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Family formation and demand for health insurance

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Abstract

We study how demand for health insurance responds to family formation using a unique panel of young Australian women. Our data allow us to simultaneously control for the influence of state dependence and unobserved heterogeneity as well as detailed information on children and child aspirations. We find evidence that women purchase insurance in preparation for pregnancy but then transition out of insurance once they have finished family building. Children have a large, negative impact on demand for insurance, although this effect is smaller for those on higher incomes. We also find that state dependence has a large impact on insurance demand. Our results are robust to a variety of alternative modelling strategies.

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1 Introduction

The literature on private health insurance (PHI) has focused on health risk as the driver of an individual's decision to purchase insurance conditional on socio-economic characteristics and the menu of available policies and services. Recently, attention has also been focused on preference heterogeneity, for example the degree of risk aversion, as an important aspect of this decision (Doiron et al., 2008; Fang et al., 2008; Buchmueller et al., 2013; Einav et al., 2013). In this paper, we focus on a different source of demand for health insurance namely the presence of young children and the desire for additional children. The younger women we study are healthier than the average consumer studied in previous papers and could generate quite different demand parameters. While we expect the desire for future children to have a positive effect on the demand for health insurance, once the children are present, there is both an increase in expected usage of health services and a negative income shock to the household. Which of these effects dominates in the purchase or retention of health insurance is one of the main questions addressed in this study.[1]

The influence of family formation on the demand for PHI is an important aspect of health insurance generally since most individuals will have children at some stage over their lifetime. Younger people in their family-formative years also make up a large proportion of potential insurance purchasers. Women aged 18-32 years, who are the primary age group in our study, represent around 19% of women with PHI in Australia.[2] Moreover, given empirical results on the large degree of persistence in this market, the decision by young families may greatly determine the demand by older households as well. In this paper, we use a longitudinal sample of young Australian women for the period 1996-2006. The dataset includes details on the age of children, childbirth, and aspirations for future children as well as other characteristics found to be important for the decision to insure.[3] The

[1]This is a substantially revised version of a paper presented at the 2008 Econometrics Society Australasian Meeting entitled "Family Formation and the Demand for Private Health Insurance".

[2]This figure was calculated using the 2011-12 National Health Survey.

[3]The research on which this paper is based was conducted as part of the Australian Longitudinal Study on Women's Health, the University of Newcastle and the University of Queensland. We are grateful to the

use of longitudinal data allows us to control for state dependence and individual specific heterogeneity. Few studies control for state dependence yet substantial inertia has been revealed in health insurance markets (e.g. Finn & Harmon, 2006; Bolhaar et al., 2012; Handel, 2013). Failure to control for this may result in biased coefficient estimates.

The treatment of the role of family formation in the PHI literature to date has taken the form of various controls for family composition. Kiil (2012) reviews the literature for countries with universal health care and finds mixed evidence for the impact of children on demand for PHI. A common control variable for PHI demand is an indicator for the presence of dependent children. Depending on the data and the model specification, within the Australian context studies find this variable to have no effect, (Hopkins & Kidd, 1996) significant positive (Srivastava & Zhao, 2008) or negative (Cheng & Vahid, 2011) effects on health insurance cover. Similarly controls for the number of children has yielded conflicting results (Doiron et al., 2008; Johar et al., 2011). The sensitivity of results is consistent with the hypotheses that children have complex and conflicting effects on the decision to purchase PHI. Barret and Conlon (2003) find that being married with children increases the probability of being insured, additional children reduce the probability of insurance and having a child under five increases the probability of insurance. This is indicative of a dynamic response to the presence and age of children.

A few papers have also added controls for child aspirations. Doiron and Kettlewell (2018) provide some evidence that the desire for children is likely to be important. Finally, this paper is an extension of work by Salale (2006), that uses a shorter time series from the same dataset as we do. Although some controls for family formation are included, Salale focuses on establishing the presence of state dependence and testing the correlates of PHI more generally. She finds that indicator variables for presence of children and wanting children (regardless of how many children the women already has) are statistically insignificant when the model estimated is dynamic.

Australian Government Department of Health for funding and to the women who provided the survey data.

Empirically, our study is also closely related to research for the Irish PHI system by Finn and Harmon (2006) and Bolhaar et al. (2012). The Australian and Irish PHI systems are similar on many dimensions, such as community rating, with similar rates of coverage (Kiil, 2012). In Finn and Harmon (2006), the objective is to determine how state dependence influences coefficient estimates for various personal household characteristics. Bolhaar et al. (2012) are interested in separating long run and short run selection effects. They find that once long run selection is accounted for (household fixed effects) short run changes in health states account for limited variation in insurance demand.

The Australian system offers several advantages to the economic modeller and in many ways permits a cleaner identification of demand parameters. PHI is not tied to employment and is generally driven by personal choice. The market is community rated so that insurers cannot refuse to sell insurance to any person and cannot price discriminate, regardless of prior or expected health service usage (limited exceptions are discussed in Section 2). At the end of our sample period (2006), not-for-profit insurers accounted for 84% of market share (Private Health Insurance Ombudsman, 2006). Price changes to all policies are subject to government approval. Together, these conditions mean that insurance choices are predominately the result of personal cost/benefit analysis. In addition, the supplementary nature of PHI, owing to the presence of universal health insurance through Medicare, means that the institutional settings for our study are broadly consistent with most other developed economies (Colombo & Tapay, 2004). Australian data have been used in several studies of PHI demand (Hopkins & Kidd, 1996; Barret & Conlon, 2003; Doiron et al., 2008; Buchmueller et al., 2013). By focusing on younger women, our study provides new evidence for an important group of the community that has not received much attention thus far.

Our main empirical model of insurance demand is a dynamic probit with a one period lag on insurance status. We use the Wooldridge (2005) conditional maximum likelihood approach to control for unobserved time invariant heterogeneity and the endogeneity of initial insurance status. A drawback of this approach is that we need to specify the distribution function for the unobserved fixed effects. As a sensitivity check, we also follow Bolhaar et al. (2012) and estimate linear dependent variable models that involve weaker distributional assumptions but do not account for the discrete nature of insurance cover. Additional sensitivity analysis is undertaken where we control for attrition bias using inverse probability weighting procedures (Wooldridge, 2002).

We find that family formation is an important factor in the demand for PHI among young women. In our main specification, we estimate that women who desire additional children are 2.6 percentage points (ppts) more likely to be insured (an increase of around 6% compared to the pooled sample mean). We find that overall the cost effect from the presence of children appears to dominate any risk effect, however responses are heterogeneous. Specifically, additional children reduce the probability of insurance cover by 5.4 ppts (13%). This effect is not present for those with higher incomes, which is consistent with the interpretation of children causing a substantial shift down in the budget constraint of the household. Women retain insurance in the first year after childbirth and some women appear to purchase insurance during this period, providing evidence of heterogeneity in response to actual children. However, after one year there is a strong negative relationship between the age of the youngest child and insurance, which suggests women transition out of insurance when they are not family building. Overall, our results support a pattern of insurance whereby women purchase in preparation of pregnancy and then leave insurance once they have finished family building.

We also estimate a large role for state dependence. Being insured in the previous period (three years prior) increases the probability of insurance by 25.4 ppts (62%) today. Ignoring state dependence does not significantly affect our estimates regarding family formation. However, we do find that while failing to control for time invariant unobserved heterogeneity does not qualitatively affect our results, it does lead us to overestimate the importance of the desire for additional children and underestimate the importance of child variables.

The paper is organised as follows. In Section 2 we provide background information on the

PHI market in Australia. In Section 3 we provide a theoretical framework for our empirical analysis. In Section 4 we discuss our data and variables for family formation. In Section 5 we present some descriptive evidence supporting the importance of desire for additional children, presence of children and age of youngest child on demand for PHI. In Section 6 we present our empirical models. Our main empirical results are presented in Section 7. Section 8 concludes.

2 Regulatory settings

All Australian residents can receive free hospital treatment in public hospitals through a system of universal health care (Medicare). Alternatively, uninsured patients can be treated in private hospitals at their own expense. Insured patients can use their cover for the cost of treatment in either a public or private hospital. PHI's main benefits are greater choice over physicians (public patients must take the first available doctor) and avoidance of long waiting times in the case of elective procedures. Additionally, some patients may prefer treatment in a private hospital because of greater privacy and comfort. Many people also purchase PHI that includes cover for out-of-hospital services that receive no or limited public support, such as dental, optical and allied health.[4]

PHI is not tied to employment in Australia, which is beneficial from a modelling perspective since accounting for selection into employment and employer-provided insurance is not needed. Insurers are not allowed to refuse to insure a person on the basis of past or expected medical usage or any other factors expected to influence utilisation. Waiting periods of up to one year are imposed for pre-existing conditions and, relevant to our study, obstetrics. This means that women who wish to be insured during their pregnancy must purchase insurance before they become pregnant.

Insurers cannot price discriminate with two exceptions. First, insurers are required to

[4] A small number of women in our sample (around 6% each wave) purchase ancillaries health insurance only. These women are treated as uninsured for the purposes of our study.

increase premiums by 2% for every year a person remains uninsured after her 31st birthday (Lifetime Health Cover (LHC) loading). This policy was introduced in 2000 and accompanied by an extensive advertising campaign. Second, premiums vary by state because insurers are allowed to vary prices in response to uneven state government insurance levies and policies that influence the cost of health care. Prices are reviewed once a year and increases are subject to government approval.

In 1996, PHI coverage was around 34% in Australia and on a downward trajectory.[5] In response to this, three policy initiatives were introduced in the late 1990s to encourage greater purchase of PHI. These policies included a tax penalty imposed on higher income earners who did not have complying PHI (the Medicare Levy Surcharge), a 30% rebate for the cost of insurance and LHC loading.[6] Following the introduction of policy incentives, participation in PHI increased markedly from a historical low of 30% to 46% by September 2000. Coverage then decreased slightly to 43.6% in December 2006 but has since increased to around 45%.

To conclude this section, we consider how to account for the policy incentives mentioned above in our specification of the demand for PHI. The rebate was not means tested and applied equally to everyone during our study period and therefore does not require modelling adjustment. Studies suggest that the LHC loading did have a significant effect on insurance participation in 2000 when it was introduced (Palangkaraya & Yong, 2005; Ellis & Savage, 2008). Our sample is generally too young for this policy to affect their incentives for insurance and only a subset of women reach the age of 30 during the analysis period. Nevertheless, we examined our coverage data for those women around the age of 31 and could see no clear discontinuity in the pattern of insurance at this age. Also, the inclusion of a year dummy will capture residual advertising effects. Controlling for the tax surcharge incentive would require more detailed income records than are available to us. We do not consider this as a

[5] This trend has been studied in Barret and Conlon (2003) Statistical trends in coverage and information on changes in the policy environment over time are available at https://www.apra.gov.au/publications.

[6] The impact of these reforms has been studied in Palangkaraya and Yong (2005) and Ellis and Savage (2008).

serious limitation since recent research indicates that the surcharge has not had a significant impact on the overall demand for insurance in Australia (Stavrunova & Yerokhin, 2014).

3 Theoretical framework

As mentioned earlier, the empirical literature to date has found mixed evidence for the role of children. In this study, we provide a more detailed and focused treatment of family formation and its effects on health insurance demand. We control more precisely for the age and number of children while also taking into account the desire for more children. Controlling for desired children is important if this variable influences insurance demand since failing to do so will result in biased estimates for the presence of actual children as these variables tend to be highly correlated.

We predict that family formation will influence demand for PHI through both adverse selection and budgetary effects. Under classic adverse selection, people with higher expected utilisation of the insured services will be more willing to purchase insurance. We view expected future pregnancy as a potential source of adverse selection to health insurers. In Australia almost all births occur in hospitals and the state of being pregnant itself may increase the probability of hospitalisation if complications occur. We therefore make the following hypothesis:

Hypothesis 1: Demand for insurance will be higher for women who desire more children.

The presence of actual children is likely to have more complicated effects. Children are generally a free addition to family PHI policies (although they can increase the price of insurance for single parents). However, even if children do not have a direct effect on the cost of insurance, the cost of childrearing is expected to shift the family's budget constraint down. If demand for insurance responds positively to income, as predicted theoretically for mixed public/private health care systems (Propper, 1999; Costa & García, 2003) and found empirically in numerous Australian studies (e.g. Hopkins & Kidd, 1996; Doiron et al., 2008;

Johar et al., 2011; Buchmueller et al., 2013; Doiron et al., 2014), this would generate a negative effect on insurance cover.

Countering this cost effect is a risk effect. Additional family members mean additional risk of a family member being hospitalised (this may be mitigated to some extent by the mother ceasing to be pregnant, thereby reducing one source of risk). The risk effect may be particularly high in the infants first year since children's health is most fragile during this period (in Australia, 84% of deaths for children under 5 occur in the first year (National Health Performance Agency, 2014)). The overall relationship between PHI and children will depend on the relative importance of the cost effect and the risk effect, which themselves are likely to depend on household income and the age of the child. We make the following predictions.

Hypothesis 2: Women will be more likely to be insured in the first year after childbirth.

Hypothesis 3: The probability of insurance cover will fall as the age of the youngest child rises.

Hypothesis 4: High income women will be less responsive to the negative income effect from the presence of children.

We empirically test each of these hypotheses, as well as estimate the effect of the total number of children and state dependence on health insurance demand.

4 Data

The data for this study are from the Australian Longitudinal Survey of Women's Health (ALSWH). The ALSWH began in 1996 with representative samples of Australian women comprising three cohorts aged 18-23 years, 45-50 years and 70-75 years. Participants were randomly selected from the national Medicare database. Since we are interested in family formation, our analysis sample is taken from the youngest cohort. Self-completion questionnaires are submitted approximately once every three years.[7]

There were 14247 respondents in wave 1. Attrition is non-trivial for the young cohort. This is mainly attributable to high levels of mobility, changes in surname, not having telephone listings and low voter registration for this cohort (Lee et al., 2005). For reasons discussed below, we use a balanced panel of respondents for waves 1–4 in this study (survey years 1996, 2000, 2003, 2006). In wave 4, there were 9145 respondents. After balancing our sample across the first four waves and eliminating respondents who did not provide information on PHI in all waves we are left with 6624 women in our analysis sample. (We discuss attrition further below.)

Table 1 shows the proportion of women with PHI across the waves and transitions into and out of insurance. Across our panel, the probability that a woman has insurance in any period conditional on having had insurance in the previous period is 0.81, indicating a significant degree of persistence in our raw data. For comparison, we also calculate this statistic using data from the 2004 and 2009 Household Income and Labour Dynamics in Australia Surveys (HILDA).[8] The corresponding figure is 0.92 for women (0.91 overall). Restricting attention to women aged 22-32, the HILDA figure is 0.80, almost identical to the figure for our sample and supporting the hypothesis of less persistence among younger groups.

Table 1 also shows that transition rates to and from insurance generally increase over time. The one exception is wave 2, where the rate of coverage drops slightly and there are a number of women who leave insurance. This may be partially driven by dependent students dropping from their parents policies when they finish studying or turn 25 (we include controls for student status in our models). It could also include some young women who are covered under their parent's policies because they are a 'dependent child' according to the insurance

[7]Women living in rural and remote areas were intentionally sampled at twice the rate of other women in order to capture the heterogeneity of health service for this group (Lee et al., 2005). We control for urbanisation in our empirical analysis.

[8]This is a large, nationally representative panel dataset that commenced in 2001.

policy. We conduct sensitivity tests by restricting our sample to the later waves where dependence is unlikely.

To further gauge the representativeness of our sample, we compare our rates of coverage to those found in the Australian National Health Survey (NHS).[9] We use the 2001 NHS to compare with our wave 2 (2000) sample (ages 22-27) because this is the first NHS that provides a continuous measure of age. In the NHS, the rate of coverage is 29%, which is similar to our sample (32%). The slightly higher coverage in our sample could reflect non-random attrition. Powers and Loxton (2010) find that those who stay in the sample differ from leavers (e.g. more educated, less money stress) but also that this does not have a meaningful impact on the correlations between general and mental health and a variety of socio-demographic characteristics. Sensitivity analysis is also conducted where we correct for selection into the analysis sample by reweighting the data.

One of our main variables of interest is child aspirations. We use the following question to construct a desired children variable: "*by age 35, would you like to have: no children, 1 child, 2 children or 3 or more children*". Starting in wave 3 participants were asked to record the dates of birth for each of their children and we use the dates from these responses along with survey return dates to reconstruct measures of actual children in the earlier waves. The need to create retrospective measures of children is the reason we use a balanced panel. The variable $D > A$ is an indicator for whether desired children by age 35 exceeds actual children today. We treat women who have 3 or more children as having completed their families.[10]

It is worth noting that our definition for child aspirations is not based on current intensity, but instead is related to longer term goals. If the preferences that women form in wave 2 (most aged 22-27) are stable, then all the variation in $D > A$ will come from women no longer desiring additional children once they reach their desired family size. Indeed, for the 33% of women whose preferences for additional children change over the sample period, 74%

[9]The NHS is a large representative survey of the Australian population conducted periodically by the Australian Bureau of Statistics.

[10]14.25% of women with children have 3 or more in our sample. The risk that some of these women actually desire more children would result in downwardly biased estimates for the effect of child aspirations.

of this variation comes from women no longer desiring more children (see Appendix Table A1). The remaining variation comes from women who previously did not desire additional children changing their preferences.

To measure the 'shifting' effect having a child has on the incentive to insure, we include a dummy for presence of any children. This variable is also interacted with an indicator for high income since we expect high income earners to be less affected by the negative income effect of children. To capture the 'intensity' effect of children we also include a continuous variable for the actual number of children. A key advantage of our dataset is that we can construct a measure of time since the last child was born (age of youngest child). Because of inertia and the fact that health risks are highest in the first year of life, we expect that women may be inclined to maintain insurance during this period. Consequently, we model the effect of time since birth using a dummy for less than one year and a continuous variable (measured in days) starting at value zero one year after birth. This modelling approach is supported by descriptive evidence presented in the next section.

Other variables that we use are typical of research on PHI in Australia. We control for age using a continuous measure to one decimal point. We control for standard demographic characteristics including work/study status, highest educational qualifications, country of birth and relationship status. State and Territory dummies are used to capture possible price and institutional differences. We also control for rurality and perceived access to hospital care as this should directly influence the value of PHI. Health may influence demand for PHI under classic adverse selection if unhealthier women are more likely to insure. Our main control for health is the SF-36 General Health Subscale score.[11] This is a continuous score ranging from 0-100 (for details see Ware et al., 2000). Other health and risk related controls include body mass index, risky alcohol intake and smoking.

Risk preferences have been found to predict insurance status in previous research and we

[11] We also estimated models using categories for self-assessed health and our results are not sensitive to this. We favoured the SF-36 measure as there was little variation in self-assessed health categories over time in this young sample.

include a time-constant control for whether the respondent ever used a prohibited drug other than marijuana measured at wave 4 to capture this. We are effectively assuming that future drug use can proxy for risk preferences today and that risk preferences are stable over our sample period of 10 years. We have somewhat restrictive information on income and so use a variety of variables to capture financial resources. These include a dummy equalling one if household average gross weekly income exceeds $1000 (high income), categorical dummies for money stress, the Index of Economic Resources (IER) score[12] for the area the respondent lives and a dummy for whether her household income is also her personal income. We also control for whether the respondent holds a government Health Care Card. While these cards are in no way substitute for PHI, they may affect demand for insurance by subsidising some ancillary expenses (e.g. dental) and at least add to our controls for financial resources since they are means tested. Finally, in all models we include a set of time dummies.[13]

Table 2 presents a list of the variables included in our empirical analysis along with definitions. In Table 3, we provide means for each of our variables across the 4 waves. In wave 2, 87% of women desire more children. Predictably, this rate decreases across waves. However, even in wave 4 (where most women are 28-33 years old) 67% of women still desire more children. The question on child aspirations was not asked after this wave and consequently our analysis sample comprises the first 4 waves only. By wave 4 almost half the women in our sample have at least one child. The proportion of women with children who have higher income increases from around 18% in wave 2 to almost 60% in wave 4. This is driven by two forces: women who have higher income delay starting a family longer and more women move to higher incomes over time. Between 15%–22% of women do not report their household income each wave and we use a variety of alternative measures to capture financial resources.

[12]The IER is a construct of the Australian Bureau of Statistics that uses information on income and wealth to rank areas. Higher scores indicate socio-economic advantage.

[13]To deal with nonresponse while maintaining a reasonable sample size, we retain those observations with missing information (other than for PHI) and use dummy variables as controls. Definitions for these variables are provided in Table 2.

5 Descriptive evidence

The following stylised evidence is presented to motivate the formal empirical analysis to follow. We first show that women who desire additional children consistently insure at higher rates than those who do not desire more children and this gap is similar for woman who do and do not already have children. Next, we show that while women maintain a relatively high rate of insurance in the year after the birth of their most recent child, there is a downward trend in coverage thereafter. This evidence is presented graphically.

In Figure 1, observations have been grouped into women who desire additional children and women who do not, and then further divided by whether the woman already has a child. The relationship between PHI and age is plotted for these four groups. Women who have children are always less likely to be insured than childless women, regardless of child aspirations. This gap is particularly noticeable for women aged 22–25 years, while for older women the impact of having a child is small. This may be due to a combination of self-selection (that women who have children at younger ages are inherently less likely to insure) or simply catch up. Secondly, particularly from age 25 (where you would expect child aspirations to become pressing for many women), women who desire more children consistently insure at higher rates than those who do not. This gap varies around 10–20 ppts but interestingly is of a similar magnitude whether or not the woman already has children. It is consistent with women retaining insurance after the first child is born if they desire additional children after this.

Next we consider the impact of time since most recent child. In Figure 2, women have been grouped based on months since their last child was born (i.e. age of youngest child). We focus on 0-60 months as there are generally less than 30 women in each month-group beyond this. Linear trend lines are included to simplify the interpretation. Two clear patterns emerge. First, in the first year after childbirth, insurance rates are fairly stable (they actually increase slightly). This may be due to inertia and/or the fact that children of this age are particularly vulnerable to hospitalisation. After this period, there is a clear negative trend in the probability of insurance. The linear trend lines for each duration period are of similar slope. The results are consistent with a pattern of women purchasing insurance to support family formation, but then transitioning out of insurance when this is complete. It is interesting that women only gradually leave insurance and this is possibly driven by inertia (delaying dropping cover even when it is optimal to do so).

In Figure 3, we ask what happens when we condition on the desire to have additional children. To keep sample sizes large, we focus on the 24 months since the last child was born. The result is consistent with our predictions about family formation and insurance. Women in both groups have similar insurance rates at the birth of the child. However, while the probability of insurance remains stable for those who desire additional children, it falls for those who have finished family building, particularly in the second year.

While these descriptive results are striking, they may be driven by omitted factors. In particular, the fact that our sample comprises only younger women means that those who we observe as having a long duration since childbirth are likely to have had children at a younger age relative to those who had children more recently and this may be related to insurance status. In the next section we present our empirical strategy for identifying the role of family formation conditional on observed and unobserved factors.

6 Model

In our main specification, we model the demand for insurance as a dynamic probit regression with a single lag for PHI.[14] Specifically, the demand for PHI can be written as:

$$PHI^*_{it} = X_{it}\beta + \rho PHI_{i,t-1} + \alpha_i + u_{it} \quad i = 1, \ldots, n \quad t = 2, 3, 4 \tag{1}$$

[14]The restriction to one lag is common in this literature and is compelling in this case since we have a small number of waves and the waves are 3 years apart.

$$PHI_{it} = \begin{cases} 1, & \text{if } PHI_{it}^* > 0 \\ 0, & \text{otherwise} \end{cases}$$

where PHI_{it}^* is the net benefit of PHI, X_{it} is a vector of exogenous variables including our markers for family formation (X_{it} does not include a constant term), α_i is an individual specific fixed effect and u_{it} is a normally distributed error term with variance normalised to unity.

While regression techniques for estimating dynamic models with panel data are relatively straightforward when the dependent variable is continuous, estimating non-linear models is more complicated. Standard methods for controlling for time invariant heterogeneity will generally result in biased and inconsistent estimates. Furthermore, when lagged dependent variables are included coefficients will be inconsistently estimated unless the initial insurance status is exogenous or the dynamic process is in long-term equilibrium with time-invariant distributional properties (Heckman, 1981).

Based on the work of Mundlak (1978) and Chamberlain (1984), we model α_i as a linear function of the exogenous covariates. Following Wooldridge (2005), we include the initial state as a conditioning variable to overcome the initial conditions problem while controlling for unobserved fixed effects. We specify α_i in the following way:

$$\alpha_i = \alpha_0 + \alpha_1 PHI_{i,1} + X_{i,2}\beta_0 + \bar{X}_{i,t>2}\beta_1 + \eta_i \tag{2}$$

$$\text{where } \eta_i | PHI_{i,1}, X_{i,2}, \bar{X}_{i,t>2} \sim N(0, \sigma_\alpha^2)$$

In this equation, $X_{i,2}$ is the vector of exogenous variables measured at first period values and $\bar{X}_{i,t>2}$ is the within means for periods $t > 2$. By substituting equation (2) into equation (1), this model can be estimated as a standard random effects probit. Average partial effects can be estimated in the regular way after multiplying coefficients by $(1 + \hat{\sigma}_\alpha^2)^{-1/2}$.

Correctly specifying equation (2) is important. Recent simulation studies by Rabe-Hesketh and Skrondal (2013) and Akay (2012) suggest that the alternative Heckman (1981) estimator[15] has lower bias in short panels when α_i is modelled as a linear function of the within-means of the exogenous variables. However, Rabe-Hesketh and Skrondal (2013) also show that when the first period is excluded from the within-means, or the exogenous variables measured at every period are included separately, there is no longer any advantage to the Heckman approach.[16] Given the significant computational advantage of the Wooldridge approach, this result provides a compelling case for its use.

We also follow Bolhaar et al. (2012) and estimate linear fixed effects models as a sensitivity check to our main approach. Standard linear fixed effects regression results in biased coefficient estimates when lagged dependent variables are present because deviations from the within-mean of the lagged dependent variable are necessarily correlated with deviations from the within-mean of the random error term. We address this dependence by using the Arellano and Bond (1991) GMM estimator. This approach involves taking first differences of all variables to eliminate individual fixed effects and using lagged values of the insurance status as instruments for the change in lagged insurance status to deal with the correlation with the error term.[17]

Finally, we note that in the environment under study, we do not consider the possibility of reverse causality to be a major threat to the validity of our approach. Specifically, the lack of private insurance is unlikely to affect family formation in an environment with universal public insurance.

[15] This approach would instead involve specifying a distribution for the initial insurance status and jointly estimating in each period the probability of observing that status and of having insurance.

[16] The intuition for this is that the exogenous variables measured closer to the initial period have more explanatory power and imposing a time-constant relationship between these variables and the unobserved effect may throw away valuable information. In developing our empirical results we also specified α_i as a function of the exogenous variables measured at every period. This resulted in coefficient estimates for our main variables that were very similar to those reported in the paper.

[17] e.g. if $t = 4$ then $\Delta PHI_{i,t-1} = PHI_{i,3} - PHI_{i,2}$ can be instrumented by $PHI_{i,2}$ and $PHI_{i,1}$.

6.1 Attrition

In this section, we describe sensitivity analysis to deal with potential non-random attrition. To address this concern, we use inverse probability weighting (IPW) as detailed in Wooldridge (2002).

We denote s_i as an indicator for whether a respondent who is present in the first wave ultimately becomes part of our analysis sample. We assume that, conditional on a set of observables in the first time period, $S_{i,1}$, the probability of participation in the sample is independent of other future observables such that

$$P(s_i = 1|X_{it}, PHI_{it}, PHI_{i,t-1}, PHI_{i,1}, S_{i,1}) = P(s_i = 1|S_{i,1}) \quad t = 2, 3, 4 \tag{3}$$

where the vector $S_{i,1}$ includes all variables measured in the initial period that explain selectivity into the analysis sample. This assumption effectively states that selection is only on observables. Importantly, $S_{i,1}$ can contain all variables in X as well as additional variables not used in the main equation.

IPW is implemented in two steps. First, a probit model is estimated for equation (3) using data from the first wave of the survey. Second, our data is weighted by the inverse predicted probability so that a greater weighting is placed on respondents with a higher probability of attrition. Wooldridge (2002) shows that IPW produces consistent, $\sqrt{N}$-asymptotically normal estimators in models where the likelihood can be written as a sum of contributions across all observations. This is not the case for the random effects probit model and so we use a pooled probit specification. A pooled probit regression without weighting is presented for comparison. One shortcoming of our IPW procedure is that some variables in X_{it} are not observed in wave 1 and therefore cannot be included in $S_{i,1}$ (see Table 3). We are however able to include additional wave 1 information that does not enter the main equation.[18]

[18] Additional variables used to create our probability weights are: an indicator for living at home; life satisfaction; a continuous measure for mental stress; variables created from the SF-36 survey questions including number of activities has limited ability to do, in past four weeks whether physical/mental health interfered with work, how much body pain was experienced, whether pain interfered with work, health

7 Results

Our main results for family formation and state dependence are summarised in Table 4. We focus our discussion on the results for the Wooldridge (2005) dynamic probit model and treat our other estimates as robustness checks.

7.1 Main findings

Overall, our results support the hypotheses regarding family formation posed in Section 3. Women who desire more children are more likely to be insured, the presence of children affects the incentive to insure and age of children is also important. Desire for more children increases the probability of insurance by 2.6 ppts (6% increase relative to pooled sample mean). This is noticeably smaller than the 10-20 ppts premium suggested by our descriptive analysis in Section 5, which highlights the importance of controlling for heterogeneity. There is mixed evidence for a 'shifting' effect for having any children. The coefficient for presence of children is negative but insignificant while the interaction term between high income and presence of children is positive and highly significant. This indicates heterogeneity in response to children – high income earners are less likely to respond negatively to the presence of children, consistent with our hypothesis in Section 3. The APE for presence of children, which takes into account the interaction term and measures the overall effect of presence of children on insurance, is close to zero. The APE for the interaction term, which measures the shift in probability of insurance conditional on being high income both before and after childbirth, is positive and larger in magnitude (2.6 ppts) although it is not precisely estimated.

Additional children have a negative and large effect on insurance demand. An additional child reduces the probability of insurance by 5.4 ppts (13%), which is more than twice the effect on the incentive to insure as desire for additional children. As expected, women do

perception relative to others and expected health; how well gets along with others; whether friends understand you; educational aspirations and whether wants children at some point. Further details are available from the authors.

not seem to drop their cover in the first year after childbirth and in fact are 3.8 ppts more likely to be insured during this period. This may reflect heterogeneous responses to children, specifically that for some women having a child incentivises them to insure. However, after the child turns 1 year, women gradually transition out of insurance. Between 1-2 years after the birth of the last child, the probability of insurance decreases by 1.7 ppts (4%). The complicated relationship between PHI demand and children can explain why previous studies using basic controls have delivered inconsistent results.

The data also support the presence of state dependence in health insurance. Being insured in the previous period increases the probability of insurance today by 25.4 ppts (62%). Below we discuss the magnitude of this effect and why it might be a conservative estimate. Note that the initial period status is also significant, supporting its inclusion.

Our results for other coefficient estimates are in Table 5. Only coefficients that are statistically significant are reported for brevity. For the Wooldridge dynamic probit model, variables that are fixed across time do not have a clear interpretation since it is not possible to separate their partial correlation with the unobserved time invariant heterogeneity from their impact on insurance status (the only time invariant variable that is statistically significant is Drug use). For many of our variables there is limited variation across time and unsurprisingly these variables are often imprecisely estimated in the models that control for time invariant heterogeneity.

Focusing on those results that are consistent across specifications, we find that age is positively correlated with insurance, women who are married or have better hospital access are more likely to have insurance and women who live in rural areas or have higher levels of money stress are less likely to have insurance. These results are as expected and generally consistent with previous Australian research on the general population. An interesting result is that in models that control for unobserved time invariant heterogeneity, education is negatively correlated with insurance. However, in numerous Australian studies using cross sectional data (e.g. Hopkins & Kidd, 1996; Doiron et al., 2008; Johar et al., 2011;

Buchmueller et al., 2013; Doiron et al., 2014; Doiron & Kettlewell, 2018), as well as the pooled probit specification, education is positively correlated with insurance, highlighting the importance of controlling for unobserved effects.

Health measured by self-completion questionnaire is statistically insignificant across all specifications. This is not surprising since our sample consists of young women who are generally in good health and are therefore likely to base their insurance decision on other factors. In previous Australian studies, self-assessed health is often positively correlated with insurance, which has been explained by its correlation with income, risk preferences and optimism about the future (Doiron et al., 2008; Johar & Savage, 2012). This relationship might not be identifiable amongst a younger population who have limited variation in health status. The negative coefficient for drug use is indicative of the importance of risk preferences, although this variable should be interpreted cautiously under the Wooldridge dynamic probit specification.

7.2 Sensitivity

We now turn to the results of alternative specifications. For family formation variables, the overall findings are robust to different specifications. When using pooled probit models, there is some sensitivity in terms of the magnitude of our estimates although the qualitative results remain true. For example, the APE for additional children is about half as large (2.3 ppts), the APE on age of youngest child is also smaller while the APE on desire for additional children is slightly larger. Correcting for attrition has almost no impact on the estimates quantitatively or qualitatively suggesting that selectivity is well accounted for with our set of controls.

In the last two columns of Table 4 we use linear regression methods that avoid strong distributional assumptions. The standard fixed effects model cannot consistently estimate the coefficient for lagged insurance and consequently this variable is omitted. The coefficient estimates are similar in magnitude to our main results and qualitatively consistent. This suggests that while controlling for unobserved time invariant heterogeneity is important for obtaining unbiased estimates for family formation, controlling for state dependence may be relatively unimportant.

Finally, in the last column we provide estimates for the Arellano-Bond fixed effects model. Because this model works on first differences, we lose the first wave of data and therefore have less variation in our family formation variables. Nevertheless, our main conclusions are robust. Desire for additional children is positive although no longer significant. Number of children and age of the youngest child remain negatively correlated and highly significant while the presence of children interacted with high income remains positive and significant.

The APE on lagged insurance in the Arellano-Bond specification is 0.228, which is close to the Wooldridge dynamic probit estimate. Under the pooled probit specification, this estimate is much higher (49.1 ppts) highlighting its sensitivity to controlling for unobserved time invariant heterogeneity. Our point estimate is similar to that obtained in Bolhaar et al. (2012) using Irish data (24 ppts). However, this similarity should be interpreted cautiously since our periods are every three years rather than annual and our sample is young women rather than the general population.

We were concerned that our estimate for state dependence might be downward biased by the fact that in wave 2, many women in our sample are likely to be covered under their parent's insurance policies as dependent children. This is supported by the fact that more transitions out of insurance occur between waves 2 and 3 than any other period. To assess the sensitivity of our results to this we re-estimated our models treating wave 2 as the initial period.[19] Our results for family formation are generally not sensitive to this. The coefficient for desire for additional children remains positive but statistically insignificant under the Wooldridge estimator. Under the pooled probit this estimate remains significant and under linear fixed effects it is significant at the 10% level. The coefficient on having had a child within the last year remains positive but only significant in the pooled probit specification.

[19]These estimates are reported in Appendix Table A2. Under the Wooldridge dynamic probit specification, controls for α_i are the vector of exogenous variables measured in waves 3 and 4 and PHI status in wave 2.

Results for other variables are of similar magnitude and significance to the main results. Importantly, the estimate for state dependence is much higher with the first wave omitted. For the Wooldridge dynamic probit, the APE for this variable is 0.38. Overall, while the wave 2 data does influence the magnitude of our estimate for state dependence, it does not significantly affect our findings regarding family formation. This supports our earlier assertion that ignoring state dependence only has a small impact on our main results.

A number of alternative hypotheses were tested on the interaction effects between the main variables. However, these terms were consistently found to be statistically insignificant and are not presented as part of our main results. We hypothesised that women may prefer the comfort of private care for the first born child but then switch to public care for additional children (an experience effect), in which case desire for additional children would only increase insurance demand for childless women. We tested this by interacting $D > A$ with presence of children and number of children and found no evidence to support an experience effect.[20] We also found that interactions between $D > A$ and age of youngest child were insignificant, although this may be due to a lack of richness in our data since most women are still family building in wave 4. Interaction terms between our high income indicator and number of children and age of youngest child were also insignificant.

8 Conclusion

In this paper we estimate the demand for private health insurance for young women in family building years. Other than the inclusion of controls for family composition, this important aspect of the demand for insurance has been ignored in previous work. We use Australian panel data that allow us to specify precise details on the age of children while simultaneously controlling for aspirations for additional children, state dependence and individual specific heterogeneity. Specifically, we consider the role of desire for additional children (i.e. expected

[20] We also tried re-specifying the number of children variable as an indicator for having more than one child with the same result.

future pregnancy), childbirth, age of the youngest child and total number of children.

We find evidence that family formation is important in informing the decision to purchase health insurance. Health insurance coverage for younger women is affected by both the desire for children, including additional children, and the presence of actual children. Women who desire more children are more likely to insure while women who have finished family building or experience a long gap between children gradually drop out of insurance. The presence of actual children reduces the incentive to insure although this is less pronounced for those on higher incomes. A second finding is that state dependence is important. In our preferred specifications for estimating state dependence, we find that being insured in the previous period (three years prior) increases the probability of being insured today by 25.4 ppts. Ignoring the first wave of our panel (which may be affected by transitions from parent's policies) results in even higher estimates of 38 ppts. Controlling for unobserved time invariant heterogeneity does impact the family formation estimates while controlling for state dependence is not important.

In addition to shedding new light on the insurance decisions of families, this research suggests interesting avenues for future research. For example, one path would be to analyse the impact of family formation on selection bias in health insurance markets. Recent work by Handel (2013) found that inertia in health insurance actually reduced the extent of adverse selection for a large US employer and resulted in positive welfare effects. While purchasing insurance for childbirth is an example of classic adverse selection, in combination with state dependence it may result in younger, lower risk individuals entering the insurance market.

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Tables and Figures

Table 1: PHI coverage and transitions in and out of coverage

	Wave 1	Wave 2	Wave 3	Wave 4
PHI	0.35	0.32	0.45	0.54
Joiners		676	1107	862
Leavers		888	244	250

Note: Sample size for each wave is 6624 women.

Table 2: Variable definitions

Variable	Definition
Family formation	
$D \geq A$	Desire more children than have currently
Has child	Has at least one child
Number child	Total number of children
Time child - 1yr	Had a child less than one year ago
Time child	Days since youngest child turned 1 year
Hinc*has child	High income and has child
$D \geq A$ miss	$D \geq A$ missing
Financial resources	
Hinc	Average gross household income > $1000 per week
Inc alone	Household income is also personal income
Inc miss	Income measure missing
M_stress extreme	Over last 12 months, extremely stressed about money
M_stress very	Over last 12 months, very stressed about money
M_stress mod	Over last 12 months, moderately stressed about money
M_stress some	Over last 12 months, somewhat stressed about money
M_stress none*	Over last 12 months, not stressed about money
M_stress miss	Money stress missing
IER	Index of Economic Resources score for area
IER miss	IER missing
Employment status	
Study	Student not in work
Work	Worker not in study
Work study	Works and studies
No work study*	Neither works nor studies
Work miss	Work/study status missing
Qualifications	
Tertiary	Highest qualification is degree or higher
Diploma	Highest qualification is diploma or certificate
Trade	Highest qualification is a trade or apprenticeship
Only school*	Highest qualification HSC, school certificate or none
Qual miss	Highest qualification missing
Relationship status	
Married	Married
Defacto	In defacto relationship
Other*	Single, divorced, widowed or separated
Rel miss	Relationship status missing
Health and risk	
SF36 general	SF36 general health score
Health miss	SF36 general health score missing
Smoke	Smokes daily

Smoke miss	Smoker status missing
Alc risk	Risky or high risk drinker according to NHMRC guidelines
Alc miss	Alcohol intake missing
BMI	Body mass index (height/weight^2)
BMI miss	BMI missing
Drug use	Ever used a prohibited drug other than marijuana (Wave 4)
Drug miss	Drug use missing
Region	
Urban*	Urban centre population $\geq$ 100000
Rural	Urban centre population between 10000-99999
Remote	Urban centre population $<$ 10000
Area miss	Remoteness classification missing
State	Full set of dummies for Australia's 8 states and territories
Access	
Access 1	Perceived hospital access is excellent or very good
Access 2	Perceived hospital access is good
Access 3*	Perceived hospital access is fair or poor
Access miss	Perceived hospital access is missing
Other	
Age	Age in years
Health card	Holds a government Health Care Card
Card miss	Health Care Card status missing
Aus	Country of birth is Australia
COB miss	Country of birth is missing

Note: * indicates a control group.

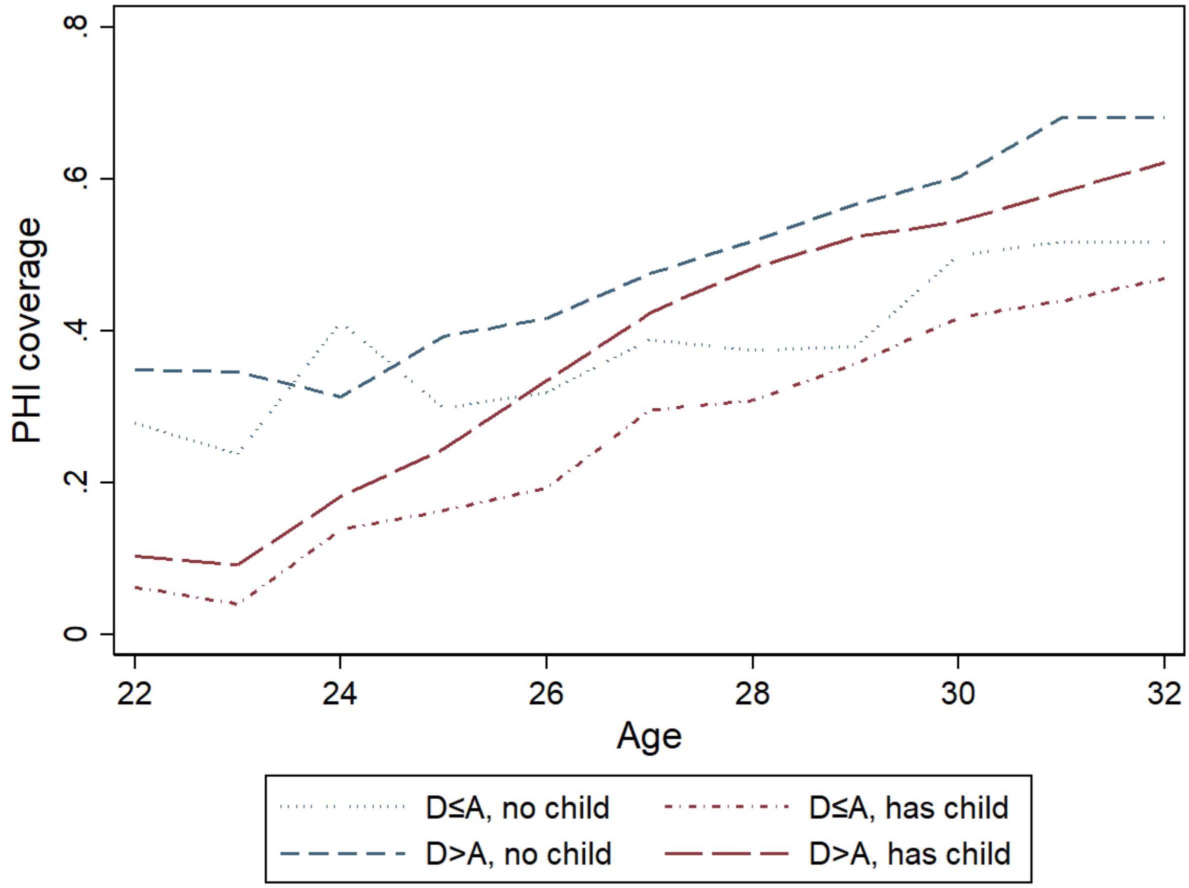
Table 3: Variable means by wave

Variable	Wave 1	Wave 2	Wave 3	Wave 4
Family formation				
$D \geq A$		0.87	0.79	0.67
Has child	0.06	0.17	0.31	0.49
Number child	0.08	0.25	0.51	0.90
Time child - 1yr	0.03	0.06	0.10	0.13
Time child	28.44	115.98	244.69	474.25
Hinc*has child		0.03	0.11	0.29
$D \geq A$ miss		0.01	0.01	0.02
Financial resources				
Hinc		0.39	0.48	0.58
Inc alone		0.05	0.06	0.08
Inc miss		0.22	0.19	0.15
M_stress extreme	0.03	0.08	0.08	0.08
M_stress very	0.13	0.15	0.14	0.13
M_stress mod	0.31	0.23	0.24	0.22
M_stress some	0.38	0.36	0.38	0.39
M_stress miss	<0.01	0.01	<0.01	<0.01
IER	1004.17	999.04	995.70	983.81
IER miss	<0.01	<0.01	<0.01	0.03
Employment status				
Study	0.34	0.04	0.04	0.03
Work	0.40	0.61	0.56	0.61
Work study	0.14	0.25	0.23	0.16
Work miss	0.02	<0.01	0.02	0.03
Qualifications				
Tertiary	0.14	0.42	0.46	0.48
Diploma	0.15	0.21	0.22	0.24
Trade	0.02	0.03	0.03	0.03
Qual miss	<0.01	0.03	0.02	<0.01
Relationship status				
Married	0.09	0.26	0.43	0.55
Defacto	0.12	0.21	0.20	0.18
Rel miss	<0.01	<0.01	<0.01	<0.01
Health and risk				
SF36 general	69.79	70.71	72.49	73.70
Health miss	<0.01	<0.01	<0.01	<0.01
Smoke	0.22	0.17	0.15	0.13
Smoke miss	<0.01	<0.01	<0.01	<0.01
Alc risk	0.05	0.03	0.03	0.03
Alc miss	0.01	<0.01	<0.01	<0.01
BMI	20.49	21.92	21.95	24.54

BMI miss	0.10	0.08	0.11	0.03
Drug use	0.26	0.26	0.26	0.26
Drug miss	0.01	0.01	0.01	0.01
Region				
Rural	0.41	0.42	0.38	0.36
Remote	0.04	0.04	0.04	0.04
Area miss	<0.01	<0.01	<0.01	0.01
Access				
Access 1		0.51	0.55	0.61
Access 2		0.29	0.28	0.24
Access miss		0.08	0.06	0.05
Other				
Age	20.83	24.62	27.59	30.62
Health card		0.19	0.15	0.14
Card miss		0.03	<0.01	<0.01
Aus	0.93	0.93	0.93	0.93
COB miss	<0.01	<0.01	<0.01	<0.01

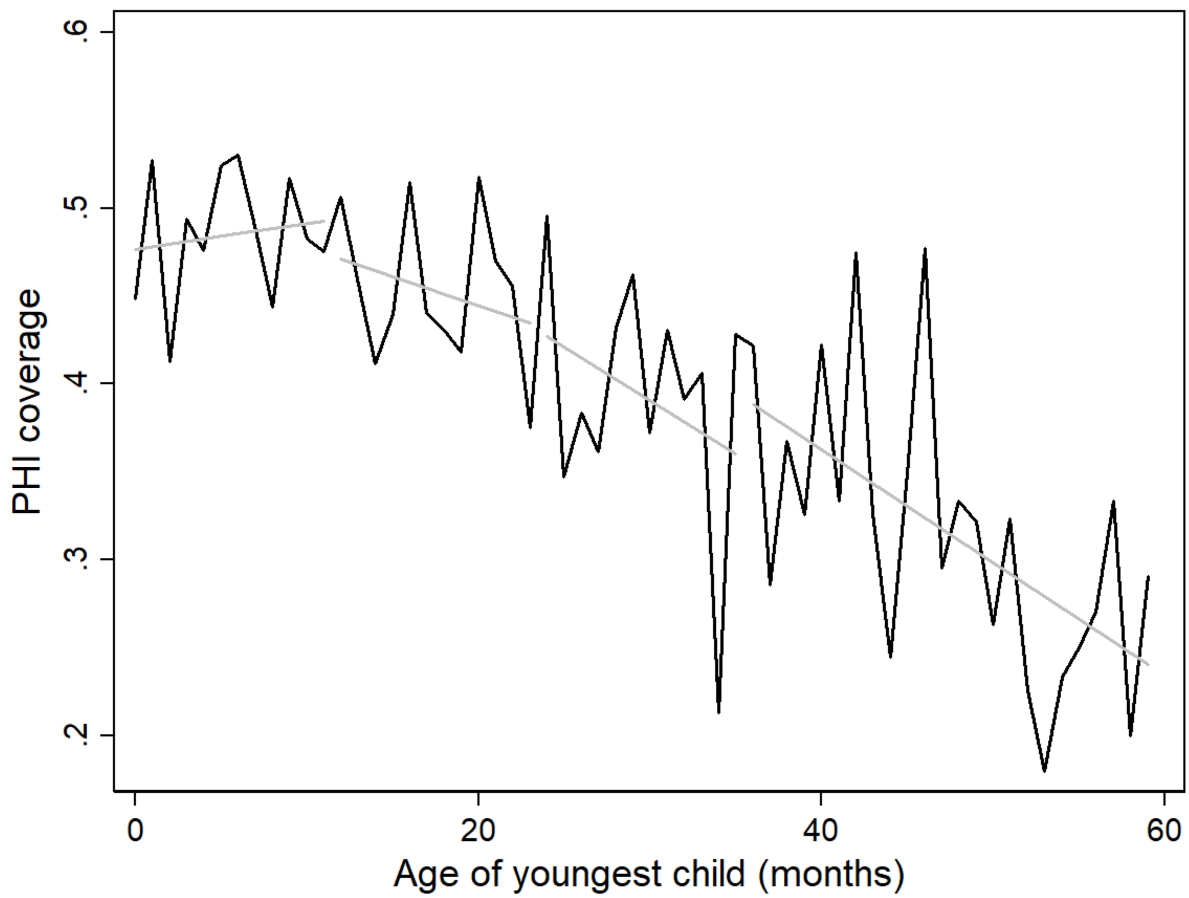
Note: Sample size for each wave is 6624 women.

Figure 1: PHI coverage by age, desired and actual children



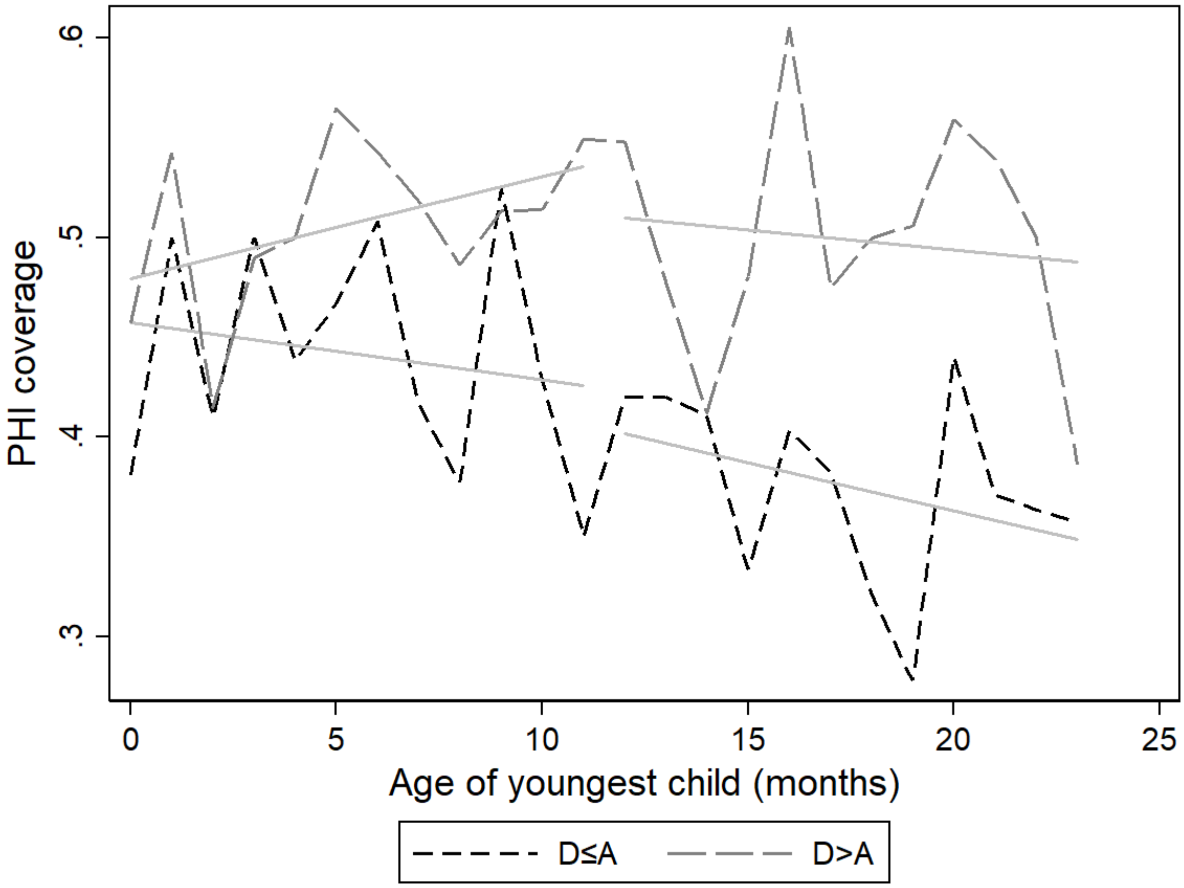
Note: Includes all respondents in wave 2-4 aged 22-32 years (N=19739). Age has been rounded down to the last birthday.

Figure 2: PHI coverage by age of youngest child



Note: Includes all respondents in wave 2-4 who do not have a youngest child 60 months or older (N=18965). Age of youngest child has been rounded down to nearest month.

Figure 3: PHI coverage by age of youngest child and desire for more children



Note: Includes all respondents in wave 2-4 who do not have a youngest child 24 months or older (N=16997). Age of youngest child has been rounded down to nearest month.

Table 4: Regression results: main variables

	Non-linear models						Linear models	
	Wooldridge dyn. prob.		Pooled prob.		IPW pooled prob.		Fixed Effects	Arellano-Bond
Variable	Coeff.	APE	Coeff.	APE	Coeff.	APE	Coeff.	Coeff.
D≥A	0.126**	0.026**	0.127***	0.031***	0.127***	0.031***	0.023**	0.013
	(0.057)	(0.012)	(0.033)	(0.008)	(0.034)	(0.008)	(0.010)	(0.010)
Has child[a]	−0.074	0.006	−0.174**	−0.023	−0.176**	−0.023	0.017	−0.003
	(0.102)	(0.020)	(0.071)	(0.016)	(0.074)	(0.017)	(0.017)	(0.018)
No. children	−0.267***	−0.054***	−0.095***	−0.023***	−0.103***	−0.025***	−0.053***	−0.073***
	(0.052)	(0.011)	(0.028)	(0.007)	(0.029)	(0.007)	(0.009)	(0.010)
Youngest <1yr[b]	0.187**	0.038**	0.165***	0.041***	0.157***	0.038***	0.012	0.020
	(0.075)	(0.017)	(0.053)	(0.013)	(0.055)	(0.014)	(0.012)	(0.013)
Age youngest	−0.023***	−0.046***	−0.117***	−0.029***	−0.118***	−0.029***	−0.058***	−0.048***
	(0.006)	(0.013)	(0.030)	(0.007)	(0.031)	(0.007)	(0.008)	(0.009)
Hinc*has child[c]	0.198***	0.026	0.155***	−0.005	0.155***	−0.005	0.063***	0.042***
	(0.075)	(0.022)	(0.050)	(0.018)	(0.051)	(0.018)	(0.014)	(0.015)
$PHI_{i,t-1}$	1.080***	0.254***	1.543***	0.491***	1.561***	0.496***		0.228***
	(0.048)	(0.013)	(0.028)	(0.009)	(0.029)	(0.009)		(0.017)
PHI_0	0.714***	0.159***	0.156***	0.040***	0.158***	0.040***		
	(0.063)	(0.009)	(0.029)	(0.007)	(0.030)	(0.007)		
N	19872		19872		19872		19872	13248

Note: Average partial effects (APEs) are the shift in predicted probabilities averaged across the sample when changing status from 0 to 1 in the case of discrete variables, and the average of the vector of marginal effects for the sample in the case of continuous variables. Standard errors in parenthesis. For coefficients, asymptotic standard errors are reported, clustered across individuals. Standard errors for APEs are calculated using non-parametric bootstrap with 200 replications for the pooled probit specifications and 100 replications for the Wooldridge dynamic probit. *, ** and *** is significance at the 10%, 5% and 1% level respectively.

[a] In the non-linear models, the APE takes into account the interaction between Has child and Hinc and therefore reflects the overall effect of presence of children.

[b] Row values have been multiplied by 1000.

[c] In the non-linear models, the APE is measuring the shift in predicted probability from having a child conditional on being rich both before and after having the child.

Table 5: Coefficient estimates: controls

Variable	Wooldridge	Pooled Probit	Fixed-effects	Arellano-Bond
Financial resources				
Hinc	0.124***	0.257***	−0.003	0.001
Inc alone	−0.045	0.145***	−0.023*	−0.028*
M_stress extreme	−0.240***	−0.259***	−0.037**	−0.049***
M_stress very	−0.162**	−0.197***	−0.032***	−0.026*
M_stress mod	−0.090	−0.125***	−0.023**	−0.014
M_stress some	−0.023	−0.090***	−0.007	−0.003
IER	0.000	0.001***	0.000	0.000
Employment status				
Work	0.011	0.082**	−0.001	0.001
Work study	0.085	0.133***	0.010	0.018
Qualifications				
Tertiary	−0.329***	0.088***	−0.064***	−0.062***
Diploma	−0.129*	−0.021	−0.032**	−0.032**
Relationship status				
Married	0.369***	0.349***	0.076***	0.088***
Health and risk				
Smokes	0.028	−0.170***	−0.004	0.005
BMI	−0.005	−0.006***	−0.001	0.000
Drug use	−0.206***	−0.157***		
Region				
Rural	−0.285***	−0.229***	−0.049***	−0.059***
Access				
Access 1	0.370***	0.356***	0.068***	0.073***
Access 2	0.164***	0.136***	0.027**	0.027**
Other				
Age	0.129*	0.079***	0.014	0.033**
Health card	0.118***	−0.094***	0.027***	0.028**
Year 2000	−0.345	−0.151***	−0.160**	−0.038
Year 2003	0.014	0.136***	−0.066	0.012
N	19872	19872	19872	13248

Note: Only variables that are statistically significant in at least one regression are shown (state and territory and controls for missing values exclusive). Statistical significance for coefficient estimates is based on asymptotic standard errors. *, ** and *** is significance at the 10%, 5% and 1% level respectively.

Appendix

Table A1: Transitions in desire for additional children ($1 = D > A$)

Group	Wave 2	Wave 3	Wave 4	Proportion (%)
1	1	1	1	59.59
2	1	1	0	15.41
3	1	0	1	2.91
4	1	0	0	8.97
5	0	0	0	7.40
6	0	1	1	2.68
7	0	0	1	1.39
8	0	1	0	1.48

Note: Sample size for each wave is 6624 women.

Table A2: Regression results no first wave: main variables

	Non-linear models						Linear models	
	Wooldridge dyn. prob.[a]		Pooled prob.		IPW pooled prob.		Fixed Effects	Arellano-Bond
Variable	Coeff.	APE	Coeff.	APE	Coeff.	APE	Coeff.	Coeff.
D≥A	0.094	0.019	0.162***	0.036***	0.152***	0.035***	0.020*	0.013
	(0.078)	(0.014)	(0.039)	(0.009)	(0.040)	(0.009)	(0.012)	(0.010)
Has child[b]	−0.124	0.008	−0.237***	−0.041**	−0.210**	−0.036**	0.013	−0.003
	(0.139)	(0.023)	(0.085)	(0.017)	(0.089)	(0.018)	(0.021)	(0.018)
No. children	−0.447***	−0.088***	−0.071**	−0.016**	−0.086***	−0.019**	−0.075***	−0.073***
	(0.081)	(0.016)	(0.031)	(0.007)	(0.033)	(0.007)	(0.012)	(0.010)
Youngest <1yr[c]	0.144	0.029	0.212***	0.048***	0.203***	0.047***	0.011	0.020
	(0.094)	(0.018)	(0.061)	(0.014)	(0.063)	(0.014)	(0.013)	(0.013)
Age youngest	−0.228***	−0.045***	−0.079**	−0.018**	−0.087***	−0.020***	−0.056***	−0.048***
	(0.085)	(0.015)	(0.032)	(0.007)	(0.033)	(0.007)	(0.011)	(0.009)
Hinc*has child[d]	0.303***	0.035	0.080	−0.035*	0.082	−0.029	0.050***	0.042***
	(0.110)	(0.022)	(0.062)	(0.019)	(0.063)	(0.020)	(0.018)	(0.015)
$PHI_{i,t-1}$	1.500***	0.380***	1.790***	0.544***	1.804***	0.545***		0.228***
	(0.092)	(0.017)	(0.033)	(0.009)	(0.034)	(0.009)		(0.017)
PHI_0	0.704***	0.159***	0.361***	0.087***	0.362***	0.086***		
	(0.156)	(0.029)	(0.049)	(0.008)	(0.033)	(0.008)		
N	13248		13248		13248		13248	13248

Note: Average partial effects (APEs) are the shift in predicted probabilities averaged across the sample when changing status from 0 to 1 in the case of discrete variables, and the average of the vector of marginal effects for the sample in the case of continuous variables. Standard errors in parenthesis. For coefficients, asymptotic standard errors are reported, clustered across individuals. Standard errors for APEs are calculated using non-parametric bootstrap with 200 replications for the pooled probit specifications and 100 replications for the Wooldridge dynamic probit. *, ** and *** is significance at the 10%, 5% and 1% level respectively.

[a] Due to convergence issues, some variables with frequencies less than 100 observations were omitted from the estimation. These were indicators for missing region, marital status, smoking status, alcohol use, health card, country of birth, money stress and SF36 health score. For the health score missing observations were given the sample average and for all other variables were allocated to the reference group.

[b] In the non-linear models, the APE takes into account the interaction between Has child and Hinc and therefore reflects the overall effect of presence of children.

[c] Row values have been multiplied by 1000.

[d] In the non-linear models, the APE is measuring the shift in predicted probability from having a child conditional on being rich both before and after having the child.