Fertility Choice of Second Child and the Diminishing Marginal Penalty on Women's Labor Market Outcomes

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Abstract

Child penalty describes the disparity in the effect of childbirth on labor market outcomes between fathers and mothers, and it largely contributes to the gender wage gap. Using panel data from China, with implementation of two-child policy which makes having a second child more general, I studied the short-term effect of the marginal child penalty. With event study approach, we can identify and estimate the difference in child effects on employment rate and yearly income between first birth and second birth, and between fathers and mothers. The results reveal a diminishing marginal child penalty pattern that the gap generated by childbirth between male and female is smaller after the second birth than the first one. This pattern could be explained by a "self-selection" speculation in certain types of family. I also proposed a transfer-utility bargaining model incorporating a social norms utility function to explain the mechanism behind fertility choices, particularly the decision to have a second child in contexts that are strongly influenced by social norms.

Keywords: child penalty, fertility choice, labor market outcomes, gender

JEL Code: J13, J16, J22, J31

1 Introduction

The gender wage gap is declining worldwide, but gender roles in family and labor, gender differences in occupations and industries, still remain to be important issues that affect the economy development (Blau & Kahn, 2017). Discrimination on women never vanishes, especially in the labor market, and child penalty serves as one of the main fundamental causes of the barrier in women's career development (Benard & Correll, 2010; Kricheli-Katz, 2012). Child penalty refers to the disparity of childbirth effects on labor market outcomes between fathers and mothers. Mothers may earn less than other childless women since they might become less productive at work or trade off high-paid job for motherfriendly jobs to allocate more time on childcare and home production. Maternal leave due to pregnant also reduces their human capital accumulation and makes them lose job experience (Budig & England, 2001). The drawback of having a child only creates discrimination against mothers, but not against fathers (Correll et al., 2007), since mothers are expected to take a more traditional family role in childcare. While mothers are undertaking the "motherhood penalty", fathers may even benefit from childbirth as having "fatherhood premium" (Weeden et al., 2016; Killewald & Gough, 2013; Killewald, 2013; Glauber, 2008).

Previous researches have found that having one or more children generally leads to drop in female labor participation rate, lower income and shorter working hours (Waldfogel, 1997; Budig & England, 2001; Correll et al., 2007). Many other researchers (Budig & England, 2001; Angrist & Evans, 1996; Rosenzweig & Wolpin, 1980) have also examined the relationship between childbirth and mother's labor market outcomes in different countries using various econometrics approaches to solve the endogeneity issue, that variables contributing to fertility decision might also be highly related to the labor market outcomes, such as education level, wealth accumulation and age (See more discussion in Section 2). However, most of the literature (Angrist & Evans, 1996; Sanders & David, 1992) studied the long-lasting gap between male and female that are caused by childbirth. It might be hard for family to make fertility decision based on long-run outcomes, even if they know the penalty will last for a long period of time, they cannot estimate whether they can bear the future cost now. The spacing between birth also matters in the size of child penalty (Gough & Noonan, 2013; Gough, 2017). Estimating the short-run effect can distinguish the overlapping child penalty from each birth and provides insightful evidence for family to decide whether they can bear the cost of childbirth, especially focusing on the years

that are influenced sharply by the child penalty, and make their fertility choice. Existing researches (Bertrand et al., 2010) that study the short-run effect are limited to pre- and post-first childbirth change. Other researches (Mu & Xie, 2016; Budig & England, 2001; Gangl & Ziefle, 2009) estimated the effect of family size on mother's labor market outcomes, which results in averaging the child penalty by number of children, but the penalty from each birth should be different. Therefore, it is necessary to identify and estimate the short-run effect of each childbirth on women's labor market outcomes, and whether they differ, which provides implication for family to decide having an extra child or not.

Starting from 1979, China entered an one-child policy era that only allow each family to have one child, to curb the population growth. As a consequence, most contemporary Chinese family only have one child, provides good sample to study the first child penalty both in long-run and short-run. To solve the aging population problem, China started introducing selective two-child policy in 2011 and further implemented universal two-child policy in late 2015, which make it more general for younger family to have two children. Since the two-child era is very recent, the data are more tractable to study the marginal (second) child penalty, but it will be restricted to a short-run estimation to reduce the overlapping effect from the first child penalty. In this paper, I used China Family Panel Studies (CFPS), a longitudinal data from 2010-2022, spanning the pre- and post- two-child policy era. This panel data allows me to adopt event study approach based on Kleven, Landais, & Søgaard (2019)'s model and apply fixed effect model to count for individual-level heterogeneity, and control for the endogeneity issue to identify and estimate the difference between first and second child penalty on mothers and fathers labor market outcomes.

My research shows that by treating the year before each birth as a benchmark, the gap between fathers' and mothers' labor market outcomes (employment rate and yearly income) is smaller after the second birth than after the first birth, with a short-run event window of $\{-2,4\}$ (i.e. two years before the birth and four years after the birth, but -2 and 4 are boundaries and -1 is the baseline, so only the effects at the year of birth and within three years after the birth play an important role). This result reveal a diminishing marginal child penalty pattern. This pattern could be explained by a "self-selection" speculation for certain type of family, in which mothers have a high-paid job and fathers and grandparents might spend more time in childcare (Posadas & Vidal-Fernandez, 2013; Yu et al., 2023).

The child penalty estimation could provide reference for family to decide whether to

have a second child or not. Previous fertility choice models focused on consumption and utility gain from having children and expected return from child investment (G. Becker, 1960; G. S. Becker, 1974; G. S. Becker & Barro, 1988; Doepke & Kindermann, 2019). There is also a debate on children quantity-quality trade-off (G. S. Becker & Lewis, 1973). But these might not be the only factors influencing family decision in fertility choice of a second child in contemporary China. China has a strong son-preferred cultural norms and high sex ratio of male over female. In one-child era, the skewed sex ratio intensified in late 1980s, when diagnostic ultrasound for sex determination became available (Yi et al., 1993). The design of second-child policy was also meant to reduce the abortion rate for girl babies by allowing family to have a second child. However, while young generation has low fertility intension (Chen et al., 2023; Zhang et al., 2022), family with first-born girl who really has a willingness for son tends to have a second child, which in return exacerbate the skewed sex ratio.

Therefore, taking social norms into consideration for fertility choice is very necessary. I developed a transfer-utility bargaining theoretical framework that incorporate social norms utility other than consumption, leisure and expected return from children utility, to uncover the mechanism in fertility choice making of having a second child.

My research could provide implication on policy design that encourage women to participate into labor market while keep the population growth, and also for demographic policy related to fertility choice.

The rest of this paper is constructed as follows: Section 2 reviews previous researches about child penalty and their limitation; Section 3 describes data; Section 4 applies event study approach to estimate the child penalty; Section 5 provides theoretical framework for fertility choice; Section 6 summarizes the limitation in this research; Section 7 concludes.

2 Literature Review

Many literature has examined the child penalty on women's labor market outcomes. The size of the penalty varies by countries, econometric approaches and datasets.

Budig & England (2001) used fixed effect estimation on a U.S. national longitudinal dataset, found mothers' wage would decrease by 7% for every one more child. Another research (Anderson et al., 2003) also estimates the child penalty in the U.S and found wage would decrease by 10% per child for women. Lundberg & Rose (2000) claimed that the first childbirth will re-allocate parents' time on work and family. In general, the

first childbirth will decrease mother's wage by 5% while increase father's wage by 9%, and decrease mother's working time by 45% while has no effect on father's working time. Global-wide studies in Spain, Norway and Denmark, all have shown the child penalty on women's labor market outcomes (Molina & Montuenga, 2009; Petersen et al., 2010; Kleven, Landais, & Søgaard, 2019). Most recent research Kleven et al. (2024) provides a child penalty atlas.

The main problem to study the child penalty on labor market outcomes is to deal with the selection-bias problem (Nakamura & Nakamura, 1992). The fertility choice is highly correlated with education, wealth, age and other variables that also play a role in deciding the labor market outcomes. Therefore, we need to solve the endogeneity problem lies in fertility and labor (Cain & Dooley, 1976). Two common approaches are introducing instrumental variables (IV) or apply fixed effect model to control for individual-level heterogeneity. Rosenzweig & Wolpin (1980) and Bronars & Grogger (1994) use twins as IV to estimate the effect of numbers of children on women's labor market outcomes. Since twins rarely occur, which limits the generality of using twinning as an IV to apply to other context, other researchers improved the validity of estimation by using parents gender-preference for babies as an IV (Angrist & Evans, 1996; Hirvonen, 2009). Mu & Xie (2016) used gender of first child as IV to identify the gendered fertility effect. The IV approach solves the endogenous variables problem and usually is conducted on a crosssectional data. To apply fixed effect approach to control for heterogeneity of women, it requires longitudinal datasets with higher quality. Glauber (2007) and Jia & Dong (2013) used panel data to control on the time-invariant variables and estimated the child penalty.

Many of these researches focus on the long-run effect of fertility on women's labor market outcomes, estimate whether the gap between male and female persistently exist. But since it is hard for people to estimate the current expected value of life-long child penalty, it might be more insightful to study the short-run effect of childbirth, focusing on the period that childbirth sharply changes the mother's career path. Other limitations of previous literature, including evaluate the child penalty by averaging the effect from each birth or only estimating the first child penalty, will be discussed in Section 4.

My research will contribute to the identification and estimation of the short run child penalty and evaluate the difference in childbirth effects on labor market outcomes between men and women, and between the first birth and the second birth.

3 Data

3.1 Data Source

This study used dataset from China Family Panel Studies¹ (CFPS), launched by the Institute of Social Science Survey of Peking University from China. The CFPS collects individual-, family-, community-level longitudinal data in contemporary China on a biennial basis, beginning from 2010. The survey scope covers 25 provinces in China and the target sample size is national-wide 16000 households. It provides information about economics activities, education outcomes, family dynamics and relationships, migration, and health. In each survey year, the CFPS distributes four questionnaires for each individual, child, family roster and family, respectively.

In this empirical research, I used the adult and child database from 2010 to 2022 in CFPS to construct a micro-level panel data, focusing on economics outcomes, education and fertility choice of parents with at least one child born after 2000.

Each child database in CFPS contains information for children under 16 years old in that survey year. The whole child dataset used in this study was constructed using child database in 2016-2022, covering children born between 2001 to 2022. Children from 2010-2014 database are also worth studying, but many households quit from the survey at an early stage, making it much harder to create the panel to study the child effect. Since the universal two-child policy was implemented at the end of 2015, using child database after 2016 could cover more two-births family benefit from the policy change. Also, the eldest cohort of children in the 2016 database were born in 2001, and they turned 10 years old in 2010, which is typically the maximum event window for studying the long-run child penalty effect on parents' labor market outcomes in prior literature (Kleven, Landais, & Søgaard, 2019; Kleven, Landais, Posch, et al., 2019).

For 2010-2022 individual database, I selected variables of interests in each survey year, focusing on demographic characteristics (birth year, gender, province, urban, etc.), economics status (employment status, yearly income, monthly salary, etc.), education experience (years of education, best education level, etc.)

¹China Family Panel Studies, https://www.isss.pku.edu.cn/cfps/en/

3.2 Data Cleaning

I matched selected children to their mother and father, combined children born in a family and used person ID of the mother or father as the leading of an entry (child's birth year, gender are considered as characteristics of their parents). Multiple children born in the same year are considered as one birth for the parents (eg: twins). I matched mothers and fathers with their variables of interests respectively in 2010-2022. There are 8378 mothers and 8236 fathers after matching.

This study mainly focus on the marginal effect of the second birth on labor market outcomes. If the third birth is close to the second birth, it will affect the estimation accuracy of the second birth effect. 344 mothers and 358 fathers are dropped due to having more than two births. I excluded 93 mothers and 158 fathers who moved from the original-covered 25 provinces to other non-targeted provinces, since they generate biased fixed-effect for non-targeted provinces. I also dropped observations without valid birth year, gender, or missing all value to describe labor market outcomes. After cleaning, there are 7388 mothers and 7153 fathers remaining in the dataset.

3.3 Descriptive Statistics

Table 1 and Table 2 show the summary of descriptive statistics of mothers and fathers dataset. The "Unemployed" represents either unemployed or out of labor market. (Table A1 and Table A2 in Appendix describe the detail of these two datasets.)

There is an increasing tread in employment rate from 2010 to 2022 for both mothers and fathers. Especially for mothers, the employment rate increased from 49.39% in 2010 to 78.33% in 2022, by 58.6%. The population female labor participation rate in China was slightly above 60% from 2010 to 2022 (World Bank China indicator²). Mothers' employment rate was lower than the population level and then increased to higher than the population level, which not only shows women empowerment, but also provides evidence that mothers may not and will not be restricted by the traditional gender role to be a housewife. However, based on their current employment status or previous working experience, 83.36% mothers were or are unemployed due to housework and 77.11% left a job because of maternal or other family reasons. Meanwhile, reasons of unemployment and leaving a job for fathers are mainly "cannot find a suitable job" or "Illness or disable".

²World Bank Group Gender Data Portal, https://genderdata.worldbank.org/en/economies/china

Therefore, family and fertility may still be the most important factor that hinder women's career development.

Another important factor that is highly correlated with the labor market is education. Although the share of female and male with college degree are quite indifferent, mothers have a much higher illiterate rate than fathers while more fathers obtain a primary/middle school/high school degree. Fathers also have more years of education than mothers.

Average yearly income for fathers are consistently more than 1.5 times of mothers. Although the ratio is becoming smaller from 2010 to 2022, the gender wage gap still shows the inequality in labor market, especially for fathers and mothers with children.

Since fertility choice is one parameter of interest in this research, comparing the difference between male and female's fertility preference provides a preview of bargaining in the family. In general, fathers want to have more children in the family, and specifically, more boys. Considering a transfer utility model, if the husband prefer to have more children (boys), he might need to transfer utility (in terms of goods and money) to the wife to compensate for her cost from birth-giving, which results in labor market outcomes.

4 Marginal Child Penalty on Women's Labor Market Outcomes

The child penalty describes the difference in the effect of having a child on earnings between men and women. Many previous articles (Angrist & Evans, 1996; Sanders & David, 1992) focus on the long-run effect of child penalty, showing that giving birth has a long-lasting effect on women. Some research study the difference between pre- and post-birth period (Kleven, Landais, & Søgaard, 2019), assuming all years after the birth (at least within a certain period) have the same or similar effects. Some other literature (Mu & Xie, 2016; Budig & England, 2001; Gangl & Ziefle, 2009) treats the number of children as a continuous variable, results in estimating the average effect of having one additional child on mothers, or only distinguish one child and two or more children's effect on mothers (Anderson et al., 2002; Angrist & Evans, 1996; Sasser, 2005; Killewald & Gough, 2013). There are also studies that only estimate the effect of first child (Kleven, Landais, & Søgaard, 2019; Kleven et al., 2024; Bertrand et al., 2010), without controlling for the effect of following births.

This research contributes to the identification and estimation of child penalty on women's

 Table 1: Descriptive Statistics: Mothers' employment, education and fertility choice

				Ŋ	/ear			
	2010	2012	2014	2016	2018	2020	2022	Total
Employment status								
Unemployed								
Percent	50.61	38.00	26.36	25.28	22.48	22.27	21.67	28.96
Frequency	(1,939)	(1,937)	(1,301)	(1,382)	(1,220)	(995)	(922)	(9,696)
Employed								
Percent	49.39	62.00	73.64	74.72	77.52	77.73	78.33	71.04
Frequency	(1,892)	(3,160)	(3,635)	(4,084)	(4,207)	(3,473)	(3,332)	(23,783)
Unemployment reason								
Housework								
Percent	80.49	61.59	85.07	84.88	89.86	88.51	85.38	83.36
Frequency	(796)	(441)	(1,060)	(1,128)	(1,046)	(840)	(765)	(6,076)
Others								
Percent	19.51	38.41	14.93	15.12	10.14	11.49	14.62	16.64
Frequency	(193)	(275)	(186)	(201)	(118)	(109)	(131)	(1,213)
Leaving job reason			, ,	, ,	, ,	, ,	, ,	
Maternal or other family reasons								
Percent			66.23	80.29	84.18	80.00	70.98	77.11
Frequency			(306)	(505)	(511)	(400)	(313)	(2,035)
Others								
Percent			33.77	19.71	15.82	20.00	29.02	22.89
Frequency			(156)	(124)	(96)	(100)	(128)	(604)
Best education level			, ,	, ,	, ,	, ,	, ,	, ,
Non-college								
Percent	89.72	88.21	85.67	83.66	80.72	77.88	76.56	83.21
Frequency	(3,594)	(4,476)	(4,539)	(4,645)	(4,496)	(3,548)	(3,332)	(28,630)
College		, , ,		, ,	, ,	, , ,	, ,	, , ,
Percent	10.28	11.79	14.33	16.34	19.28	22.12	23.44	16.79
Frequency	(412)	(598)	(759)	(907)	(1,074)	(1.008)	(1,020)	(5,778)
Years of education		,	, ,	,	() /	())	(, ,	(, ,
Mean	8.30		8.85	9.14	9.26	9.87	9.81	9.19
Ideal number of kids								
Mean			1.94		1.95		1.95	1.95
Ideal number of boys								
Mean					1.03		1.03	1.03
Income								
Mean	7515.10	9036.17	12608.90	18896.54	34552.78	38596.25	44878.23	20388.59

labor market outcomes, varying by the number of births and the specific year around the birth, within a short period that generates sharp changes on mothers. The results show that there is a diminishing marginal (second) child penalty on women's labor market outcomes, specifically, employment rate and yearly income.

4.1 Methodology

4.1.1 Event Study

This section adopts event study methodology, which is developed for estimating the dynamic treatment effect of an event that happens to each observation at different time using panel data, and has become more popular in labor economics (Jacobson et al., 1993; Miller, 2023; Sandler & Sandler, 2014). This methodology can present the trajectory of the labor market outcomes before and after the event of birth-giving. Since a

Table 2: Descriptive Statistics: Fathers' employment, education and fertility choice

				Ye	ear			
	2010	2012	2014	2016	2018	2020	2022	Total
Employment status								
Unemployed								
Percent	32.00	22.35	5.93	5.06	3.85	3.24	3.43	10.29
Frequency	(1,137)	(1,174)	(287)	(266)	(203)	(138)	(139)	(3,344)
Employed								
Percent	68.00	77.65	94.07	94.94	96.15	96.76	96.57	89.71
Frequency	(2,416)	(4,078)	(4,550)	(4,992)	(5,065)	(4,119)	(3,919)	(29,139)
Best education level								
Non-college								
Percent	88.70	87.39	85.50	83.88	81.57	78.46	77.71	83.40
Frequency	(3,264)	(4,588)	(4,622)	(4,559)	(4,338)	(3,363)	(3,193)	(27,927)
College								
Percent	11.30	12.61	14.50	16.12	18.43	21.54	22.29	16.60
Frequency	(416)	(662)	(784)	(876)	(980)	(923)	(916)	(5,557)
Years of education								
Mean	9.11	•	9.41	9.63	9.84	10.21	10.17	9.72
Ideal number of kids								
Mean		•	1.98	•	2.00		2.02	2.00
Ideal number of boys								
Mean					1.10	•	1.11	1.11
Income								
Mean	17043.94	20803.04	21828.30	31785.83	50886.71	59467.92	70190.89	36010.51

gestation period typically lasts for nine to ten months (Jukic et al., 2013), the impact of fertility on the labor market outcomes of both spouses should begin no earlier than one year before the child's birth. Therefore, choosing the year before the child's birth as a baseline can control for the pre-event trend (Freyaldenhoven et al., 2019).

4.1.2 One birth family and two births family

Under the context of contemporary China, many families from the one-child policy era chose to have only one child. This provides a strong foundation for estimating the first-child penalty, as the childbirth serves as the sole treatment in this scenario. With data from one birth family, we are able to observe the long-run effect and verify a short-run period that has the largest changes in labor market outcomes.

This short-run period will be selected as the event window to study the child penalty in two births family and compare the difference of child effect on labor market outcomes for men and women, and between the first birth and the second birth. Since the post-birth period of the first childbirth will overlap with the pre- and post-birth period of the second childbirth, therefore, the long-run effect of child penalty from each birth is hard to distinguish and cannot provide good estimation results. We need to constrain the event window for short-run so that the overlapping period is shorter and the estimation result

will be more accurate.

4.2 Model

Kleven, Landais, & Søgaard (2019) proposed an event study model to estimate the effect of having the first child, interpreted the evolution of a wide set of labor market outcomes as a function of event time. Based on their model, I introduce an updated model to count for heterogeneous effects of the first birth and the second birth on the labor market outcomes:

$$Y_{it}^{g} = \alpha^{g} + \sum_{j=1}^{2} \sum_{D=-a}^{b} \beta_{jD}^{g} \mathbb{1}(p=D) + \sum_{k} \gamma_{k}^{g} \mathbb{1}(k=age_{it}) + \sum_{y} \theta_{y}^{g} \mathbb{1}(y=t) + \epsilon_{it}^{g}$$

where

$$p = \begin{cases} b & \text{if } t - e_j^i > b, \\ t - e_j^i & \text{if } t - e_j^i \in [-a, b], \\ -a & \text{if } t - e_j^i < -a. \end{cases}$$

Denote Y_{it}^g as the outcome of interest for individual i of gender g at calendar year t, where $g \in \{m, w\}$. Let e_j^i be the year of the jth childbirth for individual i, where $j \in \{1, 2\}$. p is the event time as a function of calendar year and childbirth year. Calendar year outside of the event window does not create extra effect from the child penalty other than the boundary of the event window. Denote D as the event time, where $D \in \{-a, b\}$. $\{-a, b\}$ is the choice of event window, depends on the estimation of short-run or long-run effect, counting from a years before the childbirth and b years after the childbirth. Since the childbirth has more impact on the post-birth period, the event window should be designed as unbalanced, as a < b. Therefore, β_{jD}^g accounts for the child effect of jth childbirth at event time D on gender g. As discussed above, I omit the event time dummy at D = -1 to count as the baseline. I include a full set of age and year dummies to control non-parametrically for life-cycle trends and time trends (e.g. business cycle or inflation) that can be different for two genders. e_{it}^g measures all other individual heterogeneity, including education, marriage status, fertility choice and other factors correlated with labor market, with assumption that $\mathbf{E}(e_{it}^g|g) = 0$.

4.3 Identification

 β_{jD}^g are a sequence of parameters of interest that measure the child effect on parents' labor market outcomes. β differs in gender, the number of childbirth and the event time.

The child penalty is defined as the difference in the child effects between men and women.

Since we have omitted a base year before the childbirth to control for the pre-birth difference in men and women, the penalty is measured as the average effect in a specific event time relative to the year before the childbirth. With the model and the individual heterogeneity assumption, we can identify the child penalty as:

Child Penalty_j
$$\equiv \beta_{jd}^m - \beta_{jd}^w = \mathbf{E}(Y_{jD}^m - Y_{jD}^w|D=d) - \mathbf{E}(Y_{jD}^m - Y_{jD}^w|D=-1)$$

For family with two childbirths, the marginal child penalty is the penalty from the second childbirth. We identify the difference between penalty in two births as:

Child Penalty_1 — Child Penalty_2
$$\equiv (\beta_{1d}^m - \beta_{1d}^w) - (\beta_{2d}^m - \beta_{2d}^w)$$

4.4 Estimation

By running regression on the labor market outcomes of mothers and fathers separately, we are able to estimate the child penalty from the dataset. The outcomes are selected to be the employment rate and yearly income for those who are employed. The estimated parameter in the regression table lag_d represents $\hat{\beta}_{jd}^g - \hat{\beta}_{j-1}^g$, shows the child penalty at event time d relative to the year before the first childbirth (D = -1). Since the panel is unbalanced, with missing entries in different years for each individual, to check the robustness, I also controlled for the province fixed effect, urban/rural effect and education level. The result with controls in Appendix C shows similar pattern.

4.4.1 Employment Rate

Following Kleven, Landais, & Søgaard (2019), I begin with estimating the long-run effect of the child effect in one birth family with an event window of $\{-5,10\}$. From Figure 1a, the employment rate for fathers remains stable after the childbirth while the employment rate for mothers has a sharp drop at the year of birth and then gradually increases and recovers to the pre-birth level starting from the fourth year after the childbirth. The childbirth has very minor effect on the fathers, and generates large effect on mothers employment rate within the first three years after birth. To verify that the short-run effect are concentrated on the first three years after birth, I adjusted the event window to $\{-2,4\}$ and re-estimated the child effect. Table A3 shows that the fertility has statistically significant effects in the first three years after birth for the mothers.

To compare the child effect in two births family between fathers and mothers and between the first birth and second birth, I continued with the short-run event window

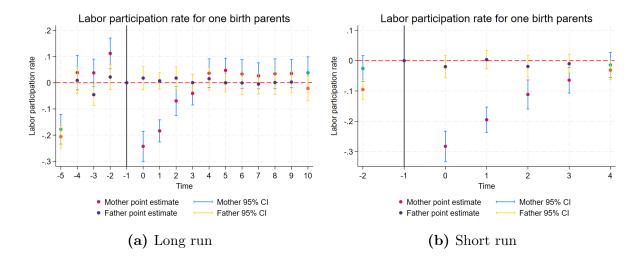


Figure 1: Employment rate in one birth family

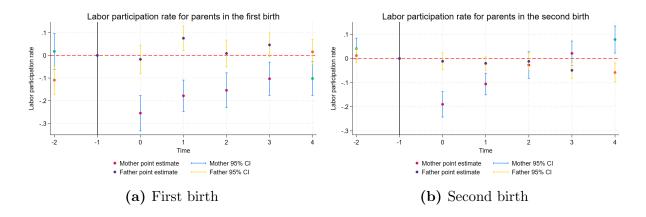


Figure 2: Employment rate in two births family: difference between fathers and mothers

{-2,4} to reduce the overlapping effect of the two births.

Figure 2 compares the difference of child effect between father and mothers in each birth. Similar to the result from one birth family, in two births family, the childbirths only have minor effect on fathers' employment rate but cause mothers' employment rate to drop sharply. The gap between the relative (to year before birth) level of fathers and mothers is smaller in the second birth, and the gap exists for more than four years in the first birth but vanishes and becomes negative two years after the birth, showing there is a diminishing marginal child penalty for women's employment rate in short-run.

Figure 3a suggests that fathers after the second birth tend to have small decrease in employment rate relative to the first birth. From Figure 3b we can observe a strong pattern that the decrease in employment rate due to fertility is much smaller in the second birth than the first birth. Table A4 provides statistical evidence for this finding.

Bearing more children requires parents to accumulate more wealth for the family and future child education investment. This creates a trade-off for the family between higher

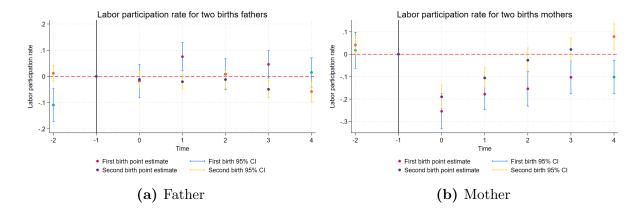


Figure 3: Employment rate in two births family: difference between two births

income and higher needs for childcare. Therefore, fathers in the two births family might need to spend more time in home production after the second birth and thus reduce the employment rate, especially when the father is the one that has lower salary in the family. Research (Posadas & Vidal-Fernandez, 2013) shows that the availability of grandparental childcare significantly increases mothers' labor force participation, which specifically explains China's extraordinarily high female labor market participation rate and low wage penalty (Yu et al., 2023). Additionally, the experience gained from raising the first child shortens the childcare learning curve for the second child and reduces the need for mothers to stay at home solely to care for their babies. With potential childcare from the fathers and grandparents, mothers are more likely to return to the labor market after the second birth.

4.4.2 Yearly Income

Wage is another important labor market outcome that serves as a proxy to demonstrate the child penalty. The discussion in Section 4.4.1 suggests potential incentive for two births parents to join the labor market and have higher family income to finance the second child. Therefore, measuring the income penalty is also necessary to quantify the child penalty and rationalize the change in the employment rate. I only included observations whose employment status is stated as "Employed" to evaluate their yearly income. I also excluded the outliers that either has income lower than 10 percentile or higher than 90 percentile by gender in each year.

To be consistent with 4.4.1, I use {-5, 10} as the event window to measure the long-run effect. Figure 4a shows there is an increasing trend in the yearly income of the fathers after childbirth. Mothers yearly income decreases in the year of childbirth and one year after the birth, in which they take the maternity leave that leads to reduction in salary, and

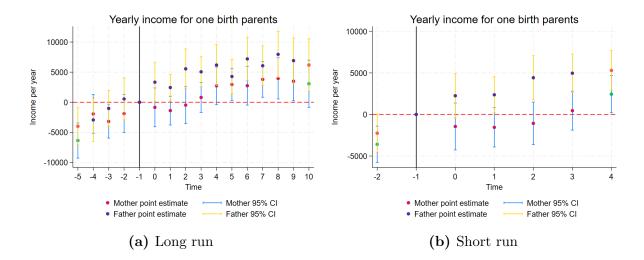


Figure 4: Yearly income in one birth family

then increases in the following years. There also exists an increasing pre-trend in yearly income before the birth, for both fathers and mothers. Parents might decide to have a child when they think they are able to afford all the cost to raise a child, which should be supported by their own career development. The yearly income for both mothers and fathers tend to be stable from six years after childbirth, in which the child starts to go to primary school and require less parental leave. The gap between relative income for fathers and mothers is larger in the first three years after birth, then tends to be smaller later. Although the income gap persists in the long-run, we can still apply the short-run event window $\{-2,4\}$ to estimate the child penalty coefficients during the period that has the most significant effect.

Similar to 4.4.1, I also use the short-run event window to estimate the difference of the child effect on yearly income between fathers and mothers in each birth, and between the first birth and the second birth.

Figure 5 illustrates very different pattern between male and female in the two births. Two births family still faces positive gender wage gap (fathers has relatively higher income than mothers compared to the year before the first birth) in period after the first birth. However, we can observe a strong pattern from the period after the second birth that there is a negative gender wage gap in the family of two births. As a result, the marginal child penalty on income also decreases from the first penalty. Fathers' income change after the two births, as shown in Figure 6a, supports our hypothesis that father might take more responsibility in childcare after the second childbirth, especially for those lower-paid fathers. We cannot directly infer the causality relationship from the data that whether low-paid fathers specialize more in the home production and childcare, or due to more

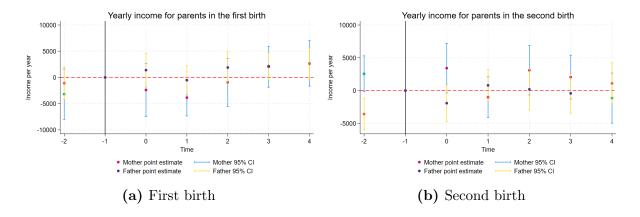


Figure 5: Yearly income in two births family: difference between fathers and mothers

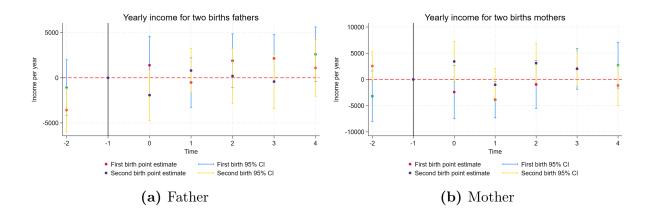


Figure 6: Yearly income in two births family: difference between two births

"faternity" leave, their wage decreases. On the mothers' side, Figure 6b demonstrates a reverse comparison relationship to the fathers. Mothers' income relatively increases from the year before the second birth, but decreases from the year before the first childbirth. It does not show that women can gain from having a second child, but it could be explained by "self-selection". The yearly income calculation only uses data from employed mothers. Mothers with low salary might decide to quit the labor market after the second birth and focus on family production which is more highly demanded in a two births family; mothers with very-low salary might even quit the labor market after the first childbirth. As a result, the yearly income for mothers after the second births concludes from "self-selected" high-paid mothers and should be higher than the base year where some low-wage mothers have not quit the market. This "self-selection" also can help to explain the diminishing marginal penalty on employment rate for mothers with two births.

4.5 Diminishing Marginal Child Penalty in Two Births Family

The child penalty refers to the disparity in the effect of childbirth on labor market outcomes between fathers and mothers. The marginal child penalty is the child penalty generated from the second childbirth. Section 4.4.1 and Section 4.4.2 provides evidence that supports the marginal (second) child penalty is smaller than the first child penalty, with respect to the employment rate and yearly income for employed parents.

This phenomenon is concluded from the observed data, however, the diminishing marginal child penalty does not indicate that women are suffering from a smaller cost of having an extra child. Moreover, it should be a result from a mixture of effects.

On one hand, the mechanism of the child penalty is mainly focus on human capital accumulation. Women who take maternal leave or quit the labor market for a long time will be discriminated by employers, obtain a lower wage as a consequence. Therefore, having a second child might even generates a higher cost for women in their labor market outcomes. On the other hand, women might have better ability in work-family time management and have more incentives to overcome the barrier from the second child cost on their labor market outcomes. Women may gain experience of pregnancy and childcare from giving birth to the first child, which saves their time to learn how to be a good mother, and allow them to allocate less time in family and go back to work sooner. Although raising an extra child increases the demand for time in home production, including housework and time to spend with children, it also requires more money for child investment, which become incentives to motivate mothers to participate in the labor market. With supports from faternal or grandparental childcare, high-paid mothers might incentivize themselves to go back to labor market, even if they are facing a larger jobsearch friction due to gender discrimination and break of human capital accumulation, which is hard to measure from the data. When this "self-selection" pattern overrides the larger cost of having an extra child, the marginal (second) child penalty would appear to be diminishing.

5 Fertility Choice of the Second Child

Under the contemporary China's context, the implementation of the two-child policy in late 2015 provides opportunities for more general households to make choices on whether to have a second child or not. Specifically, with Chinese traditional culture norms, fer-

tility choice of the second child will be more complicated, other than only consider the consumption and expected utility return of having a second child. Studying the fertility preference will also have implication on findings related to labor market outcomes, can be even expanded to a more global context.

5.1 Social Norms and policy

China has a male-preference social norm that leads to skewed sex ratio compared to more developed countries with equal gender preference (Sen, 2017). The gender preference originated from the plough agriculture (Alesina et al., 2013) and extended to a traditional gender role in which male should specialize in working while female should focus on home production. The traditional gender role also shifts parents' belief and expectation on children, influences their decision on child investment and education for different gender(Tungodden & Willén, 2023). With patrilineal system in ancient China, traditional Chinese family emphasizes the male line of descent, which prioritizes the eldest male in the family (Arnold & Zhaoxiang, 1992; Hu & Scott, 2016). In contemporary China, many family still believes that only male could continue the family lineage while married women are just the property of their husbands' families (Baker, 1979).

In 1979, China introduced one-child policy to curb the population growth, resulting in most contemporary Chinese family only have one child in the family. The sex ratio at birth started to rise after the implementation of one-child policy, and the skewed sex ratio intensified in late 1980s, when diagnostic ultrasound for sex determination became available (Yi et al., 1993). Due to lack of well-established law been enforced, even though sex determination before birth is illegal, many female babies were aborted because doctors secretly revealed sex of babies to parents. The one-child policy even increased the abortion for female babies, compared to countries with no restriction on children number limit, which already shows a sex-selective abortion patter (Dimri et al., 2024). Policy change that benefits males even exacerbate the biased sex ratio (Almond et al., 2019). The introduction of two-child policy might can reduce the abortion rate of female babies by allowing parents to have their preferred number of children, and lead to a more normal sex ratio (Zeng & Hesketh, 2016). However, since the young generation prefer a more relaxed life style, having two or more children might not be preferred (Chen et al., 2023; Zhang et al., 2022). Therefore, the two child policy might be more beneficial for those who already have a girl and still want to have a boy. Under this incentive, the sex ratio might be even more skewed.

Some other developing countries also show son-preferred cultural norm (Barcellos et al., 2014; Bhalotra et al., 2019). Even in developed countries like the United States, preference of son over daughters still exists and significantly affects the marriage outcomes (Bedard & Deschenes, 2005; Dahl & Moretti, 2008).

5.2 Theoretical Framework

Previous family decision of fertility choice models focus on the consumption in children, utility gain from having children, and expected return from child investment, including education (G. Becker, 1960; G. S. Becker, 1974; G. S. Becker & Barro, 1988; Doepke & Kindermann, 2019). There is also a quantity-quality trade-off in the fertility choice for the family (G. S. Becker & Lewis, 1973). Having one more child usually leads to lower quality for both children. Carrer (2022) proposes a model that takes social norms into consideration and mainly focus on child care. Under boy-preferred context like China, the social norms play an important role in fertility decision. Therefore, I developed a transferutility theoretical framework that explains the mechanism of fertility choice when social norms matter, based on pioneers work.

$$\mathcal{V}_n^g(g_n) = c^g + t_l^g + f^g(n, g_n, s) + h^g(n, c_n, t_n)$$

Denote n as the number of child (we will only consider $n \in \{0, 1, 2\}$ for this model to make decision on second child), $g \in \{f, m\}$ where f for female and m for male. c^g is the consumption for private goods that individual spends on his/her own, c_n is the consumption on n children investment, including the public goods in the family. t_l^g denotes the leisure time for individual g, while t_n denotes the total time to spend with n children. $f^g(\cdot)$ is an individual-specific social norm utility function, that is determined by number of children n, a vector g_n that takes gender of n children, and local social norm s, may vary by mother and father in the family. $h^g(\cdot)$ denotes the children return utility, that depends on number of children n, parents' total money spent on children c_n and parents' total time spent with children t_n , also may be different for each side of parents.

Assume each individual earns y_n^g per unit time from work after having n children and works t_w^g unit time per day (time for one day is 1). Women are suffering from motherhood penalty, while childbirth does not have much effect on father's income, there even exist a small "fatherhood premium" in fathers' income (Angrist & Evans, 1996). Women are discriminated by employers when they take or potentially will take maternal leave.

Assumption 1: $y_0^f > y_1^f > y_2^f$ and $y_0^m = y_1^m = y_2^m$ control for everything other than

number of children (including age, work experience, education, etc.).

Having more children requires extra money in child investment and more time to spend on childcare. However, since two children can share some public goods like clothes and stationery, parents can take care of the two children at the same time, the increase in money and time cost after having a second child should be diminishing.

Assumption 2:
$$\frac{\partial c_n}{\partial n} > 0$$
, $\frac{\partial t_n}{\partial n} > 0$; $\frac{\partial c_n^2}{\partial^2 n} < 0$, $\frac{\partial t_n^2}{\partial^2 n} < 0$

Denote $n^m = \sum_n \mathbb{1}(g_i = m)$ be the number of boys in the family. Under a high sex ratio context, when there are boys in the family, the parents will increase their child investment to improve their son's relative attractiveness for marriage (Wei & Zhang, 2011).

Assumption 3:
$$\frac{\partial c_n}{\partial n^m} > 0$$

The quantity-quality trade-off is a significant factor to be considered in a family. Research (Blake, 1981) shows that children with siblings tend to have worse results in college plans. Although money for child investment and time for childcare both contributes to the quality of children, they might play different roles in child development. (Del Boca et al., 2014) found that both parents' time inputs are important for the cognitive development of their children while money expenditures are less productive in terms of producing child quality.

The social norms utility term mainly reflects the gender preference, it can change by race, ethnic group, area, country, etc. For example, under China's cultural norms context, having one boy is preferred than no boys in the family, but having more than one boy does not generate large marginal utility return from the social norms. For each household, the objective function is to maximize the household utility under a bargaining model assumption, subject to the budget and time constraints.

$$\max_{n,y^f,y^m,t_w^f,t_w^m,c_n,t_n} \mathcal{U}_n(g_n) = \mathcal{V}_n^f(g_n) \cdot \mathcal{V}_n^m(g_n)$$
s.t. $c^f + c^m + c_n \le y^f \cdot t_w^f + y^m \cdot t_w^m$ and
$$t_l^f + t_l^m + t_n \le 1 - t_w^f + 1 - t_w^m$$

Since there can be utility-transfer in this bargaining model, individual will evaluate how many weight each part has in his/her own utility function, and then maximize the family utility by transferring utility, depends on bargaining power. As discussed in Section 3.3, fathers are willing to have more children and more boys than mothers in China, showing fathers tend to treat the social norms utility or the children return utility as more important. Therefore, to compensate the mother and persuade the mother to give

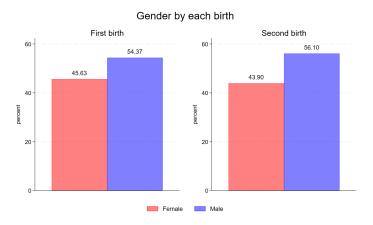


Figure 7: Share of female and male babies in each birth

another birth, the father needs to transfer utility to mothers, either in terms of money, or leisure time.

For a family with one child, when they are making decision on to have a second child or not, we assume the parents cannot decide the gender of the second child (by abortion, for example). Then they are making decision based on the current utility of having one child and expected utility of having two children with the gender of the second one unknown. They decide to have a second child when $\mathbf{E}_{g_2}(\mathcal{U}_2(g_2)) \geq \mathcal{U}_1(g_1)$. Given current son-preferred social norms, $\mathbf{E}_{g_2}(\mathcal{U}_2(\{f,unknown\})) \geq \mathcal{U}_1(\{f\})$ is more likely to happen than $\mathbf{E}_{g_2}(\mathcal{U}_2(\{m,unknown\})) \geq \mathcal{U}_1(\{m\})$.

5.3 Evidence From Data

The CFPS data shows the skewed sex ratio at birth and gender-selected fertility choice in China. In 2020, the population sex ratio (male over female) in China is 1.06³. To simplify the result for interpretation, I excluded family with twins in the first birth or the second birth, and calculated the sex ratio at birth from the dataset, as shown in Figure 7. For family with children born between 2001-2022, the sex ratio at birth of the first child is 1.19 (include both one birth family and two births family), and the sex ratio for the second child is 1.28 (only include two births family). It shows the gender-selected abortion still exists even with the implementation of two-child policy, and it might be more common for family that strongly want boys to abort girl baby in the second pregnancy. The fertility choice of having a second child also reflects the cultural norm. Figure 8a shows family with first-born girl are more likely to have a second child than family with first-born boy. The sex ratio at birth for the second child conditioned on the gender of the first child is

³Main Data of the Seventh National Population Census, https://www.stats.gov.cn/english/ PressRelease/202105/t20210510_1817185.html

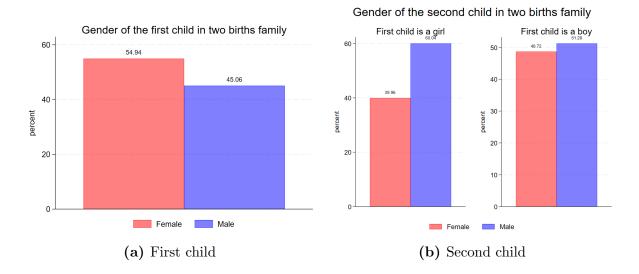


Figure 8: Gender of each child in two births family

more intuitive to show the preference for boys, as shown in 8b. When the first child is a girl, the sex ratio of the second child is as high as 1.50. When the first child is a boy, the sex ratio of the second child is 1.05, comparable to the population sex ratio.

6 Limitation and future research

The CFPS provides a national-wide longitudinal data and constructs weights to adjust for sampling design and survey nonresponses, which allow the survey sample to represent China's population characteristics (Xie & Lu, 2015). However, since some respondents moved from the 25 originally covered province to other provinces, the CFPS lacks a good official benchmark of the new provinces' current population size. Started from 2018, CFPS converted from the population weights to normalized weights, which is derived by dividing the population version of weight variable by its mean⁴. The change of weighting creates difficulty to apply the panel data to represent the whole population across time. Although the CFPS was designed to track same households behavior across time, many respondents quit from the research or join the survey in the middle. This makes the data source low quality and generates an unbalanced panel. The mothers and fathers dataset I created for analysis from this source is hereby unbalanced. Some observations even only have one or two years of entries for income and employment.

Since parenthood is closely linked to the marriage (Kleven et al., 2024), adding marriage status into analysis is also significant to serve as a control to estimate the actual child

⁴User Guide for China Family Panel Studies 2018, https://www.isss.pku.edu.cn/cfps/docs/20220302153921616729.pdf

penalty. Since the marriage status reported in 2010-2014 database has many missing values for mothers and fathers we selected, I did not include the marriage status in this research. To further study the "self-selection" speculation, we need to match the father and the mother from one household, and evaluate the choice they make before and after childbirth. Specifically, for two births family, after the second childbirth, whether the family income increase or not; and if either one of the mother or father quits the labor market to specialize in home production, is it because the other partner has a relatively higher salary. Working hours per week and time spent with children per week should also be considered as another proxy to estimate the child penalty, and quantify the trade-off between working in the market or focus on childcare and home production.

Additionally, China has implemented three-child policy in 2021, since the fertility rate was only 10.94‰, decreased by 1.49‰and 2.01‰from 2017 and 2016 respectively⁵, and continued to decrease after 2018. We will be able to estimate the third child policy and examine if there still exist a diminishing marginal child penalty on women's labor market outcomes using data in three births family. Moreover, the sex ratio at birth for the third child⁶ has reached 1.329 for male over female. The consideration of social norm in the fertility choice model should have a even higher weight that contributes to the family utility. By tuning the weighting parameter in the fertility choice model, we will be able to simulate the fertility behavior in different cultural context.

7 Conclusion

Child penalty largely contributes to gender wage gap. Previous research about how child penalty affects women's labor market outcomes focused on the long-run effect (results in lasting gap between men and women), estimated the average effect varied by number of children, or only estimated the effect of the first childbirth. My research applied event study approach, estimated the different effect of the first and second child penalty in short-run, by using China Family Panel Studies dataset. The results show that there exists a diminishing marginal child penalty on employment rate and yearly income, the gap between fathers and mothers is actually smaller in the second childbirth relative to the first childbirth. This phenomenon could be explained by a speculation of "self-selection" in a certain type of family, where high-paid mothers keep working in the labor

⁵National Bureau of Statistics of China, https://www.stats.gov.cn/sj/ndsj/2019/indexeh.htm

⁶China Population Census Year Book 2020, https://www.stats.gov.cn/sj/pcsj/rkpc/7rp/indexch.htm

market while the fathers and grandparents help with childcare and home-production. I also explained the fertility choice of having a second child under the contemporary China context, with male-preference cultural norm that matters in the fertility decision, assisting with a theoretical framework. My study of marginal child penalty and how it alters women's labor market outcomes could be extended to a more global context, varying by different cultural norms, and provide implication on policy design that could encourage more women to participate in the labor market while keeping the population growth.

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Appendix A Descriptive statistics detail

Table A1: Mothers' Descriptive Statistics Detail

Table A1. Width	ICIS	DCSCI	трыч	Duau	150105	DCta.	11	
Employment status	2010	2012	2014	2016	Year 2018	2020	2022	Total
Unemployed Percent	50.61	1.77	1.80	1.65	1.27	1.50	1.57	7.20
Frequency Employed Percent	(1,939) 49.39	(90) 62.00	(89) 73.64	(90) 74.72	(69) 77.52	(67) 77.73	(67) 78.33	(2,411) 71.04
Frequency Out of labor market	(1,892)	(3,160)	(3,635)	(4,084)	(4,207)	(3,473)	(3,332)	(23,783)
Percent Frequency Total		36.24 (1,847)	(1,212)	$^{23.64}_{(1,292)}$	(1,151)	20.77 (928)	20.10 (855)	(7,285)
Percent Frequency	100.00 (3,831)	(5,097)	(4,936)	100.00 $(5,466)$	100.00 $(5,427)$	100.00 $(4,468)$	100.00 $(4,254)$	(33,479)
Unemployment reason Do not need/want to work Percent	14.76	5.87	2.65	1.66	1.89	1.37	1.34	3.98
Frequency Housework	(146)	(42)	(33)	(22)	(22)	(13)	(12)	(290)
Percent Frequency Retired	80.49 (796)	61.59 (441)	85.07 (1,060)	84.88 (1,128)	89.86 (1,046)	88.51 (840)	85.38 (765)	83.36 (6,076)
Percent Frequency	0.20 (2)	0.56 (4)	0.32 (4)	0.38 (5)	0.26 (3)	0.63 (6)	0.89 (8)	(32)
Too old and feeble (mainly refer to elderly farmers) Percent Frequency	0.91 (9)	0.14 (1)	0.24 (3)	0.38 (5)	0.43 (5)	0.42 (4)	1.45 (13)	0.55 (40)
No working capacity due to disability/illness Percent	2.73	4.05	2.41	2.93	3.52	2.74	4.24	3.16
Frequency Cannot find a suitable job Percent	(27)	(29) 26.68	(30) 8.51	(39) 9.18	(41) 3.87	(26) 4.11	(38) 4.02	(230) 7.39
Frequency Attending school or training Percent	0.91	(191) 1.12	(106) 0.80	(122) 0.60	(45) 0.17	(39) 0.21	(36) 0.11	(539) 0.55
Frequency Covid-19 pandemic	(9)	(8)	(10)	(8)	(2)	(2)	(1)	(40)
Percent Frequency Total						2.00 (19)	2.57 (23)	(42)
Percent Frequency	100.00 (989)	100.00 (716)	100.00 $(1,246)$	100.00 $(1,329)$	100.00 $(1,164)$	100.00 (949)	100.00 (896)	100.00 (7,289)
Leaving job reason Employer Bankruptcy close dismiss Percent			2.81	4.61	3.29	3.20	4.31	3.68
Frequency Lay off			(13) 0.65	(29) 0.32	(20)	(16) 0.20	(19) 0.68	(97) 0.45
Percent Frequency Fired			(3)	(2)	(3)	(1)	(3)	(12)
Percent Frequency End of contract			0.43 (2)	0.64 (4)	0.16 (1)	0.20 (1)	0.23 (1)	0.34 (9)
Percent Frequency			2.38 (11)	0.95 (6)	0.82 (5)	1.40 (7)	0.23 (1)	1.14 (30)
End of seasonal or temporary job Percent Frequency			3.90 (18)	2.86 (18)	2.64 (16)	2.40 (12)	3.85 (17)	3.07 (81)
Maternal or other family reasons Percent			66.23	80.29	84.18	80.00	70.98	77.11
Frequency To look for another job Percent			(306) 4.55	(505) 5.41	(511) 2.80	(400) 1.00	(313) 2.04	(2,035)
Frequency Accept another job			(21) 0.65	(34) 0.64	(17) 0.16	(5)	(9) 0.23	(86) 0.34
Percent Frequency Back to school			(3)	(4)	(1)		(1)	(9)
Percent Frequency Retire			1.08 (5)	0.32 (2)	0.33 (2)	0.20 (1)	0.23 (1)	0.42 (11)
Percent Frequency			0.43 (2)	0.16 (1)	0.16 (1)	0.60 (3)	0.68	0.38 (10)
Illness or disable Percent Frequency			16.88 (78)	3.82 (24)	4.94 (30)	4.80 (24)	9.07 (40)	7.43 (196)
Covid-19 pandemic Percent			(10)	()	(44)	6.00	7.48	2.39
Frequency Total Percent			100.00	100.00	100.00	(30) 100.00	(33) 100.00	(63) 100.00
Frequency Best education level			(462)	(629)	(607)	(500)	(441)	(2,639)
Illiterate/Semi-literate Percent Frequency	17.20 (689)	16.46 (835)	12.89 (683)	14.95 (830)	13.25 (738)	10.10 (460)	10.45 (455)	13.63 (4,690)
Primary school Percent Frequency	22.44 (899)	22.78 (1,156)	22.54 (1,194)	21.33 (1,184)	16.79 (935)	13.63 (621)	15.49 (674)	19.36 (6.663)
Junior high school Percent	35.30	33.43	34.65	32.67	34.52	36.55	35.32	34.54
Frequency Senior high school/technical school Percent	(1,414) 14.78	(1,696) 15.55	(1,836) 15.59	(1,814) 14.72	(1,923) 16.16	(1,665) 17.60	(1,537) 15.30	(11,885)
Frequency 3-year college	(592)	(789)	(826)	(817)	(900)	(802)	(666)	(5,392)
Percent Frequency 4-year college	6.07 (243)	7.11 (361)	8.32 (441)	9.28 (515)	10.45 (582)	10.89 (496)	11.35 (494)	9.10 $(3,132)$
Percent Frequency	4.04 (162)	4.39 (223)	5.64 (299)	6.45 (358)	8.20 (457)	10.40 (474)	11.19 (487)	7.15 $(2,460)$
Master's degree Percent Frequency	0.17 (7)	0.28 (14)	0.36 (19)	0.61 (34)	0.63 (35)	0.83 (38)	0.87 (38)	0.54 (185)
Doctoral degree Percent	(.)	. 7	(-/	(- 7	()	()	0.02	0.00
Frequency Total Percent	100.00	100.00	100.00	100.00	100.00	100.00	(1) 100.00	(1)
Frequency Years of education Mean	(4,006) 8.30	(5,074)	(5,298) 8.85	(5,552) 9.14	(5,570) 9.26	(4,556) 9.87	(4,352) 9.81	(34,408) 9.19
Ideal number of kids Mean	0.30		1.94	9.14	1.95	9.01	1.95	1.95
Ideal number of boys Mean Income					1.03		1.03	1.03
Mean	7515.10	9036.17	12608.90	18896.54	34552.78	38596.25	44878.23	20388.59

 ${\bf Table~A2:~Fathers'~Descriptive~Statistics~Detail}$

Table A2. Tab	11015	DCSCII	porve	Duan	BUICS	DCtai.	L	
Employment status	2010	2012	2014	2016 Y	ear 2018	2020	2022	Total
Unemployed Percent	32.00	1.39	1.57	1.12	0.89	0.63	1.08	4.50
Frequency Employed	(1,137)	(73)	(76)	(59)	(47)	(27)	(44)	(1,463)
Percent Frequency Out of labor market	68.00 (2,416)	77.65 $(4,078)$	94.07 $(4,550)$	94.94 (4,992)	96.15 (5,065)	96.76 $(4,119)$	96.57 (3,919)	89.71 (29,139)
Percent Frequency		20.96 (1,101)	4.36 (211)	3.94 (207)	2.96 (156)	2.61 (111)	2.34 (95)	5.79 (1,881)
Total Percent	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Frequency Unemployment reason	(3,553)	(5,252)	(4,837)	(5,258)	(5,268)	(4,257)	(4,058)	(32,483)
Do not need/want to work Percent	33.24	5.88	7.00	5.58	7.83	7.27	2.42	12.71
Frequency Housework	(119)	(15)	(17)	(12)	(13)	(8)	(3)	(187)
Percent Frequency Retired	47.49 (170)	8.63 (22)	16.05 (39)	15.35 (33)	29.52 (49)	18.18 (20)	18.55 (23)	24.20 (356)
Percent Frequency			1.23 (3)			3.64 (4)	2.42 (3)	0.68 (10)
Too old and feeble (mainly refer to elderly farmers Percent	4.19	1.18	1.65	1.40	5.42	3.64	6.45	3.13
Frequency No working capacity due to disability/illness	(15)	(3)	(4)	(3)	(9)	(4)	(8)	(46)
Percent Frequency	9.22 (33)	12.16 (31)	13.58 (33)	20.00 (43)	16.27 (27)	20.91 (23)	13.71 (17)	14.07 (207)
Cannot find a suitable job Percent		70.98	57.61	56.74	39.16	29.09	27.42	39.02
Frequency Attending school or training	E 07	(181) 1.18	(140) 2.88	(122) 0.93	(65) 1.81	(32) 0.91	(34)	(574) 2.52
Percent Frequency Covid-19 pandemic	5.87 (21)	(3)	(7)	(2)	(3)	(1)		(37)
Percent Frequency						16.36 (18)	29.03 (36)	3.67 (54)
Total Percent	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Frequency Leaving job reason	(358)	(255)	(243)	(215)	(166)	(110)	(124)	(1,471)
Employer Bankruptcy close dismiss Percent			7.30	11.61	6.48	2.78	3.90	7.29
Frequency Lay off Percent			(10) 0.73	(18) 4.52	(7) 1.85	(2) 2.78	(3) 2.60	(40) 2.55
Frequency Fired			(1)	(7)	(2)	(2)	(2)	(14)
Percent Frequency			0.73 (1)	1.29 (2)	0.93 (1)	1.39 (1)		0.91 (5)
End of contract Percent			4.38	1.29	5.56	1.39	2.60	3.10
Frequency End of seasonal or temporary job			(6)	(2)	(6)	(1)	(2)	(17)
Percent Frequency Maternal or other family reasons			13.87 (19)	20.65 (32)	23.15 (25)	13.89 (10)	12.99 (10)	17.49 (96)
Percent Frequency			9.49 (13)	16.13 (25)	22.22 (24)	19.44 (14)	19.48 (15)	16.58 (91)
To look for another job Percent			23.36	22.58	16.67	9.72	11.69	18.40
Frequency Accept another job			(32)	(35)	(18)	(7)	(9)	(101)
Percent Frequency			2.19 (3)	1.94 (3)			1.30 (1)	1.28 (7)
Back to school Percent Frequency			2.92 (4)	1.29 (2)	0.93 (1)			1.28 (7)
Retire Percent			(1)	0.65	0.93	2.78	2.60	1.09
Frequency Illness or disable				(1)	(1)	(2)	(2)	(6)
Percent Frequency			35.04 (48)	18.06 (28)	(23)	23.61 (17)	(10)	$\frac{22.95}{(126)}$
Covid-19 pandemic Percent Frequency						22.22 (16)	29.87 (23)	7.10 (39)
Total Percent			100.00	100.00	100.00	100.00	100.00	100.00
Frequency Best education level			(137)	(155)	(108)	(72)	(77)	(549)
Illiterate/Semi-literate Percent	10.71	10.36	8.64	9.84	7.95	6.18	6.01	8.59
Frequency Primary school	(394)	(544)	(467)	(535)	(423)	(265)	(247)	(2,875)
Percent Frequency Junior high school	21.79 (802)	(1,237)	(1,293)	(1,264)	18.07 (961)	15.24 (653)	16.91 (695)	(6,905)
Percent Frequency	38.10 (1,402)	36.63 (1,923)	36.50 (1,973)	34.79 (1,891)	37.36 (1,987)	37.31 (1,599)	36.58 (1,503)	36.67 (12,278)
Senior high school/technical school Percent	18.10	16.84	16.44	15.99	18.18	19.74	18.20	17.53
Frequency 3-year college	(666)	(884)	(889)	(869)	(967)	(846)	(748)	(5,869)
Percent Frequency	6.63 (244)	7.56 (397)	8.42 (455)	8.92 (485)	10.00 (532)	(475)	(462)	9.11 (3,050)
4-year college Percent	4.32	4.70	5.59	6.31	7.71	9.47	10.05	6.81
Frequency Master's degree Percent	(159) 0.35	(247) 0.34	(302)	(343)	(410) 0.68	(406) 0.89	(413)	(2,280)
Frequency Doctoral degree	(13)	(18)	(27)	(46)	(36)	(38)	(37)	(215)
Percent Frequency				0.04 (2)	0.04 (2)	0.09 (4)	0.10 (4)	0.04 (12)
Total Percent	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Frequency Years of education	(3,680)	(5,250)	(5,406)	(5,435)	(5,318)	(4,286)	(4,109)	(33,484)
Mean Ideal number of kids Mean	9.11		9.41 1.98	9.63	9.84 2.00	10.21	10.17 2.02	9.72 2.00
Ideal number of boys Mean					1.10		1.11	1.11
Income Mean	17043.94	20803.04	21828.30	31785.83	50886.71	59467.92	70190.89	36010.51

Appendix B Event study regression table

Table A3: Child effect on employment rate in one birth family

	510_mother	510_father	24_mother	24_father
	b/se	b/se	b/se	b/se
Year=2010	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Year=2012	0.144^{***}	0.107***	0.154***	0.109***
	(0.022)	(0.013)	(0.022)	(0.013)
Year=2014	0.234***	0.213***	0.259***	0.221***
	(0.040)	(0.020)	(0.039)	(0.019)
Year=2016	0.240***	0.210***	0.272***	0.219***
** 0010	(0.059)	(0.028)	(0.057)	(0.026)
Year=2018	0.257***	0.211***	0.293***	0.220***
3 7 0000	(0.078)	(0.036)	(0.076)	(0.034)
Year=2020	0.233*	0.203***	0.273**	0.210***
Year=2022	(0.097)	$(0.044) \\ 0.191***$	(0.095)	(0.041)
rear=2022	0.226		0.268*	0.195***
0.00	$(0.116) \\ 0.002$	(0.052)	$\begin{pmatrix} 0.113 \\ 0.002 \end{pmatrix}$	$(0.049) \\ 0.006$
age	(0.002)	0.006 (0.004)	(0.002)	(0.004)
lead5	-0.178***	-0.206***	(0.009)	(0.004)
leado	(0.029)	(0.022)		
lead4	0.039	0.009		
read r	(0.034)	(0.026)		
lead3	0.038	-0.046*		
10000	(0.027)	(0.021)		
lead2	0.112***	0.022'	-0.026	-0.095***
	(0.030)	(0.024)	(0.022)	(0.017)
lag0	-Ò.243***	[0.018]	-0.283***	-0.020
	(0.029)	(0.022)	(0.025)	(0.019)
lag1	-0.184***	[0.007]	-0.195* [*] *	[0.003]
	(0.022)	(0.016)	(0.021)	(0.016)
lag2	-0.069*	0.018	-0.112***	-0.019
	(0.029)	(0.022)	(0.024)	(0.018)
lag3	-0.041	0.000	-0.064**	-0.010
1 4	(0.022)	(0.017)	(0.022)	(0.016)
lag4	0.036	0.015	-0.014	-0.031
1	$(0.028) \\ 0.047^*$	(0.022)	(0.021)	(0.016)
lag5	2 7 1 1	-0.000		
10.006	$(0.024) \\ 0.034$	(0.018) -0.001		
lag6	(0.028)	(0.022)		
lag7	0.026	-0.005		
agı	(0.025)	(0.020)		
lag8	0.034	0.001		
ago	(0.029)	(0.023)		
lag9	0.035	0.003		
14450	(0.028)	(0.021)		
lag10	0.038	-0.021		
	(0.031)	(0.024)		
Constant	0.478	0.515***	0.505	0.527***
	(0.275)	(0.127)	(0.271)	(0.123)
r2 N	0.138	0.150	0.127	0.134
N	22587.000	21872.000	22587.000	21872.000

Table A4: Child effect on employment rate in two births family

	mother_first	mother_second	father_first	father_second
	b/se	b/se	b/se	b/se
Year=2010	0.000	0.000	0.000	0.000
Year=2012	(.) 0.128***	(.) 0.115***	(.) 0.097***	(.) 0.119***
1001 2012	(0.037)	(0.035)	(0.023)	(0.023)
Year=2014	0.202**	0.186**	0.264***	0.304***
1001 2011	(0.065)	(0.061)	(0.030)	(0.030)
Year=2016	0.188*	0.171	0.288***	0.345***
	(0.095)	(0.088)	(0.041)	(0.042)
Year=2018	0.186	[0.155]	0.298***	0.370***
	(0.126)	(0.118)	(0.053)	(0.054)
Year=2020	0.190	[0.133]	0.303***	0.389***
	(0.156)	(0.147)	(0.064)	(0.066)
Year=2022	[0.179]	[0.093]	0.304***	0.397***
	(0.187)	(0.176)	(0.076)	(0.078)
age	[0.015]	[0.020]	-0.002	-0.002
1 10	(0.016)	(0.014)	(0.006)	(0.006)
lead2	0.017	0.041	-0.109***	0.012
	(0.041)	(0.022)	(0.032)	(0.015)
lag0	-0.255***	-0.190***	-0.018	-0.012
1 4	(0.040)	(0.027)	(0.032)	(0.018)
lag1	-0.178***	-0.106***	0.075**	-0.020
1 0	(0.035)	(0.023)	(0.028)	(0.014)
lag2	-0.154***	-0.027	0.008	-0.012
1 0	(0.039)	(0.028)	(0.030)	(0.018)
lag3	-0.103**	0.021	0.046	-0.049**
14	(0.037)	(0.026)	(0.027)	(0.017)
lag4	-0.102**	0.079**	0.015	-0.058**
Constant	(0.038)	(0.029)	(0.028)	(0.020)
Constant	(0.134) (0.367)	-0.086 (0.342)	0.730***	0.688***
ro	0.083	$\frac{(0.342)}{0.105}$	$\frac{(0.156)}{0.166}$	$\frac{(0.156)}{0.155}$
r2 N	9216.000	9216.000	8812.000	8812.000
	J=10.000	0210.000	JOI 2.000	JOI#.000

Table A5: Child effect on yearly income in one birth family

Teal					
Year=2010 0.000 0.000 0.000 0.000 Year=2012 5852.204*** 10997.900*** 5909.218*** 11044.704*** (768.447) (1005.601) (734.336) (949.339) Year=2014 9784.786*** 17603.294*** 10096.499*** 17861.459*** (1300.064) (1847.929) (1208.088) 1747.037 Year=2016 13155.943*** 24503.254*** 13605.412*** 24879.471*** (1890.137) (2753.799) (1779.384) (2621.622) 23643.247*** 32050.268*** 19021.766*** 32506.219*** (2435.162) (2357.3611) (2288.497) (3402.154) 42487.664*** Year=2020 23043.247*** 42002.247*** 23590.676*** 42487.664*** Year=2022 28787.234*** 52952.265*** 29362.209*** 33402.154) Year=2022 28787.234*** 52952.265*** 29362.209*** 34428.166** (275.092) (421.951) (276.683) (417.924) lead5 -6360.491*** -3987.512* (276.683)		510-mother	510 _father	24 _mother	24 _father
Year=2012 5852.204*** 10997.900*** 5909.218*** 11044.704*** (768.447) (1005.601) (734.336) (949.339) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.349) (949.		b/se	b/se	b/se	b/se
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Year=2014 9784.786*** (1300.064) 17603.294*** (1847.929) 10096.499*** (1208.088) 17861.459*** (1747.037) Year=2016 13155.943*** (1890.137) 24503.254*** (2753.799) 13605.412*** (1779.384) 24879.471*** (2621.622) Year=2018 18483.977*** (2435.162) 32050.268*** (3573.611) 19021.766*** (2288.497) 330506.219*** (3288.497) 33021.54) Year=2020 23043.247*** (3024.221) 42441.959) (2288.497) 3402.154) Year=2022 28787.234*** (3577.305) 52952.265*** (5300.954) 23502.09*** (3408.071) 5305.368) age -161.480 -1103.224** (1483.823) -179.521 -1108.364** (275.092) (421.951) (276.683) (417.924) lead4 -1939.548 -2938.478 (1635.340) (1813.478) lead3 -3186.916* (1608.839) (1770.285) (1114.395) (1179.524) lag0 -853.895 3335.873* (1645.057) -1440.731 2252.263 lag1 -1389.050 2442.752* (129.435) -151.050 2368.304* lag2 -480.640 5550.563** (1271.369)	Year=2012				
Year=2016 13155.943*** 24503.254*** 13605.412*** 24879.471***			(1005.601)	(734.336)	(949.339)
Year=2016 13155.943*** (1890.137) 24503.254*** 13605.412*** 24879.471*** Year=2018 18483.977*** 32050.268*** 19021.766*** 32506.219*** Year=2020 23043.247*** 42002.247*** 23590.676*** 42487.664*** Year=2022 28787.234*** 52952.265*** 29362.209*** 53455.371*** Year=2022 28787.234*** 52952.265*** 29362.209*** 53455.371*** (3577.305) (3500.954) (3408.071) (5090.368) age -161.480 -1103.224** -179.521 -1108.364** (275.092) (421.951) (276.683) (417.924) lead5 -6360.491*** -3987.512* (276.683) (417.924) lead4 -1939.548 -2938.478 (1635.340) (1813.478) (16405.67) lead3 -3186.916* -1025.608 (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) (1645.057) <t< td=""><td>Year=2014</td><td>9784.786***</td><td></td><td>10096.499***</td><td>17861.459***</td></t<>	Year=2014	9784.786***		10096.499***	17861.459***
Year=2018 18483.977*** 32050.268*** 19021.766*** 32506.219***		(1300.064)	(1847.929)	(1208.088)	
Year=2018 18483.977*** 32506.268*** 19021.766*** 32506.219*** Year=2020 23043.247*** 42002.247*** 23590.676*** 42487.664*** Year=2022 28787.234*** 52952.265*** 23590.676*** 42487.664*** age -161.480 -1103.224** 29362.209*** 53455.371*** age -161.480 -1103.224** -179.521 -1108.364** (275.092) (421.951) (276.683) (417.924) lead5 -6360.491*** -3987.512* (276.683) (417.924) lead4 -1939.548 -2938.478 (1635.340) (1813.478) lead3 -3186.916* -1025.608 (1147.622) (1521.386) lead2 -1886.051 551.364 -3588.446** -2253.088 (1608.839) (1770.285) (1114.395) (1179.524) lag0 -853.895 3335.873* -1440.731 2252.263 (1645.057) (1645.203) (1439.100) (1361.662) lag1 -1389.050 2442.752* <th< td=""><td>Year=2016</td><td>13155.943***</td><td>24503.254***</td><td></td><td></td></th<>	Year=2016	13155.943***	24503.254***		
Year=2020 23043.247*** 42002.247*** 23590.676*** 42487.664***			(2753.799)	(1779.384)	(2621.622)
Year=2020 23043.247*** 42002.247*** 23590.676*** 42487.664*** (3024.221)	Year=2018			19021.766***	
Year=2022 28787.234*** 52952.265*** 29362.209*** 53455.371*** (3577.305) (5300.954) (3408.071) (5090.368) age	** 2020			(2288.497)	
Year=2022 28787.234*** 52952.265*** 29362.209*** 53455.371*** age -161.480 -1103.224** -179.521 -1108.364** (275.092) (421.951) (276.683) (417.924) lead5 -6360.491*** -3987.512* (276.683) (417.924) lead4 -1939.548 -2938.478 (1635.340) (1813.478) lead3 -3186.916* -1025.608 (1407.622) (1521.386) lead2 -1886.051 551.364 -3588.446** -2253.088 lag0 -853.895 3335.873* -1440.731 2252.263 (1645.057) (1645.203) (1439.100) (1361.662) lag1 -1389.050 2242.752* -1551.050 2368.304* (1219.435) (1128.220) (1204.898) (1100.157) lag2 -480.640 5550.563*** -1070.844 4417.410** lag3 794.253 5053.401*** 460.229 4965.806*** (1271.369) (1275.967) (1195.256) (1181.450)	Year=2020				
age	** 2022	(3024.221)			
age	Year=2022				
lead5					
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	age				
$ \begin{array}{c} (1483.823) & (1567.405) \\ -1939.548 & -2938.478 \\ (1635.340) & (1813.478) \\ \\ lead3 & -3186.916^* & -1025.608 \\ (1407.622) & (1521.386) \\ \\ lead2 & -1886.051 & 551.364 & -3588.446^{**} & -2253.088 \\ (1608.839) & (1770.285) & (11114.395) & (1179.524) \\ lag0 & -853.895 & 3335.873^* & -1440.731 & 2252.263 \\ (1645.057) & (1645.203) & (1439.100) & (1361.662) \\ lag1 & -1389.050 & 2442.752^* & -1551.050 & 2368.304^* \\ (1219.435) & (1128.220) & (1204.898) & (1100.157) \\ lag2 & -480.640 & 5550.563^{***} & -1070.844 & 4417.410^{**} \\ (1559.158) & (1677.745) & (1306.155) & (1351.843) \\ lag3 & 794.253 & 5053.401^{***} & 460.229 & 4965.806^{***} \\ (1271.369) & (1275.967) & (1195.256) & (1181.450) \\ lag4 & 2731.279 & 6174.111^{***} & 2443.756^* & 5301.301^{***} \\ (1589.577) & (1714.443) & (1139.316) & (1216.102) \\ lag5 & 2942.491^* & 4273.693^{**} \\ (1353.262) & (1457.396) \\ lag6 & 2743.339 & 7197.736^{***} \\ (1640.552) & (1813.926) \\ lag7 & 3789.733^* & 6065.433^{***} \\ (1640.552) & (1813.926) \\ lag8 & 3964.709^* & 7954.245^{***} \\ (1744.638) & (1946.344) \\ lag9 & 3494.019^* & 6916.090^{***} \\ (1664.199) & (1911.501) \\ lag10 & 3073.427 & 6178.235^{**} \\ (1997.923) & (2218.048) \\ Constant & 16056.222^* & 48192.645^{***} & 16869.621^* & 48867.299^{***} \\ (7771.507) & (12635.873) & (7797.134) & (12496.806) \\ \end{array}$	1 15	(275.092)		(276.683)	(417.924)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lead5	-6360.491***			
$ \begin{array}{c} (1635.340) & (1813.478) \\ -3186.916^* & -1025.608 \\ (1407.622) & (1521.386) \\ 1860 & -1886.051 & 551.364 & -3588.446^{**} & -2253.088 \\ (1608.839) & (1770.285) & (1114.395) & (1179.524) \\ 1ag0 & -853.895 & 3335.873^* & -1440.731 & 2252.263 \\ (1645.057) & (1645.203) & (1439.100) & (1361.662) \\ 1ag1 & -1389.050 & 2442.752^* & -1551.050 & 2368.304^* \\ (1219.435) & (1128.220) & (1204.898) & (1100.157) \\ 1ag2 & -480.640 & 5550.563^{***} & -1070.844 & 4417.410^{**} \\ (1559.158) & (1677.745) & (1306.155) & (1351.843) \\ 1ag3 & 794.253 & 5053.401^{***} & 460.229 & 4965.806^{***} \\ (1271.369) & (1275.967) & (1195.256) & (1181.450) \\ 1ag4 & 2731.279 & 6174.111^{***} & 2443.756^* & 5301.301^{***} \\ (1589.577) & (1714.443) & (1139.316) & (1216.102) \\ 1ag5 & 2942.491^* & 4273.693^{**} \\ (1353.262) & (1457.396) \\ 1ag6 & 2743.339 & 7197.736^{***} \\ (1640.552) & (1813.926) \\ 1ag7 & 3789.733^* & 6065.433^{***} \\ (1506.714) & (1682.366) \\ 1ag8 & 3964.709^* & 7954.245^{***} \\ (1744.638) & (1946.344) \\ 1ag9 & 3494.019^* & 6916.090^{***} \\ (1664.199) & (1911.501) \\ 1ag10 & 3073.427 & 6178.235^{**} \\ (1997.923) & (2218.048) \\ Constant & 16056.222^* & 48192.645^{***} & 16869.621^* & 48867.299^{***} \\ (7771.507) & (12635.873) & (7797.134) & (12496.806) \\ \end{array}$	1 14				
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lead4				
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$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lead3				
$\begin{array}{c} (1608.839) & (1770.285) & (1114.395) & (1179.524) \\ lag0 & -853.895 & 3335.873^* & -1440.731 & 2252.263 \\ (1645.057) & (1645.203) & (1439.100) & (1361.666) \\ lag1 & -1389.050 & 2442.752^* & -1551.050 & 2368.304^* \\ (1219.435) & (1128.220) & (1204.898) & (1100.157) \\ lag2 & -480.640 & 5550.563^{***} & -1070.844 & 4417.410^{**} \\ (1559.158) & (1677.745) & (1306.155) & (1351.843) \\ lag3 & 794.253 & 5053.401^{***} & 460.229 & 4965.806^{***} \\ (1271.369) & (1275.967) & (1195.256) & (1181.450) \\ lag4 & 2731.279 & 6174.111^{***} & 2443.756^* & 5301.301^{***} \\ (1589.577) & (1714.443) & (1139.316) & (1216.102) \\ lag5 & 2942.491^* & 4273.693^{**} \\ & (1353.262) & (1457.396) \\ lag6 & 2743.339 & 7197.736^{***} \\ & (1640.552) & (1813.926) \\ lag7 & 3789.733^* & 6065.433^{***} \\ & (1506.714) & (1682.366) \\ lag8 & 3964.709^* & 7954.245^{***} \\ & (1744.638) & (1946.344) \\ lag9 & 3494.019^* & 6916.090^{***} \\ & (1664.199) & (1911.501) \\ lag10 & 3073.427 & 6178.235^{**} \\ & (1997.923) & (2218.048) \\ Constant & 16056.222^* & 48192.645^{***} & 16869.621^* & 48867.299^{***} \\ & (7771.507) & (12635.873) & (7797.134) & (12496.806) \\ \end{array}$	1. 10			2500 440**	0050 000
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$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	lag6				
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Constant (1997.923) (2218.048) 16056.222^* 48192.645^{***} 16869.621^* 48867.299^{***} (7771.507) (12635.873) (7797.134) (12496.806)	lag10				
Constant 16056.222* 48192.645*** 16869.621* 48867.299*** (7771.507) (12635.873) (7797.134) (12496.806)	100510				
(7771.507) (12635.873) (7797.134) (12496.806)	Constant		48192.645***	16869.621*	48867.299***
	COIDOMIN				
N 7567.000 9893.000 7567.000 9893.000	r2				
	N				

Table A6: Child effect on yearly income in two births family

	mother_first	mother_second	father_first	father_second
	b/se	b/se	b/se	b/se
Year=2010	0.000	0.000	0.000	0.000
Year=2012	(.) 8937.952*** (1181.951)	(.) 10025.764*** (1153.540)	(.) 10663.624*** (1061.734)	(.) 10836.103*** (1051.689)
Year=2014	13747.297***	15644.269***	14847.041***	14933.987***
1001 2011	(1766.440)	(1728.742)	(1451.805)	(1457.260)
Year=2016	19654.417***	22706.285***	20125.050***	19900.691***
	(2465.452)	(2426.267)	(2074.897)	(2129.235)
Year=2018	25443.264***	29309.202***	28040.700***	27192.963***
	(3109.419)	(3166.033)	(2500.271)	(2681.640)
Year=2020	32509.730***	37125.645***	34559.544***	33371.568***
	(3852.811)	(3956.872)	(2950.653)	(3242.298)
Year=2022	41742.805***	46757.530***	44039.148***	42547.094***
	(4537.836)	(4658.667)	(3402.884)	(3783.710)
age	-1113.112**	-1167.583**	123.688	67.431
	(367.076)	(354.690)	(255.150)	(256.409)
lead2	-888.275	1302.676	-1760.520	-2487.347*
	(2231.491)	(1224.551)	(1667.174)	(1184.628)
lag0	-2734.028	2908.521	618.537	[-672.524]
	(2245.509)	(1714.365)	(1767.421)	(1401.948)
lag1	-2351.443	-739.584	-1367.432	1476.118
	(1617.859)	(1475.523)	(1476.073)	(1205.730)
lag2	634.230	-515.112	183.970	1349.476
	(2108.135)	(1640.821)	(1626.745)	(1573.654)
lag3	1831.611	1471.763	731.275	-51.458
	(1806.166)	(1560.269)	(1466.601)	(1561.700)
lag4	[2269.939]	-487.859	1311.234	1995.632
	(2033.910)	(1675.039)	(1629.505)	(1623.629)
Constant	37030.925***	36591.104***	12956.778	16018.121*
	(8785.663)	(8471.888)	(6688.132)	(6635.147)
r2	0.453	0.450	0.543	0.544
N	2672.000	2672.000	4227.000	4227.000

Appendix C Event study results with controls (robustness check)

C.1 Employment Rate

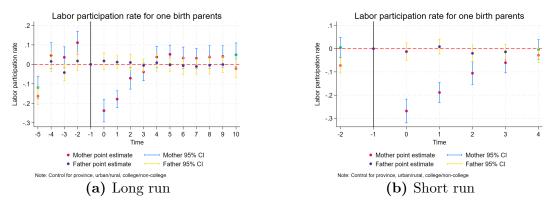


Figure A1: Employment rate in one birth family

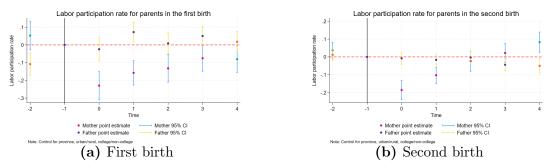


Figure A2: Employment rate in two births family: difference between fathers and mothers

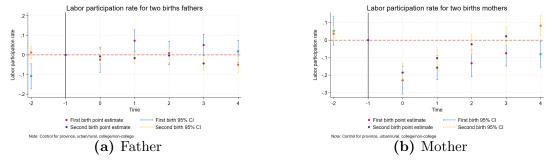


Figure A3: Employment rate in two births family: difference between two births

 $\textbf{Table A7:} \ \, \textbf{Child effect on employment rate in one birth family}$

======================================	510_mother	510_father	24_mother	24_father
Year=2010	b/se 0.000	b/se 0.000	b/se 0.000	b/se 0.000
Year=2010 Year=2012	(.)	(.) 0.107***	(.) 0.153***	(.)
	0.144*** (0.023)	(0.013)	(0.023)	0.107*** (0.013) 0.201***
Year=2014	0.227*** (0.042) 0.233***	0.197*** (0.020) 0.190***	0.249*** (0.041) 0.261***	(0.019) 0.193***
Year=2016	(0.062)	(0.027)	(0.061)	(0.026)
Year=2018	0.236** (0.082)	0.174*** (0.035)	0.268*** (0.081)	0.175*** (0.033)
Year=2020	0.216^* (0.102)	0.165*** (0.043)	0.252^* (0.101)	0.163*** (0.041)
Year=2022	(0.122)	0.152** (0.051)	0.252* (0.120)	0.147^{**} (0.049)
age	(0.001 (0.010)	$0.008* \\ (0.004)$	(0.011)	0.009* (0.004)
Beijing	0.000	0.000	0.000	0.000
Tianjin	0.013 (0.160)	$\begin{pmatrix} 0.011 \\ (0.085) \end{pmatrix}$	0.001 (0.163)	0.017 (0.085)
Hebei	-0.224*** (0.067)	(0.081)	-0.239*** (0.069)	(0.050)
Shanxi	-0.125 (0.137)	-0.118 (0.084)	-0.136 (0.138)	-0.129 (0.083)
Liaoning	-0.067 (0.087)	-0.007 (0.055)	-0.074 (0.087)	-0.011 (0.057)
Jilin	-0.025 (0.135)	-0.023 (0.134)	-0.086 (0.138)	(0.140)
Heilongjiang	-0.092 (0.144)	-0.298* (0.120)	-0.123 (0.144)	-0.308* (0.124)
Shanghai	0.110′ (0.107)	-0.032 (0.068)	0.095 (0.108)	-0.034 (0.068)
Jiangsu	0.096 (0.125)	-0.061 (0.061)	(0.099) (0.127)	-0.059 (0.061)
Zhejiang	-0.024 (0.096)	-0.031 (0.058)	-0.018 (0.096)	-0.029 (0.059)
Anhui	-0.044 (0.134)	-0.168* (0.073)	-0.051 (0.133)	-0.183* (0.072)
Fujian	-0.056 (0.142)	-0.103 (0.082)	-0.063 (0.144)	-0.108 (0.082)
Jiangxi	-0.187 (0.119)	-0.096 (0.071)	-0.212 (0.121)	-0.105 (0.071)
Shandong	0.049 (0.125)	-0.047 (0.071)	0.031 (0.126)	-0.036 (0.070)
Henan	-0.128 (0.084)	-0.170** (0.052)	-0.130 (0.085)	-0.172*** (0.052)
Hubei	-0.212* (0.102)	-0.193* (0.084)	-0.232* (0.104)	-0.193* (0.083)
Hunan	-0.132 (0.110)	0.035 (0.094)	-0.147 (0.112)	(0.035 (0.096)
Guangdong	0.060 (0.085)	-0.016 (0.057)	0.053 (0.087)	-0.020 (0.057)
Guangxi Zhuang Autonomous Region	0.175 (0.127)	-0.062 (0.088)	0.161 (0.125)	-0.068 (0.089)
Chongqing	-0.123 (0.097)	-0.373** (0.125)	-0.127 (0.097)	-0.373** (0.122)
Sichuan	-0.047 (0.137)	-0.197 (0.109)	-0.041 (0.135)	-0.204 (0.115)
Guizhou	0.087 (0.136)	-0.110 (0.079)	(0.095) (0.136)	-0.120 (0.078)
Yunnan	0.142 (0.194)	-0.088 (0.086)	0.146 (0.190)	-0.089 (0.090)
Shaanxi	-0.035 (0.118)	-0.133 (0.079)	-0.032 (0.121)	-0.145 (0.078)
Gansu	-0.104 (0.089)	-0.142* (0.056)	-0.115 (0.091)	-0.156** (0.056)
Rural	0.000	0.000	0.000	0.000
Urban	-0.005 (0.014)	0.028* (0.011)	-0.001 (0.015)	0.032** (0.011)
Non-college	0.000 (.) 0.259***	0.000	0.000	0.000
College	(0.022)	0.222*** (0.022) -0.163***	0.304*** (0.023)	0.268*** (0.023)
lead5	-0.120*** (0.029)	(0.022)		
lead4	0.046 (0.034)	$\begin{pmatrix} 0.015 \\ (0.026) \end{pmatrix}$		
lead3	0.036 (0.028)	-0.042* (0.021)	0.00*	0.080***
lead2	0.111*** (0.030)	0.017 (0.024)	0.005 (0.022)	-0.072*** (0.017)
lag0	-0.238*** (0.029)	0.018 (0.022)	-0.268*** (0.026)	-0.013 (0.019)
lag1	-0.178*** (0.022)	(0.012 (0.016)	-0.189*** (0.022)	0.009 (0.016)
lag2	-0.071* (0.029)	$\begin{pmatrix} 0.010 \\ (0.022) \\ 0.007 \end{pmatrix}$	-0.106*** (0.025)	-0.020 (0.018)
lag3	-0.039 (0.023)	-0.005 (0.017)	-0.060** (0.022)	-0.014 (0.016)
lag4	0.038 (0.028)	$\begin{pmatrix} 0.009 \\ (0.022) \\ 0.002 \end{pmatrix}$	(0.022)	-0.028 (0.016)
lag5	0.052* (0.024)	-0.003 (0.018)		
lag6	0.033 (0.028)	-0.007 (0.022)		
lag7	0.031 (0.026)	-0.010 (0.020)		
lag8	0.038 (0.029)	-0.004 (0.023)		
lag9	0.041 (0.028)	-0.001 (0.021)		
lag10	0.049 (0.031) 0.524	-0.022 (0.024)	0.546	U EU0***
Constant	0.524 (0.299) 0.149	0.511*** (0.135) 0.162	0.546 (0.297) 0.143	0.508*** (0.131) 0.153
r2 N	21929.000	21021.000	21929.000	21021.000

Table A8: Child effect on employment rate in two births family

	1 1			
	mother_first b/se	mother_second b/se	father_first b/se	father_second b/se
Year=2010	0.000	0.000	0.000	0.000
Year=2012	0.128***	0.117***	0.095***	0.116***
Year=2014	(0.037) 0.191**	(0.034) 0.176**	(0.023) 0.257***	(0.023) 0.296***
Year=2016	$(0.065) \\ 0.178$	$(0.060) \\ 0.161$	(0.031) 0.277***	(0.031) 0.331***
Year=2018	$(0.094) \\ 0.161$	$(0.087) \\ 0.131$	(0.042) 0.272***	(0.042) 0.340***
Year=2020	(0.125) 0.170	(0.116) 0.112	(0.054) 0.276***	(0.055) 0.357***
	(0.156)	(0.144)	(0.065)	(0.067)
Year=2022	0.166 (0.186)	0.079 (0.173)	0.284*** (0.077)	0.370*** (0.079)
age	(0.015)	(0.019)	(0.002)	(0.001)
Beijing	0.000	(.)	(.)_	`0.000´ (.)
Tianjin	-0.237 (0.177)	-0.276 (0.177)	-0.117 (0.143)	-0.129 (0.141)
Hebei	-0.090	-0.055	0.016	0.010
Shanxi	(0.155) -0.180	(0.154) -0.195	(0.092) -0.048	(0.091) -0.027
Liaoning	(0.213) -0.013	$(0.199) \\ 0.045$	(0.086) -0.022	(0.087) -0.042
Jilin	$(0.334) \\ 0.000$	$(0.316) \\ 0.000$	(0.113) -0.261**	(0.106) -0.325***
	(.) 0.000	(.) 0.000	(0.094) -0.348***	(0.093) -0.414***
Heilongjiang	(.) 0.275	(.) 0.302	(0.080)	(0.078)
Shanghai	0.275 (0.211)	0.302 (0.206)	(0.109)	0.118 (0.098)
Jiangsu	(0.183)	(0.176)	(0.103)	(0.104)
Zhejiang	(0.072 (0.173)	0.079 (0.167)	0.130	0.143
Anhui	-0.289	-0.306	(0.099) 0.348*	(0.098) 0.363*
Fujian	(0.215) -0.231	(0.198) -0.274	(0.177) -0.106	(0.168) -0.105
Jiangxi	(0.198) -0.127	(0.188) -0.099	(0.106) 0.098	(0.103) 0.081
Shandong	(0.208) -0.733***	(0.207) -0.652**	(0.102) -0.024	(0.103) -0.014
Henan	(0.221) -0.384*	(0.226) -0.329*	(0.077) -0.039	(0.075) -0.035
Hubei	(0.157)	(0.151)	(0.089)	(0.087)
	0.248 (0.344)	0.286 (0.314)	0.223 (0.124)	0.224 (0.123)
Hunan	-0.260 (0.215)	-0.203 (0.204)	(0.103)	-0.014 (0.101)
Guangdong	-0.026 (0.178)	-0.011 (0.170)	0.063 (0.095)	0.059 (0.093)
Guangxi Zhuang Autonomous Region	-0.100 (0.207)	-0.008 (0.204)	-0.039 (0.122)	-0.050 (0.118)
Chongqing	-0.076 (0.265)	-0.056 (0.248)	-0.088 (0.114)	-0.094 (0.111)
Sichuan	-0.292	-0.320*	-0.098	-0.118
Guizhou	(0.159) 0.056	(0.153) 0.064	(0.159) -0.031	(0.153) -0.020
Yunnan	(0.205) 0.021	(0.197) 0.043	(0.108) 0.153	(0.105) 0.140
Shaanxi	(0.279) -0.185	(0.271) -0.227	$(0.110) \\ 0.003$	$(0.104) \\ 0.013$
Gansu	(0.372) -0.378	(0.374) -0.361	(0.117) -0.121	(0.110) -0.124
Rural	(0.196)	(0.195)	(0.103)	(0.101)
	0.000	(.)	(.)	(.)
Urban	$0.005 \\ (0.023)$	$\begin{pmatrix} 0.000 \\ (0.022) \end{pmatrix}$	0.006 (0.015)	$0.009 \\ (0.015)$
Non-college	0.000	0.000	0.000	0.000
College	0.119** (0.042)	0.100* (0.040)	0.113*** (0.028)	0.131*** (0.029)
lead2	0.053	[0.037]	-0.108***	0.012
lag0	(0.041)	(0.023) -0.185***	(0.032) -0.024	(0.015) -0.008
lag1	(0.040) -0.158***	(0.027) -0.103***	(0.033) 0.072*	(0.018) -0.016
lag2	(0.035) -0.132***	(0.023) -0.024	(0.028) 0.009	(0.015) -0.003
lag3	(0.039) -0.075*	$(0.029) \\ 0.022$	$(0.030) \\ 0.050$	(0.018) -0.044*
	(0.037)	(0.027) 0.083**	(0.028)	(0.017)
lag4	-0.080* (0.038)	(0.029)	0.018 (0.029)	-0.050* (0.020)
Constant	0.315 (0.401)	(0.372)	0.720*** (0.181)	0.674*** (0.180)
r2 N	0.093 8922.000	0.113 8922.000	0.176 8459.000	0.165 8459.000

C.2 Yearly Income

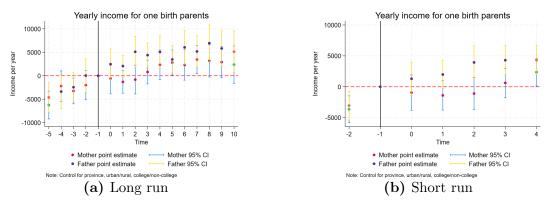


Figure A4: Yearly income in one birth family

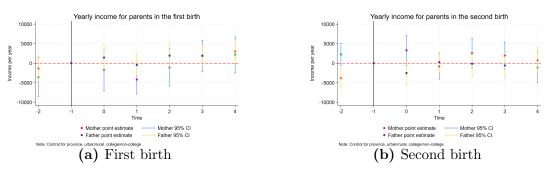


Figure A5: Yearly income in two births family: difference between fathers and mothers

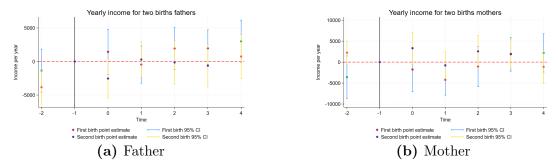


Figure A6: Yearly income in two births family: difference between two births

 $\textbf{Table A9:} \ \, \textbf{Child effect on yearly income in one birth family}$

Year=2012		510_mother	510_father	24_mother	24_father
Year=2014	Year=2010	b/se 0.000	0.000	b/se 0.000	b/se 0.000
Year=2014	Year=2012			(.) 5964.306***	
Year=2018	Year=2014	(790.972) 10077.253***	(1065.502) 16971.490***	(757.163) 10246.305***	
Year=2020	Year=2016			13587.197***	(1876.129) 23920.356***
Year=2020 (23517.175) (3823.712) (2385.740) (3658.920) (7457.621)	Year=2018	(1956.180) 18639.693***	(2932.147) 31399.334***	(1854.829) 18904.614***	(2805.989)
Year=2022 28015-788-78 185-508-79 14	Year=2020	(2517.175)	(3823.712)	(2385.740) 23507.222***	(3658.920)
age 180278 17023944 203275 1705-608* Beijing 0.000 0.000 0.000 0.000 Tianjin 5618.224 -1.55e+044* 5064.865 -1.50e+044* Bebei 3975.223 7721.2659 4310.631 7419.545 Behei 3975.223 7721.2659 4310.631 7419.545 Behei 3975.223 7721.2659 4310.631 7419.545 Shanxi -1.35e+041 8232.326 -1.37e+04 8185.369 Liaoning 748.076 7419.545 7419.545 Shanxi -1.35e+041 8232.326 -1.37e+04 8185.369 Liaoning 748.076 7419.545 7419.545 Beliongjiang 9875.93 -2.70e+04* -1.453.398 -2.73e+04* Beli	Year=2022	(3132.131)	(4749.119)	(2994.809)	(4552.907)
Beijing	age	(3703.401)	(5667.488) -1022.904*	(3559.110)	(5462.703)
Hebei	Beijing		(455.253)	(289.146) 0.000	
Bebei	Tianjin		(.) -1.55e+04**	(.) 5064.865	
Shanxi	Hebei			(10548.742) -4310.631	
Liaoning (4509.515 (5896.337) - 5599.246 5407.129 (5465.929) (7100.460) (6356.630) (6356	Shanxi	-1.35e+04		(5041.023)	(4209.744)
Jilin	Liaoning				
Heliongijang					(7214.349)
Shanghai	Heilongjiang	(6495.909)	(.)	(6549.646)	(.)
Times		(6645.754)	(10332.222)	(6699.284)	(10482.466)
Chepiang 3017.735 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4077.631 2559.839 4170.9629 4079.6325		(7170.058)	(6817.453)	(7142.734)	(6908.867)
Anhui (6823.998) (5235.994) (6845.132) (5219.922) (5219		(7195.749) 3017.735	(5061.673)	(7076.829)	(5071.271)
Fujian		(6823.098)	(5235.994)	(6845.132)	(5219.922)
Jangxi		(6077.015)	(8902.716)	(5896.554)	(9065.382)
Shandong	·	(9549.660)	(7020.524)	(9651.291)	(7090.108)
Henan	Shandong	(7989.314)	(6994.021)	(8023.392)	(7006.981)
Hubei	-	(7287.078)		(7473.104)	(4521.711)
Hunan	Hubei	(5366.755)	(4244.844)	(5367.405)	
Guangdong 1577.301 - 766.645 1005.280 - 911.112 (5520.157) - 766.645 1005.280 - 911.112 (5520.157) (4884.987) (5580.659) (4869.400)		(7934.751)	(8395.432)	(8053.266)	(8314.123)
Caungxi Zhuang Autonomous Region (5520.157) (4884.987) (5580.659) (4869.400) (4869.400) (4869.400) (4869.400) (4869.400) (4869.401) (4869.400) (4869.2851) (5320.451) (5820.451) (6674.186) (7869.709) (6674.186) (7869.709) (780.191) (6674.186) (7869.709) (8303.121) (10112.526) (1012.526) (10221.509) (8303.121) (10112.526) (1012.526) (10221.509) (8303.121) (10112.526) (7537.772) (962.263) (7615.141) (8968.370) (7537.772) (962.263) (7615.141) (8968.370) (7541.187) (8426.474) (7727.379) (8300.290) (7541.187) (8426.474) (7727.379) (8300.290) (7541.187) (8426.474) (7727.379) (8300.290) (7541.187) (7541.187) (8426.474) (7727.379) (8300.290) (7553.44) (7528.494) (7528.493) (75554.147) (758.987) (758.362) (758.656.150) (7592.893) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (756.300) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512) (759.28.493) (759.512)	Guangdong	(5204.157)		(5407.131)	(8491.635)
Chongqing		(5520.157)	(4884.987)	(5580.659)	(4869.400)
Sichuan (6576.497) (7730.191) (6674.186) (7869.709) Guizhou -2045.188 1546.034 -2101.209 1276.725 Guizhou -5007.117 -5251.835 -5391.134 -5732.522 Yunnan 1671.850 484.114 1940.756 -15.354 Yunnan 1671.850 484.114 1940.756 -15.354 Shaanxi -1.34e-04 593.266 -1.38e-04* 1005.753 Gansu -7186.987 -5781.514 -7528.043 -3668.170 Gansu -7186.987 -5781.514 -7528.043 -3668.171 Rural 0.000 0.000 0.000 0.000 0.000 (.) (.) (.) (.) (.) (.) Urban 1497.787 956.428 1521.566 1004.864 808.501) (898.769) (799.512) (897.577) Non-college 0.000 0.000 0.000 (.) (.) (.) (.) (.) (.) (.) (.) <td></td> <td>(8689.476)</td> <td>(8418.029)</td> <td>(8692.851)</td> <td>(8320.451)</td>		(8689.476)	(8418.029)	(8692.851)	(8320.451)
Guizhou	Sichuan	(6576.497) -2045.188	(7730.191)	(6674.186)	1276.725
Yunnan	Guizhou	(8115.813)			(10112.526) -5732.522
Shaanxi	Yunnan	(7537.772) 1671.850	484.114	1940.756	(8968.370) -15.354
Gansu (6886.071) (5948.032) (6856.150) (5928.493) (5958.177 Rural (75554.147) (4136.710) (5623.262) (4141.414) (100.000 (100.00	Shaanxi	-1.34e+04		-1.38e+04*	1005.753
Rural 0.000 () 0.000 () 0.000 () 0.000 () Urban 1497.787 (898.769) (1004.864) 1521.566 (1004.864) 1604.864 (808.501) (898.769) (799.512) (897.577) Non-college 0.000 ()	Gansu	-7186.987	-5781.514	-7528.043	
Non-college	Rural	0.000	0.000		0.000
Non-college 0.000 0.000 0.000 0.000 0.000 0.000 (.) College 2993.557** 5205.708** 3099.890** 5607.892** (1070.277) (1756.028) (1067.809) (1756.300) lead5 -6253.862** -4624.196** (1600.790) (1652.166) (1652.166) (1854.091) (1652.166) (1854.091) (1662.166) (1854.091) (1662.166) (1854.091) (1662.166) (1854.091) (1662.166) (1854.091) (1662.166) (1662.1	Urban			1521.566	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Non-college	0.000	0.000	0.000	0.000
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	College	(.) 2993.557**			(.) 5607.892**
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lead5	-6253.862***	-4624.196**	(1067.809)	(1756.300)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lead4	-2203.262	-3377.179		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lead3	-3244.688*	-2454.217		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lead2	-2012.795	28.839		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lag0	-607.483	2443.915	-951.861	1294.889
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lag1	-1324.826	2061.816	-1406.088	1977.629
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lag2	`-823.716	5102.215**	-1106.117	3935.084**
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	lag3	800.913	4392.701***	612.855	4292.027***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	lag4	2331.959	5070.596**	2360.803*	4305.133***
lag6 2293.737 6038.158** (1647.620) (1844.660)	lag5	2809.976*	3473.975*	(1144.132)	(1225.946)
	lag6	2293.737	6038.158**		
1ag1 3449.1U3 3114.303	lag7	3449.103*	5174.563**		
lag8 (1522.684) (1706.804) 3159.609 6939.751***	lag8	3159.609	6939.751***		
lag9 (1756.362) (1976.834) 2903.976 5813.155**		(1756.362) 2903.976	(1976.834) 5813.155**		
$\begin{array}{ccc} & (1689.095) & (1946.944) \\ \text{lag10} & 2365.991 & 5126.160^* \end{array}$	-	2365.991	(1946.944) 5126.160*		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Constant	19221.796*	(2255.796) 49454.721***		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	r2 N	0.492	0.539	0.489	0.538

Table A10: Child effect on yearly income in two births family

			on year			
			mother_first b/se	mother_second b/se	father_first b/se	father_second b/se
Year=2010			0.000	0.000	0.000	0.000
Year=2012			(.) 8831.594*** (1172.214)	(.) 9823.589*** (1159.719)	(.) 10888.327*** (1059.732)	11128.151*** (1074.337)
$Year{=}2014$			13440.424***	15147.112*** (1730.449)	15232.249***	15471.483***
$Year{=}2016$			(1740.150) 19222.032***	21092.100	(1478.992) 20540.213***	(1548.213) 20484.678***
$Year{=}2018$			(2407.061) 24952.767***	(2444.479) 28278.126***	(2123.907) 29418.090***	(2281.327) 28816.218***
$Year{=}2020$			(3050.032) 31998.230***	(3194.178) 35909.272***	(2538.783) 36505.681***	(2866.903) 35526.744***
Year=2022			(3790.304) 41033.743***	(4012.377) 45237.539***	(3041.666) 45634.806***	(3516.460) 44409.730***
age			(4451.138) -1058.085**	(4718.708) -1135.428**	(3517.574) -129.289	(4114.363) -183.969
Beijing			(356.447) 0.000	(351.922) 0.000	(264.669) 0.000	(288.302) 0.000
Tianjin			-7020.034	-5421.357	-9501.569	-1.02e+04
Hebei			(6875.986) -2034.649	(7390.780) -1834.979	(9890.075) -633.578	(10205.670) -1587.124
Shanxi			(6119.446) -3133.797	(6839.482) -3754.133	(6378.280) -6770.709	(6632.853) -6863.795
Liaoning			(8024.912) 0.000	(8113.820) 0.000	(9456.227)	(9785.931) -1.03e+04
Jilin			0.000	0.000	-1.06e+04* (5295.576) -8158.786	(5648.392) -7521.866
Heilongjiang			(.) 0.000	0.000	(6529.935) 0.000	(6696.493) 0.000
Shanghai			(.) -1.97e+04*	(.) -1.93e+04*	(.) -9820.189	(.) -9436.430
Jiangsu			(8909.343) 12158.432	(8688.955) 12016.784	(7737.132) 3996.461	(7716.047) 3556.827
Zhejiang			(8228.780) 11910.865	(8284.153) 12613.298	(6239.953) -1.27e+04*	(6439.556) -1.28e+04*
Anhui			(8801.357) 0.000	(8624.114) 0.000	(5859.283) 0.000	(6064.903) 0.000
Fujian			(.) -1.95e+04*	(.) -1.71e+04*	(.) -2.14e+04	(.) -2.18e+04
Jiangxi			(8839.608) 19023.938*	(8148.585) 20159.651*	(10980.932) -2.15e+04*	(11125.928) -2.27e+04*
Shandong			(8940.797) 20505.135*	(8686 235)	(8856.003) 16233.473	(9193.608) 15368.146
Henan			(8101.695) 4696.247	20208.911* (8335.510) 5942.142	(8371.099) -1.54e+04**	(7982.320)
Hubei			(7999.631) 0.000	(7794.372) 0.000	(4976.297) 5128.912	-1.51e+04** (5137.787) 4906.901
Hunan			(.) 12513.329	(.) 13999.309	(5449.945) -1.78e+04**	(5550.295)
Guangdong			(8619.005) 9338.557	(8492.678) 10337.187	(6399.637) -7253.942	-1.84e+04** (6544.927)
	A	D	(8043.786)	(7955.371)	(5372.081)	-7809.681 (5514.907)
Guangxi Zhu	ang Autonoi	nous region	-1.87e+04* (8432.186) -6.13e+04***	-1.51e+04 (8186.860) -6.20e+04***	-1.56e+04 (8143.011)	-1.65e+04* (8247.620) -6421.004
Chongqing			(9047.690)	(8865.811)	-7018.857 (24353.536)	(24369.296)
Sichuan			1955.409 (9551.686)	2553.459 (10632.685)	-2.18e+04*** (5958.431)	-2.25e+04*** (6106.596)
Guizhou			6805.600 (8843.605)	6870.462 (8654.022)	-9408.752 (6616.351)	-9443.936 (6697.237)
Yunnan			(8273.379)	6608.248 (8268.311)	4640.610 (8695.424)	4015.609 (9011.267)
Shaanxi			-31.439 (8165.683)	153.821 (8438.786)	-1.22e+04 (9329.839)	-1.33e+04 (9581.665)
Gansu			-2095.712 (8138.563)	-1453.657 (8327.629)	-1.43e+04** (5117.630)	-1.45e+04** (5243.703)
Rural			0.000	0.000	0.000	0.000
Urban			241.369 (1120.950)	365.620 (1119.392)	1318.595 (1193.472)	1355.449 (1192.216)
Non-college			0.000	0.000	0.000	0.000
College			521.742 (2043.956)	955.225 (2038.102)	2010.647 (1971.552)	1979.671 (1947.983)
lead2			-1289.362 (2351.160)	1107.956 (1240.452)	-2014.520 (1699.780)	-2906.505* (1229.095)
lag0			-2541.529 (2280.710)	2681.519 (1751.573)	364.735 (1822.656)	-1391.499 (1448.182)
lag1			-2626.875 (1700.340)	-1122.972 (1523.600)	-1446.294 (1495.187)	994.402 (1288.813)
lag2			371.351 (2168.740)	-720.738′ (1689.870)	87.605 (1668.920)	(1014.650) (1653.456)
lag3			1320.630 (1829.463)	(1458.410 (1625.817)	437.691 (1501.172)	-195.291 (1646.043)
lag4			1518.352 (2096.112)	-54.509 (1738.565)	1544.364 (1662.349)	1695.730 (1669.133)
Constant			32515.157** (11052.753)	31650.875** (11059.092)	27476.432*** (7824.890)	31127.322*** (8616.809)
r2 N			0.470 2550.000	0.469 2550.000	0.560 4004.000	0.561 4004.000