Estimation of Treatment Effects of the One-Child Policy Using Self-Reported Information*

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Abstract

This paper proposes a novel method to identify the One-Child Policy's impact on couples' childbearing using self-reported survey measures. We use couples' pre-policy ideal number of children together with the answers in the post-policy period to back out the counterfactual number of children without the One-Child Policy. Findings indicate a significant average reduction of 0.2714 children per couple in 2014 due to the policy. Variations in policy effects are explored across educational, urban/rural, and occupational groups, with highly educated urban women in government jobs experiencing the most pronounced impact. Sub-region analysis suggests significant policy stringency differences among provinces.

Keywords: Self-reported measures, One-Child Policy, treatment effect, heterogeneous treatment effect

*The usual disclaimer applies.

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1 Introduction

In 1979, China introduced an unprecedented one-child policy, imposing penalties on households surpassing the established birth quota. Evaluating the policy's impact on family outcomes presents complexities. Its nationwide enforcement across China complicates the identification of a clear control group for assessing the treatment effect. Additionally, the policy followed an aggressive family planning policy in the early 1970s and coincided with China's market-oriented economic reforms, both of which lowered fertility rates over subsequent decades. Therefore, it is both important and challenging to establish robust methods to identify the effect of the One-Child Policy on various family outcomes in China.

This paper proposes an innovative approach to quantify the impact of the One-Child Policy on couples' childbearing decisions. By utilizing a self-reported survey measure that captures couples' aspirations regarding the ideal number of children, we introduce a novel methodology to identify and estimate the treatment effect of the One-Child Policy on the actual number of children born. Such a self-report approach is generally applicable to heterogeneous treatment effect models. This is because, in most economic applications, the individual herself has the best knowledge of her heterogeneous potential outcomes, which makes self-reported information useful for identifying the treatment effect. To be specific, in the 2014 wave of the survey, couples were asked about the ideal number of children they would want to have without considering the One-Child Policy restriction. The answer to this question provides information on the fertility decisions the couple would make in a counterfactual scenario where there were no policy restrictions. The One-Child Policy was removed in 2016. In the survey wave 2018, couples were asked the same question again. This time, they were directly asked how many children they would ideally want to have since the policy restriction was already removed.

We utilize the answers to the question in two waves, one before the policy relaxation and one after, and we impose the assumption that, in the absence of any policy constraint, the conditional distribution of the ideal number of children given the actual number of children should remain constant over time. In other words, the gap between the ideal and actual numbers of children would be caused by the same factors in 2014 and 2018 if there were no policy constraints. With this assumption, we prove that we are able to estimate the distribution of the potential number of children couples would have if there were no One-Child Policy at that time and thus identify the policy's effect on fertility decisions for couples. Furthermore, we show that this method provides a straightforward way to estimate the heterogeneous treatment effect for different groups of people, since we can follow the same strategy to recover the conditional distribution of the potential number of children couples would have given various individual characteristics, therefore identifying the heterogeneous treatment effects for subgroups of people.

Our empirical findings show that, on average, couples had 0.2714 fewer children than they would have if the One-Child Policy had not been instituted. This result suggests a significant negative impact of the One-Child Policy on couples' fertility rates. In addition to the overall average treatment effect, we also estimate the heterogeneous treatment effect of the policy on different subgroups of people. Results show that this policy has mostly affected women with higher education levels (-0.4806), residing in urban areas (-0.3463), and engaged in governmental employment (-0.3928), revealing stark differentials that could have far-reaching societal implications.

Finally, we also study variations in the treatment effect treatment impact across provinces. This analysis sheds light on the regional differences in policy effects, showing how the interplay of geographical and policy-specific contexts amplified or muted the One-Child Policy's impact. The results indicate that provinces located on the eastern coast of China and the four municipalities were mostly affected by the One-Child Policy. Provinces located in the west and middle regions exhibit a weak policy effect due to high agriculture intensity and ethnic minority existence. The findings of this paper provide quantitative evidence of the significant impact of the One-Child policy on people's fertility decisions and, at the same time, highlight the heterogeneous policy effects among people with different socioeconomic characteristics and across geographical regions. More importantly, this paper proposes a novel method to use the self-reported survey measure to identify and estimate the treatment effect as well as heterogeneous treatment effects in a clean way, which can be applied to a broad range of empirical questions where self-reported measures are available in the data set.

Related literature This study contributes to two streams of literature. The first one is estimating the policy effect of the One-Child Policy on various outcomes. One popular approach in the literature to identify the policy effect is to use cross-sectional and temporal variations on fines across provinces (McElroy and Yang , 2000; Liu, 2014; Huang et al., 2016). For example, McElroy and Yang (2000) studied regional variations in fines and rural fertility. Huang et al. (2016) used the fines as a measure for the one-child policy implementation to estimate its reduced-form effect on girls' educational attainment. The problem with this method is that fines might not be exogenously determined and it might be correlated with the local fertility demand.

Another common approach is to compare the fertility rates of Han and minority women in a difference-in-differences framework where minority women are used as a control group since the One-Child Policy did not regulate them (Li et al., 2005; Li and Zhang, 2007). However, the common trend assumption for Han and minority groups might not hold as the economic reforms that happened in the 1980s might affect them differently. What's more, although the One-Child policy did not regulate minority women, there might be a spillover effect from Han to minority groups if minority women adopt Han women's lifestyle and fertility decisions. Another approach developed recently is to use the excess fertility rate to measure the largely exogenous regional policy stringency in the one-child policy implementation, which is taken as the pure policy variable (Li and Zhang, 2017; Zhang, 2017). This paper differs from the existing literature by taking advantage of the self-reported ideal number of children to directly identify the potential number of children couples would have without the One-Child Policy, thus recovering the treatment effect of the policy on people's fertility behaviors in a clean way.

The second stream of literature this study relates to using self-reported subjective measures as proxy variables to gain identification for unobserved attributes. To name a few examples, several papers on child development use proxy measures about cognitive and non-cognitive abilities to understand human capital formation (Cunha et al., 2010; Del Boca et al., 2013). Papers on how different gender attitudes affect household behaviors utilize subjective belief reports about gender roles (Gouss et al., 2017; Oh, 2021). This paper contributes to this literature by applying self-reported subjective measures to directly identify the treatment effect of an important policy, which broadens the application of self-reported subjective measures in the literature.

The rest of the paper is organized as follows. We first provide the institutional background on the One-Child Policy in Section 2, and we discuss the data we use in Section 3. We then present the model we use to identify and estimate the treatment effect of the policy in Section 4, followed by the estimation results in Section 5. Finally, Section 6 concludes.

2 Institutional Background

In response to rapid population growth, the Chinese government implemented a series of family planning policies in the 1970s to control births. The policies began with a mild version that discouraged couples from having many children before 1979. This eventually led to the strict One-Child Policy in 1979, which allowed couples to have only one child. The policy was gradually enforced firmly across the country in 1980. A series of actions were implemented to ensure the effectiveness of the policy by the local governments. For instance, if the parents refuse to pay the fine, the unauthorized children will be blacklisted from hukou birth registration, which will deny them access to various public services, including schooling.

Although this policy was implemented nationwide in China, there were variations among provinces in the strictness of the policy implementation. For instance, in 1981, the fine was 1.23 times the annual household income in Beijing, but only 0.647 times the annual household income in the province of Shaanxi (Ebenstein, 2010). There were also variations in policy strictness across people with different characteristics. For example, in addition to paying fines, parents with an excess birth may also be expelled from work if they work for the government or state-owned enterprises. There were also differences between urban and rural areas, where the policy was generally more restrictive and firmly enforced in urban areas than in rural areas. In fact, in most of the provinces, people from rural areas were allowed to have a second child if their first child was a girl (the so-called 1.5-child policy). Finally, the policy only restricted Han ethnic couples (which comprise around 92% of the total population in China), whereas the ethnic minorities were not subject to any policy restrictions.

The One-Child Policy went through several rounds of relaxation since the early 2000s in fear of the falling fertility rate. In 2011, all provinces started to permit couples who were both only children to have two children. In November 2013, this new policy came out, allowing couples in which at least one of the marital partners was an only child to have two children. However, even eligible couples under the policy would need to apply for permission to have a second child. In December 2015, the universal Two-Child Policy was announced, which allowed all couples to have two children, effective on January 1, 2016. Unlike the earlier rounds of relaxation, this universal Two-Child Policy no longer requires couples to apply for a birth permit in order to give birth to a second child legally. This drastic shift in the policy was intended to address the combined problems of the falling fertility rate, skewed sex ratio, and vast aging population that resulted from the strict One-Child Policy before.

3 Data

The primary dataset we use is the China Family Panel Study (CFPS), a nationally representative, bi-annual longitudinal survey. This dataset employs a household-based survey design, featuring a survey for the household asking about its socioeconomic characteristics and one survey for each gene or core member living in this household. Taking advantage of the household linkage data, we are able to obtain the complete fertility histories of each couple, and we can track each couple over the years using their personal surveys. The dataset provides information on the couple's basic characteristics such as age, education, province of residence, etc. Additionally, it has a detailed module on the job history of respondents, including the wage and income they receive from their jobs, their working hours, and the employer type, industry, and occupation for each job. The baseline families were determined in the first wave in 2010 and have been tracked every two years, resulting in six waves up to now, which covers the policy change period in 2016.

What makes this dataset ideal for our research is that, it includes a self-reported measure of fertility intentions by asking the wife and husband about their ideal number of children. The questions were asked in two waves: the first in 2014 before the policy change and the second in 2018 after the policy change. The question in 2014 is as follows:

"Regardless of policy constraints, how many children do you think would be ideal?"

As of 2014, the One-Child Policy was still in effect. This question aims to determine how many children the couple would ideally want to have in a counterfactual world without the policy restriction. The question is asked separately to both the wife and the husband. In 2018, the question was asked again using the following statement:

"How many children do you think you would ideally have?"

As the One-Child Policy was removed before 2018, this question directly inquires about the ideal number of children the couple desires. The question is again asked separately to both the wife and the husband. The answers to these questions are crucial to our identification, as they reveal information about the counterfactual choices the couple would have made in the absence of the One-Child Policy before 2016.

As previously mentioned, we can observe the fertility histories of each couple in the data, in addition to their ideal number of children. In other words, we can observe the realized number of children in 2014 and 2018 for each couple. To derive the final dataset for estimation, we follow the steps below. Firstly, to decide what age range we use for the couple, we want to satisfy two restrictions: (1) the wife should not be too young such that she hasn't finished fertility by 2014, and (2) the wife should not be too old such that she has no chance for further fertility after 2016, even if she wants to. As a result, we look at couples where the wife is between 25 and 38 years old in 2014 (born between 1976 and 1989). Secondly, we only keep those women whose ideal and realized number of children are one or two, because it is rare for married couples in China to have or want zero or more than two children. Therefore, we choose to delete those data points given their small sample size. Finally, we only focus on women who answered the ideal number of children questions in both years. Going through the entire filtering procedure results in 1727 women (3454 observations) in total.

Table 1 presents the summary statistics for key variables. The average age for the 1727 women is 31.57 in year 2014, and around half of the household is from urban areas. As for the educational levels, most women have less than high school degrees, with only 33% of them having high school degrees or higher. In 2014, the average ideal number of children women wanted was 1.8269. However, when surveyed again in 2018, this number had decreased to 1.7881. Regarding the number of children, in 2014, women had an average of 1.4146 children, while in 2018, they had an average of 1.5953 children. For the work status, we look at a combined total of 3454 observations across both waves. Of these, 13.58% were unemployed and 11.81% were self-employed. Additionally, 27.68% were working in the agricultural sector, which was a significant proportion. Finally, 46.93% of the observations were employed by an employer.

Out of the employed observations, the majority (66.44%) were employed by private companies, while 25.35% were employed by the Chinese government or state-owned enterprises. The remaining population consisted of 5.37% employed by foreign-owned companies and 2.84% employed by other types of companies. When estimating the treatment effect of the One-Child Policy on the number of children people had, we will calculate both the average treatment effect for the overall population and the heterogeneous treatment effect for different subgroups of people.

Table 1: Summary Statistics for Key Variables

Variables	Mean	Std. Dev.	Min	Max	Obs
Age in year 2014	31.57	4.07	25	38	1,727
Urban residence	0.5061	0.5001	0	1	1,727
Educational level					
- Less than high school	0.6688	0.4708	0	1	1,727
- High school graduate	0.1627	0.3692	0	1	1,727
- College and higher	0.1685	0.3744	0	1	1,727
Fertility					
- Ideal number of children in 2014	1.8269	0.3785	1	2	1,727
- Ideal number of children in 2018	1.7881	0.4088	1	2	1,727
- Actual number of children in 2014	1.4146	0.4928	1	2	1,727
- Actual number of children in 2018	1.5953	0.4910	1	2	1,727
Job status					
- Unemployed	0.1358	0.3426	0	1	3,454
- Self-employed	0.1181	0.3228	0	1	3,454
- Agriculture	0.2768	0.4475	0	1	3,454
- Employed	0.4693	0.4991	0	1	3,454
- Private	0.6644	0.4723	0	1	1,621
- Government	0.2535	0.4352	0	1	1,621
- Foreign	0.0537	0.2254	0	1	1,621
- Other	0.0284	0.1661	0	1	1,621

Note: The dataset contains 1727 women, and each woman has two periods of records in 2014 and 2018, resulting in 3454 observations in total. For age, urban residence, and educational level, we calculate statistics using data from 2014 only. For the ideal and realized number of children, we calculate summary statistics for data in 2014 and 2018 separately. For job status, we combine data from 2014 and 2018 together and calculate the summary statistics for the whole sample. Conditional on being employed, we calculate the statistics for different employer types respectively. “Private” refers to companies privately owned by individuals, while “Government” includes government positions and state-owned enterprises. “Foreign” refers to companies owned by foreigners, and “Other” aggregates all the other types of employers.

4 Model

This section presents the model we use for identifying and estimating the treatment effect of the One-Child Policy on the number of children couples had by utilizing the self-reported ideal number of children. Consider a population with members $i = 1, ..., N$. For each member of the population, we use $\{Y_i, S_i, D_i\}, i = 1, ..., N$ to denote the key variables for couple i, where

$$\begin{cases} Y_i & = \text{Outcome variable: number of children} \\ D_i & = \text{Treatment indicator: whether under One-Child Policy} \\ S_i & = \text{Self-reported number of children a couple wants} \end{cases}.$$

$D_i = 1$ if the couple was under the One-Child Policy and $D_i = 0$ otherwise.

We can then define the potential or latent outcomes as the following:

$$\begin{cases} Y_i(0) & = \text{Number of children a couple has if not under One-Child Policy} \\ Y_i(1) & = \text{Number of children a couple has if under One-Child Policy} \end{cases}.$$

Similarly, we define the potential ideal number of children as the following:

$$\begin{cases} S_i(0) & = \text{Self-reported number of children a couple wants if not under One-Child Policy} \\ S_i(1) & = \text{Self-reported number of children a couple wants if under One-Child Policy} \end{cases}.$$

Furthermore, our identification is based on a panel data from before and after the One-Child Policy was relaxed. Let $\{Y^b(0), Y^a(0)\}$ denote the number of children couples have if not under the One-Child Policy before and after the policy change, respectively. Let $\{S^b(0), S^a(0)\}$ denote the self-reported number of children couples want if not under the One-Child Policy before and after the policy change, respectively.

After defining the basic notations, we now introduce the key assumption for our identification argument.

Assumption 1. *The distribution of self-reported potential outcomes conditional on the true potential outcome does not change before and after the policy change, i.e.,*

$$f_{S^b(0)|Y^b(0)} = f_{S^a(0)|Y^a(0)}, \tag{4.1}$$

The distribution $f_{S^b(0)|Y^b(0)}$ denotes the conditional distribution of $S(0)$ given $Y(0)$ before the policy change, and $f_{S^a(0)|Y^a(0)}$ denotes the conditional distribution of $S(0)$ given $Y(0)$ after the policy change. In other words, the gap between the self-reported ideal number of children and the actual number of children should be caused by the same factors before and after the policy change if there were no policy constraints, leading to a stationary conditional distribution over time. To make sure our assumption is true, we have restricted our analysis to women who were over the age of 25 in 2014. This ensures that they had completed their fertility by that time.

Let the support of S^b be $\mathcal{S}^b = \{s_1^b, s_2^b, ..., s_L^b\}$ and the support of S^a be $\mathcal{S}^a = \{s_1^a, s_2^a, ..., s_L^a\}$, the support of $Y^b(0)$ be $\mathcal{Y}^b(0) = \{y_1^b, y_2^b, ..., y_L^b\}$, and finally the support of Y^a be $\mathcal{Y}^a = \{y_1^a, y_2^a, ..., y_L^a\}$.

We define

$$\overrightarrow{p(S^b)} = [f_{S^b}(s_1^b), f_{S^b}(s_2^b), ..., f_{S^b}(s_L^b)]^T$$
$$M_{S^a|Y^a} = \left[f_{S^a|Y^a}(s_l^a|y_p^a)\right]_{l=1,2,...,L;p=1,2,...,L}.$$

We have the following lemma.

Lemma 1. *Suppose that Assumption 1 holds and that $M_{S^a|Y^a}$ is invertible. The average treatment effect of the policy $E[Y^b(1) - Y^b(0)]$ is identified and can be estimated as follows:*

$$E[Y^b(1) - Y^b(0)] = E[Y^b] - (y_1^b, y_2^b, ..., y_L^b) \times M_{S^a|Y^a}^{-1} \times \overrightarrow{p(S^b)}.$$

Proof. We can write the marginal distribution of $S^b(0)$ using the following equation:

$$f_{S^b(0)}(s) = \sum_{y \in \mathcal{Y}^b(0)} f_{S^b(0)|Y^b(0)}(s|y) f_{Y^b(0)}(y), \tag{4.2}$$

where $f_{Y^b(0)}$ is the marginal distribution of $Y^b(0)$. Before the relaxation of the One-Child policy, the individuals are asked to self-report the number of children that the couples would want without considering the policy constraint. Therefore, we observe $S^b(0)$ as S^b

$$S^b(0) = S^b. \tag{4.3}$$

In other words, the self-reported ideal number of children S_j observed in the data equals to the potential self-reported ideal number of children without any policy constraints. In addition, after the policy constraint has already been removed, we have

$$S^a(0) = S^a, \quad Y^a(0) = Y^a. \tag{4.4}$$

Given Assumption 1, we can plug equation 4.4 into equation 4.1, which gives

$$\begin{aligned} f_{S^b(0)|Y^b(0)} &= f_{S^a(0)|Y^a(0)} \\ &= f_{S^a|Y^a}. \end{aligned} \tag{4.5}$$

Plugging equation 4.3 and 4.5 into equation 4.2, we have

$$f_{S^b}(s) = \sum_{y \in \mathcal{Y}^b(0)} f_{S^a|Y^a}(s|y) f_{Y^b(0)}(y). \tag{4.6}$$

Consider the situation where $S_j, S_k, Y_k, Y_j(0)$ are all discrete variables [1]. The support of S^b is $\mathcal{S}^b = \{s_1^b, s_2^b, ..., s_L^b\}$ and the support of S^a is $\mathcal{S}^a = \{s_1^a, s_2^a, ..., s_L^a\}$. The support of $Y^b(0)$ is

[1] We use the discrete case in our proof both because of its simplicity and because in our empirical study, both number of children and self-reported ideal number of children are discrete. Nevertheless, for continuous variables the identification result still holds with similar arguments.

$\mathcal{Y}^b(0) = \{y_1^b, y_2^b, ..., y_L^b\}$, and finally the support of Y^a is $\mathcal{Y}^a = \{y_1^a, y_2^a, ..., y_L^a\}$ [2]. We define

$$\begin{aligned}
\overrightarrow{p(S^b)} &= [f_{S^b}(s_1^b), f_{S^b}(s_2^b), ..., f_{S^b}(s_L^b)]^T \\
\overrightarrow{p(Y^b(0))} &= [f_{Y^b(0)}(y_1^b), f_{Y^b(0)}(y_2^b), ..., f_{Y^b(0)}(y_L^b)]^T \\
M_{S^a|Y^a} &= \left[f_{S^a|Y^a}(s_l^a|y_p^a)\right]_{l=1,2,...,L;p=1,2,...,L}.
\end{aligned}$$

Equation 4.6 is then equivalent to

$$\overrightarrow{p(S^b)} = M_{S^a|Y^a} \times \overrightarrow{p(Y^b(0))}.$$

Since both $\overrightarrow{p(S^b)}$ and $M_{S^a|Y^a}$ can be estimated from the data, by conducting matrix inversion, we obtain the marginal distribution of $Y^b(0)$:

$$\overrightarrow{p(Y^b(0))} = M_{S^a|Y^a}^{-1} \cdot \overrightarrow{p(S^b)}. \tag{4.7}$$

Notice that $\overrightarrow{p(Y^b(0))}$ contains the same information as the distribution $f_{Y^b(0)}$. Therefore, we can identify and estimate $f_{Y^b(0)}$ from equation 4.7. The average treatment effect of the One-Child Policy on the number of children couples had before the policy was relaxed can be then estimated using the following equation:

$$\begin{aligned}
E[Y^b(1) - Y^b(0)] &= E[Y^b(1)] - E[Y^b(0)] \\
&= E[Y^b] - (y_1^b, y_2^b, ..., y_L^b) \times \overrightarrow{p(Y^b(0))},
\end{aligned}$$

where Y^b is the observed number of children a couple has before the policy was relaxed in year j and $\overrightarrow{p(Y^b(0))}$ can be estimated using equation 4.7. QED.

$\square$

In addition to estimating the average treatment effect for the entire population, we take advantage of the self-reported measure to estimate the heterogeneous treatment effects for subgroups with different characteristics. These subgroups include women with varying educational levels, women from urban and rural areas, and women with different job statuses and employment types. Furthermore, we estimate the average treatment effect for women in different provinces to study the heterogeneous treatment effects across geographic regions. To estimate the heterogeneous treatment effect, we assume that Assumption 1 still holds when conditioning on individual characteristics X:

$$f_{S^b(0)|Y^b(0),X} = f_{S^a(0)|Y^a(0),X}. \tag{4.8}$$

[2]For simplicity, we assume all the discrete variables have the same dimensionality for their support.

Using this assumption and going through the same proof as in the case above, we have

$$\begin{aligned} f_{S^b(0)|X}(s|x) &= \sum_{y \in \mathcal{Y}^b(0)} f_{S^b(0)|Y^b(0),X}(s|y,x) f_{Y^b(0)|X}(y|x) \\ f_{S^b|X}(s|x) &= \sum_{y \in \mathcal{Y}^b(0)} f_{S^a|Y^a,X}(s|y,x) f_{Y^b(0)|X}(y|x). \end{aligned} \tag{4.9}$$

Therefore, we can adopt the same matrix-inversion trick as in the main proof to obtain $f_{Y^a(0)|X}(y|x)$, which is the conditional distribution of the potential number of children people would have before the policy relaxation if there was no One-Child Policy, given individual characteristics X. Having estimated $f_{Y^b(0)|X}(y|x)$, we can then identify and estimate the conditional average treatment effect using

$$\begin{aligned} E[Y^b(1) - Y^b(0)|X = x] &= E[Y^b(1)|X = x] - E[Y^b(0)|X = x] \\ &= E[Y^b|X = x] - (y_1^b, y_2^b, ..., y_L^b) \times \overrightarrow{p(Y^b(0)|X = x)}, \end{aligned} \tag{4.10}$$

where

$$\overrightarrow{p(Y^b(0)|X = x)} = [f_{Y^b(0)|X}(y_1^b|x), f_{Y^b(0)|X}(y_2^b|x), ..., f_{Y^b(0)|X}(y_L^b|x)]^T.$$

Having described the model and the identification arguments, Section 5 presents the results for the overall treatment effect and the heterogeneous treatment effects for people with different characteristics.

5 Results

Table 2 presents the first set of results for the average treatment effect of the One-Child Policy on the number of children people had in 2014. The first column shows the estimation result for the average treatment effect for the total population, and the second column shows the average treatment effects for women from urban and rural areas separately. The last column shows the average treatment effects for women having different educational levels. When conducting the matrix inversion to back out $\overrightarrow{p(Y^b(0))}$ in equation 4.7, we use the empirical distribution in the data to estimate $\overrightarrow{p(S^b)}$ and $M_{S^a|Y^a}$. Similarly, for urban residence and educational levels, since the sample size is sufficient for each subgroup, we still use the empirical distribution in the data to estimate $\overrightarrow{p(S^b|X)}$ and $M_{S^a|Y^a,X}$. Finally, we obtain the standard errors by bootstrapping the data 100 times.

The results indicate that the estimated average treatment effect for the total population is significantly negative (-0.2714), which means that, on average, couples in 2014 had 0.2714 fewer children than they would have had if the One-Child Policy had not been in place at that time. When comparing the effects on urban and rural populations, we find that the effect on urban couples (-0.3463) is almost twice as large as that on rural couples (-0.1751). This result is consistent with the fact that the One-Child Policy was more strictly enforced for urban couples, while rural couples were allowed to have a second child if their first child was a girl.

When examining the impact of the One-Child Policy on various educational levels, there is a significant gap between the effects on women with less than a high school degree (-0.1681) and those with a high school degree (-0.4564) or higher (-0.4806). Reasons for these significant differences might include that those women with low educational levels tend to come from rural areas. Another possibility is that women with high educational levels can afford to have two children, while women with low educational levels cannot. Therefore, the policy effect on the number of children is much larger for women with higher educational levels than those with less than high school degrees. No matter the potential reasons, according to the results here, women with high educational levels were mostly affected by the One-Child Policy.

Table 2: Treatment Effect of One-Child Policy On Number of Children: Part I

Parameters	Total Population	Urban/Rural	Education
Total Treatment effect	-0.2714		
	(0.0257)		
Treatment effect: urban		-0.3463	
		(0.0350)	
Treatment effect: rural		-0.1751	
		(0.0396)	
Treatment effect: less than high school			-0.1681
			(0.0294)
Treatment effect: high school graduate			-0.4564
			(0.0674)
Treatment effect: college and higher			-0.4806
			(0.0590)

Note: This table shows the first set of estimation results for the average treatment effect of the One-Child Policy on the number of children people had in 2014. The first column shows the estimation results for the total average treatment effect, and the second column shows the average treatment effect for women from urban and rural areas separately. The last column shows the average treatment effect for women having different educational levels. Standard errors, indicated in brackets, were obtained via bootstrapping by sampling the dataset 100 times.

Table 3 presents the second set of results for the average treatment effect of the One-Child Policy on the number of children people had in 2014. The first column shows the estimation result for the average treatment effect for the total population, and the second column shows the average treatment effect for women with different employment statuses. The last column shows the average treatment effect for employed women who have different types of employers. Similar to the first set of estimations, we use the empirical distribution in the data to represent $\overrightarrow{p(S^b|X)}$ and $M_{S^a|Y^a,X}$ when conducting subgroup analysis for the treatment effect of the policy. Again, we obtain the standard errors by bootstrapping the data 100 times.

Firstly, we examine how the policy effects differ across employment statuses. Compared to the overall effect of -0.2714, working in the agricultural sector has a much smaller impact (-0.1784), while those self-employed or employed by others in the non-agricultural sector have a larger policy effect (-0.3546, -0.3309). This result makes intuitive sense because, again, people working in the agricultural sector are likely residing in rural areas and were loosely regulated by the One-Child Policy. Therefore, these people will have a relatively smaller policy effect compared to those self-employed or employed in other non-agricultural sectors.

To investigate whether the policy effect differs across employer types, we then focus on employed women in non-agricultural sectors and conduct subgroup analysis for them working for different types of employers. The results of our analysis are both interesting and consistent with our prior knowledge. Among all employer types, government-related positions (including those in state-owned enterprises) have the strongest negative policy effect on the number of children (-0.3928). This finding is not surprising, given that government workers face the highest penalties for having excess births, which can result in both fines and job loss. Employees of private firms and companies have a relatively smaller policy effect (-0.2955) since they typically only face fines for excess births without risking their jobs. It is somewhat surprising that employees in foreign-owned companies have a high policy effect (-0.3654), given that they do not face the risk of losing their jobs due to excessive births.

In addition to the subgroup analysis mentioned above, we also want to investigate variations in the aggregate policy effect across different provinces. To do so, we estimate the treatment effect for couples in each province. Due to the limited sample size for each province, we cannot calculate the empirical distribution for $\overrightarrow{p(S^b|X)}$ and $M_{S^a|Y^a,X}$ using the data. Instead, we model the conditional distribution using a logistic regression and use predicted probabilities for the outcome variables as the estimated conditional distribution. We obtained results for a total of 23 provinces, which are shown in Figure 1 below.

Colored segments on the map represent provinces with estimated policy effects. The closer the color is to red, the stronger the policy effect, while the closer it is to blue, the weaker the policy effect. It is evident that numerous provinces on the east coast of the country experience a strong policy effect, whereas several provinces located in the west and middle regions exhibit a weak policy effect. This is because the provinces located in the western and central regions tend to be agriculturally intensive and have a large proportion of ethnic minority groups. As a result, the degree of policy regulation is low. Provinces situated on the eastern coast tend to be more economically developed and urban-intensive. Therefore, they experienced a larger policy effect of the One-Child Policy on the number of children.

Table 3: Treatment Effect of One-Child Policy On Number of Children: Part II

Parameters	Total Population	Employment Type	Employer
Total Treatment effect	-0.2714		
	(0.0257)		
Treatment effect: employed		-0.3309	
		(0.0363)	
Treatment effect: self-employed		-0.3546	
		(0.0864)	
Treatment effect: agriculture		-0.1784	
		(0.0362)	
Treatment effect: employed–government			-0.3928
			(0.0737)
Treatment effect: employed–private			-0.2955
			(0.0470)
Treatment effect: employed–foreign			-0.3654
			(0.1192)
Treatment effect: employed–other			-0.2588
			(0.1497)

Note: This table shows the second set of estimation results for the average treatment effect of the One-Child Policy on the number of children people had in 2014. The first column shows the estimation results for the total average treatment effect, and the second column shows the average treatment effect for women with different employment statuses. The last column shows the average treatment effect for employed women who have different types of employers. Standard errors, indicated in brackets, were obtained via bootstrapping by sampling the dataset 100 times.

Another observation is that, the four municipalities (Beijing, Tianjin, Shanghai, Chongqing) had large policy effects on the number of children, which makes sense as the One-Child Policy strictly regulated these four regions. Finally, two provinces in the north-east region (Jilin and Heilongjiang) also had large policy effects, as they had many state-owned enterprises before, therefore regulating couples at a substantial penalty. The majority of the treatment effect findings for provinces align with our intuition and previous knowledge.

6 Conclusion

This paper uses a self-reported survey measure of the ideal number of children to identify the treatment effect of the One-Child Policy on the number of children couples had. We utilize the self-reported information to identify the treatment effect because, often the time, the individual herself has the best knowledge of her heterogeneous potential outcomes. Taking advantage of the fact that couples were asked about their ideal number of children without considering any policy restrictions in 2014, the answer to this survey question reveals information about how many children couples would have in a counterfactual world with no policy restrictions. Since the question was asked again in 2018 when the One-Child Policy was removed and by making the assumption that the

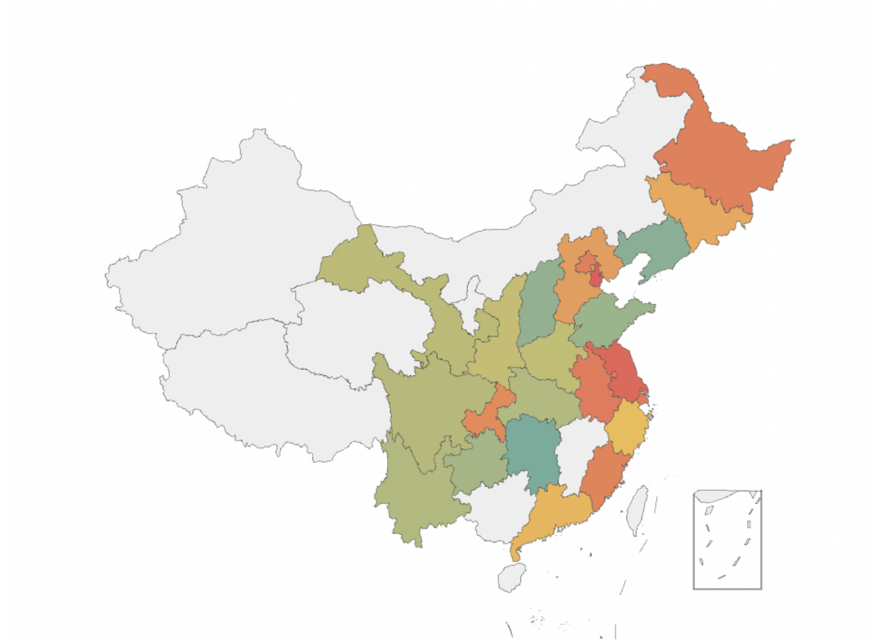

Figure 1: Provincial Variations in Treatment Effects

conditional distribution of the ideal number of children on the actual number of children should stay the same across years if there were no policy restrictions, we are able to identify and estimate the treatment effect of the policy on the number of children couples had.

The results suggest that, on average, couples in 2014 had 0.2714 fewer children than they would have had if the One-Child Policy had not been in place at that time, which demonstrates that the One-Child policy had a quite significant negative impact on the fertility rates of people. Meanwhile, we estimate the heterogeneous policy effect for various subgroups of people and show that there exists substantial variations in the policy effect among people with different socioeconomic statuses. In particular, women of high education, who live in urban areas and work for the government are the most affected population. Finally, we identify and estimate the variations in treatment effects among provinces. The results partially reflect differences in the strictness of policy regulations on an aggregate provincial level.

We admit that the identification of our study relies on the crucial assumption that the conditional distribution of the ideal number of children on the actual number of children does not vary across time if there were no policy restrictions. To satisfy this assumption, we limit our sample to women who were old enough in 2014 such that they were likely to complete their fertility by that time. Still, this assumption can be strong and may need more validation. Nevertheless, this paper proposes a novel method to take advantage of the self-report survey measure, the ideal number of children, to identify the treatment effect of the One-Child policy on fertility outcomes. It adds to the literature both on how self-reported subjective measures can be employed to design a clean strategy to quantify the policy effect of the One-Child policy and provide empirical evidence on the significant impact of the One-Child Policy on the family outcomes in China.

References

Cunha, F., J. J. Heckman, and S. M. Schennach. 2010. “Estimating the technology of cognitive and noncognitive skill formation.” *Econometrica,* 78(3), 883931.

Del Boca, D., C. Flinn, and M. Wiswall. 2013. “Household choices and child development.” *Review of Economic Studies,* 81(1), 137185.

Ebenstein, Avraham. 2010. “The “Missing Girls” of China and the Unintended Consequences of the One Child Policy.” *Journal of Human Resources,* 45 (1): 87-115.

Gouss, M., N. Jacquemet, and J.-M. Robin. 2017. “Marriage, labor supply, and home production.” *Econometrica,* 85(6), 18731919.

Huang, Wei, Xiaoyan Lei, and Ang Sun. 2016. “When Fewer Means More: Impact of One-Child Policy on Education of Girls.” *Working paper,* Harvard University.

Li, Hongbin, and Junsen Zhang. 2007. “Do High Birth Rates Hamper Economic Growth?” *Review of Economics and Statistics,* 89(1): 11017.

Li, Bingjing, and Hongliang Zhang. 2017. “Does Population Control Lead to Better Child Quality? Evidence from Regional Variation in the Enforcement Intensity of Chinas One-Child Policy.” *Journal of Comparative Economics,* 45(2): 246-260

Li, Hongbin, Junsen Zhang, and Yi Zhu. 2005. “The Effect of the One-Child Policy on Fertility in China: Identification Based on the Differences-in-Differences.” *Working Paper.*

Liu, Haoming. 2014. “The QualityQuantity Trade-off: Evidence from the Relaxation of Chinas One-Child Policy.” *Journal of Population Economics,* 27(2): 565602.

McElroy, Marjorie, and Dennis Tao Yang. 2000. “Carrots and Sticks: Fertility Effects of Chinas Population Policies.” *American Economic Review,* 90(2): 38992.

Oh, G. Y. 2021. “Allocating time as a couple: Effects of relative wages and gender role bias.” *Working Paper.*

Zhang, Junsen. 2017. “The Evolution of Chinas One-Child Policy and Its Effects on Family Outcomes.” *Journal of Economic Perspectives,* 31(1): 141-160.