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ABSTRACT

The One-Child Policy Amplifies Economic Inequality across Generations in China

This study finds that China's one-child policy (OCP), one of the most extreme forms of birth control in recorded history, has amplified economic inequality across generations in China since its introduction in 1979. Poor Chinese families, whose fertility choices are less constrained by the OCP than rich ones, have more children but invest less in human capital per child. Since human capital is a major determinant of earnings, the income inequality persists and enlarges across generations as a consequence. Based on nationally representative longitudinal household survey data, our estimation results show that the OCP accounts for 32.7%-47.3% of the decline in intergenerational income mobility. The OCP has significant ramifications for Chinese society, not only intragenerationally but also intergenerationally.

JEL Classification: E24, J13

Keywords: One-Child Policy, differential fertility, child quantity-quality tradeoff, intergenerational mobility

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Introduction

The People's Republic of China was one of the poorest countries in the world until1979, with per capita GDP that was 1/90 of the U.S. level. Since the economic reform in 1979, China has experienced rapid economic growth; GDP per capita has increased 20-fold and is now almost 1/7 that of the U.S (1). At the same time, the distribution of income has sharply skewed, deviating from the communist utopia that would distribute income equally. The Gini coefficient—a snapshot of income inequality across families in the same generation—rose from 0.26 in 1983 to 0.47 in 2016, exceeding the U.S. Gini coefficient of 0.42 for the same year (2) (Fig. 1). Moreover, the amplified economic inequality across generations—measured by the degree of income persistence across generations of same families—concerns both the public and policymakers. Increasing intergenerational persistence undermines opportunities to escape poverty and begets socioeconomic disparities that persist across generations. This is confirmed by recent empirical studies that chart an increasing trend in intergenerational income persistence (i.e., a declining trend in intergenerational income mobility) (3, 4) (*SI Appendix* 1.1). For example, using data from the China Family Panel Studies (CFPS) survey in 2010-2016, Fan et al. (4) estimate the intergenerational income rank-rank slope, which rises from 0.449 to 0.485 across 1970-1980 and 1981-1988 birth cohorts. They also attempt to associate the decline in intergenerational mobility with changes in socioeconomic factors after the economic reform, such as market structures and education and fiscal policies. In addition, historical events may contribute to the change in intergenerational mobility in the long run, such as the Chinese Communist Revolution (5) and the Cultural Revolution (6).

In this study, we examine the effect of China's population control policy—one of the most extreme forms of birth control in recorded history—on intergenerational income mobility, and find that the one-child policy (OCP) accounts for 32.7%-47.3% of the decline in intergenerational income mobility. Fearing a Malthusian catastrophe, Communist Party leaders enacted the OCP in 1979. Despite extensive propaganda, regulations, incentives, and sanctions, the OCP encountered serious resistance. Many rural families, particularly those with one female child only, strongly resisted this purportedly utopian policy for practical and cultural reasons, such as prospects for the family's economy, the son's role of carrying on the family name, and providing parents with security in their old age. Widespread opposition and difficulties with enforcement led to a conditional two-child policy (7-9). Central Document No. 7, issued in April 1984, allowed rural families to have a second child if the first were a daughter, while the OCP remained in force in urban areas. China's population control policy, therefore, is technically a one-and-a-half-child policy (*SI Appendix* 1.2).

We combine datasets from two nationally representative biannual longitudinal household surveys, the 2010-2018 CFPS and the 2011-2015 China Health and Retirement Longitudinal Study (CHARLS), and quantify the causal effects of the OCP on intergenerational income mobility. To overcome the endogeneity concern that other unobserved factors may correlate simultaneously with fertility and intergenerational mobility, we conduct an instrumental variable (IV) estimation using the staggered rollout of Central Document 7 across cohorts and provinces as a quasi-experiment. Specifically, the IV is a constructed measure of exposure intensity to the OCP, which varies across birth cohorts and provinces. Its validity lies in a significant relationship between policy exposure intensity and fertility decision, and exogenous rollout of the policy, which mostly likely depends on the political decision process and enforcement by the Party Central Committee (10). We find that as fertility decreases by 1, the rank-rank slope—which is a measure of intergenerational income persistence—increases by 0.33 and is statistically significant at the 1% level. We also calculate that the OCP accounts for as much as 32.7%-47.3% of the declining intergenerational income mobility in China.

How does the population control policy impact intergenerational mobility? We find that differential fertility caused by the OCP and inequality in child human capital investment between rural/poor and urban/rich families are contributing factors. The one-and-a-half-child policy allowed rural families, rather than urban ones, to have a second child if the first one were a girl. This widens the fertility gap between rural/poor and urban/rich families. Moreover, poor/rural residents are either too poor to pay fines for above-quota births or receive too few social benefits to matter. However, failure to abide by the policy is costly for rich/urban residents because of the more realistic risks of having to pay fines or lose a job and any related social welfare benefits (7, 8).

We find that the OCP results in differential fertility between rich and rural families. The enlarged fertility gap between rich and poor families amplifies the inequality in child human capital investment in these two types of families via a quantity-quality trade-off. The theory predicts that children born to larger families receive less human capital investment because of resource dilution (11, 12). As human capital is a major determinant of earnings, the income disparity between children of the rich and the poor increases, compared with the counterfactual case without the OCP. Consequently, differential fertility caused by the OCP decreases intergenerational income mobility.

Our study not only contributes to analysis of the trend in intergenerational income mobility in China, but also advances understanding of the mechanism by which the population control policy impacts intergenerational mobility, using the richest available data file compiled on fertility and intergenerational mobility in China.

Data Source and Sample Construction

To construct our estimation sample, we combine datasets from two nationally representative biannual longitudinal household surveys: the 2010-2018 CFPS and the 2011-2015 CHARLS.

The CFPS is a nationally representative and biannual longitudinal survey of Chinese individuals, families, and communities. Its national baseline survey was launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University in China. Four follow-up surveys were conducted in 2012, 2014, 2016, and 2018. The baseline CFPS covers 25 provinces, municipalities, and autonomous regions (excluding Inner Mongolia, Xinjiang, Tibet, Hainan, Ningxia, Qinghai, Hong Kong, Macau, and Taiwan), and targets 16,000 households, with a response rate of 79% (5, 13-15). The CHARLS is also a nationally representative and biannual longitudinal survey launched by the National School of Development, ISSS, and Youth League Committee at Peking University. Its national baseline survey, which targeted individuals aged 45 and above, was launched in 2011 and covers 150 counties; 450 villages; 28 provinces, municipalities, and autonomous regions; and 12,400 households (16, 17).

The combined dataset from CFPS and CHARLS is considered the best available for studying intergenerational mobility in China for three reasons. First, both CFPS and CHARLS samples are nationally representative. The two surveys cover urban and rural areas in 25 and 28 out of 34 provinces, municipalities, and autonomous regions, respectively. Distributions of important demographic and socioeconomic variables—such as age, gender, and education—in the two surveys are consistent with those from the population census (5, 13-18). Second, the panel structure of the two surveys facilitates calculating lifetime income. Individuals included in the two surveys are tracked across waves. Each wave of the CFPS collects information on individual income from the previous year. Solid technical support and self-correcting mechanisms employed by the CFPS ensure the reliability of the income information. We can thus calculate lifetime income by averaging individual income across waves to estimate intergenerational income mobility (4, 19). *SI Appendix* 2.2 details calculation of the lifetime income. Third, and most importantly, the two surveys uniquely collect a comprehensive set of demographic and socioeconomic information for all household members and their non-coresiding spouses, parents, children, and siblings. We are thus able to generate a nationally representative sample with 27,238 father-child pairs with children born between 1964 and 1985 and from 28 provinces.

We divide the full sample into 110 groups by child's birth cohort and province. Specifically, we first divide this full sample into five cohorts by the child's birth year: 1964-1973, 1974-1976, 1977-1979, 1980-1982, and 1983-1985. This should yield 140 groups by the child's birth cohort and province, since the data cover five birth cohorts and 28 provinces. However, by dropping groups with sample size less than 80 father-child pairs and merging Chongqing Municipality—an area that has historically been included in Sichuan Province—with Sichuan, our analytic sample finally includes 110 groups by the child's birth cohort and province with 25,618 father-child pairs. *SI Appendix* 2.1 describes our sample construction in detail. Table S1 summarizes statistics for the full sample and Table S2 tabulates the sample size by cohort and province.

Intergenerational Mobility and Fertility

Intergenerational mobility is the outcome variable of interest for our empirical analysis. For each group, we separately estimate three measures of intergenerational income mobility. The first measure is the rank-rank slope. We compare each child's/father's lifetime income with that of their peers and calculate the respective percentile rank at the national level by child's birth cohort, ranging from 0 to 100. The rank-rank slope is then estimated by regressing the child's percentile rank on the father's percentile rank for each group:

$$rank_{ipc} = \alpha_{0pc} + \alpha_{1pc}Rank_{ipc} + \varepsilon_{ipc}, \tag{1}$$

where $rank_{ipc}$ is the income percentile rank of child i in birth cohort c and province p, and $Rank_{ipc}$ is his/her father's income percentile rank. We control for both child's and father's demographic variables, including child's gender, age, and age squared and father's age and age squared. The coefficient, α_{1pc}, is the estimate of the income rank-rank slope for birth cohort c in province p. It measures the units of change in the child's percentile rank with respect to a one-percentile-rank increase in the father's income (20-22). A positive (negative) rank-rank slope estimate indicates high (low) income persistence across generations, and therefore low (high) intergenerational income mobility.

Although the rank-rank slope provides an intuitive linear estimate, one drawback is that a high degree of intergenerational mobility measured by this estimate can be driven by either the upward mobility of children from families in the bottom income percentiles or the downward mobility of children born to parents in the top percentiles. To address this shortcoming, we further estimate two measures of absolute mobility. One is the mean income percentile rank of children born to fathers at the 25th income percentile rank, which measures the mobility of children from low- (i.e., bottom-quartile) income families:

$$income_{pc}^{25} = \alpha_{0pc} + \alpha_{1pc} \times 25, \tag{2}$$

where α_{0pc} and α_{1pc} are estimates from Eq. (1), and $income_{pc}^{25}$ is the mean income percentile rank of children born to fathers at the 25th income percentile rank for birth cohort c in province p. A larger estimate, $income_{pc}^{25}$, indicates higher upward mobility of children from families in the bottom income percentiles.

The other measure is the mean income percentile rank of children born to fathers at the 75th income percentile rank, which measures the mobility of children from high- (i.e., top-quartile) income families:

(3) $$income_{pc}^{75} = \alpha_{0pc} + \alpha_{1pc} \times 75.$$

Similarly, α_{0pc} and α_{1pc} are estimates from Eq. (1). The estimate, $income_{pc}^{75}$, is the mean income percentile rank of children born to fathers at the 75th income percentile rank for birth cohort c in province p. A smaller estimate, $income_{pc}^{75}$, indicates higher downward mobility of children born to parents in the top percentiles. However, estimating the three measures of intergenerational income mobility is difficult because of the conventional lifecycle bias, attenuation bias, and selection bias (4, 23). Our constructed measures overcome these conventional biases, as detailed in *SI Appendix* 2.2.

Fertility is the main independent variable, and is measured by the average number of siblings for all children in each group.

Figure 2 displays the trend of intergenerational income mobility measured by rank-rank slope and the trend of fertility across child's birth cohorts. The intergenerational income rank-rank slope rises from 0.26 for the 1964-1973 birth cohort to 0.37 for the 1983-1985 cohort, increasing by 42% across two decades. This sharp decrease in intergenerational mobility is accompanied by a prominent decline in fertility, which drops from 2.42 for the 1964-1973 cohort to 1.56 for the 1983-1985 cohort, along with the rollout of the OCP across the nation.

Econometric Model

Our main empirical estimation exploits cross-province and cross-cohort variation in fertility to identify the effect of fertility on intergenerational income mobility. We start with fixed effect (FE) estimation, and the statistical analysis is conducted at the group level:

(4) $$Y_{pc} = \alpha_0 + \alpha_1 Fertility_{pc} + X_{pc}\alpha_X + \mu_p + \lambda_c + \varepsilon_{pc},$$

where Y_{pc} is one of the three measures of intergenerational income mobility for birth cohort c in province p, including rank-rank slope, mean percentile rank of children born to fathers at the 25th percentile rank, and mean percentile rank of children born to fathers at the 75th percentile rank; $Fertility_{pc}$ is measured by the average number of siblings for birth cohort c in province p. We control for observed socioeconomic factors, X_{pc}, which are related to intergenerational mobility and vary across provinces and cohorts, such as the Gini coefficient and a set of socioeconomic variables of a child's environment up to age 6. The latter includes gross regional product (GRP) per capita, industrial output value per capita, urbanization rate, number of doctors per 10,000 persons, number of beds per 10,000 persons, share of primary industry, and share of tertiary industry. *SI Appendix* 2.2 defines these variables and Table S4 details data sources. We use province fixed effects, μ_p, to control for unobserved factors relating to intergenerational mobility that differ across provinces but are common to all cohorts; we use cohort fixed effects, λ_c, for unobserved time shocks that differ across cohorts but are common to all provinces. The error term, ε_{pt}, captures measurement errors. Bootstrapped standard errors are reported because the sample size is small and dependent variables and major independent variables are calculated or estimated based on the full sample.

We are interested in the coefficient, α_1, which measures the change in intergenerational mobility when fertility increases by 1, holding all control variables constant. However, the FE estimate of α_1 in Eq. (4) is likely biased, because the decrease in fertility across cohorts may be driven by unobserved socioeconomic changes beyond the OCP. For example, Chinese families may prefer smaller family sizes along with the market-oriented reform and education reform (24). We thus advance an IV estimation to address this endogeneity concern by using the staggered rollout of Central Document No.7 across cohorts and provinces as a quasi-experiment.

Our IV estimation is capable of isolating the causal effects of the OCP on intergenerational income mobility through fertility. On the one hand, Central Document No. 7, issued in April 1984, allowed rural mothers who were still young when the policy started to have a second child if the first were a girl. Based on this fact, fertility per group in our estimation sample depends on the policy exposure of mothers during their childbearing years and the share of rural mothers. We thus use the policy exposure of mothers, the share of rural mothers, and the interaction term of the two as IVs. *SI Appendix* 3.2 details the steps in constructing IVs for each group. Our empirical results show that the IVs are closely related to fertility. On the other hand, the policy rollout is likely exogenous to other socioeconomic changes affecting intergenerational mobility in addition to fertility. Central Document No. 7 was issued by the Party Central Committee in response to severe political strains at the local level (10). The timing of implementing this policy across regions depended on the Communist Party's political decision process and enforcement. The literature has extensively used this exogenous cross-region variation in policy enforcement to identify its effect on fertility and gender imbalance in China

(7, 25).

The first-stage regression of our IV estimation is based on a difference-in-differences (DD) framework (25):

(5)
$$Fertility_{pc} = \beta_0 + \beta_1 Exposure_{pc} + \beta_2 RuralMother_{pc}$$
$$+\beta_3 Exposure_{pc} \times RuralMother_{pc} + X_{pc}\beta_X + \mu_p + \lambda_c + \varepsilon_{pc},$$

where $Exposure_{pc}$ is the policy exposure of mothers for (child's) birth cohort c in province p, $RuralMother_{pc}$ is the share of rural mothers, and other variables are the same as in Eq. (2). The variable $RuralMother_{pc}$ picks up the difference in fertility between urban and rural mothers without the policy, and $Exposure_{pc}$ picks up the effect of the policy on urban mothers. The interaction term, $Exposure_{pc} \times RuralMother_{pc}$, captures the differential effect of the policy between rural and urban mothers.

The identification of Eq. (5) exploits cross-province and cross-cohort variations in the policy exposure of mothers. The policy exposure of mothers varies across provinces because provinces introduced the Central Document No. 7 in different years. For example, Liaoning and Jiangxi took the lead in implementing the policy in 1985, whereas Guangdong and Guizhou introduced the policy as late as in 1998. It also varies across child's birth cohorts because only rural mothers of childbearing age when the policy went into effect were allowed to have a second child if the first were a girl. For example, mothers aged 20 at that point were almost fully exposed because their childbearing years would be covered by the policy, but mothers aged 40 were less likely to be exposed because they were coming to the end of their childbearing years.

Results and Discussions

Summary Statistics. Panels A-D in Table 1 present summary statistics for the measures of intergenerational income mobility, fertility, control variables, and instrumental variables, respectively. As the dependent variable, intergenerational income mobility is measured by rank-rank slope, and mean percentile rank of children born to fathers at the 25th and 75th income percentile rank. The mean of income rank-rank slope is 0.32, with a standard deviation of 0.12. On average, a child's income percentile rank increases by 0.32 with a one-percentile increase in father's rank. For children from low- (25th percentile) and high-income (75th percentile) families, the mean income percentile ranks are 44.08 and 57.44, respectively. Fertility, as measured by the number of siblings, is our main independent variable. This is 1.92 on average, which far exceeds one child per family, despite the fact that the OCP had been in place for more than two decades. This is not surprising, however, as our full sample includes children born before the OCP in 1979. Moreover, Central Document No. 7 has allowed rural mothers to have a second child if the first one were a girl ever since 1984.

Panel C displays summary statistics of control variables. Both the GRP per capita and industrial output value per capita are low, implying a low level of economic development during early childhood up to age 6. Similar evidence is shown by the urbanization rate (0.19), number of doctors/beds per 10,000 persons (11.27/19.85), share of primary/tertiary industry (36.19/21.37), and Gini coefficient (0.17).

Summary statistics of our IVs demonstrate substantial variations in average share of rural mothers (0.76) and average policy exposure of mothers (0.28) across groups. These variations facilitate our estimation of Eq. (5), which is the first stage in our IV estimation of the effect of fertility on intergenerational mobility.

Main Results. Table 2 presents our main findings on the effect of fertility on intergenerational income mobility. Panel A shows the FE estimates from Eq. (4) and Panel B displays corresponding ones under IV estimation. Columns (1)-(3) report estimation results using three measures of intergenerational income mobility. As expected, fertility has a negative correlation with the rank-rank slope (Column (1) in Panel A), indicating that a reduction in fertility is associated with an increase in intergenerational income persistence, and thus a decrease in intergenerational mobility. However, this estimate is not statistically significant at conventional levels. A negative correlation is also shown between fertility and the mean percentile rank of children born to fathers at the 25th percentile rank (Column (2) in Panel A), although with statistical insignificance. A statistically significant and negative correlation is demonstrated between fertility and the mean percentile rank of children born to fathers at the 75th percentile rank (Column (3) in Panel A). The magnitude is as large as 9.93 and statistically significant at the 1% level. With fertility decreasing by 1, the mean percentile rank of children in rich families rises by almost 10 percentile ranks.

Nevertheless, the FE estimates are highly likely to be biased because of the endogeneity concern discussed above. We thus turn to IV estimates to identify the causal impact of fertility on intergenerational mobility. We begin by examining the first-stage results from Eq. (5), as shown in Column (4) of Panel B. The estimated coefficient before the policy exposure of mothers is -1.1, with statistical significance at the 10% level. It suggests that when the policy exposure of mothers increases from the 25th percentile (0) to the 75th percentile (0.49), the fertility of urban mothers decreases by 0.55. This is consistent with previous evidence that the fertility of rich/urban families drops significantly with the imposition of fines for above-quota births, whereas that of poor families does not vary much (26). The estimate of coefficient before the interaction term between the policy exposure of mothers and share of rural mothers is 2.30, with statistical significance at the 1% level. A compelling interpretation is that as the policy exposure of mothers increases from the 25th to the 75th percentile, fertility increases by 0.57 for groups composed of rural mothers compared with those that are one-half rural and one-half urban mothers. This consolidates our argument that the OCP has differential effects on fertility between rural/poor and urban/rich families. The estimated coefficient before the share of rural mothers is 0.45, which suggests that rural mothers bear 0.45 more children than urban ones in the case without the OCP.

With solid first-stage results, we present the second-stage estimates in Columns (1)-(3) of Panel B. Fertility shows a negative impact of 0.33 on the rank-rank slope (Column (1)), with statistical significance at the 1% level. This affirms that the decline in fertility, caused by the OCP, reduces intergenerational income mobility in China. The magnitude of the IV estimate is larger than the corresponding one under FE estimation, which confirms the suspected bias in FE estimates due to omitted variables. Nonetheless, fertility has no statistically significant effect on the mean percentile rank of children born to fathers at the 25th percentile rank (Column (2) in Panel B). However, it has a statistically significant and strong impact on the mean percentile rank of children born to fathers at the 75th percentile rank, as shown in Column (3) of Panel B. The estimate is as large as -10.56 and is statistically significant at the 1% level. Comparing the result for poor families (Column (2)) with that for rich families (Column (3)), we conclude that the positive effect of fertility on intergenerational mobility is likely driven by the increasing mobility of children born to high-income families under the OCP.

Robustness. Four sets of robustness analyses are carried out. First, we check whether our estimated effect of fertility on intergenerational mobility is influenced by other socioeconomic variables. We test this using three comprehensive sets of socioeconomic variables to capture a child's environment: up to age 3, age 3 to 6, and up to age 9. Second, we investigate whether the IV we used in our main analysis is a good measure of the intensity of policy exposure to the OCP. We construct an alternative one for the policy exposure of mothers by sidestepping mother's educational attainment. Third, we examine whether our estimated effect of fertility on intergenerational mobility is biased by other important historical and political events. Specifically, we restrict the first cohort to children born between 1968 and 1973 who are less influenced by early historical and political events. Fourth, we check whether our results appear only in the restricted sample, i.e., father-child pairs, by extending the analyses to parent-child pairs. *SI Appendix* 3.3 presents the details of these robustness analyses and Table S8 shows the corresponding IV estimates. Our results are robust in both magnitudes and levels of statistical significance across the four tests, with reasonable variations.

Mechanism of Human Capital Investment. How does differential fertility caused by the OCP decrease intergenerational mobility? We consider one important channel to be human capital investment. As shown, a prominent consequence of the population control policy is a widening fertility gap between rural and urban families. Since rural households are typically poorer than urban ones in China, this technically one-and-a-half-child policy increases the fertility of the poor relative to that of the rich. Moreover, to enforce this policy, local governments instituted a series of coercive measures, including monetary fines and administrative penalties, for above-quota births. Fines for above-quota births are a more realistic threat for urban and rich families than their rural and poor counterparts. Many rural households, especially those living below the poverty line, were less constrained from defaulting on fines for above-quota births, because they were unable to bear the onerous economic burden (27-29). Other penalties, such as demotion in a state-owned enterprise or withdrawal of the children's right to go to school, were more realistic for urban residents (30). Thus, urban and rich families had fewer children in reality compared with the counterfactual case without this policy, resulting in enlarged differential fertility between urban/rich and rural/poor areas (31). Details on the population control policy are provided in *SI Appendix* 1.2.

This enlarged fertility gap amplifies the inequality in human capital investment in children born to rich and poor families via a quantity-quality trade-off. We predict that children born to larger families receive less human capital investment because of resource dilution (11, 12). An increase in fertility decreases child quality, measured by schooling levels, academic performance, or assessed health (32-34). Evidence from China indicates that with one additional child born to families with twins at the first delivery, the children's educational level and enrollment rate in school is decreased (35). On the other hand, children born to rich families, which have fewer children due to the OCP, receive more human capital investment because of resource concentration. As rich families tend to invest more in children than poor families, even in the case without the population control policy, the enlarged fertility gap further amplifies the inequality in human capital investment—and thus income disparity—in children born to the two types of families (31). As a consequence, intergenerational income mobility decreases.

We explicitly examine the human capital mechanism by investigating the impact of the OCP on intergenerational education mobility via fertility. Three measures of intergenerational education mobility are used, which are similar to those for intergenerational income mobility (details in *SI Appendix* 2.3). We repeat the IV estimations, but use intergenerational education mobility as the dependent variable. Table S6 presents the results, which are consistent with those presented in Table 2. The result for intergenerational education mobility supports the channel of child quantity-quality trade-off. Rich families have few children, but each with higher human capital under the OCP than in the counterfactual case without the OCP. The income disparity between children of the rich and the poor enlarges, which induces decreasing intergenerational income mobility.

One potential concern is that the OCP, which allows a second birth in rural areas if the first child were a girl, increases child labor supply in poor and rural families, which may bias our estimation results. On the one hand, labor supply from the additional child contributes to household income and therefore father's lifetime income. The intergenerational income mobility is likely biased downward because of the higher father's income, which is more difficult for the child to surpass. On the other hand, due to the child quality-quantity trade-off, the additional child presumably receives inferior education and thus lower lifetime income, which further biases intergenerational mobility downward. If this is the case, our estimate of the increase in intergenerational income persistence serves as a lower bound of the true increase. Nevertheless, we believe that this channel is not likely to undermine our estimates. First, our empirical results show that fertility has no statistically significant impact on the intergenerational educational mobility of children born to poor fathers (Column (2), Panel B, Table S6). Instead, the fertility drop induced by the OCP significantly increases the intergenerational mobility of children born to rich fathers (Column (3), Panel B, Table S6). Second, instead of using level of income, we use percentile rank, which is more robust to lifecycle bias and attenuation bias.

Discussion. How much does the OCP account for the decline in intergenerational income mobility? We calculate that the OCP accounts for as much as 32.7%-47.3% of the increase in rank-rank slope—i.e., the decline in intergenerational income mobility—based on (i) estimates of the effect of the OCP on fertility from the literature, and (ii) estimates of the effect of fertility on intergenerational mobility from our study.

First, the literature shows that the OCP has reduced fertility by 0.11 to 0.16. Li et al. (36) find that the OCP decreases the probability of having a second child by 11 percentage points, based on the 1982 and 1990 Chinese population censuses. Since the OCP affected not only the probability of having a second child, but also that of having a third or higher-order child, the estimate of 0.11 serves as a lower bound for the true effect of the policy on fertility. Regarding the upper bound, McElroy and Yang (9) find that raising the penalty for above-quota births from 0 to 41.3% of a worker's annual income would reduce fertility per woman by 0.33; typical monetary penalties for a second child in cities/towns ranged from 10% to 20% of parents' total wage. So, the introduction of the penalty would reduce fertility by 0.16 ($0.33 \times 20\% \div 41.3\%$) at most. Putting everything together, the OCP is estimated to reduce fertility by 0.11 to 0.16.

Second, we calculate the contribution of fertility induced by the OCP to the decrease in intergenerational income mobility. Our IV estimates in Table 2 show that the income rank-rank slope increases by 0.325 when fertility decreases by 1. Thus, the increase in income rank-rank slope induced by the OCP is between 0.036 (0.325×0.11) and 0.052 (0.325×0.16). Given that the rank-rank slope increases by 0.11 (0.37-0.26) from the first to the last cohort (Fig. 2), the OCP accounts for as much as 32.7%-47.3% of the decrease in intergenerational mobility in China.

Conclusion

Our results show that the OCP contributes significantly to declining intergenerational income mobility in China. The policy causes differential fertility between rich and poor families. Together with the child quantity-quality trade-off, the inequality in human capital investment in children born to rich and poor families increases. As human capital is a major determinant of earnings, income inequality in one generation persists into the next. Our estimation results suggest that the OCP accounts for as much as 32.7%-47.3% of the decline in intergenerational income mobility, measured by rank-rank slope. Our study not only contributes to analyzing the trend in intergenerational income mobility in China, but also advances understanding of the mechanism by which the population control policy decreases intergenerational mobility. The OCP has significant ramifications, not only intragenerationally but also intergenerationally, for Chinese society.

In 2011, the Chinese government announced a two-child policy for couples if both parents were only children. Five years later, this policy was extended throughout the nation, regardless of whether parents have any siblings. The impact of this policy on intergenerational mobility will be an avenue for future study, as the magnitude of its impact on rich and poor families is unclear and the fertility preferences of the two types of families may change over time.

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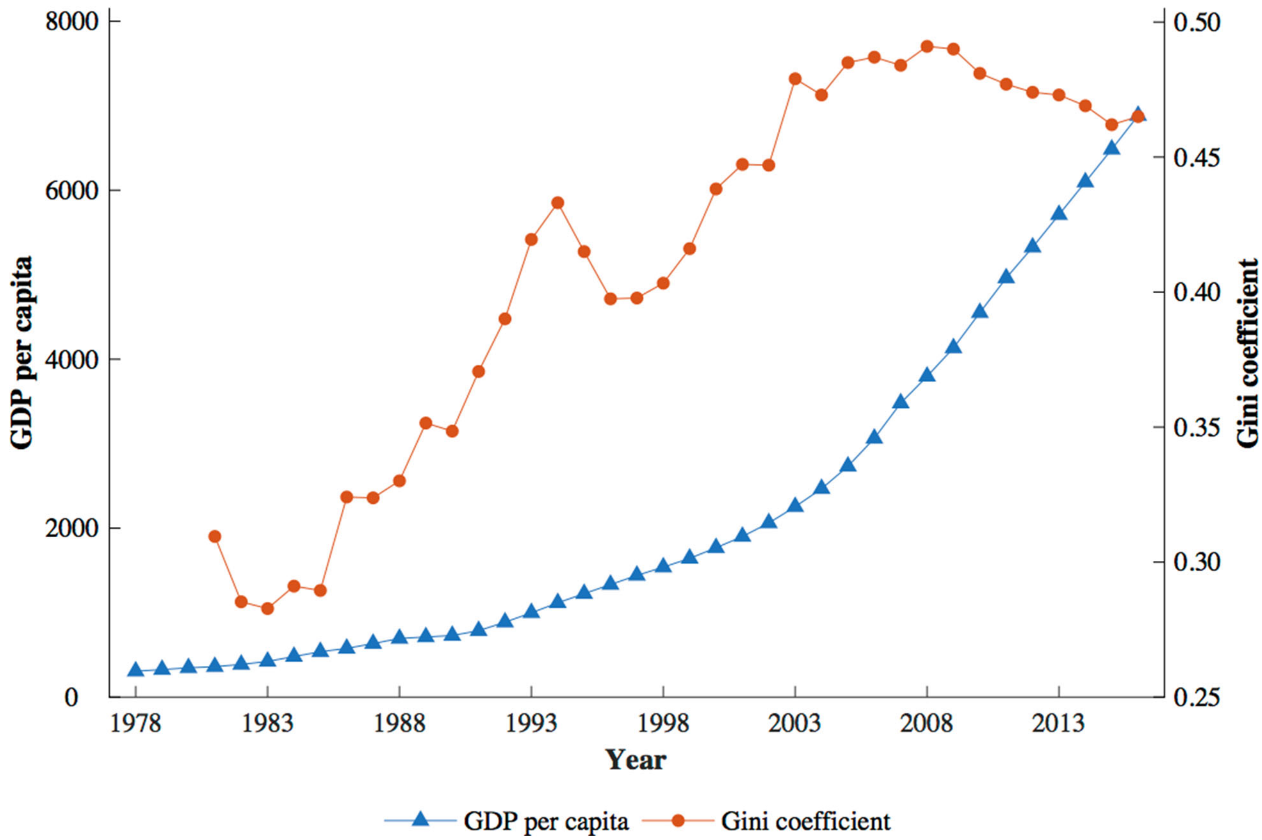

Figure 1. GDP per capita and Gini coefficient in China, 1978-2016. Data on GDP per capita are from the World Bank (1978-2016). Gini coefficients for 1978-2002 are from the United Nations University World Institute for Development Economics Research (UNU-WIDER); Gini coefficients for 2003-2016 are from the National Bureau of Statistics of China. GDP per capita is measured in constant 2010 U.S. dollars.

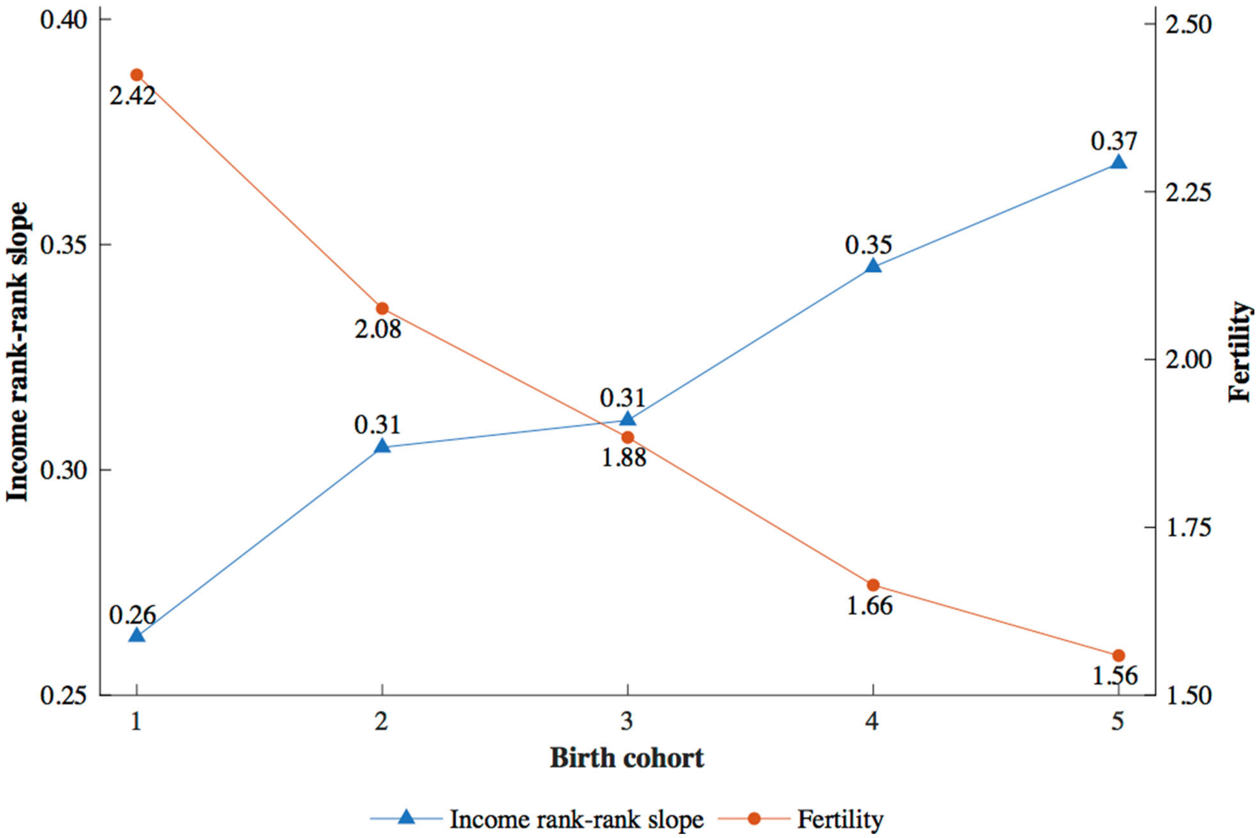

Figure 2. Trends in intergenerational rank-rank slope and fertility. The trend in intergenerational income mobility measured by rank-rank slope (blue line with triangles) and the trend in fertility measured by average number of siblings across the child's birth cohorts (red line with circles) (n=25,618). We combine two nationally representative biannual longitudinal household surveys: the 2010-2018 China Family Panel Studies (CFPS) and the 2011-2015 China Health and Retirement Longitudinal Study (CHARLS). The combined dataset generates a sample of 25,618 father-child pairs, and the same sample is measured throughout the analysis. We first divide the sample into five birth cohorts by the child's birth year: 1964-1973, 1974-1976, 1977-1979, 1980-1982, and 1983-1985. We further divide the sample into 110 groups by the child's birth cohort and province. For each group, we estimate income rank-rank slope and calculate the average number of child's siblings. Finally, for each child's birth cohort, we separately average the estimates of income rank-rank slope across provinces and the average number of child's siblings.

Table 1. Summary statistics for variables. Panel A: Summary statistics for our dependent variables, three measures of intergenerational income mobility. Panel B: Summary statistics for our main independent variable, fertility. Panel C: Summary statistics for control variables. Panel D: Summary statistics for instrumental variables.

Variable	Observations	Mean	SD
Panel A. Intergenerational Income Mobility			
Income rank-rank slope	110	0.318	0.119
Mean income percentile rank of children born to fathers at the 25th income percentile rank	110	44.075	7.962
Mean income percentile rank of children born to fathers at the 75th income percentile rank	110	57.439	5.856
Panel B. Main Independent Variable: Fertility			
Fertility	110	1.921	0.498
Panel C. Control Variables			
Logarithm of GRP per capita	110	5.987	0.479
Logarithm of industrial output value per capita	110	0.046	0.031
Urbanization rate	110	0.187	0.084
Number of doctors per 10,000 persons	110	11.269	3.938
Number of beds per 10,000 persons	110	19.847	7.533
Share of primary industry	110	36.19	9.093
Share of tertiary industry	110	21.374	3.841
Gini coefficient of income	110	0.173	0.044
Panel D. Instrumental Variables			
Policy exposure of mothers	110	0.282	0.259
Share of rural mothers	110	0.764	0.121

Table 2. Effects of fertility on intergenerational income mobility. Panel A: FE estimates of fertility and intergenerational income mobility. Dependent variables are rank-rank slope (column 1, n=110), mean percentile rank of children born to fathers at the 25th percentile rank (column 2, n=110), and mean percentile rank of children born to fathers at the 75th percentile rank (column 3, n=110). The explanatory variable of interest is fertility, which is measured by average number of siblings; control variables are the Gini coefficient and a set of socioeconomic measures of a child's environment up to the age of 6—GRP per capita, industrial output value per capita, urbanization rate, number of doctors per 10,000 persons, number of beds per 10,000 persons, share of primary industry, and share of tertiary industry; province fixed effects and cohort fixed effects are also controlled for. Panel B: IV estimates of fertility and intergenerational income mobility. Columns (1)-(3): Second-stage estimation results. Column (4): First-stage estimation results, where the dependent variable is fertility (n=110) and the explanatory variables of interest are policy exposure of mothers, share of rural mothers, and the interaction term. Data source: CFPS (2010-2018), CHARLS (2011-2015), China Compendium of Statistics (1949-2008), and China Compilation of Demographic Data (1949-1985). Bootstrapped standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Dependent variable	Rank-rank slope	Mean percentile rank of children born to fathers at the 25th percentile rank	Mean percentile rank of children born to fathers at the 75th percentile rank	Fertility
	(1)	(2)	(3)	(4)
Panel A. FE Estimation Results				
Fertility	-0.138	-2.382	-9.929***	
	(0.089)	(3.228)	(2.291)	
R-squared	0.718	0.905	0.930	
Panel B. IV Estimation Results				
Fertility	-0.325***	5.584	-10.560***	
	(0.119)	(5.234)	(3.847)	
Policy exposure of mothers				-1.115*
				(0.606)
Share of rural mothers				0.449
				(0.469)
Policy exposure of mothers *				2.303***

share of rural mothers				(0.735)
R-squared	0.737	0.906	0.913	0.975
Control variables	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Observations	110	110	110	110

Supplementary Information for

The One-Child Policy Amplifies Economic Inequality
across Generations in China

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This PDF file includes:

1. Background

1.1. Economic Growth, Inequality, and Intergenerational Mobility in China

Since 1979, China has experienced rapid economic growth, with the annual growth rate of GDP per capita being above 8%, and real GDP per capita increasing from 1/90 of the U.S. level in 1979 to 1/7 of the U.S. level in 2018. At the same time, the distribution of income has skewed. The Gini coefficient—a snapshot of income inequality across different families in the same generation—rose from 0.31 in 1981 to 0.47 in 2016, exceeding the U.S. Gini coefficient of 0.42 for the same year, as shown in Fig. 1 in the text. Inequality has become an urgent social problem (1-4). What worries both the public and policymakers is the increase in the persistence of inequality within families across generations, which severely undermines the opportunity to escape poverty (5).

The change in intergenerational income mobility—a measure of income inequality across different generations of the same families—is an increasingly heated topic for the public, policymakers, and social scientists. Pioneering research mainly focuses on the U.S. to measure intergenerational mobility and to estimate the trend (6). Recently, several researchers have extended the scope to China (5). Using urban survey data from the China Household Income Project in 1995 and 2002, Deng et al. (7) find that the estimated intergenerational income elasticity (IGE) for father-son pairs increases from 0.47 in 1995 to 0.53 in 2002. Using the same data, Fan (5) shows that the estimated IGE is 0.43 and 0.51 for cohorts educated prior to and after the market reform in 1979, respectively; it reaches 0.71 for households with above-average income in the post-reform era (5). Using survey data from the China Family Panel Studies (CFPS) in 2010, 2012, 2014, and 2016, Fan et al. (8) estimate the intergenerational income rank-rank slope, rising from 0.449 to 0.485 across 1970-1980 and 1981-1988 birth cohorts. The results of these studies consistently reveal a declining trend in intergenerational income mobility in China.

Which factors account for the change in intergenerational mobility in China? Evidence suggests that in the long run, historical events may contribute to the change in intergenerational mobility, such as the Chinese Communist Revolution (9) and Cultural Revolution (10, 11), which was a class-based revolution with peasants as its main supporters. Meng and Zhao (10) find that interruptions in parents' education during the Cultural Revolution have a negative impact on their children's educational achievement through the transmission channel of parental educational achievement. The Chinese Communist Revolution, which features a skewed educational distribution toward children born to the working class, has had a long-lasting effect on multigenerational social mobility (9). These results highlight the importance of human capital investment in the process of intergenerational transmission, especially for children born to disadvantaged parents, such as poor and rural ones (12). Other studies attempt to associate the decline in intergenerational mobility with changes in socioeconomic factors after the economic reform, such as market structures, economic development, and educational and fiscal policies (8, 13, 14). Fan et al. (8) find that the mean income percentile rank of children born to parents at the 20th income percentile rank decreases with the increase in public education expenditure and college expansion. Because of the unequal distribution of public education expenditure, attending elite schools becomes more difficult for children from low-income families (13). Using the Chinese College Student Survey conducted in 2010, Li et al. (15) find that the share of students in elite universities who come from rural and western regions has decreased. In 2010, 22% of college students were from families whose annual income was less than the average annual expenditure of college. Loans and scholarships accounted for less than 10% of the annual expenditure on college. Need-based aid that targeted low-income students is clearly misallocated (15).

1.2. China's Population Control Policy

Driven by the concern that China would be destined for a "Malthusian trap"—in which an increase in population puts increasing strain on resources and leads to a decrease in quality of life—China initiated the population control policy in 1979, which is popularly known as the one-child policy (OCP). This is one of the most extreme forms of birth control in recorded history, and consists of a set of policies that vary in implementation measures and rigidity levels across regions and years.

Although mild economic and administrative enforcement and extreme sanctions were used, its purportedly utopian goal of restricting each family to one child has never been achieved. The OCP was introduced in China in 1979 and officially written into the Constitution in 1982. Despite extensive propaganda, regulations, incentives, and sanctions, the OCP encountered serious resistance. Many rural families, particularly those with only one female child, strongly resisted the policy for practical and cultural reasons, such as prospects for the family's economy, the son's role of carrying on the family name, and providing parents with security in their old age. Due to widespread opposition and implementation problems, the central government issued Central Document No.7 in April 1984, which allowed rural families to have a second child if the first were a daughter; in contrast, the OCP remained in force in urban areas. This conditional two-child policy was rolled out across most provinces over the next few years. China's population control policy, therefore, was technically a one-and-a-half child policy.

Although Central Document No.7 was applied to the entire nation, rollout varied across provinces. The Liaoning and Jiangxi provincial governments took the lead in implementing the reformulated policy in 1985, whereas the Guangdong and Guizhou provincial governments introduced the policy as late as 1998. The staggered rollout of Central Document No.7 induced changes in interprovincial disparities in the fertility gap between rich and poor. For example, the fertility gap is significantly higher in eastern provinces than in western provinces. Earlier introduction of the policy in eastern regions triggered a larger change in urban and rich mothers' fertility choices than the counterfactual case without the policy. Enlarged fertility differentials in eastern provinces increased the interprovincial difference. The demographic structure has thus changed.

Coercive means instituted by local governments in order to enforce Central Document No.7, such as economic fines and administrative penalties for above-quota births, also varied across rural and urban areas, rich and poor, and provinces. For most families, fines proportional to monthly salary were an onerous burden (16-18). Many rural households, especially those living below the poverty line, may have defaulted because they were unable to pay heavy fines. As a result, urban and rich Chinese families' fertility choices were more restricted to fines than rural and poor ones. Evidence shows that the fertility of the poor did not vary with the imposition of fines, whereas the effect of fines on the fertility of the rich was significantly negative. Other penalties, such as demotion in a state-owned enterprise or withdrawal of the children's right to go to school, were also more realistic for urban residents. By contrast, the policy had a smaller effect on rural residents who received few benefits from the government. In sum, violating the policy was costlier for urban and rich residents. They thus had fewer children in reality compared with the counterfactual case without this policy, which caused larger differential fertility between urban and rural areas (19).

1.3. Differential Fertility, Inequality, and Intergenerational Mobility

Differential fertility accounts for inequality through the mechanism of human capital accumulation (20). Chu and Koo (21) find that an increase in the fertility of the poor will exacerbate income inequality. The argument is straightforward: Children born in larger families receive less human capital investment because of resource dilution, as predicted by the child quantity-quality trade-off theory (22); because fertility differentials between rich and poor thus result in differences in human capital investment for children in these two types of families; and because human capital is a major determinant of income, income inequality arises.

Differential fertility also has significant implications for intergenerational mobility in a dynastic framework. Lam (20) characterizes both differential fertility and intergenerational income mobility in a dynastic model. In his model, the dynamics of period-to-period changes in the relative size of the poorest class affects both intergenerational income mobility—dynastic income transitions manifested in two generations of family members—and income inequality—steady-state income distribution (20).

As Wang and Zhang (19) find, the enlarged fertility gap between rich and poor families in China induced by the OCP increases the inequality in children's human capital. Consequently, income inequality persists across generations, indicating a declining trend of intergenerational mobility (20, 23).

2. Data

2.1. Data Sources and Sample Construction

Our main data are drawn from the CFPS and the China Health and Retirement Longitudinal Study (CHARLS). Specifically, for CFPS, we focus on the baseline survey, which was carried out in 2010, and the follow-up surveys in 2012, 2014, 2016, and 2018; for CHARLS, we focus on the national baseline survey, which was carried out in 2011 and the follow-up surveys in 2013 and 2015. Below, we detail the steps we took to construct our analytic sample using the combined dataset from CFPS and CHARLS.

Step 1 Construct the nationally representative sample of father-child pairs from the combined dataset.

Due to national representation and the large sample size of both the CFPS and CHARLS, the constructed sample of father-child pairs from the combined dataset is a good microcosm of China's population. The unique feature of a few designed sub-surveys/modules guarantees the uniqueness of this nationally representative sample. Both the baseline CFPS and the baseline CHARLS adopt three-stage probability-proportion-to-size (PPS) sampling with implicit stratification. The baseline CFPS sample covers approximately 30,000 individuals and represents 95% of China's population; the baseline CHARLS includes 17,500 individuals. We therefore mainly focus on the baseline surveys to construct a nationally representative sample. The baseline survey of the CFPS consists of four sub-surveys—a community survey, household survey, adult survey, and child survey—that collect detailed information on all household members and their direct relatives. Using the information from (i) self-reports in the adult survey, (ii) interviews with family representatives in the household survey, and (iii) interviews with spouses, children, and siblings in the adult survey, we are able to construct a nationally representative sample of father-child pairs from the CFPS. Similarly, the baseline survey of the CHARLS includes demographics and family structure modules, in which each respondent self-reports information on family relations and basic information on the parents, spouse, all children, and siblings, regardless of whether these direct relatives live in the same household. This unique feature allows us to construct another nationally representative sample of father-child pairs from the CHARLS. We then combine these two samples of father-child pairs from the CFPS and the CHARLS. The combined sample is unique and nationally representative.

Following the criteria below, we refine the combined sample. (i) *The age restriction on children*. We drop father-child pairs with children born before 1964 to exclude the influence of the Cultural Revolution on education and intergenerational income mobility (10, 24). We also drop pairs with children aged 24 and below in 2010, since they are likely to still be in school or at the start of their careers, when income is a poor measure of lifetime income. (ii) *The upper age restriction on parents*. We drop pairs with parents aged 65 and above in 2010, because they usually do not work. (iii) *The restriction on basic demographic variables*. We further drop pairs with age gaps between parents and children smaller than 16, and pairs with missing information on whether parents are alive. Moreover, we restrict the sample to pairs with intact information on siblings, which is important for two reasons. First, fertility is the focus of our research. Based on the sample of father-child pairs, we count the number of siblings for each child; the fertility of his/her mother is thus measured by the number of siblings. Second, we use the information on the number of siblings to correct for selection bias, which we discuss in Section 2.2.1.1. (iv) *The restriction on residential place*. The combined sample consists of pairs from 28 provinces, municipalities, and autonomous regions (excluding Tibet, Hainan, Ningxia, Hong Kong, Macau, and Taiwan). Chongqing Municipality was formally established in 1997, an area that has historically been included in Sichuan Province, and thus we merge Chongqing with Sichuan for simplicity. We drop Beijing, Tianjin, and Shanghai Municipalities due to their special socioeconomic and institutional characteristics, and drop Qinghai and Xinjiang due to limited sample sizes.

The full sample consists of 25,618 father-child pairs with children from 22 provinces and autonomous regions, in which 16,942 pairs are from the CFPS and 8,676 pairs are from the CHARLS. The information on individual demographics and socioeconomic variables is intact, including age, gender, schooling years, *hukou* status, number of siblings, and residential location, as summarized in Table S1, However, information on the individual's observed income is missing for some individuals for two possible reasons. One is that a large proportion of either fathers or adult children temporarily work outside the residence, and the CFPS and CHARLS do not record those migrants' income. The other is that fathers and adult children do not live together, which is a common phenomenon in China. The CFPS only records the individual income of the surveyed household.

Due to concerns about selection bias, we do not drop pairs with missing information on income. Missing information on income may lead to a standard incidental sample truncation problem (25). Father-child pairs living in the same household may differ from those not living together or who are temporarily living apart. Within the same survey year, fathers and their children born early are older than fathers and their children born late. The probability of living with one's father or one's children varies with age, because the youngest children have the highest probability of living with their parents. Likewise, the probability of being a temporary migrant changes over one's life cycle. As a result, the probability that the CFPS or CHARLS sample does not record one's income is correlated with his/her age. The sample truncation problem therefore influences fathers and children differently, depending on age. Once we drop pairs with missing information on income, selection bias arises. To address this concern, we apply the Heckman selection model to compute lifetime income for both children and fathers, which we discuss in Section 2.2.1.1.

Step 2 Divide the full sample of father-child pairs into 110 groups by the child's birth cohort and province.

We first divide this full sample into five cohorts by the child's birth year: 1964-1973, 1974-1976, 1977-1979, 1980-1982, and 1983-1985. We further divide the sample into 110 groups by the child's birth cohort and province, as shown in Table S2.

2.2. Variable Construction

2.2.1. Three Measures of Intergenerational Income Mobility

We separately estimate three measures of intergenerational income mobility for each group. The first is the rank-rank slope. This measures the association between a child's position in the income distribution and his/her father's position in the income distribution, which answers the question of the change in the child's income percentile rank in his/her generation when his/her father's income percentile rank increases by 1 in the father's generation. We focus on the rank-rank slope rather than IGE, another commonly used measure of intergenerational mobility, for several reasons. IGE measures not only income mobility but also the change in income inequality within each generation. By contrast, the income rank-rank slope only measures mobility. Moreover, measuring income using percentile ranks rather than dollar levels has significant statistical advantages. A positive rank-rank slope estimate indicates high income persistence across generations and therefore low intergenerational income mobility. Although the rank-rank slope provides an intuitive linear estimate, one drawback is that a lower rank-rank slope may be undesirable if it is caused by worse outcomes for the rich rather than better outcomes for the poor. To address this concern, we estimate two measures of absolute mobility: the mean income percentile ranks of children born to fathers at the 25th and 75th percentile ranks of the national income distribution of fathers. These two estimates measure the mobility of children from low- (e.g., bottom-quartile) and high- (e.g., high-quartile) income families, respectively. Estimating intergenerational income mobility is difficult because of the conventional lifecycle bias, attenuation bias, and selection bias. We detail construction of these three measures below to overcome the three biases.

2.2.1.1. Intergenerational Income Rank-Rank Slope

Step 1 Compute lifetime income for both children and fathers.

First, we calculate observed income for both children and fathers. Each wave of the CFPS collects information on the individual's income in the previous year, which is the sum of five categories: wage, farming/self-employment, property, transfers, and others (e.g., gifts in kind). Income for 2012, 2014, 2016, and 2018 is adjusted by the Consumer Price Index to the 2010 price level. We calculate observed income by averaging individual income across waves in the CFPS. Information on observed income is missing for some individuals.

Second, we estimate the following probit model using the CFPS sample of children with and without observed income:

$$I_i = \alpha_0 + \alpha_z z_i + X_i \alpha_X + \varepsilon_i, \tag{S1}$$

where I_i is a dummy variable equal to 1 if the information on child i's observed income is available in the CFPS sample, and 0 otherwise; z is the number of siblings the child has; X is a comprehensive set of demographic and socioeconomic variables, including gender, schooling years, age, age squared, age cubed, and full interactions with *hukou* status and coastal dummy, and cohort. Educational attainment is a key predictor of lifetime income by schooling. In this study, we use the age in 2010. We address the lifecycle bias by controlling explicitly for age polynomials for children and fathers. *Hukou* status is a dummy variable equal to 1 if the child held an agricultural or rural *hukou* when he was 3 years old, and 0 otherwise. The coastal dummy is equal to 1 if the household is living in any of the coastal provinces, which are the most developed areas in China, and 0 otherwise. Column (1) in Table S3 reports the estimates of Eq. (S1) for children.

Third, using the estimates of Eq. (S1) for the CFPS sample of children, we calculate the inverse Mills ratio, λ_i, for children with and without observed income from CFPS and include it in the income equation using the CFPS sample of children with observed income to correct for selection bias. Note that although Eq. (S1) is estimated using the full CFPS sample, Eq. (S2) below can only be estimated using the CFPS sample with observed income:

$$\text{(S2)} \qquad inc_i = \beta_0 + \beta_\lambda \lambda_i + X_i \beta_X + \varepsilon_i,$$

where inc is the logarithm of the child's observed income and X is the same as in Eq. (S1). Because the CFPS records fathers' and children's income for the five cohorts at different ages in the same survey years, we are unable to account for the possibility that returns to education may change over time. However, we account for *hukou* status and regional variations in returns to education by including full interactions of education with *hukou* status and costal dummies in $X_i$in Eq. (S2). Column (3) in Table S3 presents the estimates of Eq. (S2), correcting for selection bias for children. The R-squared in column (3) is 0.243.

The variable z, the number of siblings the child has, is included in Eq. (S1) but not Eq. (S2). We use this variable as the excluded variable from the income equation to address the selection problem due to missing income. First, the greater the number of siblings, the higher the probability that a sibling will take care of the father, and therefore (i) the lower the probability of cohabitating with his father, and (ii) the higher the probability that the child works outside the home county. In both cases, the CFPS sample is less likely to record income information for children with more siblings. Thus, the variable z satisfies the monotonicity assumption in the two-stage estimation. We control for other variables, such as education, to mitigate the direct impact of the number of siblings on the child's income through the child quantity-quality trade-off (22). As expected, the number of siblings is highly negatively correlated with the probability that the CFPS records income information, presented in column (1) in Table S3.

Fourth, based on the estimates of Eq. (S2), we compute lifetime income for all children from the CFPS using individual characteristics X_i, the calculated inverse Mills ratio λ_i, and the estimated coefficients β_0, β_λ and β_X. For all children from CHARLS, we first calculate the inverse Mills ratio λ_i using the estimates of Eq. (S1). We then compute lifetime income for all children from CHARLS using the estimates of Eq. (S2), individual characteristics X_i, and the calculated inverse Mills ratio λ_i. We use the CFPS sample to estimate Eqs. (S1) and (S2) because the quality of income information recorded in CFPS is better than that in CHARLS (9).

We apply a similar procedure to compute lifetime income for fathers of the full sample. Here, z is the number of children. Column (2) in Table S3 reports the estimates of Eq. (S1) for fathers of the CFPS sample. Column (4) in Table S3 presents the estimates of Eq. (S2), correcting for selection bias for fathers. The R-squared in column (4) is 0.180. Table S1 summarizes the computed lifetime income for children and fathers.

Step 2 Calculate each child's (father's) income percentile rank based on his/her (his) position in the national distribution of children's (fathers') income by child's cohort, ranging from 0 to 100.

Using computed lifetime income (instead of observed income) to calculate the income percentile rank minimizes the attenuation bias arising from transitory income shocks.

Step 3 Estimate the income rank-rank slope by regressing the child's income percentile rank on the father's income percentile rank at the group level according to Eq. (1) in the text.

Figure 2 in the text displays the trend in intergenerational income mobility measured by the rank-rank slope across the child's birth cohorts, in which we average the estimates of the income rank-rank slope across provinces for each child's birth cohort.

2.2.1.2. Mean Income Percentile Rank of Children Born to Fathers at the 25th Income Percentile Rank

We calculate the mean income percentile rank of children born to fathers at the 25th income percentile rank according to Eq. (2) in the text.

2.2.1.3. Mean Income Percentile Rank of Children Born to Fathers at the 75th Income Percentile Rank

We calculate the mean income percentile rank of children born to fathers at the 75th income percentile rank according to Eq. (3) in the text.

2.2.2. Three Measures of Intergenerational Education Mobility

We separately estimate three measures of intergenerational education mobility for each group. The definitions of these three measures are similar to those for the three measures of intergenerational income mobility. The rank-rank slope measures the association between a child's position in the education distribution and his/her father's position in the education distribution, which answers the question of the change in the child's education percentile rank in his/her generation when his/her father's education percentile rank increases by 1 in the father's generation. A positive rank-rank slope estimate indicates high education persistence across generations and therefore low intergenerational education mobility.

We further estimate two measures of absolute mobility: the mean education percentile ranks of children born to fathers at the 25th and 75th education percentile ranks. These two estimates measure the mobility of children from low- (e.g., bottom-quartile) and high- (e.g., high-quartile) education families, respectively. We detail the construction of these three measures below.

2.2.2.1. Intergenerational Education Rank-Rank Slope

Step 1 Calculate each child's (father's) education percentile rank based on his/her (his) position in the national distribution of children's (fathers') education by child's cohort (9).

First, we compute the share of children (fathers) who completed each level of education in the national distribution of children's (fathers') education by child's cohort.

Second, we compute the cumulative percentages of children (fathers) at each level of education, from illiterate to doctoral, at the national level by child's cohort.

Third, we adjust the cumulative percentages of children (fathers) by subtracting half of the shares at that level of education to get the education percentile rank for each child (father) given that the education category is discrete (9).

Step 2 Estimate the education rank-rank slope as in Step3 in Section 2.2.1.1.

Figure S1 displays the trend in intergenerational education mobility measured by the rank-rank slope across the child's birth cohorts, in which we average estimates of the education rank-rank slope across provinces for each child's birth cohort. The intergenerational rank-rank slope rises from 0.31 for the 1964-1973 birth cohort to 0.36 for the 1983-1985 cohort, implying declining intergenerational education mobility.

2.2.2.2. Mean Education Percentile Rank of Children Born to Fathers at the 25th Education Percentile Rank

We calculate the mean education percentile rank of children born to fathers at the 25th education percentile rank as in Section 2.2.1.2.

2.2.2.3. Mean Education Percentile Rank of Children Born to Fathers at the 75th Education Percentile Rank

We calculate the mean education percentile rank of children born to fathers at the 75th education percentile rank as in Section 2.2.1.3.

2.2.3. Fertility

Fertility is the main independent variable, and is measured by the average number of siblings for all children in each group. Figure 2 (and Figure S1) displays the trend in fertility across birth cohorts.

2.2.4. Control Variables

We control for observed socioeconomic factors related to intergenerational mobility that vary across cohorts and provinces, such as the Gini coefficient and a set of socioeconomic measures of a child's environment up to age 6. Specifically, the socioeconomic measures are gross regional product (GRP) per capita, industrial output value per capita, urbanization rate, number of doctors per 10,000 persons, number of beds per 10,000 persons, share of primary industry, and share of tertiary industry. Data on these measures are mainly drawn from the *China Compendium of Statistics 1949-2008*, which is published by the National Bureau of Statistics of China.

Below, we use the variable of GRP per capita to illustrate the procedures for constructing these measures of a child's environment up to age 6.

Step 1 For child i born in year y and province p, calculate the value of GRP per capita:

(S3) $$GRP\ per\ capita_{ipy} = \frac{\sum_{t=0}^{5} GRP\ per\ capita_{p,y+t}}{6}.$$

Step 2 For each group, the variable of GRP per capita is the averaged value of $GRP\ per\ capita_{ipy}$ across all children within the group.

We use the computed lifetime income (schooling years) of fathers to calculate the Gini coefficient of income (education) for each group.

Table S4 summarizes the steps to construct all variables. Table 1 in the text and Table S5 report summary statistics for these variables.

3. Methodology

3.1. Fixed Effect Estimation

We also use Eq. (4) in the text to examine the effect of fertility on intergenerational education mobility. The difference is that we replace the dependent variable Y_{pc} with one of the three measures of intergenerational education mobility, and we replace the Gini coefficient of income with the Gini coefficient of education. Panel A of Table S6 reports the FE estimation results for intergenerational education mobility. This model produces a reasonable fit to the data, scoring R-squared over 0.56 across three columns. Column (1), in which the dependent variable is rank-rank slope, shows that the estimated coefficient before fertility is -0.178, which is statistically significant at the 5% level. The estimate implies that as fertility decreases by 1, the rank-rank slope increases by 0.178. The results show that intergenerational education mobility decreases with the decline in fertility. We use the mean percentile rank of children born to fathers at the 25th percentile rank as the dependent variable in column (2). The FE estimated coefficient before fertility is -0.595, which is small and statistically insignificant. By contrast, column (3), in which the dependent variable is the mean percentile rank of children born to fathers at the 75th percentile rank, shows that the estimated coefficient before fertility is -11.198 and statistically significant at the 1% level. The estimate implies that as fertility decreases by 1, the mean percentile rank of children born to fathers at the 75th percentile rank increases by 11.198. All results are similar to those in Panel A of Table 2 in the text, and suggest a similar pattern for intergenerational education mobility using three corresponding measures for education.

3.2. Instrumental Variable Estimation

3.2.1. Instrumental Variables Construction

FE estimates are subject to omitted variable bias, because the decrease in fertility across cohorts can be driven by unobserved socioeconomic changes beyond the OCP. For example, the market-oriented reform and the open-door policy could change the fertility preferences of Chinese families. Thus the association estimated between fertility and intergenerational income mobility embodied in Eq. (4) in the text cannot be interpreted as a causal relationship. To overcome this issue, we employ the staggered rollout of Central Document No.7 across cohorts and provinces to isolate the impact of Central Document No.7 on intergenerational mobility through the differential fertility channel in a difference-in-differences (DD) framework. The identification examines the fact that Central Document No.7 allowed rural mothers who were still young when the policy started to have a second child if the first were a girl. Fertility in a group therefore depends on the mothers' policy exposure during their childbearing years and the share of rural mothers. We thus use mothers' exposure to the policy, the share of rural mothers, and their interaction as instrumental variables (IVs). Below, we describe the steps for constructing the variable of mothers' policy exposure.

Step 1 Use the 1% Sample of the 1982 Chinese Population Census, which was conducted by the China Bureau of Statistics, to calculate the standardized probability of a mother with education e, $ProbBirth_e(a)$, giving birth at age a.

First, following Guo et al. (26), we focus on a restricted sample of mothers born in 1930-1939, because Central Document No.7 primarily affected mothers born after 1940. Educational attainment in the survey is divided into five categories: (i) illiterate or semiliterate, (ii) primary school, (iii) junior-middle, (iv) senior-middle, and (v) undergraduate or college graduate.

Second, we divide the number of mothers with education e who gave birth at age a by the total number of mothers with education e to get the probability of giving birth at age a, $probbirth_e(a)$. We restrict age to 17 to 46.

Third, we standardize the probability of giving birth at age a with education e. Because some mothers may have several children at different ages, the total number of children that mothers with education e have may exceed 1. That is, $\sum_{a=17}^{46} probbirth_e(a) \geq 1$. So we standardize the probability below:

(S4) $$ProbBirth_e(a) = \frac{probbirth_e(a)}{\sum_{a=17}^{46} probbirth_e(a)}.$$

Step 2 Calculate the policy exposure of child i's mother at a based on (i) the start year of implementing Central Document No.7 in province p, $PolicyYear_p$, (ii) the mother's birth year, τ, and (iii) the mother's probability of giving birth at age a, $ProbBirth_e(a)$ (26, 27).

The indicator variable, $I[\tau + a \geq PolicyYear_p]$, is equal to 1 if child i's mother born in year τ and province p was subject to Central Document No.7 at age a, and 0 otherwise. The product of $ProbBirth_e(a)$ and $I[\tau + a \geq PolicyYear_p]$ measures the effect of Central Document No.7 on the probability of giving birth at age a for child i's mother born in year τ. For example, this policy was implemented in 1985 in Liaoning Province; child i's mother was born in Liaoning Province in 1965 and completed senior-middle schooling. Her fertility choice was therefore constrained by this policy when she was 20 years old, because $I[1965 + 20 \geq 1985] = 1$. The intensity of the effect of this policy on her fertility at age 20 is captured by $ProbBirth_{senior-middle}(20)$. $ProbBirth_{senior-middle}(20)$—the product of $ProbBirth_{senior-middle}(20)$ and 1(=$I[1965 + 20 \geq 1985]$)—thus measures the policy exposure of this mother when she was 20 years old.

Step 3 Calculate the total policy exposure of child i's mother, $exposure_{ipc}$, by summing the policy exposures between 17 and 46 years old:

(S5) $$exposure_{ipc} = \sum_{a=17}^{46} ProbBirth_e(a) \cdot I\left[\tau + a \geq PolicyYear_p\right],$$

where c is child i's birth cohort. The policy exposure is 1 if a mother was 16 or younger when the policy started in her province, and zero if she was 47 or older when the policy started in her province. Policy exposure monotonically decreases with the mother's age at the start of Central Document No.7, and the decline is faster at an age when the probability of giving birth is higher.

Step 4 For each group, calculate the variable of mothers' policy exposure, $Exposure_{pc}$, by averaging the value $exposure_{ipc}$ across all children within the group.

Panel D in Table S4 summarizes the procedures of IV construction. Table 1 in the text reports summary statistics for IVs.

3.2.2. First-stage Estimation Results

We first examine the performance of our IVs when studying the effect of fertility on intergenerational education mobility. Specifically, we repeat the estimation of Eq. (5) in the text by replacing the Gini coefficient of income with the Gini coefficient of education. Column (4) in Panel B of Table S6 reports first-stage estimation results. The estimated coefficient before the interaction term between policy exposure of mothers and share of rural mothers is 2.236, which is statistically significant at the 1% level. The estimate suggests that when the policy exposure of mothers increases from the 25th percentile (0) to the 75th percentile (0.49), fertility increases by 0.55 for groups composed of rural mothers compared with those that are one-half rural and one-half urban mothers. The estimated coefficient before the share of rural mothers is 0.311, which is statistically insignificant. The estimate suggests that rural mothers tend to bear 0.311 more children than urban mothers in the case without the population control policy. All results are similar to those reported in column (4) in Panel B of Table 2, which implies that the OCP has differential effects on fertility between rural and urban families and contributes to the enlarged fertility gap.

3.2.3. Second-stage Estimation Results

Columns (1)-(3) in Panel B of Table S6 report the second-stage regression results for intergenerational education mobility. This model produces a reasonable fit to the data, scoring R-squared over 0.60 across three columns. Column (1), in which the dependent variable is rank-rank slope, shows that the estimated coefficient before fertility is -0.470, which is statistically significant at the 1% level. The estimate implies that as fertility decreases by 1 as a result of the OCP, the rank-rank slope increases by 0.470. This suggests that the decline in fertility induced by the OCP has reduced intergenerational education mobility in China. Column (2), in which the dependent variable is the mean percentile rank of children born to fathers at the 25th percentile rank, shows that the estimated coefficient before fertility is -0.380, which is statistically insignificant. By contrast, column (3), in which the dependent variable is the mean percentile rank of children born to fathers at the 75th percentile rank, shows that the estimated coefficient before fertility is -25.256 and statistically significant at the 1% level. This implies that as fertility decreases by 1, the mean percentile rank of children born to fathers at the 75th percentile rank increases by 25.256. Comparing column (2) with column (3), we conclude that the positive effect of fertility on intergenerational education mobility is driven by the increase in mobility of children born to high-income families.

The results are consistent with those presented in columns (1)-(3) of Panel B in Table 2 in the text, which support the child quantity-quality trade-off as a channel through which differential fertility induced by the OCP amplifies the inequality in human capital investment in children between rich and poor families. In other words, rich families have fewer children but better child quality (i.e., higher human capital per child), compared with the counterfactual case without the OCP. Consequently, the income disparity between children of the rich and the poor increases, and intergenerational income mobility decreases.

3.3. Robustness Analyses

3.3.1. Alternative Socioeconomic Measures of a Child's Early Childhood Environment

Previous studies suggest that the environment in early childhood has a profound and persistent influence on children's outcomes, including educational attainment and income (28). To check whether our estimates of the fertility effect on intergenerational mobility are driven by the socioeconomic environment in which children grow up, we conduct robust analyses by using different socioeconomic measures of a child's early environment—up to age 3, up to age 9, and aged 3 to 6. We use the variable of GRP per capita to illustrate the procedures used to construct socioeconomic measures of a child's environment up to age 3. We first calculate the value of GRP per capita for child i born in year y and province p according to Eq. (S6), which is similar to Eq. (S3). We then do the same step as Step2 in Section 2.2.4:

$$\text{(S6)} \qquad GRP\ per\ capita_{ipy} = \frac{\sum_{t=0}^{2} GRP\ per\ capita_{p,y+t}}{3}.$$

Panels A, B, and C in Table S7 report summary statistics for these variables, respectively. Panels A, B, and C in Table S8 present IV estimates for these three cases, respectively.

3.3.2. Alternative Measure of IV

The variable of the policy exposure of mothers—the effects of Central Document No.7 on women's fertility—is constructed using the standard probability of a mother with a specific educational attainment giving birth. We consider an alternative measure for policy exposure that ignores the mother's educational attainment and does not standardize the probability.

Panel D in Table S7 reports summary statistics for this IV, and Panel D in Table S8 presents the IV estimates.

3.3.3. Alternative Definition of Birth Cohort

The full sample is divided into five cohorts by the child's birth year: 1964-1973, 1974-1976, 1977-1979, 1980-1982, and 1983-1985. However, the time span for the 1964-1973 cohort is larger than that for other cohorts. To address this concern, we further restrict the first cohort to birth years between 1968 and 1973. Previous studies have found that experiencing important historical and political events, such as the Cultural Revolution, affects the educational attainment of children and intergenerational mobility, especially for children born before 1964 (9-11). Children in this restricted cohort—the 1968-1973 cohort—are thus less likely to be influenced by early historical and political events than those in the unrestricted cohort—the 1964-1973 cohort; therefore, we can isolate the impact of the population control policy on intergenerational mobility from other historic events.

Panel E in Table S7 reports summary statistics for all variables. Panel E in Table S8 presents the IV estimates.

3.3.4. Different Sample Pairs

Our analysis so far focuses on the intergenerational mobility between fathers and children, because fathers are more likely to work than mothers, and the information on fathers' income is more likely to be accessible. Several researchers have studied the intergenerational mobility between parents and children (5, 8). We replicate our main analysis for parent-child pairs.

We first compute the father's lifetime income and the mother's lifetime income separately in the same way we compute the father's lifetime income, then add them up to generate household lifetime income. Second, we repeat the estimations of intergenerational mobility, then conduct the IV estimation. Panel F in Table S7 reports summary statistics for three measures of intergenerational mobility. Panel F in Table S8 presents the IV estimates.

All IV estimates in robustness analyses are similar to those in our main analysis, and thus indicates that our results—the causal effect of fertility induced by China's population control policy on intergenerational mobility in China—are robust.

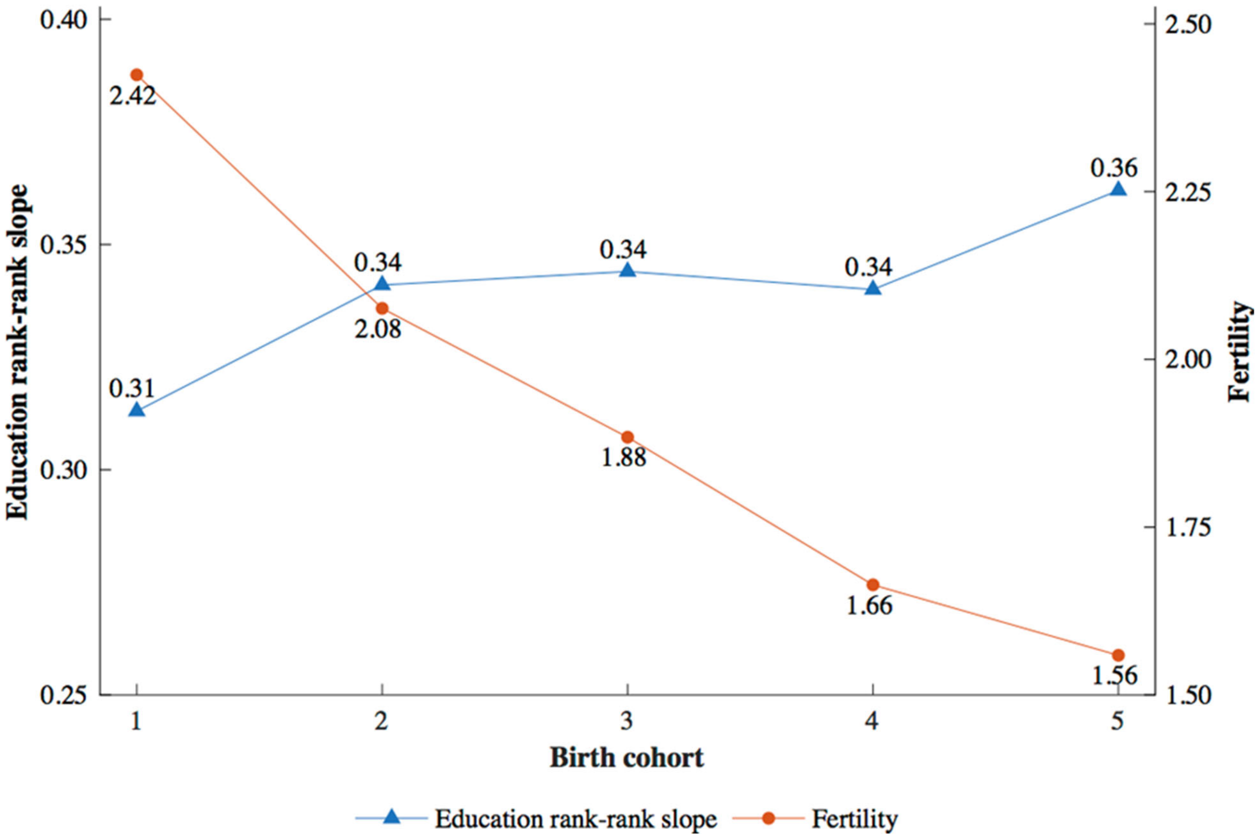

Fig. S1. Trends in education rank-rank slope and fertility. This figure replicates Fig. 2 in the text, but replaces the income rank-rank slope with the education rank-rank slope.

Table S1. Summary statistics for the full sample. We combine two nationally representative biannual longitudinal household surveys—the 2010-2018 China Family Panel Studies (CFPS) and the 2011-2015 China Health and Retirement Longitudinal Study (CHARLS). Because Chongqing Municipality was formally established in 1997, an area that has long been included in Sichuan Province, we merge Chongqing with Sichuan for simplicity. We drop Beijing, Tianjin, and Shanghai Municipalities due to their special socioeconomic and institutional characteristics, and drop Qinghai and Xinjiang due to limited sample sizes. The combined dataset generates a sample with 25,618 father-child pairs with children born between 1964 and 1985 from the remaining 22 provinces and autonomous regions in China; 16,942 pairs are from the CFPS and 8,676 are from the CHARLS. Panels A and B in this table report summary statistics for children and fathers, respectively.

Variable	Observations	Mean	SD
Panel A. Children			
Number of siblings	25,618	1.886	1.237
Gender (male = 1)	25,618	0.49	0.5
Schooling years	25,618	8.494	4.35
Hukou status (rural = 1)	25,618	0.724	0.447
Age	25,618	31.674	4.649
Age squared/100	25,618	10.249	3.046
Age cubed/1000	25,618	33.874	15.279
Coast (coastal region = 1)	25,618	0.325	0.468
Computed lifetime income (in logarithmic form)	25,618	9.785	0.362
Panel B. Fathers			

Schooling years	25,618	5.756	4.366
Hukou status (rural = 1)	25,618	0.746	0.435
Age	25,618	57.915	4.426
Age squared/100	25,618	33.737	5.008
Age cubed/1000	25,618	197.601	42.794
Coast (coastal region = 1)	25,618	0.325	0.468
Computed lifetime income (in logarithmic form)	25,618	9.375	0.324

Table S2. Tabulation of the sample size by the child's birth cohort and province. This table presents the sample size of father-child pairs by the child's birth cohort and province. We first divide the full sample into five cohorts by the child's birth year: 1964-1973, 1974-1976, 1977-1979, 1980-1982, and 1983-1985. We further divide the full sample into 110 groups by the child's birth cohort and province.

	Birth cohort					
Province	1	2	3	4	5	Total
Anhui	171	163	181	207	189	911
Fujian	84	116	128	147	174	649
Gansu	491	386	434	520	554	2,385
Guangdong	235	248	386	530	529	1,928
Guangxi	81	100	146	196	227	750
Guizhou	95	127	156	183	188	749
Hebei	272	222	284	370	355	1,503
Heilongjiang	185	188	207	195	159	934
Henan	519	471	567	678	644	2,879
Hubei	82	94	145	137	147	605
Hunan	146	165	172	216	208	907
Inner Mongolia	109	90	107	153	132	591
Jiangsu	114	116	139	144	141	654
Jiangxi	155	170	203	192	203	923
Jilin	157	115	140	137	106	655
Liaoning	333	298	391	389	283	1,694
Shandong	216	234	287	327	302	1,366

Shannxi	161	122	126	131	189	729
Shanxi	228	211	222	280	311	1,252
Sichuan	377	349	296	395	347	1,764
Yunnan	204	242	283	247	290	1,266
Zhejiang	121	94	111	107	91	524
Total	4,536	4,321	5,111	5,881	5,769	25,618

Table S3. Estimation results of the Heckman selection model. Columns (1) and (2) report the estimates of Eq. (S1)—based on the sample of children and fathers with and without observed income, respectively—for children and fathers, respectively. Columns (3) and (4) report the estimates of Eq. (S2)—based on the sample of children and fathers with observed income, respectively—for children and fathers, respectively. The number of siblings is statistically significantly negatively correlated with the probability that the CFPS records income information, presented in columns (1) and (2). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Outcome Variable:	With observed income (=1)		Ln (observed income)	
	Probit		OLS	
	(1)	(2)	(3)	(4)
	Children	Fathers	Children	Fathers
Number of siblings	-0.279***	-0.396***		
	(0.011)	(0.018)		
Inverse Mills Ratio (λ)			-0.145***	-0.033
			(0.041)	(0.054)
Child birth cohort (= 2)	-0.145**	0.273***	-0.007	-0.197*
	(0.067)	(0.081)	(0.059)	(0.117)
= 3	-0.204*	0.367***	0.025	-0.112
	(0.112)	(0.078)	(0.100)	(0.112)
= 4	-0.273*	0.578***	0.094	-0.172
	(0.151)	(0.078)	(0.135)	(0.113)
= 5	-0.212	0.861***	0.113	-0.167

	(0.174)	(0.080)	(0.152)	(0.115)
Schooling years	0.025***	0.018*	0.047***	0.055***
	(0.007)	(0.010)	(0.006)	(0.009)
Hukou	-16.111*	81.573	3.222	-29.558
	(9.702)	(56.421)	(8.750)	(76.714)
Schooling years * *hukou*	-0.018**	-0.004	-0.003	-0.039***
	(0.008)	(0.011)	(0.007)	(0.010)
Coast	-19.642	226.113**	16.116	-135.782
	(13.385)	(97.910)	(11.544)	(106.218)
Schooling years * coast	0.003	-0.022	-0.008	-0.023*
	(0.011)	(0.015)	(0.010)	(0.012)
Hukou * coast	12.779	-265.967**	-17.387	168.367
	(15.946)	(107.223)	(13.702)	(125.020)
Schooling years * *hukou* * coast	-0.014	0.004	0.022*	0.006
	(0.014)	(0.017)	(0.012)	(0.015)
Gender	0.176***		0.240***	
	(0.050)		(0.040)	
Gender * *hukou*	0.358***		0.169***	
	(0.060)		(0.050)	
Gender * coast	0.019		0.152**	
	(0.080)		(0.064)	
Gender * *hukou* * coast	-0.115		-0.140*	
	(0.098)		(0.080)	
Age	-1.498	-1.397	-0.134	-1.211
	(0.922)	(2.738)	(0.835)	(3.699)

Age * *hukou*	1.600*	-4.410	-0.263	1.517
	(0.904)	(3.081)	(0.828)	(4.264)
Age * coast	1.844	-12.530**	-1.398	7.529
	(1.246)	(5.319)	(1.087)	(5.893)
Age * *hukou* * coast	-1.122	14.740**	1.446	-9.447
	(1.483)	(5.837)	(1.287)	(6.967)
Age squared/100	4.814*	3.203	0.652	1.830
	(2.829)	(4.948)	(2.604)	(6.802)
Age squared/100 * *hukou*	-5.178*	7.916	0.658	-2.513
	(2.780)	(5.582)	(2.580)	(7.873)
Age squared/100 * coast	-5.756	23.014**	3.980	-13.795
	(3.825)	(9.595)	(3.375)	(10.857)
Age squared/100 * *hukou* * coast	3.352	-27.053**	-3.956	17.561
	(4.546)	(10.551)	(3.983)	(12.892)
Age cubed/1000	-0.518*	-0.236	-0.090	-0.087
	(0.285)	(0.297)	(0.267)	(0.416)
Age cubed/1000 * *hukou*	0.554**	-0.471	-0.053	0.133
	(0.282)	(0.336)	(0.265)	(0.483)
Age cubed/1000 * coast	0.594	-1.400**	-0.368	0.837
	(0.387)	(0.575)	(0.345)	(0.664)
Age cubed/1000 * *hukou* * coast	-0.334	1.645***	0.352	-1.082
	(0.460)	(0.633)	(0.406)	(0.792)
Constant	15.105	17.896	10.074	35.155
	(9.843)	(50.292)	(8.735)	(66.792)

Observations	16,942	16,942	4,280	1,712
R-squared			0.243	0.180

Table S4. Summary of variable construction. Panel A: Construction of our dependent variables—measures of intergenerational mobility. Panel B: Construction of our main independent variable, fertility. Panel C: Construction of control variables. Panel D: Construction of instrumental variables.

Variables	**Steps**	**Data Source**
	Panel A. Measures of Intergenerational Mobility	
Intergenerational income rank-rank slope	1. Compute lifetime income for both children and fathers 2. Calculate each child's and father's income percentile rank by child's cohort 3. Regress the child's income percentile rank on the father's income percentile rank at the group level	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Mean income percentile rank of children born to fathers at the 25th income percentile rank	Use Eq. (2) in the text based on the estimates of Eq. (1) in the text	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Mean income percentile rank of children born to fathers at the 75th income percentile rank	Use Eq. (3) in the text based on the estimates of Eq. (1) in the text	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Intergenerational education rank-rank slope	1. Calculate each child's and father's education percentile rank by child's cohort 2. Regress the child's	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015

	education percentile rank on the father's education percentile rank at the group level	
Mean education percentile rank of children born to fathers at the 25th education percentile rank	Similar procedures as calculating mean income percentile rank of children born to fathers at the 25th income percentile rank	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Mean education percentile rank of children born to fathers at the 75th education percentile rank	Similar procedures as calculating mean income percentile rank of children born to fathers at the 75th income percentile rank	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Panel B. Main Independent Variable: Fertility		
Fertility	Average the number of siblings of children at group level	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Panel C. Control Variables		
GRP per capita	1. For child i born in year y and province p, calculate the value of GRP per capita, $\text{GRP per capita}_{ipy}$, according to Eq. (S3) 2. For each group, average the value of $\text{GRP per capita}_{ipy}$ across all children within the group	China Compendium of Statistics 1949-2008

Industrial output value per capita	Similar procedures as calculating GRP per capita	China Compendium of Statistics 1949-2008
Urbanization rate	Similar procedures as calculating GRP per capita	China Compendium of Statistics 1949-2008; China Compilation of Demographic Data 1949-1985; and RDJJLT BBS (https://bbs.pinggu.org/forum.php?mod=viewthread&tid=5929678&page=1&fromuid=532125)
Share of primary industry	Similar procedures as calculating GRP per capita	China Compendium of Statistics 1949-2008
Share of tertiary industry	Similar procedures as calculating GRP per capita	China Compendium of Statistics 1949-2008
Number of doctors per 10,000 persons	Similar procedures as calculating GRP per capita	China Compendium of Statistics 1949-2008
Number of bed per 10,000 persons	Similar procedures as calculating GRP per capita	China Compendium of Statistics 1949-2008
Gini coefficient of income	Use the computed lifetime income of fathers to calculate the Gini coefficient of income for each group	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Gini coefficient of education	Use the schooling years of fathers to calculate the Gini	CFPS in 2010, 2012, 2014, 2016, and 2018; and

	coefficient of education for each group	CHARLS in 2011, 2013 and 2015
	Panel D. Instrumental Variables	
Policy exposure of mothers	1. Calculate the standardized probability of a mother with education e, giving birth at age a 2. Calculate the policy exposure of child i's mother at age a based on the start year of implementing the policy in province p, the mother's birth year, and the mother's probability of giving birth at age a 3. Calculate the total policy exposure of child i's mother by summing the policy exposures between 17 and 46 years old according to Eq. (S5) 4. For each group, average the total policy exposure of mother across all children within the group	the 1% Sample of the 1982 Chinese Population Census; CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015
Share of rural mothers	For each group, average the value of hukou status of mother across all children within the group	CFPS in 2010, 2012, 2014, 2016, and 2018; and CHARLS in 2011, 2013 and 2015

Table S5. Summary statistics for variables. Panel A: Summary statistics for our dependent variables—three measures of intergenerational education mobility. Panel B: Summary statistics for our main independent variable, fertility. Panel C: Summary statistics for control variables. Panel D: Summary statistics for instrumental variables.

Variable	Observations	Mean	SD
Panel A. Intergenerational Education Mobility			
Education rank-rank slope	110	0.34	0.107
Mean education percentile rank of children born to fathers at the 25th education percentile rank	110	42.259	6.923
Mean education percentile rank of children born to fathers at the 75th education percentile rank	110	59.201	6.804
Panel B. Main Independent Variable: Fertility			
Fertility	110	1.921	0.498
Panel C. Control Variables			
Logarithm of GRP per capita	110	5.987	0.479
Logarithm of industrial output value per capita	110	0.046	0.031
Urbanization rate	110	0.187	0.084
Number of doctors per 10,000 persons	110	11.269	3.938
Number of beds per 10,000 persons	110	19.847	7.533
Share of primary industry	110	36.19	9.093
Share of tertiary industry	110	21.374	3.841
Gini coefficient of education	110	0.418	0.098

Panel D. Instrumental Variables

Policy exposure of mothers	110	0.282	0.259
Share of rural mothers	110	0.764	0.121

Table S6. Effects of fertility on intergenerational education mobility. Panel A: FE estimates of fertility and intergenerational education mobility. Dependent variables are rank-rank slope (column 1, n=110), mean percentile rank of children born to fathers at the 25th percentile rank (column 2, n=110), and mean percentile rank of children born to fathers at the 75th percentile rank (column 3, n=110). The explanatory variable of interest is fertility, which is measured by average number of siblings; control variables include the Gini coefficient and a set of socioeconomic measures of a child's environment up to the age of 6—GRP per capita, industrial output value per capita, urbanization rate, number of doctors per 10,000 persons, number of beds per 10,000 persons, share of primary industry, and share of tertiary industry; province fixed effects and cohort fixed effects are also controlled for. Panel B: IV estimates of fertility and intergenerational income mobility. Columns (1)-(3): Second-stage estimation results. Column (4): first-stage estimation results where the dependent variable is fertility (n=110) and the explanatory variables of interest are the policy exposure of mothers, share of rural mothers, and the interaction term. Data source: CFPS (2010-2018), CHARLS (2011-2015), China Compendium of Statistics (1949-2008), and China Compilation of Demographic Data (1949-1985). Bootstrapped standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ for two-sided t tests.

Dependent variable	Rank-rank slope	Mean percentile rank of children born to fathers at the 25th percentile rank	Mean percentile rank of children born to fathers at the 75th percentile rank	Fertility
	(1)	(2)	(3)	(4)
Panel A. FE Estimation Results				
Fertility	-0.178**	-0.595	-11.198***	
	(0.088)	(3.396)	(3.682)	

R-squared	0.560	0.839	0.808	
		Panel B. IV Estimation Results		
Fertility	-0.470***	-0.380	-25.256***	
	(0.163)	(4.974)	(5.902)	
Policy exposure of mothers				-1.177
				(0.765)
Share of rural mothers				0.311
				(0.590)
Policy exposure of mothers * share of rural mothers				2.236**
				(0.909)
R-squared	0.606	0.839	0.833	0.973
Control variables	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Observations	110	110	110	110

Table S7. Summary statistics for variables in robustness analyses. Panel A-C: Summary statistics for variables when using alternative socioeconomic measures of a child's early environment—up to age 3 (A), up to age 9 (B), and ages 3-6 (C), respectively. Panel D: Summary statistics for an alternative measure of IV when the probability of giving birth is unstandardized and the mother's educational attainment is ignored. Panel E: Summary statistics for variables when the first cohort is restricted to children born between 1968 and 1973. Panel F: Summary statistics for variables when focusing on parent-child pairs.

Variable	Observations	Mean	SD
Panel A. Alternative Socioeconomic Measures of a Child's Early Environment: Up to Age 3			
Logarithm of GRP per capita	110	5.869	0.46
Logarithm of industrial output value per capita	110	0.04	0.026
Urbanization rate	110	0.181	0.081
Number of doctors per 10,000 persons	110	10.812	3.83
Number of beds per 10,000 persons	110	19.126	7.355
Share of primary industry	110	37.227	9.381
Share of tertiary industry	110	20.495	3.345
Panel B. Alternative Socioeconomic Measures of a Child's Early Environment: Up to Age 9			
Logarithm of GRP per capita	110	6.109	0.488
Logarithm of industrial output value per capita	110	0.053	0.036
Urbanization rate	110	0.194	0.086
Number of doctors per 10,000 persons	110	11.732	4.046
Number of beds per 10,000 persons	110	20.488	7.712
Share of primary industry	110	35.132	8.863
Share of tertiary industry	110	22.49	4.267

Panel C. Alternative Socioeconomic Measures of a Child's Early Environment: Ages 3- 6			
Logarithm of GRP per capita	110	6.055	0.491
Logarithm of industrial output value per capita	110	0.05	0.033
Urbanization rate	110	0.191	0.086
Number of doctors per 10,000 persons	110	11.559	4.029
Number of beds per 10,000 persons	110	20.328	7.691
Share of primary industry	110	35.504	9.021
Share of tertiary industry	110	21.926	4.307
Panel D. Alternative Measure of IV: Unstandardized Probability of Giving Birth			
Unstandardized policy exposure of mothers	110	0.455	0.428
Panel E. Alternative Definition of the First Cohort: Children Born between 1968 and 1973			
Intergenerational Income Mobility			
Income rank-rank slope	110	0.318	0.121
Mean income percentile rank of children born to fathers at the 25th income percentile rank	110	44.077	7.924
Mean income percentile rank of children born to fathers at the 75th income percentile rank	110	57.457	5.791
Intergenerational Education Mobility			
Education rank-rank slope	110	0.341	0.106
Mean education percentile rank of children born to fathers at the 25th education percentile rank	110	42.278	6.894
Mean education percentile rank of children born to fathers at the 75th education percentile rank	110	59.248	6.755
Main Independent Variable			
Fertility	110	1.915	0.49
IVs			

Policy exposure of mothers	110	0.282	0.259
Share of rural mothers	110	0.763	0.122
Control Variables			
Logarithm of GRP per capita	110	6.004	0.461
Logarithm of industrial output value per capita	110	0.047	0.03
Urbanization rate	110	0.187	0.084
Number of doctors per 10,000 persons	110	11.302	3.926
Number of beds per 10,000 persons	110	20.102	7.447
Share of primary industry	110	35.799	8.813
Share of tertiary industry	110	21.3	3.871
Gini coefficient of income	110	0.173	0.044
Gini coefficient of education	110	0.417	0.098
Panel F. Different Sample Pairs: Parent-Child Pairs			
Intergenerational Income Mobility			
Income rank-rank slope	110	0.345	0.125
Mean income percentile rank of children born to fathers at the 25th income percentile rank	110	43.067	8.062
Mean income percentile rank of children born to fathers at the 75th income percentile rank	110	58.467	5.583
Intergenerational Education Mobility			
Education rank-rank slope	110	0.393	0.106
Mean education percentile rank of children born to fathers at the 25th education percentile rank	110	41.018	6.489
Mean education percentile rank of children born to fathers at the 75th education percentile rank	110	60.484	5.956

Table S8. Robustness analysis. Panels A-C: IV estimates when using alternative socioeconomic measures of a child's growing-up environment—up to age 3 (A), up to age 9 (B), and ages 3-6 (C), respectively. Panel D: IV estimates when the probability of giving birth is unstandardized and the mother's educational attainment is ignored. Panel E: IV estimates when the first cohort is restricted to children born between 1968 and 1973. Panel F: IV estimates when focusing on parent-child pairs. Dependent variables are rank-rank slope (column 1, n=110), mean percentile rank of children born to fathers at the 25th percentile rank (column 2, n=110), and mean percentile rank of children born to fathers at the 75th percentile rank (column 3, n=110). Dependent variables and control variables are the same as in columns (1)-(3) in Panel B of Table S6. Data source: CFPS (2010-2018), CHARLS (2011-2015), China Compendium of Statistics (1949-2008), and China Compilation of Demographic Data (1949-1985). Bootstrapped standard error are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

	(1)	(2)	(3)
	Rank-rank slope	Mean percentile rank of children born to fathers at the 25th percentile rank	Mean percentile rank of children born to fathers at the 75th percentile rank
Panel A. Alternative Socioeconomic Measures of a Child's Early Environment: Up to Age 3			
Income			
Fertility	-0.394**	9.732	-9.998**
	(0.158)	(6.246)	(4.050)
R-squared	0.726	0.898	0.910
Education			
Fertility	-0.494***	-1.041	-27.045***
	(0.158)	(5.217)	(6.246)

R-squared	0.622	0.847	0.829
Panel B. Alternative Socioeconomic Measures of a Child's Early Environment: Up to Age 9			
Income			
Fertility	-0.316**	4.846	-10.754***
	(0.128)	(5.637)	(3.056)
R-squared	0.741	0.911	0.917
Education			
Fertility	-0.473***	1.071	-23.802***
	(0.137)	(5.046)	(6.717)
R-squared	0.603	0.837	0.835
Panel C. Alternative Socioeconomic Measures of a Child's Early Environment: Ages 3- 6			
Income			
Fertility	-0.313**	4.666	-10.605***
	(0.138)	(4.109)	(3.442)
R-squared	0.740	0.905	0.913
Education			
Fertility	-0.429***	-0.214	-23.017***
	(0.149)	(5.994)	(6.186)
R-squared	0.581	0.828	0.828
Panel D. Alternative Measure of IV: Unstandardized Probability of Giving Birth			
Income			
Fertility	-0.319**	5.339	-10.398***
	(0.153)	(5.230)	(3.541)
R-squared	0.736	0.906	0.913
Education			

Fertility	-0.464***	-0.162	-24.736***
	(0.139)	(5.202)	(6.812)
R-squared	0.605	0.838	0.832
Panel E. Alternative Definition of the First Cohort: Children Born between 1968 and 1973			
Income			
Fertility	-0.339**	5.149	-11.291***
	(0.143)	(5.168)	(3.825)
R-squared	0.719	0.898	0.911
Education			
Fertility	-0.484***	-0.626	-26.220***
	(0.147)	(5.431)	(7.065)
R-squared	0.587	0.829	0.838
Panel F. Different Sample Pairs: Parent-Child Pairs			
Income			
Fertility	-0.397**	10.847*	-7.965*
	(0.165)	(5.991)	(4.216)
R-squared	0.727	0.904	0.899
Education			
Fertility	-0.374**	0.345	-21.679***
	(0.167)	(4.842)	(7.356)
R-squared	0.512	0.811	0.781
Control variables	YES	YES	YES
Cohort FE	YES	YES	YES
Province FE	YES	YES	YES

Observations	110	110	110

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