RIETI Discussion Paper Series 22-E-033

The Hidden Cost of Having More Children: The Impact of Fertility on the Elderly's Healthcare Utilization

XIE, Mingjia
CentER, Tilburg University

YIN, Ting
RIETI

ZHANG, Yi
China Center for Human Capital and Labor Market Research, Central University of Finance and Economics

OSHIO, Takashi
Institute of Economic Research, Hitotsubashi University

RIETI
Research Institute of Economy, Trade & Industry, IAA
The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 22-E-033

April 2022

The Hidden Cost of Having More Children: The Impact of Fertility on the Elderly's Healthcare Utilization*

Mingjia Xie[a],
CentER, Tilburg University
Ting Yin[b,c]
Center for Intergenerational Studies, Institute of Economic Research, Hitotsubashi University
Research Institute of Economy, Trade and Industry
Yi Zhang[d]
China Center for Human Capital and Labor Market Research, Central University of Finance and Economics
Takashi Oshio[e]
Center for Intergenerational Studies, Institute of Economic Research, Hitotsubashi University

Abstract

Declining fertility and increasing health expenditure associated with aging populations pose great challenges to public finance globally. This paper studies the hidden cost of fertility by analyzing the causal effect of fertility on the elderly's healthcare utilization. We use the instrumental variable approach to account for the potential endogeneity in the fertility choice, exploiting the exogenous variations in fertility induced by the "1.5-Child Policy" in rural China. We find that having more children increases the probability and out-of-pocket expenditures of using formal and informal healthcare. Increased healthcare use can be driven by deteriorating physical and mental health and increasing intergenerational support. Children of the elderly are more likely to help them pay health costs and make monetary transfers to their parents, suggesting that the increased burden of healthcare cost is partly borne by the children. Women and lower educated parents who have limited economic resources and less generous health insurance tend to bear a higher increase in health costs with more children. The results imply that the true cost of birth-encouraging policies can be underestimated if the effect of fertility on healthcare utilization is overlooked, and such policies might increase inequality if no supportive measures are provided to disadvantaged groups.

Keywords: fertility, family planning policy, "1.5-Child Policy", healthcare utilization, intergenerational support, China

JEL classification: I10, J13, J14

*This study was conducted as a part of the project titled "Studies on Transformations of International Systems and their Impact on Japan's Mid- & Long-term Competitiveness" undertaken by the research group on "Empirical Research on the Changing Chinese Economy-Upgrading, Expansion, Structural Reform" at the Research Institute of Economy, Trade, and Industry (RIETI). The authors thank the China Health and Retirement Longitudinal Study (CHARLS) team for providing data. We wish to thank Elena Bassoli, Julien Bergeot, Zhixiong Guan, Asei Ito, Kai Kajitani, Lei Lei, Zhiqiang Liu, Shiko Maruyama, Masayuki Morikawa, Bin Ni, Bettina Siflinger, Martin Salm, Arthur van Soest, Mariko Watanabe, Tetsuya Watanabe, Makoto Yano, Nina Yin, the participants at the 24th Tokyo Labor Economics Workshop, JCER Seminar (2021 Fall), CHLR Applied Microeconomics Seminar (2021 Fall), RIETI Seminar (January 2022), and Netspar International Pension Workshop 2022 for their helpful comments and suggestions. We also thank the RIETI staff for their kind help and cooperation. Any errors are our own. There are no conflicts of interest.

[a] CentER, Tilburg University. Email: m.xie_1@tilburguniversity.edu
[b] Center for Intergenerational Studies, Institute of Economic Research, Hitotsubashi University. Email: yin-ting@ier.hit-u.ac.jp
[c] Research Institute of Economy, Trade and Industry, IAA. Email: yin-ting@rieti.go.jp
[d] Corresponding author at: China Center for Human Capital and Labor Market Research, Central University of Finance and Economics, 39 South College Road, Haidian District, Beijing, P.R. China. Zip code: 100081. Email: yi.zhang@cufe.edu.cn
[e] Center for Intergenerational Studies, Institute of Economic Research, Hitotsubashi University. Email: oshio@ier.hit-u.ac.jp

1 Introduction

Declining fertility is driving the population aging trend, which, combined with the rapidly growing health expenditures associated with an aging society, poses significant challenges to public finance in developed and developing economies. China, for example, saw its birth rate hit a new record low of 8.5‰ in 2020 (National Bureau of Statistics of China 2020) and its health expenditure has grown by 11.6%, which is much faster than its GDP growth, over the past two decades (Zhai et al. 2017). In 2021, its government announced the "three-child policy" to encourage births. China is not the only country that uses family planning policies to manage fertility. Ever since the 1960s, from contraceptive programs in the US to family planning outreach programs in Bangladesh, policy-induced fertility changes have long been believed by policy makers to influence parent and child health and wellbeing, and even to affect regional poverty and economic development (Seltzer 2002).

A growing body of literature has attempted to explain the effects of fertility on parent and child health and socioeconomic outcomes (e.g., mortality, labor supply, and human capital investment).[2] However, little is known regarding the impact of policy-induced fertility changes on parent healthcare utilization and costs. In particular, the latter is indispensable for properly assessing the effectiveness and fully understanding the consequences of family policies. For example, if the fertility increase induced by a birth-encouraging policy leads to a significant increase in parent healthcare utilization and health expenditures, then ignoring this effect will underestimate the true cost of the policy. Therefore, the goal of such a policy for more sustainable public finance will likely remain unachieved.

In this study, we examined the effects of fertility on elderly parent healthcare utilization. The theoretical prediction of the direction of these effects was unclear a priori. The ambiguous effects of fertility on health drive the demand for healthcare utilization in uncertain directions. Having more children can be associated with a higher risk of physical (e.g., Ness et al. 1994, Weng et al. 2004, Zhang et al. 2009, Skilton et al. 2010, Peters et al. 2017, Deems and Leuner 2020, etc.) and mental health problems (e.g., Gove and Geerken 1977, Lu et al. 2020, Li et al.

[2] See Schultz (2007) and Miller and Babiarz (2016) for a thorough review.

2021, etc.), and fewer resources for parental health investment in the early years (Wu and Li 2012), which can result in worse health and greater demand for healthcare at old ages. However, additional children may provide more old-age support to their parents, which may be beneficial to their physical health and psychological wellbeing (Chen and Lei 2009), thereby reducing the demand for healthcare use. The number of children may also have an ambiguous impact on the budget constraints of parents. Additional children with additional old-age support can relax budget constraints for parents and allow for more healthcare utilization that may otherwise have been suppressed. However, having more children can also mean that more downward monetary transfers to children are required, which may tighten the budget for parental health investment. It is unclear a priori which mechanism would dominate.

There is no direct empirical evidence regarding the effects of fertility on parental healthcare utilization. The existing medical and economic literature mainly focuses on how fertility influences parent health with mixed evidence. Hurt et al. (2006) and Modig et al. (2017) find that the number of births is associated with lower mortality and greater longevity. Chen and Lei (2009) find that the number of children has no significant long-term "fertility effect," but a positive "supporting effect" on parent health. In contrast, Spence (2008), Cáceres-Delpiano and Simonsen (2012), Wu and Li (2012), Kruk and Reinhold (2014), Islam and Smyth (2015), and Bucher-Koenen et al. (2020) identify negative long-term effects of the number of children on parental physical and mental health.[3]

However, it is unclear how these mixed health effects translate into the healthcare utilization and financial implications of family planning policies, particularly in developing countries, where the demand for healthcare and actual utilization can often be disjointed. The most relevant evidence from Cáceres-Delpiano and Simonsen (2012) indicates that having additional children leads to an increase in Medicaid use and reduction in the purchasing of private medical insurance. Chen and Fang (2021) find that being exposed to the "Later, Longer, Fewer" campaign in the early 1970s in China reduced fertility, but had no significant impact on

[3] Related studies evaluate how family planning programs influence fertility rates and health in the long term. The results are also mixed. For example, Canning and Schultz (2012), and Joshi and Schultz (2013) find that a family planning program in Bangladesh reduced the fertility and improved parental health. Chen and Fang (2021) find that the "Later, Longer, Fewer" campaign in the early 1970s in China reduced fertility and had a negative impact on parent mental health at old ages. However, it had no significant impact on physical health.

household healthcare expenditures. However, these studies did not focus directly on the effects of fertility on healthcare utilization.

We attempt to fill this gap in the literature by directly studying the causal effect of the number of children on elderly parent healthcare utilization in rural China. The econometric challenge in estimating causal effects is that fertility choice can be endogenous to healthcare utilization. For example, low-income families may raise more (or fewer) children and use fewer healthcare services. To account for the potential endogeneity in fertility choice, we exploit the exogenous variations in fertility induced by the "1.5-Child Policy" in the mid 1980s in rural China, which represented a major relaxation of the "One-Child Policy" (OCP) introduced at the end of the 1970s. The 1.5-Child Policy essentially allowed rural families to have a second child if the first-born child was a girl. Therefore, we constructed a policy-exposure type of instrumental variable (IV) for fertility by interacting the first-born gender with the intensity of exposure to the policy. Using data from the "China Health and Retirement Longitudinal Study" (CHARLS, waves 2011, 2013, and 2015), a representative survey of elderly Chinese individuals aged 45 years and above, we find that an increase in the number of children significantly increases the incidence and out-of-pocket (OOP) expenditures of using outpatient care, inpatient care, and self-treatment. These results are robust to alternative specifications and sample restrictions. Furthermore, specification tests cannot reject the validity of our instruments.

The analysis of potential mechanisms indicates that increased healthcare use may be driven by deteriorating health as measured by self-reported health, mental health, and the incidence of chronic diseases. Although parent income does not increase with additional children, children are more likely to pay for out-of-pocket self-treatment costs and health checkups for their parents. They are also more likely to transfer money to their parents, suggesting that the children partially bear the increased burden of healthcare costs.

To gain a better understanding of these results, we investigate the heterogeneity of effects further. With additional children, both men and women increase their healthcare use, but women, who are generally covered with less generous health insurance than men, tend to have higher OOP healthcare costs. Less-educated parents who have limited economic resources and ungenerous public insurance suffer from the adverse health effects of fertility and bear a significant increase in OOP medical costs. In contrast, the higher education group's health condition and healthcare expenditure are negligibly affected, raising concerns regarding widening health disparities across socioeconomic groups. Fertility has a comprehensive impact on the healthcare utilization of younger parents (45 to 58 years old), but its effects can be long lasting because they persist into older ages.

To the best of our knowledge, this study is the first evidence on the causal effect of the number of children on healthcare use. We also contribute to the understanding of these effects by shedding light on their underlying mechanism. Our results imply that the true cost of relaxing birth control policies as a policy tool against the low birth rate and rapidly aging demographic trend can be underestimated if policymakers do not consider long-term impacts on healthcare utilization. Subgroups with limited economic resources and less generous health insurance tend to bear higher health costs from fertility, necessitating supportive measures for these disadvantaged groups (and potentially their children, who bear portions of the increased cost) alongside birth policies. Our results are particularly relevant for developing countries with high copayments and heavy reliance on family transfers as an essential source of old-age support.

The remainder of the paper is organized as follows. Section 2 provides an overview of the institutional background. Section 3 describes the data sample and defines the main variables used in our analysis. Section 4 presents our empirical strategy and Section 5 presents the empirical results. Section 6 presents sensitivity analyses and Section 7 summarizes and discusses the implications of our study.

2 Institutional background

We briefly introduce the family planning policy in China that we consider for our IV construction. We provide a snapshot of the public social security system and old age support in rural China.

2.1 Family planning policy in China

China has implemented nationwide birth control policies since the 1970s, which can be considered as a natural experiment affecting fertility. Zhang (2017) provides a detailed review of the evolution of these policies. In this section, we briefly summarize these policies.

Following the principle of “more people, more power” raised by the supreme leader Mao Zedong, China's fertility has surged since 1949. In the early 1960s, the total fertility rate reached more than six births per woman (Banister 1987). High birth rates raised concerns that “rapid population growth would hinder economic development” (Donaldson and Tsui 1990).

In the early 1970s, the first nationwide family planning policy called “later, longer, fewer” (LLF), was implemented. With relatively lenient policy enforcement, this campaign encouraged marriages at a later age, waiting longer before the next birth, and having fewer total children (Zhang 2017). Chen and Fang (2021) find that “the LLF policies reduced the total fertility rate by 1.57 from 1969 to 1978, explaining approximately half of the decline in fertility during this period.”

In 1979, the well-known OCP came into effect with strong enforcement. Parents with above-quota births faced large fines and risked losing jobs in the public sector. The strict OCP experienced several relaxations in the mid 1980s. Rural families in 19 provinces were allowed to have a second child if their first child was a girl, which became known as the 1.5-child policy. In five provinces, two children were allowed[4] (Gu et al. 2007). Since this period, the birth control policy has been localized with different birth quotas and fine amounts.[5] In 2000, couples were allowed to have two children if both parents were only children. In 2013, either parent being an only child allowed a couple to have a second child. In 2016, the OCP was formally relaxed to the two-child policy. The three-child policy was then passed in 2021 (Li and Qiu 2021).

For our main analysis, we exploit the exogenous variations in fertility induced by the 1.5-child policy in rural China. Families were allowed to have a second child if their first child was a girl. Therefore, we construct an IV for fertility by interacting the first-born gender with policy

---

[4] The 19 provinces with the 1.5-child policy were Anhui, Fujian, Gansu, Guangxi, Guangdong, Guizhou, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangxi, Jilin, Liaoning, Shaanxi, Shandong, Shanxi, and Zhejiang. The five provinces with the two-child policy were Guangdong, Hainan, Ningxia, Qinghai, and Yunnan.

[5] In some rural areas, three children were allowed under certain conditions (e.g., parents with highly risky occupations or a first child born with disability. People with minor ethnicities were also generally subject to a more lenient policy.

exposure (assuming that earlier cohorts who remained with fewer fertile years were less affected by the policy). We explain the construction of IVs in detail in Section 4.

2.2 Public social security system and old age support in rural China

Rural China has a less-developed public social security system compared to developed countries and urban China.

Public health insurance was uncommon in rural China until the past decade. In 2003, 96% of rural families had no medical insurance (You and Kobayashi 2009). From 2003 and 2008, when the New Cooperative Medical Scheme (NCMS) was introduced, rural families began to have access to public medical insurance. Although it has high participation rates (95% of rural counties in 2009), NCMS is characterized by high deductibles, low reimbursement ceilings, and high copayments (Li and Zhang 2013). On average, 42% of inpatient services are reimbursed (Barber and Yao 2010), but outpatient care coverage and reimbursement rates vary considerably across regions (Cheng et al. 2015).

Not only long-term care insurance is absent in rural China,[6] but also the rural pension system is not generous. The New Rural Pension Scheme was initiated in 2008 and became a nationwide program by 2012. On average, the basic pension benefit (11.8 USD)[7] was 17% of the rural household average per capita living expenses (812 USD) in 2012. Although this pension provides help for basic subsistence, it may not be sufficient to maintain a minimum living standard (Cheng et al. 2018).

Partly as a result of the weak public social security system and partly as a result of the deeply rooted filial piety culture (Whyte, 2005), the rural elderly rely heavily on family members as old age support providers. For example, 72.8% of the rural survey respondents of CHARLS in 2015, which is a nationally representative survey for elderly Chinese, selected "children" as their main financial source for old age support. Only 20% selected "pension" (Chen and Fang 2021).

---

[6] Trials of long-term care insurance were conducted in 35 cities in 2016 in urban China. In 2019, another 14 cities were added to the experiment list. See: http://www.gov.cn/xinwen/2016-07/08/content_5089283.htm and http://www.gov.cn/gongbao/content/2020/content_5570107.htm for policy details.

[7] Throughout this paper, the exchange rate is assumed to be 1 CNY = 0.15 USD

3 Data

3.1 Data sources and sample restrictions

We use data from CHARLS in this study. CHARLS is a sister study of its counterpart Health and Retirement Study in the US, English Longitudinal Study of Aging in the UK, and Survey of Health, Aging, and Retirement in Europe. It is a biennial longitudinal survey that began in 2011 with a representative sample of 17,500 individuals aged 45 years or older and their spouses in continental China. It collected rich information regarding respondent health and healthcare use, work and income, demographic characteristics, and family information (Zhao et al., 2013). It also collected detailed community-level information on policies and public facilities. Therefore, it provided an ideal dataset for our study. We use data from the 2011, 2013, and 2015 waves.[8]

We restrict our sample to birth cohorts between 1930 and 1970. This amounts to keeping individuals between the ages of 45 and 85 years, and dropping 3,222 observations. We then drop ethnic minority groups because they have different birth policies and tend to have different cultures, eliminating another 3731 observations. We restrict our sample to non-OCP areas[9] (mainly rural areas) for our main analysis, eliminating 17,864 observations. Families in these regions have no incentive to have abortions based on gender at first birth, which facilitates our IV estimation strategy. In Section 6, we relax this sample restriction and include observations from OCP areas. By using an alternative specification, we demonstrate that the results are essentially the same. The restrictions discussed above left us with a sample of 34,978 observations from 14,211 individuals.

[8] The fourth wave from 2018 has recently been made available. We did not use it because some health utilization questions changed in this wave (e.g., our target outcome variables such as forgone outpatient and inpatient care were not included and the definition of self-treatment has changed).

[9] OCP areas are derived from the community survey question "*What was the specific family planning policy for ethnic Han in your village/community?*" The dummy variable for being in an OCP area takes a value of one if "*(1) one child policy*" is selected and zero if "*(2) two children if the first-born child is a girl*", "*(3) two children*", or "*(4) more than two children*" are selected. Even within a city/county, there are community variations in the birth policy.

3.2 Variables and summary statistics

Outcome variables

For our main analysis, we consider three sets of outcome variables. For outpatient care use, we consider *outpatient incidence, number of doctor visits, OOP outpatient costs,* and *outpatient care incidence* in the last month as the main outcome variables. For inpatient care use, we consider *inpatient incidence, number of hospital stays, OOP inpatient costs,* and *forgone inpatient care incidence* in the past year as the main outcome variables. In addition to formal healthcare use, we also consider informal healthcare use such as *self-treatment incidence* (e.g., buying over-the-counter drugs, traditional herbs, tonic/health supplements, and using healthcare equipment) and *OOP self-treatment costs* in the past month. See Appendix A for the definitions of each variable.

All cost variables are in Chinese Yuan (CNY). We translate them into USD according to the current exchange rate of 1 CNY= 0.15 USD in the main text, but keep them in CNY in all estimation results and summary statistics tables. All cost variables are unconditional, meaning they are set to zero if no cost is incurred.

Mechanism variables

We also consider the following variables as outcomes in our mechanism analysis. For health variables, we consider the categorical variables *self-reported health* (1: excellent; 2: very good; 3: good; 4: fair; 5: poor), *mental health score* (CES-D score on a scale from 0 to 30, with larger values indicating worse mental health.), and *chronic disease incidence* (whether the respondent has any of the following diseases: hypertension, dyslipidemia, diabetes, malignant tumor, chronic lung diseases, liver disease, heart disease, stroke, kidney disease, digestive disease, psychiatric problems, memory-related disease, arthritis or rheumatism, and asthma). For the income variables, we consider *annual earned income after tax* and *annual household income per capita*. For intergenerational interactions, we consider economic assistance variables such as the *incidence and amount of transfer from children*, social contact variables such as the *incidence of weekly contact with children in person and by phone or email*, and intergenerational support for healthcare use such as *indicators of whether children have paid for the health checkups,* the *OOP self-treatment cost,* and *OOP dental care cost for parents*. See Appendix A for the definition of each intergenerational interaction-related variable.

Control variables

In addition to using the *number of children* to measure fertility, in our regression, we also control for predetermined individual characteristics such as *age* (defined by birth year and month), *birth cohort*, *wave dummies*, an *indicator for males*, *level of education* (1: lower than lower secondary education; 2: upper secondary education and vocational training; 3: tertiary education)[10], *having a rural hukou* (household registration), and *partnered or not*.

Summary Statistics

Table 1 presents summary statistics for the main sample in the non-child-policy area. Among the entire sample, approximately 49% of respondents are men. On average, they were born in 1954 (59 years old). The majority are partnered (88%), with rural hukou (88%) and a level of education less than middle school (91%). On an average, they have three children. Half of the first-born children are boys.

Table B.1 in Appendix B presents the summary statistics for the healthcare use and mechanism variables. On average, individuals have more than a 20% chance of receiving outpatient care in the past month. The OOP outpatient care cost conditional on being positive is approximately $121 in the past month. Inpatient care is less frequent, but more expensive. We find that 12% of individuals use inpatient care in the past year and the average OOP inpatient care cost conditional on being positive is $1553 in the past year. Additionally, 8% and 6% of the sampled individuals forego outpatient and inpatient care, respectively, despite recommendations from a doctor. In contrast to formal healthcare utilization, individuals have a more than 50% chance of using self-treatment in the past month. The monthly average OOP self-treatment cost conditional on being positive is approximately $30. This pattern of low-frequency, but high-

[10] The "less than lower secondary education" group refers to: "illiterate," "did not finish primary school, but can read," "home school (Sishu)," "elementary school," or "middle school." The "upper secondary education & vocational training" group refers to "high school" or "vocational school." The "tertiary education" group refers to "higher vocational education," "college/university," or "post-graduate education."

OOP-cost formal healthcare use and high-frequency use of informal healthcare is consistent with the ungenerous features of the health insurance system in rural China.

Table 1 Summary Statistics

Variable	Obs.	Mean	Std. dev.	Variable	Obs.	Mean	Std. dev.
		Entire sample				Entire sample	
Number of children	33,968	2.766	1.405	Birth year	34,978	1953.776	9.683
First-born child being a boy	33,692	0.519	0.5	Education	34,959	1.094	0.318
Male	34,978	0.492	0.5	Rural	33,274	0.879	0.326
Age	33,956	58.824	9.588	Partner	33,965	0.88	0.325
		Number of children<2				Number of children≥2	
		Outpatient care use				*Outpatient care use*	
Outpatient incidence	4,530	0.179	0.383	Outpatient incidence	29,066	0.223	0.417
# Doctor visits	4,464	0.368	1.339	# Doctor visits	28,676	0.482	1.494
OOP outpatient cost	4,046	77.110	837.257	OOP outpatient cost	25,456	84.592	892.040
Positive OOP outpatient cost	304	1026.267	2894.981	Positive OOP outpatient cost	2,764	779.081	2605.706
Forgone outpatient incidence	4,522	0.080	0.272	Forgone outpatient incidence	29,041	0.080	0.271
		Inpatient care use				*Inpatient care use*	
Inpatient incidence	4,545	0.098	0.297	Inpatient incidence	29,151	0.122	0.328
# Hospital stays	4,542	0.146	0.591	# Hospital stays	29,137	0.183	0.645
OOP inpatient cost	4,200	304.083	4402.776	OOP inpatient cost	26,511	341.152	3640.231
Positive OOP inpatient cost	95	13443.684	26217.992	Positive OOP inpatient cost	902	10026.906	17107.446
Forgone inpatient incidence	3,945	0.054	0.226	Forgone inpatient incidence	26,179	0.056	0.229
		Informal healthcare use				*Informal healthcare use*	
Self-treatment incidence	4,516	0.488	0.500	Self-treatment incidence	29,024	0.519	0.500
OOP self-treatment cost	4,516	96.555	597.021	OOP self-treatment cost	29,024	91.678	370.046
Positive OOP self-treatment cost	1,933	225.578	896.577	Positive OOP self-treatment cost	13,542	196.489	522.399

Table 1 further compares healthcare use by the number of children. In general, multi-children parents have a higher probability of using all forms of healthcare. They tend to have more doctor visits and hospital stays. Their unconditional OOP outpatient and inpatient costs are higher, whereas positive OOP costs are lower, indicating that the extensive margin effect may drive higher costs.

4 Empirical strategy

We are interested in the causal effect of the number of children on healthcare utilization. We specify the linear model for this effect as follows[11]:

[11] For binary outcome variables, we still use linear models for our main analysis because it is convenient for specification

$$Y_{it} = \beta_0 + \alpha NC_{it} + X_{it}'\beta_1 + W_i{}'\beta_2 + \omega_t + u_{it} \quad (1)$$

Here, Y_{it} represents for the outcome variables for individual i in year t.

NC is the number of children and α is the parameter of interest. An alternative measure of fertility would be to control for the number of sons and daughters separately, facilitating observations of the heterogeneous effects of sons and daughters on parental outcomes (Ho 2019, Guo and Zhang 2020, Kabátek and Ribar 2021). We examine this alternative specification in Section 6 and present the results in Table 7. For all outcomes, the effects of the numbers of sons and daughters are close and statistically indifferent. Therefore, we control for the number of children in our primary analysis.

X_{it} represents individual characteristics such as age, age squared, partnered or not, gender, rural hukou, and education level. W_i represents time-invariant community-fixed effects and birth-year-fixed effects and ω_t refers to wave dummies.[12] Standard errors are clustered at the community level.[13]

NC can be endogeneous. Parent fertility decisions may correlate with unobserved factors or preferences that influence healthcare utilization. For example, families that prefer more children may be wealthier because they are more likely to be able to afford the expenses of raising additional children. Additionally, wealthier families can afford to use more healthcare services.

To correct for potential endogeneity, we exploit the exogenous variations in fertility induced by the 1.5-child policy implemented in the mid 1980s in rural China. Families could have a second child given a first-born girl, implying that the first-born gender can introduce exogenous variations into the total number of children. Figure 1(a) reveals that in general, in areas where the 1.5-Child Policy or having multiple children are allowed, parents with a first-born girl did

testing. In Table B.2, we estimate an IV-Probit model for binary outcomes. The results are robust. For OOP expenditure variables, we use log(Y + 1) as the outcome variable. In Table B.3, we estimate an IV-Tobit model with the original expenditure variables. The results are robust. In Table B.3, we also present the 2SLS results of the original expenditure variables for reference.

12 The results are robust to adding extra controls such as age cubed, age of having a first child, parent's number of living siblings fixed effects, early-life health level fixed effects, and different types of health insurance.

13 Alternatives include clustering standard errors at the household level or individual level because an individual and their spouse may appear in different waves in our sample, which could result in correlation within the individual or household levels. However, the results are almost the same as those for standard errors clustered at the community level.

have more children on average than those with a first-born boy. For cohorts earlier than 1937, who could be infertile and were unlikely to be influenced by the policy in the mid 1980s, the relationship between the number of children and first-born gender is mixed.

(a) Number of children (b) Number of extra children with first-born girls

Figure 1 Number of (extra) children by parent birth cohorts and first-born gender in non-one-child-policy (NOCP) areas

Note: In Figure 1(b), the number of extra children with a first-born girl for each cohort is calculated as $\overline{NC}_{cohort,firstborn\ girl} - \overline{NC}_{cohort,firstborn\ boy}$.

Figure 1(b) reveals that the average number of extra children with the first-born child being a girl (calculated as: $\overline{NC}_{cohort,firstborn\ girl} - \overline{NC}_{cohort,firstborn\ boy}$) increases with the parent birth year. This is intuitive because the younger the parents, the more remaining fertile years they have after the policy is enacted and the more likely they are to be influenced by it.

Therefore, we construct a policy-exposure type of IV for the number of children as $\mathbf{1}_{firstborn\ being\ a\ boy} \times \mathbf{1}_{birth\ year \geq 1937} \times (\text{birth year} - 1929)$ (i.e., interacting the first-born gender with the dummy variable for the cohort no earlier than 1937, and with a normalized birth cohort linear trend).[14] Table 2 presents the correlation between the IV and number of children, which mirrors the pattern shown in Figure 1. On average, respondents having a first-born boy who are born in later years have fewer children. For example, a parent born in 1953

[14] This IV constructed from first-born gender implies that our estimation only relies on individuals with at least one child. Sample selection is less of a concern here because only 604 observations (i.e., 1.78% of the entire sample) have no children. In Section 6, we demonstrate that these results are robust if we predict the gender of the first-born child and include childless individuals. We normalized birth year related to 1929 because we restrict our sample to cohorts no earlier than 1930. Our results are insensitive to using cohorts no earlier than 1935 or other years around 1937 to construct the IV, or using the wife's birth year to construct the IV.

with a first-born boy has approximately $0.013 \times (1953 - 1929) \approx 0.3$ fewer children than a parent with a first-born girl. The Sanderson-Windmeijer F statistic is 306.14, which confirms the strength of this instrument.

Table 2 First stage of estimation results

Variable	Number of children
IV (Boy*byr1937*T)	-0.013***
	(0.001)
Other controls	Yes
Sanderson-Windmeijer F test statistics	306.14
Observations	31,963

Notes: *Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The IV (Boy*byr1937*T) is constructed as $\text{first} - \text{born boy} \times (\text{birth year} \geq 1937) \times (\text{birth year} - 1929)$. Other controls include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies.

The exclusion restriction assumption for a valid IV implies that there is no selective abortion by first-born sex, which correlates with healthcare use. Such child gender selection is unlikely in our setting because we restrict our sample to NOCP areas, where parents have no incentive to perform selective abortions for their first child. Table 1 supports this argument. The probability of having a first-born boy is 0.519, which is close to a random event. This evidence is consistent with the findings of Cao (2019) and Chen et al. (2013), the former of whom finds that the first-born gender is random. The latter also finds that ultrasound technology for detecting a baby's gender only affects second- and higher-parity births.

In Section 6, we further highlight evidence for the exclusion restriction assumption for our IV. The results of over-identification tests indicate that the joint validity of the instruments is not rejected. When controlling for the IV directly in the second stage, the effects of the IV on healthcare use are insignificant for all outcomes.

5 Results

5.1 Main results

Table 3 summarizes the effects of the number of children on healthcare utilization, where column (1) shows the OLS estimates and column (2) shows the two-stage least square (2SLS) estimates with our IV.

We focus on three sets of healthcare utilization: outpatient care, inpatient care, and informal healthcare. In general, having more children increases healthcare utilization. The OLS and 2SLS estimates share a similar pattern, but the 2SLS estimates are generally larger in magnitude. One possible reason may be that families with less knowledge and awareness of health tend to do less family planning and use less healthcare.

The 2SLS estimates show that having one additional child increases the probability of receiving outpatient care in the past month by 0.032, which is approximately 15% of the sample mean likelihood of receiving outpatient care. The number of doctor visits and OOP outpatient expenditures increase by 0.99 and 18%, respectively, with one additional child. We do not find a significant effect on the probability of being sick and not seeing a doctor, suggesting no change in unmet outpatient care.

Regarding inpatient care utilization, we find a marginally significant increase in the probability of inpatient care use and corresponding costs. We also observe a significant increase in the number of hospital stays of 0.046, which is approximately 25% of our sample's average number of hospital stays in the past year. There is no significant effect on the incidence of not staying in the hospital when recommended by doctors.

Regarding informal healthcare use such as self-treatment, we also observe a significant increase in the probability of having self-treatment by 0.057 or approximately 11% of the average rate of self-treatment in the past month for the sample. This significant effect on self-treatment costs indicates that self-treatment cost increase by approximately 28% when having one additional child. Panel A in Table B.4 further highlights the reasons for self-treatment. We decompose "self-treatment incidence" into six dummy variables indicating using self-treatment in the past month for (1) purchasing OTC drugs, (2) purchasing prescribed drugs, (3) purchasing traditional herbs or traditional Chinese medicines, (4) buying tonics or health supplements, (5) using healthcare equipment, and (6) other reasons. The results indicate that the number of children increases self-treatment incidence and costs for curative (purchasing OTC drugs) and preventive (buying tonics and health supplements) reasons.

Table 3 Estimated effects of the number of children on healthcare utilization

Dependent variables	OLS (1)	2SLS (2)
Panel A Outpatient care		
Outpatient incidence	0.004**	0.032**
	(0.002)	(0.014)
# Doctor visits	0.012	0.099**
	(0.009)	(0.048)
Log(OOP outpatient cost+1)	0.023**	0.181***
	(0.010)	(0.065)
Forgone outpatient incidence	-0.002	-0.006
	(0.002)	(0.009)
Panel B Inpatient care		
Inpatient incidence	0.004*	0.019*
	(0.002)	(0.010)
# Hospital stays	0.003	0.046**
	(0.004)	(0.021)
Log(OOP inpatient cost+1)	0.015	0.085*
	(0.010)	(0.048)
Forgone inpatient incidence	0.000	0.012
	(0.001)	(0.008)
Panel C Informal healthcare		
Self-treatment incidence	0.009***	0.057**
	(0.003)	(0.020)
Log(OOP self-treatment cost+1)	0.050***	0.280***
	(0.013)	(0.091)

Notes: *Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy×(birth year≥1937)×(birth year-1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. The numbers of observations for each outcome are listed in Table B.1.

We also check whether the number of children affects preventive care or dental-care use. Panel B in Table B.4 reveals no significant effects on health checkup incidence, dental care visits, or costs.

In summary, fertility significantly increases the incidence of healthcare utilization, including outpatient care, inpatient care, and self-treatment. These increases in formal and informal healthcare use translate into an increase in corresponding OOP expenditures.

5.2 Possible mechanisms

We now discuss the potential mechanisms of the effects of fertility on healthcare utilization. The first possible mechanism is the health effects of fertility, which can drive demand for healthcare utilization.[15] Raising children is expensive and brings additional pressure. Having more children typically requires more investment in child development, so there are fewer resources to devote to one's own health. This negative effect of fertility on health in early adulthood may be responsible for poorer health outcomes later in life, leading to a higher demand for healthcare services. Panel A in Table 4 highlights the effect of the number of children on different health measures. Overall, having more children leads to more health issues. With one additional child, the self-rated health score increases significantly by 0.106 or approximately one standard deviation of our measure (a higher score represents a worse health status), CES depression score increases significantly by 0.669 or approximately 0.1 the standard deviation of our measure (a higher score represents a worse mental health status). The incidence of any chronic disease increases significantly by 0.07. A worse health status indicates that individuals with more children are less healthy in old age, which increases their demand for healthcare utilization.

With the increased demand for healthcare consumption, having additional children does not seem to bring more income to meet this demand. As shown in Panel B in Table 4, the effects of the number of children on earned income and per capita household income are negative and insignificant.

Table 4 Effects of the number of children on health and income

Dependent variables	Number of children
Panel A: Health	
Self-reported health	0.106***
	(0.040)
Mental health score	0.749***
	(0.247)
Incidence of any chronic disease	0.068***

[15] We checked if the number of children would influence health insurance adoption, which may change the actual price of healthcare services. The results in Table B.10 indicate no evidence of such an effect on any type of health insurance. Therefore, we conclude that the increase in healthcare use with additional children is unlikely to be driven by additional adoption of generous health insurance schemes.

	(0.021)
Panel B: Income	
Log(annual earned income after tax + 1)	-0.153
	(0.173)
Log(annual household income per capita+1)	-0.095
	(0.125)

Notes: *Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The 2SLS estimates are reported with the same specifications as in Equation (1). The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy×(birth year≥1937)×(birth year-1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. Mental health scores are calculated using CES-D scores. Higher values of self-reported health and mental health scores indicate worse (mental) health. The incidence of any chronic disease is defined as the incidence of at least one of the 14 chronic diseases described in Section 3.2. The numbers of observations for each outcome are listed in Table B.1.

More children, on the other hand, can mean more intergenerational support from children, which facilitates parents utilizing additional healthcare services. [16] This intergenerational support can be a monetary transfer to share parent medical expenses or care and contact to remind them of necessary medical treatments.

Table 5 provides evidence of this mechanism of intergenerational support. Panel A summarizes the effects of fertility on the monetary transfer from children. Having additional children is associated with higher monetary transfers from children. For parents with one additional child, the likelihood of receiving any monetary transfer is 0.237 higher (1.76 times higher in terms of the amount of money). These results suggest that parents receive more financial support from children when they have more children, which can potentially be spent on additional healthcare services.

In addition to direct transfer, Panel B in Table 5 shows that it is more likely that children will pay for some medical expenses for their parents if there are more children. With one additional child, a parent is 0.013 more likely to have children pay for health checkups and OOP self-treatment cost, and 0.007 more likely to have OOP dental costs paid by children. Having additional children helps (at least partially) cover medical costs, making it more affordable for

[16] We check if more children would influence parent annual earnings and find no significant effect. The coefficient of the number of children on log(Earnings+1) is −0.153 with a standard error of 0.173.

parents to use healthcare services.

Table 5 Effects of the number of children on intergenerational support

Dependent variables	Number of children
Panel A: Monetary transfer	
Incidence of transfer from children	0.237***
	(0.023)
Log(Amount of transfer from children+1)	1.759***
	(0.169)
Panel B: Child-paid medical cost	
Child-paid health check	0.013**
	(0.005)
Child-paid OOP self-treatment cost	0.013**
	(0.006)
Child-paid OOP dental cost	0.007*
	(0.004)
Panel C: Contact	
Any contact	0.032**
	(0.013)
Contact in person	0.026
	(0.021)
Contact by phone/email	0.179***
	(0.034)

Notes: *Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The 2SLS estimates are reported with the same specifications as in Equation (1). The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. The numbers of observations for each outcome are listed in Table B.1.

Individual health utilization behavior may also be affected by non-pecuniary support from children such as daily contact. For example, with more frequent contact, children can remind their parents to see a doctor and accompany them for medical treatment when necessary, which may translate into parents using more healthcare services. Panel C in Table 5 suggests a positive impact of the number of children on the incidence of any contact and the incidence of contact by phone or email.

In summary, an increase in parent healthcare use can be driven by higher demand induced by deteriorating physical and mental health. Apart from the health services channel, additional intergenerational support from children in the form of more contact, transfers, and sharing medical bills may prompt parents to use more healthcare services.

5.3 Heterogeneity

To gain a better understanding of the results discussed above and characterize which subpopulation is most affected by the policy-induced fertility increase, we conduct the same analysis as that discussed in Section 5.1 by subgroups.

By gender

Mothers may suffer from the direct health impacts of childbearing and childrearing, including higher risks of cardiovascular diseases and stroke (e.g., Ness et al. 1994, Zhang et al. 2009), which may lead to a greater increase in demand for healthcare use compared to men. On the other hand, women typically have lower lifetime income and economic resources to support increased demand, which may lead to a different level of actual utilization of healthcare compared to men. Therefore, we check whether female healthcare utilization responds differently to fertility changes compared to male healthcare utilization.

Columns (1) and (2) in Table 6 present the 2SLS estimates of the impact of the number of children on healthcare use and mechanism variables, as well as the sample means of the subgroup characteristics.

Both genders increase their healthcare use with additional children, despite the fact that they tend to increase different types of healthcare use. Fertility increases inpatient and informal healthcare in men. An additional child increases the probability of men using inpatient care by 0.032 and the number of hospital stays by 0.076, which are one-quarter and one-half of the sample average, respectively. Informal healthcare such as the probability and OOP cost of self-treatment also increases by 0.074 and 31%, respectively. For women, fertility mainly

Table 6 Heterogeneous effects of the number of children on healthcare utilization

	By gender		By level of education		By age cohort	
	Male	Female	High education	Low education	Old(byr.<1955)	Young(byr.≥1955)
Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
				Panel A: Outpatient care		
Outpatient incidence	0.014	0.049*	-0.071	0.043***	0.008	0.037**
	(0.017)	(0.021)	(0.051)	(0.015)	(0.025)	(0.017)

# Doctor visits	0.019	0.179**	-0.189	0.128**	-0.036	0.144***
	(0.055)	(0.071)	(0.166)	(0.051)	(0.098)	(0.051)
Log(OOP outpatient cost+1)	0.093	0.272***	-0.208	0.226***	-0.017	0.233***
	(0.070)	(0.098)	(0.217)	(0.068)	(0.114)	(0.078)
Forgone outpatient incidence	-0.015	0.002	-0.036	-0.003	0.000	-0.008
	(0.012)	(0.014)	(0.033)	(0.009)	(0.017)	(0.011)
				Panel B: Inpatient care		
Inpatient incidence	0.032**	0.007	0.058*	0.013	0.033	0.013
	(0.014)	(0.015)	(0.035)	(0.011)	(0.020)	(0.012)
# Hospital stays	0.076**	0.020	0.124*	0.035	0.060	0.033
	(0.030)	(0.027)	(0.070)	(0.022)	(0.044)	(0.021)
Log(OOP inpatient cost+1)	0.106	0.066	0.136	0.075	0.152	0.070
	(0.066)	(0.066)	(0.139)	(0.051)	(0.108)	(0.053)
Forgone inpatient incidence	0.006	0.018	-0.015	0.015*	0.002	0.012
	(0.011)	(0.011)	(0.022)	(0.009)	(0.014)	(0.009)
				Panel C Informal healthcare		
Self-treatment incidence	0.074***	0.040	0.012	0.063***	0.068**	0.049**
	(0.025)	(0.025)	(0.064)	(0.021)	(0.034)	(0.022)
Log(OOP self-treatment cost+1)	0.313***	0.252**	0.064	0.304***	0.302*	0.271***
	(0.117)	(0.117)	(0.296)	(0.095)	(0.172)	(0.102)
				Panel D Health & Economic resource		
Self-report health	0.115**	0.100*	-0.033	0.119***	0.111*	0.119**
	(0.049)	(0.054)	(0.141)	(0.041)	(0.064)	(0.047)
Mental health score	0.867***	0.670**	0.112	0.737***	0.975*	0.626**
	(0.285)	(0.336)	(0.851)	(0.265)	(0.518)	(0.294)
Incidence of any chronic disease	0.098***	0.038	-0.016	0.079***	0.062*	0.071***
	(0.032)	(0.027)	(0.141)	(0.022)	(0.035)	(0.026)
Log(household income per capita + 1)	-0.060	-0.128	0.221	-0.129	0.045	-0.130
	(0.133)	(0.129)	(0.312)	(0.130)	(0.155)	(0.173)
Log(Amt. of transfer from children+1)	1.750***	1.764***	1.659***	1.760***	1.258***	2.009***
	(0.178)	(0.177)	(0.484)	(0.176)	(0.245)	(0.204)
First-stage coefficient of IV	-0.014***	-0.013***	-0.013***	-0.014***	-0.016***	-0.013***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Sanderson-Windmeijer F test statistics	299.147	262.84	35.15	284.12	78.72	267.73
				Panel E Sample mean of individual characteristics		
Age	59.25	58.42	55.35	59.16	66.56	51.10
Work or not	0.79	0.67	0.77	0.73	0.61	0.85
Earned income	6751.19	1842.15	12461.07	3465.29	1637.57	6827.01
Per capita household income	8008.59	7778.42	15177.01	7196.49	6393.86	9573.18
Amount of transfer from children	3578.00	3773.44	4181.45	3630.41	3911.78	3445.92
Having generous health insurance or not	0.15	0.10	0.37	0.10	0.13	0.12
Observations	15,487	16,476	2,780	29,183	15,897	16,066

Notes:*Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The 2SLS estimates are reported with the same specifications as in Equation (1). The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. "Having generous health insurance or not" indicates whether a parent has any of Urban Employee Medical Insurance, Urban Resident Medical Insurance, Urban and Rural Resident Medical Insurance, or Government Medical Insurance.

increases outpatient care and the cost of self-treatment. Having an additional child increases the probability of receiving outpatient care in the past month by 0.049 and the number of doctor visits by 0.179, representing 20% and 35% of the sample average, respectively. Fertility significantly increases OOP self-treatment expenditure by 25% for women.

One possible reason for this pattern across genders may be that having additional children negatively affects both male and female health, and may even have a larger effect on men. As shown in Panel D in columns (1) and (2) in Table 6, with an additional child, men have worse self-reported health and mental health than women, and they have a higher probability of having a chronic disease. Therefore, it is not surprising that men use more inpatient care, which is typically associated with more severe diseases.

Panel E in Table 6 highlights another possible explanation. On average, women have fewer economic resources for handling fertility shock because they have lower earned income and per capita household income than men. Having additional children increases the amount of transfer from children, but not to a greater extent than that for men. With limited economic resources, women may resort to relatively cheaper outpatient care options. Moreover, they are covered by less generous insurance and the higher marginal cost of using healthcare may explain the substantial increase in OOP healthcare costs for women.

By level of education

Fertility can affect people with different socioeconomic statuses differently. For example, parents with higher education levels may have better health knowledge and more economic resources to hedge against fertility shocks. Therefore, we divide the sample and check the effects by education level. The low education group includes individuals completing middle school or below, whereas the high education group includes individuals completing high school or above.[17]

As shown in Columns (3) and (4) in Table 6, fertility negligibly affects the healthcare use of parents with higher education, except that having additional children has a marginally significant positive effect on inpatient incidence and the number of hospital stays. In contrast, the less educated group is the main driver of increased healthcare use. With one additional child, their outpatient incidence increases by 0.04, the number of doctor visits increases by 0.128, OOP outpatient cost increases by 23%, self-treatment incidence increases by 0.06, and OOP self-treatment cost increases by 30%. Although inpatient care use does not increase

[17] Low education group includes "No formal education or illiterate", "Did not finish primary school, but capable of reading", "Sishu (home school)", "Elementary school", and "Middle school". High education group includes "High school", "Vocational school", "Two/Three Year College/Associate degree", "Four Year College/Bachelor's degree", and "Post-graduated (Master/PhD)".

significantly with additional children, the forgone inpatient incidence increases by 0.015. This increasing unmet demand for inpatient care suggests that budget constraints are binding for the low education group.

The differences in these results suggest that parents with higher education may be more capable of mitigating the adverse impacts of having additional children. Fertility has almost no impact on the health of a more educated parent, but hurts a less educated parent significantly (Panel D in Columns (3) and (4) in Table 6). With greater adverse health effects of fertility, the lower education group has much lower income and less generous medical insurance (Panel E in Columns (3) and (4) in Table 6), explaining why they have to use more healthcare, face higher OOP health costs, and are more likely to forgo expensive inpatient care in the meantime.

Less educated parents bear increased medical costs and possible unmet demand for healthcare, and suffering from worse health with additional children raises concerns regarding health disparities in birth-encouraging policies.

By age cohort

Cohort differences can also exist in the effects of fertility on healthcare use. Older cohorts have responded to the fertility shock on their health and healthcare use over a longer horizon. Therefore, the effects of fertility may be attenuated. In contrast, younger cohorts may have greater health knowledge and more economic resources to respond to fertility shocks in health and healthcare, but they may face tighter time constraints for time-consuming care because most of them are not retired.

We divide our sample by whether the parent was born before 1955 (close to the sample average age of 58). The average ages of the older and younger cohorts were 67 and 51, respectively. Columns (5) and (6) in Table 6 summarize the results.

In younger cohorts, fertility has adverse effects on mental and physical health and significantly increases the utilization and OOP costs of outpatient care and self-treatment. Inpatient care use does not significantly increase with additional children (with small point estimates), potentially because 85% of young parents are working parents and face a higher opportunity cost for their time (Panel E in Table 6).

For older cohorts, having additional children also negatively impacts health. Having additional children seems to have a particularly large negative impact on mental health. Fertility also increases self-treatment incidence and cost for older cohorts, with an even larger effect than that on younger cohorts, but the effects on formal care use are no longer significant. Table B.11 analyzes the effects of fertility on self-treatment types by cohort. Increased self-treatment use in older cohorts is driven mainly by buying OTC drugs. It is likely that older cohorts resort to self-treatment to manage their health based on a longer time to respond to fertility shocks.

The comparison of cohorts indicates that fertility has a comprehensive influence on healthcare use in the relatively short term. The effects of fertility that deteriorate health and increase OOP health costs persist as parents get older.

In summary, we find that fertility increases healthcare utilization for most subgroups, but with heterogeneous patterns. Fertility negatively affects the health of both the sexes. Men tend to increase inpatient care use with additional children, whereas women resort to more outpatient care. Women with less generous health insurance than men tend to experience a larger increase in OOP health costs with additional children. Less educated parents with limited economic resources and ungenerous insurance suffer from the adverse health effects of fertility and bear a significant increase in OOP medical costs. In contrast, health conditions and healthcare expenditures are negligibly affected in the more educated group. Fertility increases different types of healthcare use for younger parents (born after 1955), but its effects on health and self-treatment costs persist into older ages.

6 Assumption checks and sensitivity analysis

Controlling for the number of daughters and sons separately

When daughters and sons have differential effects on parental healthcare utilization, this indicates that the genders of children may affect parent healthcare utilization through a mechanism other than the number of children, failing the exclusion restriction. To address this concern, we replace the number of children with two other variables called "the number of sons" and "the number of daughters" in our regression. In addition to the IV of "Boy*byr1937*T," we add "first-born child being a boy or not" and interact it with "the first child born after 1984" (i.e., Boy*First-child1984) as an additional IV. This additional IV utilizes the fact that the1.5-child policy was first implemented in 1984 (Cao 2019). Therefore, parents with their first child born after 1984 were fully exposed to the policy and their fertility may be affected more by the policy.

Columns (3) and (4) in Panel C in Table 7 present the first-stage estimation results. The two IVs exhibit strong correlation with the endogenous variables. The Kleibergen-Paap rk Wald F statistic is 30.83, which is much greater than 10, rejecting the null hypothesis of the weakly identified endogenous variables.

The remaining columns in Table 7 present the estimated coefficients for the numbers of sons and daughters. Although most point estimates become insignificant as a result of the correlation between the numbers of sons and daughters, they are still close to the main results. For all outcomes, sons and daughters exhibit similar effects. These differences are not statistically significant at the 10% level.

Evidence for the exclusion restriction assumption

Although the exclusion restriction assumption is not directly testable, we still present evidence for it. We first estimate the main model with the additional IV Boy*First-child1984. With multiple IVs, the monotonicity assumption for the interpretation of a positively weighted average of local average treatment effects for multiple compliers is less likely to hold (Mogstad et al. 2021). However, with two IVs, we can still test for over-identifying restrictions. The results in Table 8 are similar to the main results. The Hansen J-test results indicate that the joint validity of the instruments is not rejected.

Table 7 2SLS Controlling for the number of sons and daughters separately

	Panel A Outpatient care			
	(1)	(2)	(3)	(4)
Variables	Outpatient incidence	# Doctor visits	Log(OOP outpatient cost+1)	Forgone outpatient incidence
Num. of daughters	0.037	0.118	0.195	-0.011
	(0.029)	(0.088)	(0.125)	(0.018)
Num. of sons	0.040	0.129	0.202	-0.013
	(0.044)	(0.135)	(0.187)	(0.027)
Test n.of d = n.of s.	0.873	0.844	0.918	0.806
Obs.	31,963	31,525		31,934

Panel B Inpatient care

Variables	(1) Inpatient incidence	(2) # Hospital stays	(3) Log(OOP inpatient cost+1)	(4) Forgone inpatient incidence
Num. of daughters	0.025	0.052	0.130	0.016
	(0.020)	(0.034)	(0.090)	(0.015)
Num. of sons	0.028	0.055	0.155	0.018
	(0.030)	(0.052)	(0.140)	(0.022)
Test n.of d = n.of s.	0.758	0.878	0.652	0.814
Obs.	32,057	32,043	29,252	28,621

Panel C Informal healthcare & First stage

Variables	(1) Self-treatment incidence	(2) Log(OOP self-treatment cost+1)	(3) First-stage Number of daughters	(4) First-stage Number of sons
Num. of daughters	0.071**	0.367**		
	(0.033)	(0.163)		
Num. of sons	0.078	0.413*		
	(0.050)	(0.248)		
Boy*byr1937*T			-0.042***	0.731***
			(0.001)	(0.020)
Boy*First-child1984			0.198***	-0.527***
			(0.038)	(0.036)
Test n.of d = n.of s.	0.696	0.625		
Kleibergen-Paap Wald rk F statistic			30.83	
Obs.	31,915	31,915	31,963	31,963

Notes:*Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The model is similar to the main analysis except that the number of children is replaced with the number of daughter" and number of sons. Columns (3) and (4) in Panel C present the first-stage results. The remaining columns present the 2SLS estimates of the effect of the number of children on each outcome. "Test n.of d = n.of s." indicates where the coefficient of the number of daughters is equal to that of the number of sons. P-values are reported. The number of daughters and the number of sons are instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929), and Boy*First-child1984, which is constructed as first-born boy or not × the first child born after 1984 or not. Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies.

A similar exercise is to test if the Boy*byr1937*T IV still affects healthcare utilization when controlling for the number of children. We directly control for Boy*byr1937*T in the second stage and use Boy*First-child1984 to instrument the number of children. Table B.5 presents the 2SLS estimates. The coefficients for the number of children, though no longer significant due to the correlation with Boy*byr1937*T, are very close to the main results. The point estimates of Boy*byr1937*T are very small and insignificant, suggesting that Boy*byr1937*T does not directly influence healthcare use once we control for the number of children.

Table 8 2SLS estimates for the main model with additional IVs

Panel A Outpatient care

Var.	(1) Outpatient incidence	(2) # Doctor visits	(3) Log(OOP outpatient cost+1)	(4) Forgone outpatient incidence
Num. of children	0.033**	0.102**	0.183***	-0.007
	(0.014)	(0.044)	(0.063)	(0.009)
Hansen J (P)	0.871	0.842	0.913	0.805

Obs.	31,963	31,525	28,082	31,934
		Panel B Inpatient care		
	(1)	(2)	(3)	(4)
Var.	Inpatient incidence	# Hospital stays	Log(OOP inpatient cost+1)	Forgone inpatient incidence
Num. of children	0.020**	0.047**	0.090**	0.013*
	(0.010)	(0.019)	(0.045)	(0.008)
Hansen J (P)	0.755	0.875	0.649	0.811
Obs.	32,057	32,043	29,227	28,621
		Panel C Informal healthcare & First-stage		
	(1)	(2)	(3) First-stage	
Var.	Self-treatment incidence	Log(OOP self-treatment cost+1)	Num. of children	
Num. of children	0.059***	0.291***		
	(0.019)	(0.086)		
Boy*byr1937*T			-0.010***	
			(0.001)	
Boy*First-child born after 1984			-0.196***	
			(0.042)	
Hansen J (P)	0.691	0.618		
Kleibergen-Paap rk Wald F statistic			179.06	
Obs.	31,915	31,915	31,963	

Notes:*Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. Column (3) in Panel C presents the first-stage results. The remaining columns present the 2SLS estimates of the effect of the number of children on each outcome. For the Hansen J-test, p-values are reported. The control variables are the same as those used in the main analysis. The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929), and Boy*First-child1984, which is constructed as first-born boy or not × the first child born after 1984 or not. Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies.

An alternative measure of fertility

To account for the potential nonlinear effect of the number of children, we use "having multiple children (≥2) or not" as an alternative measure of fertility. The results in Table B.6 exhibit the same pattern as those of the main analysis using the number of children. The first-born child being a boy and the parent being younger significantly reduce the probability of having at least two children. The effect of having multiple children is approximately three times as large as that in the main results (i.e., the effect of having one additional child, which is consistent with the fact that approximately 90% of the sample has no more than four children).

Accounting for multiple hypothesis testing

To examine if the statistical significance of our results remains robust if we account for multiple hypothesis testing, we group the outcomes into "outpatient care," "inpatient care," and "informal healthcare," and then calculate group-wise Romano-Wolf adjusted p-values (Romano and Wolf 2005) for the coefficients of the number of children. Table B.7 compares the original p-values from the main model to the adjusted p-values. Excluding inpatient incidence and OOP inpatient cost, for most outcomes, the effects of the number of children remain significant at the 10% level or lower.

Retaining observations in OCP regions

To facilitate a valid identification strategy, we restrict the main sample to people living in NOCP regions. Although this restriction is supposed adopted to help increase the internal validity of the results within NOCP sample, one may still be concerned regarding the use of a less representative sample, which could hinder the external validity of the findings. For example, those who were outside our sample may be less affected because they could be healthier and more risk seeking, able to afford to raise more children, and be less likely to use healthcare services.

To address this concern, we check the extent to which our results could be generalized to a sample in which we include people from OCP areas. This sample consists of 22,017 individuals and 52,842 observations, with the other sample restrictions remaining unchanged.[18]

Because the firstborn gender may be an invalid IV in OCP areas, we use Boy*byr1937*T interacting correlated with "being in an NOCP area or not" as our first IV for the new sample. The second IV is "if the community is in the OCP area or not", which essentially exploits the community-level variations of birth policies. As shown in Figure C.1, which plots the average number of children for each parental birth cohort by first-born gender and being in an OCP area or not, being in an OCP region has an extra negative effect on the number of children in addition to first-born boys.

With these two new IVs, we implement a 2SLS estimation similar to the main analysis, except that we control for city-fixed effects instead of community-fixed effects because "OCP area or not" is defined at the community level. This specification assumes away community-specific confounders that influence both parental healthcare use and IVs. Therefore, we also report over-identification test results to check the validity of this instrument.

[18] The number of observations in our regression is 48,586 because we have to drop missing values in the required variables.

Table B.8 presents the 2SLS estimation results for this alternative sample and specification. The Hansen J test results indicate that the joint validity of the instruments cannot be rejected. The estimation results are essentially the same as those in the main analysis, with healthcare utilization increasing with the number of children.

Selection into fertility

Finally, we address the concern of fertility selection. The IV Boy*byr1937*T is conditional on individuals with at least one child. In other words, we estimate the intensive margin effect on fertility. We argue that sample selection at the extensive margin is less of a concern because only 604 observations (1.78% of the entire sample) have no children. We are aware of no reason that couples with no children are systematically more likely to have first-born girls or boys. To check the robustness of our results, if we account for the extensive margin effect, we impute the first-born gender for 604 observations without a child and 67 observations with missing first-born gender information. This imputation is performed based on a logistic regression where the predictors are age, age squared, partnered or not, gender, rural hukou or not, education level, work or not, yearly earnings, number of living siblings, self-reported-health-level-fixed effects, mental health, having a chronic disease or not, outpatient incidence, number of doctor visits, inpatient incidence, number of hospital stays, self-treatment incidence, community-fixed effects, individual-birth-year-fixed effects, and wave dummies. Among the 671 observations, 50.07% were imputed with a first-born boy. We then add these observations with imputed first-born genders to our main sample and conduct the same 2SLS estimation as that reported in Table 3. As shown in Table B.9, the results are very similar to those of the main analysis.

7 Discussion

Declining fertility and increasing health expenditure associated with an aging population pose significant challenges to public finance globally. Family planning policies such as birth-encouraging policies have been employed to manage fertility to combat undesirable trends in the population. However, fully understanding the long-term impact of such policies will not be possible if we fail to account for the long-term impact of fertility on healthcare utilization and costs.

This study adds to the existing literature on this topic. We study the causal effect of fertility on elderly parent healthcare utilization. We exploit the exogenous fertility changes induced by the 1.5-child policy in rural China to facilitate an IV approach. We find that overall, having additional children increases formal healthcare use, including the incidence and OOP expenditure of using outpatient and inpatient care, as well as the number of doctor visits and hospital stays. Furthermore, there is also an increase in informal healthcare use (e.g., the probability and OOP expenditure of self-treatment) after having additional children.

Further mechanism analysis indicates that increasing healthcare use with additional children may be driven by deteriorating physical and mental health and increasing intergenerational support from children. Although parent income does not increase with fertility, children are more likely to pay for OOP self-treatment costs, dental costs, and health checkups for their parents and make monetary transfers to their parents, suggesting that a portion of the increased burden of healthcare cost is borne by children.

The pattern of the results differs between men and women. In addition to self-treatment use increasing with the number of children of both genders, having additional children leads to increased inpatient care use for men and female outpatient care use. Less educated parents suffer more from the adverse health effects of fertility and bear a significant increase in OOP medical costs. In contrast, the more education group's health condition and expenditures are negligibly affected, raising health disparity concerns. Fertility comprehensively affects relatively younger parents, but also persists in older parents, indicating that the effects of fertility on healthcare can be long lasting.

Our results imply that the true cost of birth-encouraging policies is underestimated if we consider long-term impacts on health and healthcare use. Effect heterogeneity suggests that subgroups (e.g., women and less educated parents) with limited economic resources and less generous health insurance bear a larger increase in OOP health costs as a result of fertility. Our results call for supportive measures for these disadvantaged groups (and potentially their children, who partially bear increased costs) alongside birth policies.

This result is particularly relevant for developing countries with high copayments and less developed public service systems for the elderly (i.e., heavy reliance on old-age support from family members). More evidence from other countries could be included in future research to examine how these effects interact with different institutional and cultural contexts. Additional evidence from young parents could also help us investigate the immediate effects of fertility on healthcare use.

Acknowledgement

This study was conducted as part of the Project "Studies on Transformations of International Systems and their Impact on Japan's Mid- & Long-term Competitiveness" undertaken by the research group on "Empirical Research on the Changing Chinese Economy-Upgrading, Expansion, Structural Reform" at the Research Institute of Economy, Trade, and Industry (RIETI). The authors thank the China Health and Retirement Longitudinal Study (CHARLS) team for providing data. We also wish to thank Elena Bassoli, Julien Bergeot, Zhixiong Guan, Asei Ito, Kai Kajitani, Lei Lei, Zhiqiang Liu, Shiko Maruyama, Masayuki Morikawa, Bin Ni, Bettina Siflinger, Martin Salm, Arthur van Soest, Mariko Watanabe, Tetsuya Watanabe, Makoto Yano, Nina Yin, the participants at the 24th Tokyo Labor Economics Workshop, JCER Seminar (2021 Fall), CHLR Applied Microeconomics Seminar (2021 Fall), RIETI Seminar (January 2022), and Netspar International Pension Workshop 2022 for their helpful comments and suggestions. We also thank the RIETI staff for their kind assistance and cooperation. All errors are on our own and we declare no conflicts of interest.

References

Banister, Judith. 1987. *China's Changing Population*. Stanford University Press.

Barber, Sarah L., and Lan Yao. "Health insurance systems in China: a briefing note." *World Health report* (2010).

Bucher-Koenen, Tabea, Helmut Farbmacher, Raphael Guber, and Johan Vikström. "Double trouble: the burden of child-rearing and working on maternal mortality." *Demography* 57.2 (2020): 559–576.

Canning, David, and T. Paul Schultz. "The economic consequences of reproductive health and family planning." *The Lancet* 380.9837 (2012): 165–171.

Cao, Yuan. "Fertility and labor supply: evidence from the One-Child Policy in China." *Applied Economics* 51.9 (2019): 889–910.

Cáceres-Delpiano, Julio, and Marianne Simonsen. "The toll of fertility on mothers' well-being." *Journal of Health Economics* 31.5 (2012): 752–766.

Chen, Guodong, and Xiaoyan Lei. "" Fertility effect" or" Supporting effect?"—Quantity of children and parental health." *Frontiers of Economics in China* 4.4 (2009): 601–616.

Chen, Yi, and Hanming Fang. "The long-term consequences of China's "Later, Longer, Fewer" campaign in old age." *Journal of Development Economics* 151 (2021): 102664.

Chen, Yuyu, Hongbin Li, and Lingsheng Meng. "Prenatal sex selection and missing girls in China: Evidence from the diffusion of diagnostic ultrasound." *Journal of Human Resources* 48.1 (2013): 36–70.

Cheng, Lingguo, Hong Liu, Ye Zhang, Ke Shen, and Yi Zeng. "The impact of health insurance on health outcomes and spending of the elderly: evidence from China's new cooperative medical scheme." *Health Economics* 24, no. 6 (2015): 672–691.

Cheng, Lingguo, Hong Liu, Ye Zhang, and Zhong Zhao. "The health implications of social pensions: Evidence from China's new rural pension scheme." *Journal of Comparative Economics* 46, no. 1 (2018): 53–77.

Deems, Nicholas P., and Benedetta Leuner. "Pregnancy, postpartum and parity: Resilience and vulnerability in brain health and disease." *Frontiers in Neuroendocrinology* 57 (2020): 100820.

Donaldson, Paul and Amy Tsui. "The international family planning movement." *Population Bulletin* vol. 45,3 (1990): 1–46.

Ho, Christine. "Child's gender, parental monetary investments and care of elderly parents in China." *Review of Economics of the Household* 17.3 (2019): 741–774.

Gove, Walter R., and Michael R. Geerken. "The effect of children and employment on the mental health of married men and women." *Social Forces* 56.1 (1977): 66–76.

Baochang, Gu, Wang Feng, Guo Zhigang, and Zhang Erli. "China's local and national fertility policies at the end of the twentieth century." *Population and Development Review* (2007): 129–147.

Guo, Rufei, and Junsen Zhang. "The Effects of Children's Gender Composition on Filial Piety and Old-Age Support." *The Economic Journal* 130.632 (2020): 2497–2525.

Hurt, Lisa S., Carine Ronsmans, and Suzanne L. Thomas. "The effect of number of births on women's mortality: systematic review of the evidence for women who have completed their childbearing." *Population Studies* 60.1 (2006): 55–71.

Islam, Asadul, and Russell Smyth. "Do fertility control policies affect health in old age? Evidence from China's one-child experiment." *Health Economics* 24.5 (2015): 601–616.

Joshi, Shareen, and T. Paul Schultz. "Family planning and women's and children's health: Long-term consequences of an outreach program in Matlab, Bangladesh." *Demography* 50.1 (2013): 149–180.

Kabátek, Jan, and David C. Ribar. "Daughters and Divorce." *The Economic Journal* 131.637 (2021):

2144–2170.

Kruk, Kai Eberhard, and Steffen Reinhold. "The effect of children on depression in old age." *Social Science & Medicine* 100 (2014): 1–11.

Li, Chuanxiao, et al. "The prevalence and risk factors of depression in prenatal and postnatal women in China with the outbreak of Corona Virus Disease 2019." *Journal of Affective Disorders* 282 (2021): 1203–1209.

Li, Xin, and Wei Zhang. "The impacts of health insurance on health care utilization among the older people in China." *Social Science & Medicine* 85 (2013): 59–65.

Li, Xun, and Yu Qiu. "Are more children better than one? Evidence from a lab experiment of decision making." *China Economic Review* (2021): 101653.

Lu, Li, et al. "Mental health outcomes among Chinese prenatal and postpartum women after the implementation of universal two-child policy." *Journal of Affective Disorders* 264 (2020): 187–192.

Miller, Grant, and Kimberly Singer Babiarz. "Family planning program effects: Evidence from microdata." *Population and Development Review* 42.1 (2016): 7–26.

Modig, Karin, et al. "Payback time? Influence of having children on mortality in old age." *Journal of Epidemiology & Community Health* 71.5 (2017): 424–430.

Mogstad, Magne, Alexander Torgovitsky, and Christopher R. Walters. "The causal interpretation of two-stage least squares with multiple instrumental variables." *American Economic Review* 111.11 (2021): 3663–98.

National Bureau of Statistics of China. *National Data*. National Bureau of Statistics of China, Beijing, 2020. https://data.stats.gov.cn/english/easyquery.htm?cn=C01. 6 January. 2022.

Ness, Roberta B., Helena M. Schotland, Katherine M. Flegal, and Frances S. Shofer. "Reproductive history and coronary heart disease risk in women." *Epidemiologic Reviews* 16.2 (1994): 298–314.

Peters, Sanne A.E., et al. "Parenthood and the risk of cardiovascular diseases among 0.5 million men and women: findings from the China Kadoorie Biobank." *International Journal of Epidemiology* 46.1 (2017): 180–189.

Romano, Joseph P., and Michael Wolf. "Exact and approximate stepdown methods for multiple hypothesis testing." *Journal of the American Statistical Association* 100.469 (2005): 94–108.

Seltzer, Judith R. *The origins and evolution of family planning programs in developing countries*. Rand Corporation, 2002.

Schultz, T. Paul. "Population policies, fertility, women's human capital, and child quality." *Handbook of development economics* 4 (2007): 3249–3303.

Skilton, Michael R., Fabrice Bonnet, Lisa M. Begg, Markus Juonala, Mika Kähönen, Terho Lehtimäki, Jorma SA Viikari, and Olli T. Raitakari. "Childbearing, child-rearing, cardiovascular risk factors, and progression of carotid intima-media thickness: the Cardiovascular Risk in Young Finns study." *Stroke* 41.7 (2010): 1332–1337.

Spence, Naomi J. "The long-term consequences of childbearing: physical and psychological well-being of mothers in later life." *Research on Aging* 30.6 (2008): 722–751.

Weng, Haoling H., Lori A. Bastian, Donald H. Taylor Jr, Barry K. Moser, and Truls Ostbye. "Number of children associated with obesity in middle-aged women and men: results from the health and retirement study." *Journal of Women's Health* 13.1 (2004): 85–91.

Whyte, Martin King. "Continuity and change in urban Chinese family life." *The China Journal* 53 (2005): 9–33.

Wu, Xiaoyu, and Lixing Li. "Family size and maternal health: evidence from the One-Child policy in China." *Journal of Population Economics* 25.4 (2012): 1341–1364.

You, Xuedan, and Yasuki Kobayashi. "The new cooperative medical scheme in China." *Health Policy* 91.1 (2009): 1–9.

Zhai, Tiemin, John Goss, and Jinjing Li. "Main drivers of health expenditure growth in China: a decomposition analysis." *BMC Health Services Research* 17.1 (2017): 1–9.

Zhang, Junsen. "The evolution of China's one-child policy and its effects on family outcomes." *Journal of Economic Perspectives* 31.1 (2017): 141–60.

Zhang, Xianglan, Xiao-Ou Shu, Yu-Tang Gao, Gong Yang, Honglan Li, and Wei Zheng. "Pregnancy, childrearing, and risk of stroke in Chinese women." *Stroke* 40.8 (2009): 2680–2684.

Zhao, Yaohui, John Strauss, Gonghuan Yang, John Giles, Peifeng (Perry) Hu, Yisong Hu, Xiaoyan Lei, Albert Park, James P. Smith, and Yafeng Wang. "China Health and Retirement Longitudinal Study, 2011-2012 National Baseline Users' Guide." *Beijing: National School of Development, Peking University* (2013): 1–56.

Appendix

Appendix A Variables used in the main and further analysis

Main outcome variables:

1. *Outpatient incidence*: A dummy variable indicating whether the respondent had used outpatient care in the past month. Outpatient care refers to visiting a public hospital, private hospital, public health center, clinic, or health worker or doctor's practice, or home visits by a health worker or doctor. It should be noted that there are no general practitioners in China. To see a doctor, one typically needs to visit a hospital or clinic.
2. *Number of doctor visits*: Number of doctor visits in the past month. More precisely, the total number of visits to general hospitals, specialized hospitals, Chinese medicine hospitals (“Zhongyi”), community healthcare centers, township hospitals, healthcare posts, private clinics, and other healthcare organizations.
3. *OOP outpatient cost:* OOP expenditure for outpatient care in the past month in CNY.
4. *Forgone outpatient incidence*: A dummy variable indicating whether the respondent was sick, but did not seek outpatient care in the past month.
5. *Inpatient incidence*: A dummy variable indicating whether the respondent received inpatient care in the past year.
6. *Number of hospital stays*: The number of times the respondent received inpatient care during the past year.
7. *OOP inpatient cost*: OOP expenditure for inpatient care in the past year. Inpatient expenditures include fees paid to the hospital, including ward fees, but excluding wages paid to a hired nurse, transportation costs, and accommodation costs for the respondent or family members.
8. *Forgone inpatient incidence*: A dummy variable indicating whether or not a doctor had suggested that the respondent needed inpatient care, but was not hospitalized in the past year.
9. *Self-treatment incidence*: A dummy variable indicating whether the respondent treated his or herself in the past month. Self-treatment refers to treatment without resorting to professional medical care such as over-the-counter drugs, traditional herbs or medication,

tonic/health supplements, and the use of healthcare equipment.

10. *OOP self-treatment cost*: OOP expenditure for self-treatment in the past month.

Additional outcomes of health checkups and dental care use:

11. *Health check incidence*: A dummy variable indicating whether the respondent had undergone any health checkups in the past two years.
12. *Dental care incidence:* A dummy variable indicating whether the respondent used dental care in the previous year.
13. *Number of dental care visits:* Total number of dental visits in the previous year.
14. *OOP dental care cost:* OOP expenditure for dental visits in the past year in CNY.

Income variables:

1. *Annual earned income after tax*: Wages and bonus income in the year after tax. Wages include income from agricultural work, nonagricultural jobs, side jobs, and all other bonuses. The wage is zero if an individual has no jobs or agricultural work.
2. *Annual household income per capita*: The sum of all household income levels divided by the number of household members. Income here includes earned income, capital income, pension income, income from government transfers, other income, and total income from other household members.

Intergenerational interaction variables:

1. *Incidence of transfer from children*: Whether the respondent and their spouse received any economic assistance from their children or grandchildren in the past year. Note that in the surveys for 2011 and 2013, questions include economic assistance from non-resident children and grandchildren, whereas the 2015 survey does not include transfers from grandchildren. However, this should not be a major concern because direct transfers from grandchildren without transferring through children are rare.
2. *Amount of transfer from children*: The amount of economic assistance that the respondent and their spouse received from children or grandchildren in the past year.
3. *Incidence of contact with children in person*: Indicator of any contact with children in person in the past week.
4. *Incidence of contact with children by phone or email*: Indicator of any contact with children

by phone or email in the past week.

5. *Incidence of contact with children in any form*: Indicator of any contact with children in person, by phone, or by email in the past week.
6. *Incidence of children paying for health check*: Indicator if children have paid for health checkups for a parent in the past two years.
7. *Incidence of children paying for OOP self-treatment cost*: Indicator if children have paid for any OOP self-treatment expenses for a parent in the past month.
8. *Incidence of children paying for OOP dental care cost*: A dummy variable indicating whether children paid most of the OOP cost for dental visits in the past year.

Appendix B Tables

Table B.1 Summary statistics of outcomes and mechanism variables for the entire sample

Variable	Obs.	Mean	Std. dev.	Variable	Obs.	Mean	Std. dev.
Outpatient care use				*Mechanism: Health*			
Outpatient incidence	33,596	0.217	0.413	Self-reported health	29,650	3.853	0.936
# Doctor visits	33,140	0.467	1.474	Mental health	31,336	8.352	6.315
OOP outpatient cost	29,502	83.566	884.718	Chronic disease	33,886	0.696	0.46
Forgone outpatient incidence	33,563	0.08	0.271				
Inpatient care use				*Mechanism: Income*			
Inpatient incidence	33,696	0.119	0.324	Annual earned income after tax	32,921	4237.098	12857.39
# Hospital stays	33,679	0.178	0.638	Annual household income per capita	21,124	7890.954	20281.11
OOP inpatient cost	30,711	336.082	3753.612				
Forgone inpatient incidence	30,124	0.056	0.229	*Mechanism: Intergenerational interactions*			
Other healthcare use				Incidence of transfer from children	32,469	0.621	0.485
Self-treatment incidence	33,540	0.515	0.5	Amount of transfer from children	32,424	3678.073	13483.43
OOP self-treatment cost	33,540	92.334	408.022	Contact in person	33,150	0.792	0.406
Health check incidence	32,591	0.423	0.494	Contact by phone/email	25,332	0.546	0.498
Dental visit incidence	23,185	0.166	0.372	Any contact	33,157	0.913	0.282
Number of dental visits	23,099	0.414	1.646	Child-paid health check	32,591	0.030	0.171
OOP dental cost	22,822	95.196	480.407	Child-paid OOP self-treatment cost	33,522	0.046	0.21
Positive OOP dental cost	3,445	630.646	1091.565	Child-paid OOP dental cost	22,826	0.012	0.110

Table B.2 Estimated coefficients of the number of children for binary healthcare use outcomes with IV-Probit models

Dependent Var.	Estimated coefficient of the number of children (1)
Outpatient incidence	0.119**
	(0.051)
Forgone outpatient incidence	-0.038
	(0.066)
Inpatient incidence	0.105*
	(0.061)
Forgone inpatient incidence	0.132
	(0.081)
Self-treatment incidence	0.148***
	(0.051)
Obs.	31,963

Notes: * Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The coefficient of the number of children was estimated using the conditional maximum-likelihood estimator in a probit model. The number of children is instrumented as Boy*byr1937*T, which is constructed as $\text{first} - \text{born boy} \times (\text{birth year} \geq 1937) \times (\text{birth year} - 1929)$. In the first stage, the estimated coefficient of first-born boys was −0.013 with a standard error of 0.001. Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies.

Table B.3 IV-Tobit and 2SLS estimates for unconditional health expenditure variables

Dependent Var.	Estimated coefficient of the number of children (1)
	Panel A: IV-Tobit
OOP outpatient cost	582.526**
	(228.557)
OOP inpatient cost	5,831.561*
	(3,470.475)
OOP self-treatment cost	52.576*
	(27.596)
	Panel B: 2SLS
OOP outpatient cost	54.782*
	(29.352)
OOP inpatient cost	59.937
	(143.543)
OOP self-treatment cost	4.647
	(13.652)

Notes: * Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. Panel A shows the results of the IV-Tobit model and Panel B shows the 2SLS estimates. The estimated coefficient of IV in Panel A is −0.013 and the standard error is 0.001.

Table B.4 Effects of the number of children on six types of self-treatment use, dental care, and health checkups

Dependent Var.	Estimated coefficient for the number of children (1)	Dependent Var.	Estimated coefficient for the number of children (2)
	Panel A: self-treatment types		
Self-treatment incidence:		Log(OOP self-treatment cost+1):	
OTC medicine	0.042**	OTC medicine	0.218***
	(0.018)		(0.075)
Self-treatment incidence:		Log(OOP self-treatment cost+1):	
Prescribed medicine	0.011	Prescribed medicine	0.025
	(0.012)		(0.051)
Self-treatment incidence:		Log(OOP self-treatment cost+1):	
Traditional herbs	0.012	Traditional herbs	0.057
	(0.009)		(0.041)
Self-treatment incidence:		Log(OOP self-treatment cost+1):	
Tonic/health supplement	0.028***	Tonic/health supplement	0.119***
	(0.008)		(0.030)
Self-treatment incidence:		Log(OOP self-treatment cost+1):	
Equipment	0.005*	Equipment	0.014
	(0.003)		(0.010)
Self-treatment incidence:		Log(OOP self-treatment cost+1):	
Other	-0.003	Other	-0.008
	(0.003)		(0.007)
	Panel B: dental care & health checkups		
Dental care incidence	-0.005	Log(OOP dental care cost+1)	0.017
	(0.015)		(0.085)
#dentist visits	-0.040	Health check incidence	0.020
	(0.073)		(0.016)

Notes:*Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. We decompose self-treatment incidence into six dummy variables indicating different reasons for using self-treatment. A total of 11,157 observations used self-treatment because they purchased OTC medicine. Additionally, 4965 observations used self-treatment in the form of purchasing prescribed medicine. A total of 2,821 observations used self-treatment to buy traditional Chinese herbal medicines, 1,812 observations purchased tonic or health supplements, 211 observations purchased healthcare equipment. Additionally, 280 observations used self-treatment of other types. The number of observations for self-treatment outcomes was 31,963 and those for dental care outcomes and health checkup incidence were 21,817 and 31,015, respectively. The dental care variables only existed in the 2013 and 2015 waves. Therefore, the number of observations for these regressions is smaller.

Table B.5 Direct effects of the Boy*byr1937*T IV controlling for the number of children

		Panel A Outpatient care		
	(1)	(2)	(3)	(4)
Var.	Outpatient incidence	# Doctor visits	Log(OOP outpatient cost+1)	Forgone outpatient incidence
Boy*byr1937*T	0.000	0.001	0.000	-0.000
	(0.001)	(0.003)	(0.004)	(0.001)
Num. of children	0.042	0.139	0.210	-0.016
	(0.060)	(0.185)	(0.255)	(0.036)
Obs.	31,963	31,525	28,082	31,934
		Panel B Inpatient care		
	(1)	(2)	(3)	(4)
Var.	Inpatient incidence	# Hospital stays	Log(OOP inpatient cost+1)	Forgone inpatient incidence
Boy*byr1937*T	0.000	0.000	0.001	0.000
	(0.001)	(0.001)	(0.003)	(0.000)
Num. of children	0.032	0.058	0.180	0.020
	(0.040)	(0.072)	(0.197)	(0.030)
Obs.	32,057	32,043	29,227	28,621
		Panel C Informal healthcare & First-stage		
	(1)	(2)	(3) First-stage	
Var.	Self-treatment incidence	Log(OOP self-treatment cost+1)	Num. of children	
Boy*byr1937*T	0.000	0.002	-0.010***	
	(0.001)	(0.005)	(0.001)	
Num. of children	0.086	0.458		
	(0.068)	(0.341)		
Boy*First-child1984			-0.196***	
			(0.042)	
Kleibergen-Paap rk Wald F statistic			21.55	
Obs.	31,915	31,915	31,963	

Notes:*Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The model is similar to the main estimation, except that we directly control for Boy*byr1937*T in the second stage instead of using it as an IV. Boy*byr1937*T is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). The number of children is instrumented as Boy*First-child1984, which is constructed as first-born boy or not × the first child born after 1984 or not. Other control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. Column (3) in Panel C presents the first-stage estimation results.

Table B.6 2SLS estimates of the main model with an alternative definition of fertility

	Panel A Outpatient care			
	(1)	(2)	(3)	(4)
Var.	Outpatient incidence	# Doctor visits	Log(OOP outpatient cost+1)	Forgone outpatient incidence
Multiple children	0.104**	0.317**	0.581***	-0.020
	(0.046)	(0.155)	(0.216)	(0.029)
Obs.	31,963	31,525	28,082	31,934
	Panel B Inpatient care			
	(1)	(2)	(3)	(4)
Var.	Inpatient incidence	# Hospital stays	Log(OOP inpatient cost+1)	Forgone inpatient incidence
Multiple children	0.060*	0.147**	0.268*	0.041
	(0.034)	(0.068)	(0.155)	(0.027)
Obs.	32,057	32,043	29,227	28,621
	Panel C Informal healthcare & First-stage			
	(1)	(2)	(3) First-stage	
Var.	Self-treatment incidence	Log(OOP self-treatment cost+1)	Multiple children	
Multiple children	0.183***	0.896***		
	(0.065)	(0.301)		
Boy*byr1937*T			-0.004***	
			(0.0004)	
Kleibergen-Paap rk Wald F statistic			101.17	
Obs.	31,915	31,915	31,963	

Notes: * Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. We use having multiple children (≥2) or not as an alternative measure of fertility. Multiple children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies.

Table B.7 Romano-Wolf adjusted p-values for the coefficients of the number of children

	Independent variable: the number of children	
Outcome variable	(1) Main model p-value	(2) Romano-Wolf p-value
Panel A Outpatient care		
Outpatient incidence	0.0220	0.0459
# Doctor visits	0.0376	0.0679
Log(OOP outpatient cost+1)	0.0054	0.0160
Forgone outpatient incidence	0.4916	0.5230
Panel B Inpatient care		
Inpatient incidence	0.0686	0.1776
# Hospital stays	0.0272	0.0978
Log(OOP inpatient cost+1)	0.0788	0.1776
Forgone inpatient incidence	0.1231	0.1776
Panel C Informal healthcare		
Self-treatment incidence	0.0039	0.0080
Log(OOP self-treatment cost+1)	0.0021	0.0080

Notes: Column (1) reports the p-values of the estimated coefficients for the number of children in the main model. Column (2) reports the Romano-Wolf p-values of the coefficients of the numbers of children in the main model, accounting for multiple hypothesis testing. We group the outcomes by type of healthcare as “outpatient care outcomes,” “inpatient care outcomes,” and “Informal healthcare outcomes.” We then calculate group-wise Romano-Wolf adjusted p-values. We consider 500 bootstrap replicates for each group.

Table B.8 2SLS estimates for the main model with the alternative sample and specification

	Panel A Outpatient care			
	(1)	(2)	(3)	(4)
Var.	Outpatient incidence	# Doctor visits	Log(OOP outpatient cost+1)	Forgone outpatient incidence
Num. of children	0.030**	0.068	0.184***	0.003
	(0.014)	(0.045)	(0.061)	(0.010)
Hansen J (P)	0.691	0.150	0.738	0.192
Obs.	48,089	47,414	42,141	48,049
	Panel B Inpatient care			
	(1)	(2)	(3)	(4)
Var.	Inpatient incidence	# Hospital stays	Log(OOP inpatient cost+1)	Forgone inpatient incidence
Num. of children	0.017	0.039*	0.081	0.013
	(0.011)	(0.021)	(0.050)	(0.008)
Hansen J (P)	0.943	0.937	0.738	0.859
Obs.	48,221	48,198	43,837	43,326
	Panel C Informal healthcare & First-stage			
	(1)	(2)	(3) First-stage	
Var.	Self-treatment incidence	Log(OOP self-treatment cost+1)	Num. of children	
Num. of children	0.061***	0.261***		
	(0.021)	(0.096)		
Boy*byr1937*T			-0.013***	
			(0.001)	
OCP area or not			-0.370***	
			(0.061)	
Hansen J (P)	0.689	0.805		
Kleibergen-Paap rk Wald F statistic			98.93	
Obs.	48,089	48,023	31,963	

Notes:*Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the city level. Column (3) in Panel C presents the first-stage results. The remaining columns show the 2SLS estimates of the effect of the number of children on each outcome. For the Hansen J-test, p-values are reported. The number of children is instrumented as Boy*byr1937*T interacting with the community being an NOCP area or not, as well as the community being an OCP area or not. Boy*byr1937*T is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). The control variables are the same as those in the main analysis, except that the community-fixed effects are replaced with city-fixed effects.

Table B.9 2SLS estimates of the main model with imputed first-born genders for childless individuals

	Panel A Outpatient care			
	(1)	(2)	(3)	(4)
Var.	Outpatient incidence	# Doctor visits	Log(OOP outpatient cost+1)	Forgone outpatient incidence
Num. of children	0.033**	0.099**	0.198***	-0.006
	(0.014)	(0.049)	(0.066)	(0.009)
Obs.	32,634	32,196	28,684	32,604
	Panel B Inpatient care			
	(1)	(2)	(3)	(4)
Var.	Inpatient incidence	# Hospital stays	Log(OOP inpatient cost+1)	Forgone inpatient incidence
Num. of children	0.019*	0.045**	0.085*	0.012
	(0.011)	(0.021)	(0.050)	(0.008)
Obs.	32,728	32,714	29,836	29,191
	Panel C Informal healthcare & First-stage			
	(1)	(2)	(3) First-stage	
Var.	Self-treatment incidence	Log(OOP self-treatment cost+1)	Num. of children	
Num. of children	0.060***	0.299***		
	(0.020)	(0.093)		
Boy*byr1937*T			-0.013***	
			(0.001)	
Kleibergen-Paap rk Wald F statistic			289.14	
Obs.	32,586	32,586	32,634	

Notes: * Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929) (with imputation). For individuals with no children, the first-born gender is imputed based on a logit regression in which the predictors are age, age squared, partnered or not, gender, rural hukou or not, education level, work or not, yearly earnings, number of living siblings, self-reported health-level-fixed effects, mental health, having a chronic disease or not, outpatient incidence, number of doctor visits, inpatient incidence, number of hospital stays, self-treatment incidence, community-fixed effects, individual-birth-year-fixed effects, and wave dummies.

Table B.10 Effect of the number of children on insurance purchasing

Dependent Var.	Estimated coefficient of the number of children (1)	Share of sample covered by the corresponding insurance (2)
Having Urban Employee Medical Insurance or not	-0.010	6.98%
	(0.010)	
Having Urban Resident Medical Insurance or not	-0.005	3.52%
	(0.007)	
Having New Rural Cooperative Medical Insurance or not	0.009	87.32%
	(0.011)	
Having Urban and Rural Resident Medical Insurance or not	0.013	3.55%
	(0.009)	
Having Government Medical Insurance or not	-0.007	1.97%
	(0.005)	
Having Medical Aid or not	-0.001	0.39%
	(0.003)	
Having employer-provided private medical insurance or not	-0.001	0.45%
	(0.003)	
Having self-purchased private medical insurance or not	0.017	2.61%
	(0.011)	
Having Critical Illness Health Insurance for Urban Non-Employed Residents or not	-0.001	0.27%
	(0.002)	
Having other medical insurance or not	0.001	1.28%
	(0.004)	
Having no medical insurance or not	0.006	6.19%
	(0.010)	

Notes: *Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. Having Critical Illness Health Insurance for Urban Non-Employed Residents or not was only available for the 2013 and 2015 surveys, so the number of observations for this insurance type is 20,043. For the remaining types of insurance, the number of observations varies from 30,652 to 31,978. The sample shares of medical insurance do not add up to 100% because some insurance types such as private insurance and medical aid are not mutually exclusive with others.

Table B.11 Effect of the number of children on types of self-treatment use by age cohort

	Estimated coefficient of the number of children	
	Old (Birth year<1955)	Young (Birth year⩾1955)
Dependent Var.	(1)	(2)
Self-treatment incidence: OTC medicine	0.091***	0.024
	(0.031)	(0.021)
Self-treatment incidence: Prescribed medicine	-0.015	0.015
	(0.023)	(0.014)
Self-treatment incidence: Traditional herbs	0.022	0.009
	(0.018)	(0.012)
Self-treatment incidence: Tonic/health supplement	0.015	0.032***
	(0.016)	(0.009)
Self-treatment incidence: Equipment	0.002	0.005
	(0.004)	(0.003)
Self-treatment incidence: Other	-0.006	-0.002
	(0.006)	(0.004)
Log(OOP self-treatment cost+1): OTC medicine	0.347***	0.177**
	(0.133)	(0.087)
Log(OOP self-treatment cost+1): Prescribed medicine	-0.068	0.043
	(0.103)	(0.060)
Log(OOP self-treatment cost+1): Traditional herbs	0.086	0.049
	(0.081)	(0.050)
Log(OOP self-treatment cost+1): Tonic/health supplement	0.056	0.139***
	(0.055)	(0.035)
Log(OOP self-treatment cost+1): Equipment	-0.006	0.021*
	(0.016)	(0.013)
Log(OOP self-treatment cost+1): Other	-0.015	-0.004
	(0.012)	(0.008)
Observation	15,897	16,066

Notes:*Significant at 10%; ** at 5%; *** at 1%. The numbers in parentheses are robust standard errors clustered at the community level. The number of children is instrumented as Boy*byr1937*T, which is constructed as first-born boy × (birth year ≥ 1937) × (birth year − 1929). Control variables include age, age squared, partnered or not, gender, rural hukou status, education level, community-fixed effects, parent-birth-year-fixed effects, and wave dummies. We decompose self-treatment incidence into six dummies indicating different reasons for using self-treatment.

Appendix C Figure

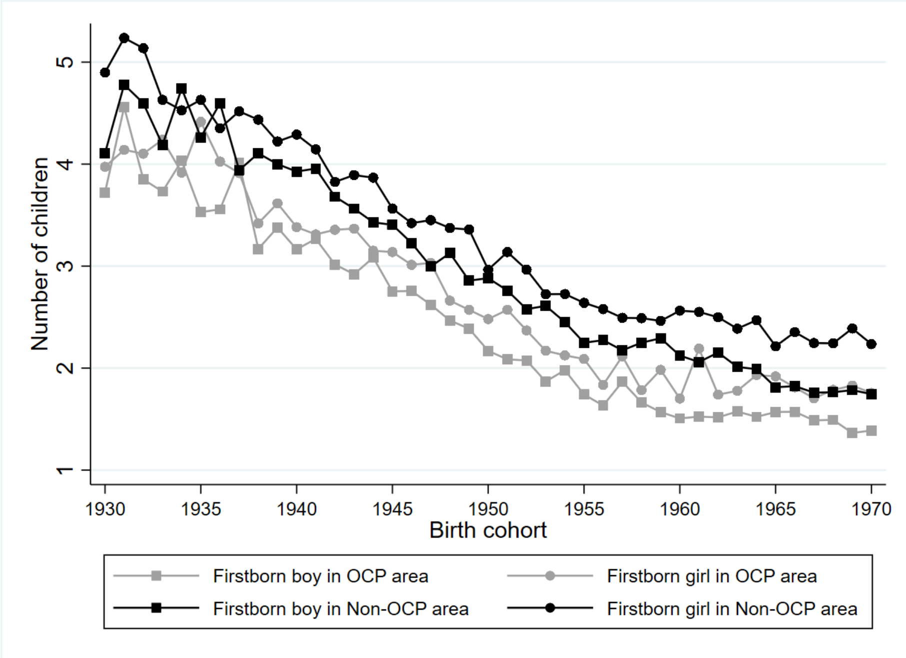

Figure C.1 Number of children by parent birth cohort, first-born gender, and OCP area or not