Does Maternity Leave Effect Child Health? Evidence from Parental Leave in Australia Survey

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Abstract

One of the arguments that is advanced in support of paid maternity leave (PML) policies is that the mother's time away from work, around childbirth, is expected to improve maternal health and child health and development. However evidence on these links is scarce and, until recently, little was known about the link, if any, between child health and maternity leave. Moreover, the limited literature that does exist tends to use aggregate data (i.e., an "ecological design") to test the hypotheses that maternity leave affects maternal and child health. Evidence from micro-level data is rare because of the unavailability of such data on household level. We employ such data from the Parental Leave in Australia Survey (PLAS), which is a nested survey of the Longitudinal Study of Australian Children (LSAC), to examine the impacts of maternity leave on child health. Using the PLAS and the first two waves of the LSAC we find that maternity leave, as measured by the duration of paid maternity leave (PML) and other forms of leave around childbirth have strong and statistically significant effects on: child health, the decision to breastfeed, the duration of breastfeeding, and the probability that child immunisations are up-to-date. Our results show that mothers who take maternity leave are more likely to breastfeed their children and also that longer-term maternity leave is associated with an increase in the duration of breastfeeding. Our results also confirm that both mothers' PML and fathers' paid paternity leave (PPL) have statistically significant and positive effects on general health status of children. We also find that, in most specifications, the effects of PML are significant if the duration of leave is at least 6 weeks. PML is also significantly associated with a lower probability of some childhood chronic conditions such as asthma and bronchiolitis, but the effects of PPL on these conditions is ambiguous.

Keywords: PLAS, Child Health, Parental Leave, Australia
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1 Introduction

One of the arguments that drives maternity leave policies is that the mother's time away from work, around childbirth, is expected to improve maternal health and child health and development. However the evidence of such links is scarce; and until recently, little was known about the association, if any, between child health and maternity leave. Moreover, the limited literature that does exist tends to use aggregate data (Winegarden and Bracy, 1995; Ruhm, 2000; Tanaka, 2005) to test the hypotheses that maternity leave affects mother and child health. Furthermore, relatively little is known about how paid and unpaid maternity leave affect the time and non-time health inputs that parents provide to children. See Smith (2009) for a recent overview. Evidence from micro-level data is rare, mostly because such data are usually not available at the household level. This study examines the relationship between paid maternity leave (PML) and child health using the Parental Leave in Australia Survey (PLAS). The PLAS is a between-wave survey that was conducted in conjunction with the Longitudinal Study of Australia Children (LSAC). The PLAS contains detailed, unit record data on a range of variables of interest. We use the PLAS to make two contributions to the literature: first, we study the role of paternal leave as well as maternal leave and second, we test for longer-term effects of parental leave on child health. Our results reveal that PML is strongly associated with better child health and with an increase in the duration of breastfeeding. Interestingly, the duration of paid paternity leave (PPL) of fathers also is associated better child health. The results also show that mothers who have taken paid maternity leave are more likely to have kept the immunization of their children up-to-date. Finally, PML is also associated with statistically significant reductions in the probability of a child having some chronic conditions such as asthma and bronchiolitis.

2 Literature review

2.1 Maternity Leave and Child Health

The relationship between parental leave and child health outcomes has been analysed mainly using aggregate data. In a pioneering study of this issue, Winegarden and Bracy (1995), used data from 17 OECD countries in four periods – 1959, 1969, 1979 and 1989 – and found that parental leave contributed to lowering the infant mortality rate. The marginal effects from their estimates suggest that an additional week of paid maternity leave was associated with a reduction in infant mortality of approximately 0.5 deaths per 1000 live births. Ruhm (2000) examined the data of 16 OECD countries in the 1969-1994 periods and produced similar findings. Ruhm (2000) found that longer maternity leave leads to lower infant mortality rate (e.g., 10 weeks increase in PML would lead to 1-2 per cent reduction of infant mortality rate). However, Ruhm's (2000) study did not include two important OECD countries: the United States and

Japan. Ruhm (2000) also did not examine the effect of types of maternity leave other than paid/job-protected maternity leave. Tanaka (2005) extended the work of Ruhm (2000) to include the USA and Japan and updated the dataset from 1994 to 2000. The author also examined health outcomes other than mortality rates and controlled for other social policies that were in effect and might also affect child health. Her results also revealed that longer paid maternity leave was associated with lowered infant mortality rates. However, there were no significant effects of other leave (i.e., unpaid leave and other leave that was not job-protected) on infant mortality. In addition, paid maternity leave was associated with a statistically significantly lower probability of having a low birthweight child, but did not affect the probability of immunization against measles and DTP.

Although most of the early studies of maternity leave and child health have used aggregate data, there have been several studies since 2000 that have used microdata.Most of these studies have used data from the National Longitudinal Survey of the Young (NLSY), which has been conducted as a nation-wide longitudinal study in the United States since 1979. For example, Han et al. (2001), Waldfogel et al. (2002), Brooks-Gunn et al. (2002) and Ruhm (2004) used NLSY data to show that maternal employment in the first year of life is associated with adverse effects on child cognitive outcomes. These studies did not, however, address the question of what the critical time-frame is for young children wihtin that first year of life.

To answer that question, Berger et al. (2005) focused on analysing the effects of mothers who return to work within 12 weeks of giving birth. using OLS and propensity matching score approaches, and found a significant effects on child-caring activities such as breastfeeding and immunization. They argued that children whose mothers return to work early are less likely to have regular health check-ups and are also less likely to be breastfed. Gregg et al. (2005) also investigated the issue of early maternal employment and child outcomes in the UK and came to similar conclusions: a return to full-time employment within 18 months after giving birth resulted in poorer cognitive outcomes for children.

The long-term effect of maternity leave on child health is also an issue that has received little attention in previous studies. An exception is the work of-Baker and Milligan (2008). These authors examined the effects of parental leave reforms in Canada on the decision to breastfeed and on the health of the mother and child. For children 7-12 months of age, their results confirmed that the extension of parental leave increased the duration of breastfeeding. They did not, however, find any significant impact of this increased duration on on health *per se.* The authors did find that extended maternity leave created beneficial effects on the incidence of asthma, allergies and chronic conditions but these effects did not persist in older ages.

2.2 Maternity leave in Australia

Australia is one of the last countries in the OECD to introduce universal paid parental leave, but this is to change on 1 December 2010 with the introduction of the Paid Parental Leave Scheme. Since the 1970s employees in the public sector in Australia have been entitled to paid maternity leave. For private sector employees unpaid parental leave has, since 1979, been an entitlement for permanent employees with at least 12 months of continuous employment before the birth of the child(Whitehouse et al., 2005). Access to paid maternity leave in the private sector is less common, and depends upon the worker's sector of employment, and employment status (full-time, part-time and casual) . As a result, about 60 per cent of women who work in Australia do not have access to paid maternity leave (Baird, 2004).

Apart from the historical lack of a universal paid maternity leave provision, Australia also suffers from a shortage information on the prevalence of maternity leave. For example, a report by the Human Rights and Equal Opportunity Commission (HREOC) in 2002 revealed that Australia lacks of information on such basic issues such as the proportion of employees that is eligible for maternity leave, the number of women who take paid and unpaid maternity leave and the return-to-work activities of women, following childbirth. According to Whitehouse et al. (2007), the main source of information about maternity leave in Australia to date has been state-level surveys on caring and responsibilities that have been undertaken by the Australian Bureau of Statistics. with the exception of a survey conducted by the Australian Institute of Family Studies in 1986 (Glezer, 1988).

The Parental Leave in Australia Survey (PLAS) is an attempt to fill the data gap on such issues . In addition, the PLAS collected data on parental leave by fathers. Paternal leave and its effects have not been investigated by previous studies (Gregg and Waldfogel, 2005). The preliminary findings by Whitehouse *et al.* (2006; 2007) reveal that 34 per cent of employed mothers and 20 per cent of employed fathers took paid leave prior to the birth of their child. However, the most important form of leave for mothers is unpaid maternity leave (53 per cent) whilst for fathers it was paid holiday leave (46 per cent). The most common duration of maternity leave was 6 weeks and 52 weeks for paid and unpaid maternity leave, respectively (Whitehouse et al., 2008). It is not surprising, therefore, that 46 per cent of mothers who worked for an employer in the past 12 months prior to birth state that they would like to take more leave and would do so if they had more paid leave. Interestingly, Whitehouse et al. (2008) found that, compared to those take leave of 40 to 52 weeks, people who take 53 weeks of leave or more would be less satisfied if they take further leave (although this result was not statistically significant). Another salient point from the study by Whitehouse et al. (2008) is that they excluded individuals who were not eligible for maternity leave (e.g., those who did not have 12 months of continuous employment prior birth or self-employed) from consideration. Thus, their study included only 1223 observations out of 3573 households that participated in the PLAS. This modelling approach was appropriate for their study, which was concerned with the satisfaction of mothers for whom paid maternity leave was available. It would not, however, be an appropriate sample restriction for the purposes of this paper..

Another study that has used the PLAS examined the determinants of returns to work by mothers Baxter (2008). A major difference of this study, compared to Whitehouse et al. (2008) was its focus on the use of leave rather than the entitlement to leave.[1] The author of this study showed that most mothers returned to work when their child was 12 months old, and this is likely to be associated with the 12 months of unpaid ("job-protected") leave available for those who were permanently employed before childbirth. Pre-birth employment type was also an important determinant of the decision to return to work. Baxter (2008) found that, at 18 months, those who were most likely to return to work were self-employed (84 per cent), permanent employees (76 per cent), contract employees (64 per cent) and casual employees (58 per cent). However, at earlier time points (e.g., nine and 12 months), there were little differences in the likelihood of return to work by employment type prior to childbirth.

In summary, parental leave and child health have not been investigated extensively in the literature. In addition, most previous studies use aggregate data due to the scarcity of appropriate unit record data. The PLAS represents the most comprehensive unit record dataset available in Australia that is amenable to work of this kind. Few previous studies have examined the effects of paternity leave, or the longer-term effects of leave (Gregg and Waldfogel, 2005). These two main contributions of this paper are to shed light on these issues. In addition, it produces new empirical results based on the PLAS on the relationship between paid maternity leave, breastfeeding, and child health..

3 Methodology

3.1 Analytical framework

The relationship between child health and parental leave can be represented in an extended Grossman (1972) model of the kind used by Ruhm (2000) and others (e.g., Jacobson, 2000), in which parents maximise their utility , which is described by a function $U(H, X)$, where H is child health, and X is other consumption. The parents of the household face a time constraint of the form $T = R + L + V$ where R, L and V are time for work, leave and produce non-market outputs; and a budget constraint $Y = P_m M + P_x X = wR + sL + N$, where M is the medical care; P_m and P_x are prices of M and X; w and s are wage rate and parental leave payment; and N is non-earned income. The health of the child is produced by the production function $H(B, M, L + V, \varepsilon)$ where B is the baseline health level and ε is a stochastic error. According to this formulation, duration of leave affect the amount of time available to care for children, which in turn affects the production of child health.

More generally, the health production model is based on the Grossman (1972) model in which individuals are born with a stock of health that depreciates over time and where the net depreciation depends on gross depreciation less the health product of gross investment. The baseline health stock of chil-

[1] The statistical methods also accounted for the influence of the clustered sampling approach that was undertaken for the PLAS.

dren is affected by factors such as biological inheritence and health investments during pregnancy, including medical and other (e.g., dietary) inputs. Postnatal health inputs, including market and non-market inputs may be affected by PML, but its effects may also be ambiguous. Paid aternity leave may affect child health by increasing the parental time available to care for young children *ceteris paribus*. For example, paid parental leave may reduce the (time and other) costs of breastfeeding, which may in turn can lead to better infant (and perhaps child and adult) health. Paid maternity leave allows parents to spend more time taking care of their infants, which may lead to better bonds between children and parents. However, the influence of paid parental leave of child health is theoretically ambiguous. Ruhm (2000) suggested that paid maternity leave (PML) may also induce women to work early in their pregnancy in order to qualify for the paid leave, which may reduce the time for early pregnancy care. Furthermore, it has been argued that Lifestyle factors such as the consumption of alcohol and cigarettes also may affect neonatal health including the probability of a premature birth, neonatal mortality and of low birthweight (Butler et al., 1972).

3.2 Econometric models

The general equation for estimating the relationship between parental leave and child health is presented as:

$$H_i = \beta_0 + \beta_1 X_i + \beta_2 L_i + \varepsilon_i$$

where H_i is a measure of child health and other health outcome of interest (e.g., breastfeeding, immunization, chronic diseases, and child development indices), X_i is a set of household and child characteristics, L_i is a measure of maternity leave of mothers and/or parental leave of fathers and their interaction, and ε_i is the random error assumed to have identical and independent distribution. For both paid and unpaid forms of maternity leave and parental leave, we use two measures: a continuous count of days of leave and a binary indicator equal to one if any leave was taken, and zero otherwise. For paid maternity leave, we also use binary measures for leave of up to six weeks, and three binary variables for leave of longer duration. The break point of six weeks of PML was selected on the basis that it is taken most frequently by mothers who responded to the PLAS (Whitehouse et al., 2008).

For categorical measures of health outcomes (e.g., parental-reported child health, breastfeeding durations) ordered probit regressions are applied whilst probit regressions are used for binary measures of health outcomes (e.g., poor health , and the presence of asthma and bronchiolitis). For outcomes that use child development indices outcomes, we employ tobit regressions that are left-censored at zero.

Breastfeeding has been used fairly frequently in previous studies as an indicator of child health outcomes. However, we argue that breastfeeding is an input to, not an output of, the child health production function. . Thus, the effects of parental leave on child health can be measured via its intermediate effects on breastfeeding: both the decision to/not to breastfeed, and breastfeeding duration. The estimation of parental leave effect on breastfeeding is therefore examined using the following system of equations:

$$H_i = \beta_0 + \beta_1 X_i + \beta_2 L_i + \beta_3 BF_i + \varepsilon_i$$
$$BF_i = \gamma_0 + \gamma_1 X_i + \gamma_2 L_i + \epsilon_i$$

where BF_i is breastfeeding, expressed as a binary variable (1=breastfed, 0=otherwise); a series of binary variables (0=no breastfeeding, breastfeeding up to 18 months, breastfeeding for more than 18 months); and continuous (number of months the child is breastfed) formats. In this study we estimate the above system of equations using the conditional recursive mixed process estimator approach proposed by Roodman (2007; 2009). This approach fits seemingly unrelated regressions for a large family of multi-equation system in which dependent variable may have different formats (e.g., binary, categorical, and continuous).

4 Data

4.1 Data sources

This study utilises the data from the Parental Leave Australia Survey (PLAS), which was conducted in 2005, nested within the between-wave mail-out survey that occurred between the first two waves of the nationally-representative Longitudinal Study of Australian Children (LSAC) (Australian Institute of Family Studies, 2007). The data were collected using a two-stage clustered sampling design, where postcodes were used as the primary sampling unit (PSU). To ensure proportional geographic representation, postcodes were selected as a stratified sample by state of residence, and urban and rural geographical status. The PLAS targeted the infant cohort of the LSAC, which included some 5000 children born between March 2003 and February 2004. The sampling frame of the LSAC was constructed using Medicare Australia database, which essentially included all children of the sampling age (i.e. 0-12 months for the infant cohort) in Australia. The recruitment process resulted in a response rate of 64 per cent, with a sample of 5107 infants included in Wave 1 of the LSAC (Soloff et al., 2005). From this frame, the PLAS sent 5061 questionnaires and received 3573 responses, which constitutes a (secondary) response rate of 70.6 per cent (Whitehouse et al., 2007). The PLAS questionnaires include questions in three main components: the work history of parents, parental leave experiences, and return-to-work information on the parents of the infant. Other information of interest, such as child health, and further household and child characteristics were obtained from Wave 1 and Wave 2 of the LSAC using the common household identification code from the PLAS. Thus, the complied dataset enables us to explore the relationship between parental leave and health status of the child at 0-1 years and 2-3 years.

One noteworthy point about this study is that observations for mothers who were ineligible for paid maternity leave are included. Previous studies such as Whitehouse et al. (2008) excluded mothers who were ineligible for maternity leave, which results in about two thirds of all of the observations covered by the

PLAS being dropped. A statistical complication that may be associated with the latter approach, *viz.* that, given the prevalence of no paid maternity leave, whole clusters may be dropped (e.g., in some postcodes, no mother might be eligible for maternity leave and/or data may be missing). The consequence of this would be that one cannot produce robust standard errors of the estimates using the cluster information from the survey. In this study, we use a dummy variable to capture the characteristics of those who were ineligible for paid maternity leave and treat the duration of their paid leave as zero. This approach is similar to the innovation proposed by Battese (1997) to deal with zero values of inputs in the estimation of a Cobb-Douglas production function. This treatment allows use to make use of all observations covered in PLAS, and hence, enable us to exploit the cluster survey design in all analyses.

4.2 Descriptive Statistics

It can be seen from Table 1 that the parent-reported health of children of mothers who have PML is statistically significantly greater than that of those whose mothers are without PML. For example, on average 10 per cent of children whose mothers received PML were reported to be in poor health while 12 per cent of children whose mothers did not get PML were reported to be in poor health.

Table 1: Descriptive statistics

Variables	Mean	Std. err	Non-PML	PML	Test (p-val)*
Outcome measures					
Child Health (1=excellent, 5=poor)	1.53	2.E-04	1.54	1.48	0.05
Poor health (1=yes, 0=no)	0.12	3.E-05	0.12	0.10	0.07
Light birthweight (1=yes, 0=no)	0.05	1.E-05	0.05	0.04	0.96
Injury (1=yes, 0=no)	0.06	2.E-05	0.06	0.05	0.20
Asthma (1=yes, 0=no)	0.13	3.E-05	0.13	0.10	0.01
bronchiolitis (1=yes, 0=no)	0.11	3.E-05	0.11	0.10	0.29
Breastfeeding decisions (1=yes)	0.52	8.E-05	0.51	0.48	0.16
Breastfeeding duration (days)	105.87	5.98	102.54	131.10	0.00
Significant development concern[1]	0.11	4.E-05	0.11	0.11	0.52
Physical health index[2]	83.26	0.04	83.23	83.54	0.50
Psychological health index[3]	81.28	0.04	81.20	81.87	0.17
Total pediatrics health index[4]	82.11	0.03	82.06	82.56	0.24
Pediatric emotional health index[5]	74.19	0.07	74.28	73.95	0.57
Pediatric social function index[6]	87.51	0.05	87.31	88.50	0.03
Concern about development (1=no, 2=yes, 3=little)	1.11	5.E-05	1.11	1.11	0.91
Communication and Symbolic Behavior Scale (CSBS) total measure [7]	26.72	0.03	26.56	26.58	0.96
Physical domain score	100.35	0.02	100.34	100.66	0.40
Social/emotional domain score	100.13	0.03	100.26	100.25	0.99
Learning domain score	99.37	0.03	99.28	99.52	0.55
Immunization (1=complete, 2=most, 3=some, 4=none)	1.12	5.E-05	1.14	1.06	0.00

Note: Variances are estimated using the survey design adjustment, which invokes the Taylor linearisation method (Kish, 1995; Chambers and Skinner, 2003)

[1] *- Number of answer "yes" or questions (gd01-gd04) regarding concern on: child development, speech, understanding, hands/legs coordination, behaviour*

[2] *mean of gd04a1-gd04a8: in the past months, does your child has problem with: running, walking, exercising, lifting, bathing, picking up toys, or having a hurting or ache? code as: 1=Never (100); 2=Almost never (75); 3=Sometimes (50); 4=Often (25); 5=Almost always (0).*

[3] *mean of dg01b1a-gd04b3c: in the past months, does your child: feeling afraid or scared, sad or blue, angry, trouble of sleeping, worrying, problem of playing with others, getting teased, problems with doing the samething as they often do, missing days because of not well. Coded as:1=Never (100); 2=Almost never (75); 3=Sometimes (50); 4=Often (25); 5=Almost always (0).*

[4] *mean of gd04a1-dg04b3c*

[5] *mean of gd04b1a-gd04b1e: in the past month, you child feeling afraid or scared, said or blue, angry, trouble sleeping, worrying. Coded as:1=Never (100); 2=Almost never (75); 3=Sometimes (50); 4=Often (25); 5=Almost always (0).*

[6] *mean of gd04b2a-gd04b2e*

[7] *Sum of lc01a1a to lc01c2d. Example questions: do you know when your child is upset? is the child is looking at you when playing? when you look and point at a toy, does the child look? does the child do things just make you laugh?*

**p-values of tests for differences between PML and without PML were presented. These are Kruskall-Wallis tests for categorical variables and t-tests for continuous variables*

Source: Computed from the Longitudinal Study of Australian Children (Australian Institute of Family Studies, 2007)

Table 1: Cont.

Variables	Mean	Std. err	Non-PML	PML	Test (p-val)
Maternity/parental Leaves					
Total mother leave (weeks)	18.42	0.17	11.49	43.12	0.00
Paid maternity leave-PML (weeks)	2.54	0.01	0.00	11.32	0.00
Total father's leave (weeks)	8.99	0.06	8.56	11.52	0.00
Paid paternity leave-PPL (weeks)	1.22	4.E-03	1.09	1.85	0.00
Child and family characteristics					
Gender of the child (female=1)	0.52	6.E-05	0.52	0.49	0.12
Aboriginal and Tores-strait Islanders	0.03	9.E-06	0.03	0.01	0.00
English speak at home (yes=1)	0.89	8.E-05	0.90	0.93	0.01
Household size	4.02	4.E-04	4.09	3.69	0.00
Household condition (clean=1)	0.92	3.E-05	0.92	0.95	0.01
Mother's age	31.82	0.01	31.49	32.67	0.00
Father's age	34.50	0.01	34.26	34.62	0.12
Mother completed year 12 (yes=1)	0.64	1.E-04	0.69	0.88	0.00
Mother has graduate degree (yes=1)	0.27	8.E-05	0.25	0.47	0.00
Mother has postgraduate degree (yes=1)	0.08	3.E-05	0.06	0.16	0.00
Father completed year 12 (yes=1)	0.55	1.E-04	0.53	0.69	0.00
Father has graduate degree (yes=1)	0.21	7.E-05	0.20	0.31	0.00
Father has postgraduate degree (yes=1)	0.07	3.E-05	0.06	0.11	0.00
Mother is employed (yes=1)	0.52	1.E-04	0.43	0.87	0.00
Father is employed (yes=1)	0.94	2.E-05	0.94	0.96	0.04

Note: Same as Table 1

There were no statistically significant differences in the proportion of children of low birthweight born to women with and without PML. This indicator provides some reassurance that baseline health status is not systematically correlated with PML or with some other, unobserved, source of heterogeneity that is correlated with PML. Statistically significant differences are observed between the PML and non-PML households for the incidence of child asthma, the decision to breastfeed and the duration of breastfeeding, and the likelihood of being up-to-date with immunisation. Among the child development indices, only the paediatric social function index shows any statistically significant differences between children of PML and non-PML mothers.

The results also show that parents who who take PML also have a longer mean total leave duration following childbirth (43 weeks, including 11 weeks of PML) compared with that of non-PML parents (12 weeks' duration). Similarly, partners of those with PML also have a longer mean duration of total leave (12 weeks) following the birth of their child than partners of non-PML mothers (9 weeks). Furthermore, although paid paternity leave (PPL)contributes only a small proportion to the difference in total leave, it also differs between those whose partners take PML (1.85 weeks) and those without (1.09 weeks).

Regarding the other characteristics of households, Aboriginal and Torres-strait Islander (ATSI) parents are less likely to receive PML. There is also a small but statistically significant difference between the prevalence of PML in

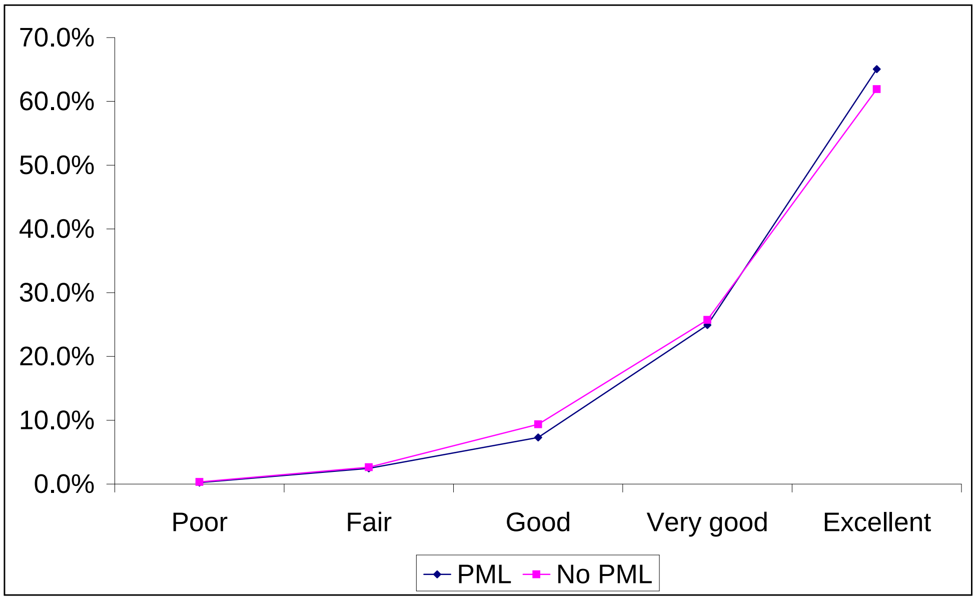

Figure 1: Maternity leave and child health

households where English is spoken at home (93 per cent) and households where a language other than English is spoken in the home (90 per cent). In addition, the education of both mothers and fathers is significantly higher among those who take PML and their housing condition is more likely to be clean. It is obvious that those who take PML are twice more likely to be employed than those did not have PML although there is less discrepancy on the partner's employment status. On average, mothers who take PML are also slightly older than those who do not take PML.

A raw sketch of the probability of a child belong to different health category presented in Figure 1 shows that children whose mother take PML are more likely to have "excellent" health and less likely to have lower health status.

4.3 Choice of Variables and Models

We explore the effects of parental leave on all outcome of interests available on PLAS: parents'-reported child health, incidence of asthma and bronchiolitis, immunisation status and child development indices. Since the decision and duration of breastfeeding are endogenous within the family, we employ a seemingly unrelated regression to examine the effects of maternity/paternity leave to breastfeeding, which in turn can effect child health. All these outcomes are measured with 12 months of life (Wave 1) and in the follow-up survey (Wave 2), and hence, we also investigate long-term effects of parental leave, which is an important extension of the literature suggested by the parental leave symposium (Gregg and Waldfogel, 2005).

As mentioned previously, the maternity and paternity leaves of this paper are measured by using continuous, binary and categorical formats as well as their interaction. We propose 6 models for each outcome of interests (e.g., child health, chronic conditions and immunisation) using combinations of the various formats of maternity/paternity leave below:

1. Total leave by mothers (weeks) : explore the effects of total leave
2. PML (weeks) and other leave (weeks): examine the effect of PML after controlling for other leave
3. Categorical measure of PML: 1) up to six weeks, and 2) more than six weeks: explore differences in the most common choice of PML, compared with those who did not take PML.
4. Total leave by partner (weeks): explore the effect overall leave duration of partners
5. Paid paternity leave by partners, and other leave (weeks): examine the effect of PPL after controlling for other leave
6. Dummy for PML, paid paternity leave and their interaction: exploring the average effects of PML and paid paternity leave

In all of the above models we also control for household characteristics : household size, log of family income, housing condition, English-speaking background, ATSI, age, education and employment status of mothers and fathers. In addition, child characteristics such as age (months) and gender of the child are include in the "standard" set of control in all models.

5 Results and Discussions

5.1 Effects on General Health Status of Children

It can be seen that the duration total maternity leave has no significant effect on the parents'-reported health of children at 0-12 months. However, Model 2 (Table 2) show that the duration of PML has significantly improved the likelihood that children have better health whilst other types of leave have no effect at all. Furthermore, Model 3 reveals that, compared to those who did not take PML, only those who take the PML for more than 6 weeks are more likely to report that their children are in excellent health.

Table 2: Effects of Maternity Leave on child health

Models	0-12 months				24-36 months			
	Child health		Poor health		Child health		Poor health	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
1) Total mother's leave	-0.001	0.001	-0.002	0.001	-0.0003	0.001	-0.002	0.001
2) PML	**-0.010	0.004	-0.007	0.005	-0.004	0.003	-0.002	0.005
Other leave	-0.001	0.001	-0.002	0.001	0.00001	0.001	-0.002	0.001
3) PML<6 weeks	-0.114	0.070	-0.160	0.107	-0.041	0.068	-0.094	0.094
PML>6 weeks	***-0.158	0.061	-0.114	0.082	-0.073	0.061	-0.127	0.092
4) Total father's leave	***-0.004	0.001	**-0.004	0.002	-0.0002	0.001	-0.003	0.002
5) Father's PPL	0.006	0.004	0.005	0.005	*0.008	0.004	0.005	0.006
Father's other leave	***-0.006	0.001	**-0.005	0.002	-0.001	0.001	*-0.003	0.002
6) Dummy PML	**-0.010	0.004	-0.007	0.005	-0.004	0.003	-0.002	0.005
Dummy PPL	0.006	0.004	0.005	0.005	*0.008	0.004	0.006	0.006
Interaction	0.076	0.094	-0.033	0.120	*-0.072	0.041	-0.022	0.054

*Notes: Other covariates include: log of household income, household size, housing condition, availability of biological mother and father, age of mother and father, education level of mother and father, employment status of mother and father, whether or not English is spoken at home, and whether or not the child is of ATSI background, age and gender of the child. Robust standard errors are estimated using sampling weights and clusters. Significant levels are: *** 1 per cent, ** 5 per cent, and * 10 per cent.*

One important finding is that father's total leave significantly improves the chance that child is having a good heath. Moreover, Model 4 shows that the effect of other types of leave is larger than that of PPL. This finding is not surprising as the role of father only supportive in the early period of child development. In addition, PPL contributes only a small proportion of the total amount of leave by a total of leave by fathers. Model 6 shows that on average PML has a significant contribution to child health, whilst the PPL is no longer significant. One possible reason is that PPL contributes only to a very small portion of the sample, and hence, its average effects may be negligible. As can be seen in the binary measure of health (i.e., a child is considered as having a poor health if he is reported as having, good, fair or poor.), fathers' leave (not necessarily PPL) is the only significant determinant.

The results also reveal that there is almost no longer-term effect of PML on child health. One exception is the effect of fathers' leave but it provides an unclear message. While Model 5 suggests that a child whose father took a leave at birth is less likely to have been reported in poor health at the age of 24-36 months. However, Model 6 provide a counter intuitive suggestion that a child is more likely in a poor health category if their fathers took PPL at birth.

5.2 Effects on Chronic Conditions

In this section we focus on examining the effect of parental leave on two physician-diagnosed conditions: asthma and bronchiolitis. The results reveals that PML have no effects on the incidence of asthma but having the expected negative signs. One exception is that Model 3 which suggests that children whose mothers takes PML for more than six weeks are less likely to be diagnosed with asthma at the age of 2-3 years but the result is only significant at 10 per cent. Again, the role of fathers' PPL provides counter intuitive results that their children are more likely to get diagnosed with asthma (Model 5 and 6). Similar results are found regarding the incidence of bronchiolitis: mothers leave, especially PML reduce the incidence whilst fathers' PPL provide opposite effects. This is perhaps the children diagnosed with Asthma and bronchiolitis were in poor health at birth (e.g. pre-term baby, needed intensive care after birth, which makes their father to take leave during a child's birth.

5.3 Effects on Postnatal Health Care

Regarding the incidence that a child is up to date with immunisation, Model 1 (Table 4) suggests that the total duration of mothers' leave matters for child's immunisation. In addition, Model 2 reveals that PML may not even significantly determine the incidence that a child is fully immunised. However, Model 3 suggest that on average, children of mothers who took PML still have more chance of being fully immunised. Regarding the roles of fathers, all estimates suggest that fathers' leave have no significant effect on children immunisation status.

Table 3: Effects of Maternity Leave on chronic conditions

Models	0-12 months				24-36 months			
	Asthma		Bronchiolitis		Asthma		Bronchiolitis	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
1) Total mother's leave	-0.001	0.001	*-0.002	0.001	-0.002	0.001	-0.001	0.001
2) PML	-0.005	0.005	*-0.008	0.005	-0.006	0.005	-0.007	0.005
Other leave	-0.001	0.001	-0.002	0.001	-0.001	0.001	-0.001	0.001
3) PML<6 weeks	0.060	0.094	0.020	0.096	0.003	0.096	-0.003	0.101
PML>6 weeks	-0.131	0.085	*-0.159	0.086	*-0.148	0.087	-0.138	0.086
4) Total father's leave	-0.00004	0.002	0.0003	0.002	-0.0005	0.002	-0.0007	0.002
5) Father's PPL	**0.011	0.005	0.008	0.006	**0.011	0.005	*0.01	0.006
Father's other leave	-0.001	0.002	-0.0004	0.002	-0.001	0.002	-0.002	0.002
6) Dummy PML	-0.005	0.005	*-0.009	0.005	-0.006	0.005	-0.008	0.005
Dummy PPL	**0.011	0.005	0.009	0.006	**0.011	0.005	*0.010	0.006
Interaction	0.120	0.123	**0.281	0.117	0.029	0.062	**0.139	0.059

*Notes: Other covariates include: log of household income, household size, housing condition, availability of biological mother and father, age of mother and father, education level of mother and father, employment status of mother and father, whether or not English is spoken at home, and whether or not the child is of ATSI background, age and gender of the child. Robust standard errors are estimated using sampling weights and clusters. Significant levels are: *** 1 per cent, ** 5 per cent, and * 10 per cent.*

Table 4: Effects of Maternity Leave on Postnatal Care

Models	0-12 months				24-36 months			
	Immunisation		Emotional index		Immunisation		Emotional index	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
1) Total mother's leave	**-0.004	0.002	0.006	0.011	**-0.003	0.002	0.002	0.010
2) PML	-0.009	0.006	0.037	0.045	-0.009	0.006	0.022	0.042
Other leave	**-0.003	0.002	0.004	0.012	*-0.003	0.002	0.0004	0.012
3) PML<6 weeks	*-0.275	0.143	0.557	0.796	-0.231	0.145	0.239	0.759
PML>6 weeks	*-0.176	0.100	**1.648	0.674	*-0.172	0.100	*1.173	0.633
4) Total father's leave	-0.002	0.002	0.010	0.011	-0.002	0.002	0.007	0.011
5) Father's PPL	-0.015	0.010	*0.085	0.047	-0.013	0.010	**0.099	0.050
Father's other leave	-0.001	0.002	0.006	0.012	-0.001	0.002	0.002	0.012
6) Dummy PML	-0.009	0.006	0.035	0.045	-0.008	0.006	0.020	0.042
Dummy PPL	-0.014	0.009	*0.083	0.047	-0.013	0.010	*0.098	0.050
Interaction	0.044	0.171	0.922	1.037	-0.059	0.055	0.083	0.488

*Notes: Other covariates include: log of household income, household size, housing condition, availability of biological mother and father, age of mother and father, education level of mother and father, employment status of mother and father, whether or not English is spoken at home, and whether or not the child is of ATSI background, age and gender of the child. Robust standard errors are estimated using sampling weights and clusters. Significant levels are: *** 1 per cent, ** 5 per cent, and * 10 per cent.*

Table 5: Effects of Maternity Leave on breastfeeding

Models	Breastfeeding decision				Breastfeeding duration			
	Health=f(BF)		BF=f(Leave)		Health=f(BF)		BF=f(Leave)	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
1) Total mother's leave	***-1.064	0.268	**0.003	0.002	*-0.009	0.005	**0.109	0.053
2) PML	***-1.041	0.262	***0.021	0.008	***-0.013	0.004	*0.189	0.113
Other leave			0.002	0.002			0.044	0.088
3) PML<6 weeks	***-0.995	0.276	0.108	0.160	***-0.011	0.003	2.556	2.788
PML>6 weeks			**0.323	0.131			**8.616	3.754
4) Total father's leave	***-1.046	0.257	*0.004	0.002	***-0.014	0.0002	***0.019	0.007
5) Father's PPL	***-1.009	0.290	0.012	0.010	***-0.014	0.0003	0.273	0.195
Father's other leave			0.003	0.002			-0.024	0.046
6) Dummy PML	***-0.993	0.282	***0.021	0.008	***-0.012	0.0047	0.351	0.320
Dummy PPL			0.011	0.010			0.070	0.522
Interaction			-0.011	0.164			1.385	3.824

*Notes: Other covariates include: log of household income, household size, housing condition, availability of biological mother and father, age of mother and father, education level of mother and father, employment status of mother and father, whether or not English is spoken at home, and whether or not the child is of ATSI background, age and gender of the child. Robust standard errors are estimated using sampling weights and clusters. Significant levels are: *** 1 per cent, ** 5 per cent, and * 10 per cent.*

As already suggested by the basic tests in Table 1, our analyses reveals that among child development indices collected only emotional measure shows differences between PML and non-PML. Particularly, children of mothers who took PML for more than 6 weeks have higher emotional index. This result persists in two years latter in Wave 2 survey. More interestingly, children of fathers who took PPL also have significantly and persistently higher emotional index, even when controlling for mothers' PML.

As mentioned previously we estimate the effects of breastfeeding (decision and duration) as a mixed-recursive system of equation with child health. In addition, we apply same treatment for missing data on breastfeeding (about on third of the sample) as did with the mother leave duration (i.e., use a dummy variable for missing data and treat the duration of breastfeeding as zeros). Also, since the likelihood of children being breastfed in the 24-36 months age group is small, we focus on the 0-12 months age group. Table 4 shows that the first stage regression suggests that children who are breastfed have significantly better health, and this impact increases with the duration of breastfeeding. Surprisingly, this result remains consistent for fathers' leave. The second stage estimate reveals that mothers' PML, especially with the duration of more than six weeks significantly determines the decision and duration of breastfeeding, which is in line with previous study such as Roe et al. (1999). We also find that father's total duration of leave has significant effects on the duration of breastfeeding but it is no longer significant when controlling for the average effect of PML. One possible explanation is that most mothers who took PML also have their partners took PPL (i.e., there is a high correlation between PML and PPL).

6 Conclusions

This paper has examined the effects of maternity leave on child health in Australia using data from PLAS and the first two waves of LSAC. Our results reveal that both PML and PPL have significant and positive effect on child health but they have no effect on prenatal health (proxied by birth weight). Also, we found that in most cases the PML effects are significant if the duration of leave is at least 6 weeks. PML also has some significant effects in reducing the probability of having chronic conditions (i.e., asthma and bronchiolitis) but effects of PPL are not clear. Also, PML have significant effect on the probability that the child has been fully updated with immunisation and positive affects on the emotional index of the child. Importantly, we find that PML strongly increases the probability of a child being breastfed and the duration of breast feeding, which in turn strongly affect child health in later stage.

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