, occupation and industry fixed effects are excluded from the regression results for brevity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B
Additional Experiments

B.1 Unemployment Duration

It is likely the impacts of unemployment on fertility vary by unemployment duration. To estimate the impacts of female and male unemployment by length of unemployment, I consider two types of unemployment: short term and long term. A short unemployment spell characterises individuals unemployed for less than 6 months. A long unemployment spell characterises individuals unemployed for more than 6 months. In Table B.1 I run two sets of estimations, one with short term unemployment as treatment and one with long term employment as treatment. Each treatment type omits the other treatment type, so both are in comparison to the control group.

The impact of female short term unemployment is a decrease in likelihood of having a child of 3.4 percentage points. In contrast, the impact of female long term unemployment is a decrease in likelihood of having a child of 1.0 percentage points. The impact of male long term unemployment is also more positive than male short term unemployment, although both estimates of male unemployment are not statistically different from zero.

These results suggest the largest shocks from unemployment on fertility occur in the short run. In line with the previous findings of this paper, it is likely the impacts of stress are largest in the short term. In addition, likelihood of reemployment and permanent wages are lower for individuals in long term unemployment (Nichols, Mitchell, and Lindner 2013). Long term unemployed individuals may therefore be more willing to have a child since their employment prospects are weaker than short term unemployed individuals. If low income or education women are more prone to longer term employment spells, then their decision to leave the labour force to have children may also have welfare implications.

Table B.1: Impact of Short Term and Long Term Unemployment on Fertility

	Likelihood of Couple Having a Child							
	Female				Male			
	$\leq$ 6 Months		$>$ 6 Months		$\leq$ 6 Months		$>$ 6 Months	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched
Lagged Unemployment	-0.0325**	-0.0344**	-0.0166	-0.00976	0.00701	0.00253	0.0182	0.00909
	(0.0121)	(0.0115)	(0.0274)	(0.0272)	(0.0135)	(0.0143)	(0.0261)	(0.0237)
N	10877	10877	10524	10524	13471	13471	13031	13031
Mean of Dependent Variable	0.064	0.064	0.064	0.064	0.118	0.118	0.121	0.121

Notes. This table reports the ATT of short term and long term unemployment on fertility. Short term unemployment is defined as an unemployment spell of six months or less and long term unemployment is defined as an unemployment spell of over six months. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Columns (1) to (4) estimate the impact of female unemployment and Columns (5) to (8) estimate the impact of male unemployment. Matched estimates are derived by matching on propensity score with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.2 Birth Parity

It is likely the impacts of female unemployment vary by birth parity. To compare the impacts of female unemployment by birth parity I compare couples with zero, one and two children. The impacts of female unemployment by birth parity are shown in Table B.2. The impact of female unemployment is a decrease in likelihood of having the first child by 3.8 percentage points, a decrease in likelihood of having the second child by 11.5 percentage points and a decrease in likelihood of having the third child by 2.2 percentage points.

However, the mean likelihood of having a child in the control group varies significantly between these three categories. Relative to the control mean, the female unemployment decreases likelihood of having the first child by 190%, likelihood of having the second child by 65% and likelihood of having the third child by 32%. These indicate results couples with no children are significantly more likely to delay fertility in the event of female unemployment relative to couples with one or two children.

One explanation for this timing issue is the preference of parents to have children of similar ages. Women who have previously had children may be less willing to delay fertility in the event of unemployment if they want those children to be of similar age. Alternatively, couples that have had fewer children may be displaying lower preferences for children, which implies unemployment would have a lower substitution effect relative to couples with preferences for children.

Table B.2: Effect of Female Unemployment Fertility for Different Birth Parities

	Likelihood of Couple Having a Child					
	First Child		Second Child		Third Child	
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) Unmatched	(6) Matched
Lagged Unemployment	-0.0344	-0.0380*	-0.0738	-0.115*	-0.0274	-0.0216**
	(-0.0193)	(-0.0185)	(-0.0470)	(-0.0467)	(-0.0155)	(-0.00753)
Observations	4507	4507	1640	1640	3099	3099
Mean of Dependent Variable	0.02	0.02	0.176	0.176	0.068	0.068

Notes. This table reports the ATT of female unemployment on fertility for different birth parities. Likelihood of couple having first, second or third child are calculated by comparing treated and untreated couples with zero, one or two children. Propensity for unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Columns (1) to (2) estimate the impact of female unemployment on likelihood of having the first child, Columns (3) to (4) estimate the impact of female unemployment on likelihood of having the second child and Columns (5) to (6) estimate the impact of female unemployment on likelihood of having the third child. Matched estimates are derived by matching on propensity score with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.3 Simultaneous Unemployment

In Table B.3 I report the impact of simultaneous male and female unemployment on likelihood of having a child. When both partners are unemployed, they are 8.7 percentage points less likely to have a child. This impact is greater in magnitude than either individual male or female unemployment. In the case of dual unemployment, the income shock appears to significantly outweigh any substitution effects of unemployment.

These results are likely attributable to the income effect and economic instability. If both of the couple are unemployed, then neither have certain future wages. Given children are a long term investment, the couple may prefer to wait until at least one partner become reemployed so that the household has stable income before having a child.

Table B.3: Impact of Simultaneous Unemployment on Fertility

	Likelihood of Couple Having a Child	
	(1)	(2)
	Unmatched	Matched
Lagged Dual Unemployment	-0.0776	-0.873**
	(0.0397)	(0.0290)
Observations	24574	24574
Mean of Dependent Variable	0.094	0.094

Notes. This table reports the ATT of dual unemployment on fertility for the full sample. Propensity of unemployment is estimated using a logit model as a function of age, personal characteristics, partner's characteristics and year fixed effects. Matched estimates are constructed with 5 nearest neighbours. Robust Abadie-Imbens standard errors are reported in parentheses. Mean of dependent variable is average likelihood of having a child for the employed group.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C
Instrumental Variable Approach

C.1 Redundancy as an Instrumental Variable

If unobservables are causing bias in the propensity matched estimation then the ATT will not be the true causal effect of unemployment on fertility. Hidden bias motivates the use of an instrumental variable for unemployment. In Australia, by legal definition, involuntary redundancy can only occur when either the business no longer requires that job to be done by someone (i.e. position is being closed) or if the business becomes insolvent or bankrupt.

Involuntary redundancy is plausibly exogenous assuming that employees fail to forsee future job loss and that it is uncorrelated with personal characteristics. Recent literature has used redundancy from firm closure as exogenous variation in unemployment to identify causal effects (for example Bono et al. 2015; Browning and Heinesen 2012; Eliason and Storrie 2009). However, it is difficult to capture involuntary redundancies using HILDA.

The HILDA survey does not report redundancy separately from dismissal. Instead, it asks whether an individual has been "fired or made redundant by an employer". If I use this variable, the exogeneity assumption would not be satisfied as dismissals may be correlated with personal characteristics. Even in surveys where redundancy is reported, it is likely that there would be measurement error since individuals may prefer to report redundancy rather than dismissal either because it is less stigmatic (Arulampalam 2001) or simply because they do not know the difference.

In order to capture involuntary redundancies I use two proxies: job loss from a declining industry and recipiency of redundancy pay. I am not convinced these proxies satisfy the exogeneity assumption so I do not claim to identify the causal effect. For this reason, I present these results in the Appendix as a comparison to the propensity matched estimates.

C.1.1 Job Loss in Declining Industry

My first proxy for involuntary redundancy is similar to an approach taken by Borland, Gregg, Knight, and Wadsworth (1999) which distinguishes between workers in growing and declining industries to enforce some exogeneity over the cause of unemployment. Industries in decline are more likely to be experiencing bankruptcy or insolvency, resulting in higher levels of firm closure and hence involuntary redundancy. I construct a dummy variable equal to 1 if an individual was fired from an industry in decline (negative employment growth over the past year in that individual's industry and state) and equal to zero otherwise. Although not a perfect measure of redundancy, this variable is intended to capture a greater share of genuine redundancies rather than dismissals.

C.1.2 Job Loss and Redundancy Payment Recipient

My second proxy for involuntary redundancy is redundancy payments. If an individual is made redundant or fired and additionally receives redundancy payments in a given year, I assume that they were made redundant. However, this proxy also captures redundancies that may be correlated with performance. For example, if a firm is downsizing, they may prefer to fire individuals with certain unobservable characteristics. Alternatively, this variable may also capture voluntary redundancies where the decision to take redundancy may be dependent on unobservable characteristics.

C.2 Compliers, Always-Takers and Never-Takers

Under the assumption of monotonicity or 'no defiers' there are three instrument-dependent subgroups capturing how individuals react to the instrument. Compliers are the subgroup who would be employed when not made redundant but unemployed when made redundant. Always-takers are the subgroup who will always be unemployed regardless of redundancy status. Never-takers are the subgroup who will never be unemployed regardless of redundancy status. I assume there are no defiers as unemployed individuals cannot be made redundant.

The local average treatment effect (LATE) gives the effect of treatment on the population of compliers, but is usually uninformative about always-takers and never-takers. This is because it cannot, by definition, capture information about how a change in employment would affect their fertility as their employment status will not change with redundancy.

C.3 Relevance

To demonstrate that relevance is satisfied I run a regression of my instruments on likelihood of unemployment. The results in Tables C.1 and C.2 indicate that the proxies for redundancy are strong predictors of unemployment for both men and women. Both instruments are strong, satisfying the rule of thumb test of an F-statistic greater than ten for both men and women (Stock and Yogo 2005). According to the estimations, both forms of job displacement increase likelihood of being unemployed at the time of the survey by about 80 to 90 percentage points. Since there are a large number of compliers, the estimate of the LATE may be a reasonable estimate of the ATE (Oreopoulos, 2006).

C.4 Results

I estimate the impact of unemployment on fertility using the two proxies for redundancy as instruments in Tables C.3 and C.4. These estimates are from a two stage least squares regression. The results of the estimation are similar to those under propensity matching, although less precisely estimated. I concentrate here on the models with fixed effects because time invariant individual factors are controlled for.

The impact of female unemployment is a decrease in likelihood of having a child by 3.6 percentage points using the industry decline instrument and 2.8 percentage points using the redundancy pay instrument. Although less precisely estimated, these estimates are similar in magnitude to the propensity matched estimate of 3.7 percentage points.

The impact of male unemployment is a decrease in likelihood of having a child by 1.1 percentage points using the industry decline instrument and an increase in likelihood of having a child by 0.8 percentage points using the redundancy pay instrument. These results are both statistically insignificant, similar to the propensity matched estimates which were also insignificant.

Although not perfect captures of involuntary redundancy, these proxies do provide supporting evidence of sex specific differences in the impacts of unemployment on fertility. Similar to the propensity matched estimates, female unemployment decreases likelihood of having a child while male unemployment does not have a significant impact.

Table C.1: Female First Stage Regression

	Dependent Variable: Unemployment					
	(1)	(2)	(3)	(4)	(5)	(6)
Job Displacement from a Declining Industry	0.868***	0.829***	0.784***			
	(0.0189)	(0.0202)	(0.0266)			
Job Displacement and Redundancy Pay Recipient				0.904***	0.888***	0.884***
				(0.0156)	(0.0181)	(0.0206)
Number of Observations	16994	16994	15816	16994	16994	15816
Controls	No	Yes	Yes	No	Yes	Yes
Individual Fixed Effects	No	No	Yes	No	No	Yes

Notes. This table reports the relationship between unemployment and the instrumental variables for women aged 15 to 45. The controls used in this model include age, personal characteristics, partner's characteristics and year fixed effects. Columns (1)-(3) estimate the relationship between unemployment and job displacement from a declining industry using an OLS estimation. Columns (4)-(6) estimate the relationship between unemployment and job displacement and redundancy pay using an OLS estimation. Standard errors are reported in parentheses and are clustered at the individual level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Male First Stage Regression

	Dependent Variable: Unemployment					
	(1)	(2)	(3)	(4)	(5)	(6)
Job Displacement from a Declining Industry	0.899***	0.877***	0.834***			
	(0.0119)	(0.0129)	(0.0175)			
Job Displacement and Redundancy Pay Recipient				0.914***	0.910***	0.902***
				(0.0108)	(0.0118)	(0.0143)
Number of Observations	19446	19446	18414	19446	19446	18414
Controls	No	Yes	Yes	No	Yes	Yes
Individual Fixed Effects	No	No	Yes	No	No	Yes

Notes. This table reports the relationship between unemployment and the instrumental variables for men aged 15 to 45. The controls used in this model include age, personal characteristics, partner's characteristics and year fixed effects. Columns (1)-(3) estimate the relationship between unemployment and job displacement from a declining industry using an OLS estimation. Columns (4)-(6) estimate the relationship between unemployment and job displacement and redundancy pay using an OLS estimation. Standard errors are reported in parentheses and are clustered at the individual level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Female LPM Second Stage Regression

	Naive			Industry Decline IV			Redundnacy Pay IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Unemployment	-0.0336***	-0.0312***	-0.0312**	-0.0344*	-0.0256	-0.0356	-0.0424**	-0.0398**	-0.0275
	(0.00862)	(0.00966)	(0.0138)	(0.0205)	(0.0206)	(0.0297)	(0.0189)	(0.0192)	(0.0266)
Number of Observations	10935	10935	10230	10935	10935	10230	10935	10935	10230
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes

Notes. This table reports the relationship between unemployment and propensity to have a child for women aged 15 to 45. The controls used in this model include age, personal characteristics, partner's characteristics and year fixed effects. Columns (1)-(3) estimate this relationship using a naive OLS regression. Columns (4)-(6) estimate this relationship using a 2SLS regression using job displacement from a declining industry as an instrument for unemployment. Columns (7)-(9) estimate this relationship using a 2SLS regression using job displacement and redundancy pay as an instrument for unemployment. Standard errors are reported in parentheses and are clustered at the individual level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Male LPM Second Stage Regression

	Naive			Job Displacement IV			Redundancy Pay IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Unemployment	0.00782	-0.00985	0.000403	-0.0194	-0.0195	-0.0190	0.0109	-0.00191	0.00766
	(0.0138)	(0.0123)	(0.0164)	(0.0245)	(0.0213)	(0.0277)	(0.0288)	(0.0243)	(0.0289)
Number of Observations	13568	13568	12908	13568	13568	12908	13568	13568	12908
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes

Notes. These tables reports the relationship between unemployment and propensity to have a child for men and men aged 15 to 45. The controls used in this model include age, personal characteristics, partner's characteristics and year fixed effects. Columns (1)-(3) estimate this relationship using a naive OLS regression. Columns (4)-(6) estimate this relationship using a 2SLS regression using job displacement from a declining industry as an instrument for unemployment. Columns (7)-(9) estimate this relationship using a 2SLS regression using job displacement and redundancy pay as an instrument for unemployment. Standard errors are reported in parentheses and are clustered at the individual level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C.5 Identification options for future research

To estimate the impact of unemployment on fertility in Australia, future researchers may want to consider using exogenous increases in Chinese exports following its introduction to the World Trade Organisation, similar to Autor, Dorn, and Hanson (2013). By calculating manufacturing exports by subdivision from China to a country similar to Australia, such as Canada, one could use this trade flow as an instrument for manufacturing employment in Australia. Alternatively, industry level employment shocks may be considered exogenous to individual decision-making but be used to predict individual unemployment. While I was unable to generate enough variation due to restrictions on geographic granularity in the general release of the HILDA dataset, by using the restricted HILDA dataset researchers can identify smaller geographical regions.

Another approach to estimating the impact of unemployment on fertility in Australia is to use large firm or plant closures that create a large shock to unemployment in a given area. For example, the shut downs in manufacturing plants in Geelong, Elizabeth and Altona following the cessation of car manufacturing in Australia could provide large exogenous shocks to instrument for unemployment. This analysis could be conducted at the aggregate level or linked with HILDA using the restricted dataset. However, this estimate should not be taken as the impact of unemployment on fertility Australia-wide as it is unlikely that this sample would be nationally representative.