Differential Fertility and Economic Opportunity: Evidence from China's One-Child Policy

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Abstract

Using China's one-child policy (OCP) as a quasi-natural experiment, we demonstrate that differential fertility between socioeconomic groups exacerbates intergenerational income inequality. Rural or poorer families, who are less constrained by the OCP than urban or richer ones, tend to have more children but invest less in their human capital development. Given the crucial role of human capital in determining earnings, this disparity leads to persistent income inequality across generations. Wealthy offspring are more likely to maintain economic advantage, while those from disadvantaged backgrounds often remain trapped in poverty. Our estimates suggest that the OCP contributes to approximately 25% of the decline in intergenerational income mobility in China.

Key words: Child quantity–quality trade-off; Differential fertility; Intergenerational transmission of inequality; One-child policy
JEL Codes: J13; J62

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1. Introduction

Effective policies to improve economic opportunities are of major concerns of governments and the public, especially regarding children born in disadvantaged families (Piketty 2000, Corak 2013, Chetty et al. 2017). This paper, from a demographic perspective, presents the first set of empirical evidence on the causal impact of differential fertility between socioeconomic groups on intergenerational economic mobility—a measure of economic opportunity based on parents' socioeconomic status.

Alongside the Industrial Revolution, the correlation between parental socioeconomic status and fertility, which used to be positive, turned negative implying that higher socioeconomic status is associated with lower fertility rates (Bar and Leukhina 2010, Vogl 2016). This reversal has significant implications for the transmission of inequality across generations. During the Malthusian era, better-educated and wealthier parents had higher fertility rates than their less-educated and poorer counterparts. However, this fertility differential reversed during the demographic transition to the modern era, as parents with higher education and earnings faced a greater opportunity cost in raising children. Consequently, more children were born into poorer families. This shift, operating under a child quality-quantity trade-off mechanism, results in these children having less human capital and lower lifetime income compared to their counterparts from wealthier backgrounds (Lam 1986, De La Croix and Doepke 2003, Doepke 2004). Therefore, the changing landscape of differential fertility alters income distribution and reduces economic opportunities for children born to disadvantaged families, leading to a decline in intergenerational mobility (Chu and Koo 1990, Vogl 2016).

This paper aims to estimate the causal impact of differential fertility on intergenerational mobility. Two key challenges are encountered: first, the shift in differential fertility during the demographic transition coincides with changes in the socioeconomic landscape, potentially introducing confounding relationships with intergenerational mobility. Additionally, from a micro-level perspective, fertility is an endogenous choice. Unobservable parental preference for child quality may influence both fertility decisions and investments in child human capital, potentially biasing ordinary least squares (OLS) estimates of the impact on intergenerational mobility. Second, obtaining reliable estimates of intergenerational mobility is hindered by issues such as lifecycle bias, attenuation bias, and selection bias (Solon 1989, 1992, Nybom and Stuhler 2017).

To address the first challenge, we use the quasi-natural experiment of differential fertility between urban and rural China induced by the one-child policy (OCP) to mimic the fertility disparities between richer and poorer families in the post-Industrial Revolution era. Implemented in 1979, the OCP was more stringently enforced in urban areas, with stricter monetary and employment penalties for above-quota births. These penalties, such as demotion or dismissal, posed a more realistic threat to urban/wealthier residents, who were more likely to be employed in the public sector or state-owned enterprises. Conversely, for rural/poorer residents, who often relied on family farms and lacked access to old-age pensions, the OCP faced stronger resistance due to son preference for farm work and elderly care. This resistance led to the issuance of Central Document No. 7 in 1984, allowing most rural families to have a second child if the first one was a girl. Additionally, punishments for higher-order births were less severe in rural areas, effectively making the OCP a one-and-a-half-child policy and leading to higher fertility in rural/poorer compared to urban/wealthier regions (Ebenstein 2010, 2011, 2014, McElroy and Yang 2000, Zhang 2017).

Figure 1a visually demonstrates this disparity, showing a stable difference in cohort sizes between rural and urban China until the early 1980s; followed by a significant widening coinciding with the OCP's launch. Figure 1b further strengthens the link between the OCP and differential fertility by plotting the difference in cohort sizes against OCP adoption years across provinces.[4]

Moving to the second challenge of generating reliable estimates of intergenerational mobility, we carefully construct three robust measures: the rank-rank slope (measuring the correlation between children's and fathers' income ranks), and the expected income percentile ranks of children born to fathers at the 25th and 75th percentiles. Our primary measure is the rank-rank correlation, known for its resistance to lifecycle bias and attenuation bias (Nybom and Stuhler 2017). Using the expected income percentile ranks allows us to differentiate whether improved mobility results from better outcomes for children of the poor or worse outcomes for children of the rich.

Combining two nationally representative longitudinal household surveys, the China Family Panel Studies (CFPS) 2010-2018 and the China Health and Retirement

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[4] Appendix Section 1 provides additional background details on the OCP and its impact on fertility patterns.

Longitudinal Study (CHARLS) 2011-2015, we create a robust dataset for studying intergenerational mobility. This data offers national representativeness, high quality, and detailed information on demographic and socioeconomic status, even for absent household members. To account for potential biases, we construct lifetime income for both children and fathers using the selection model. We divide the full sample of 22,169 father-child pairs into 105 groups based on 5 child's birth cohorts and 21 provinces, and estimate the three measures of intergenerational income mobility for each group. Appendix Section 2.1 details the data sources.

Our target is to estimate the causal effect of differential fertility on intergenerational income mobility at the group level. The dependent variables are the three estimates of intergenerational income mobility, and the independent variable is the fertility differential, measured by the difference in average number of children between rural and urban areas. Recognizing the potential endogeneity of fertility, we employ an instrumental variable (IV) estimation approach, using the staggered rollout of the OCP across provinces and birth cohorts as a quasi-natural experiment. The staggered implementation, driven by top-down political decisions and enforcement variations, minimizes concerns on potential confounding factors.

Our first-stage estimation confirms that the OCP effectively increases fertility differential between rural and urban areas, particularly in groups with larger share of urban residents. Moving to the second stage, our results reveal a significant negative effect of differential fertility on intergenerational mobility. A one-unit increase in the differential leads to a 0.133 rise in the income rank-rank slope, equivalent to a 53.2%

increase from the baseline. This decline in intergenerational income mobility is primarily driven by increased mean percentile ranks for children of high-income families, with daughters experiencing this effect more pronouncedly than sons. These findings remain robust across diverse sensitivity checks.

Further examining potential mechanisms, we focus on human capital, a crucial determinant of earnings. Our results indicate that a one-unit rise in differential fertility coincides with a 0.103 increase in the education rank-rank slope. Similar to the income mobility pattern, children born to families with higher education (75th percentile) are most affected by this negative influence. Finally, a back-of-the-envelope calculation suggests that the OCP contributes to roughly 25% of the observed decline in intergenerational income mobility in China.

Our study contributes significantly to the understanding of differential fertility, inequality, and intergenerational mobility. Prior studies have theoretically explored the implications of flipped differential fertility for human capital, inequality, and intergenerational mobility (Lam 1986, Chu 1987, De La Croix and Doepke 2003, Doepke 2004, and Vogl 2016). Our work provides the first *empirical* evidence of its causal impact, specifically within the context of China's OCP. This finding aligns with earlier theoretical predictions (Lam 1986, Chu 1987, Chu and Koo 1990).

Furthermore, we contribute to the burgeoning literature on economic opportunity and intergenerational mobility by focusing on a developing country, unlike the majority of previous studies conducted in developed nations, such as Solon (1992), Mazumder (2005), Corak (2013), Chetty et al. (2014a), Chetty et al. (2014b), and Chetty et al.

(2017). Additionally, we extend existing research on the determinants of intergenerational mobility, such as child neighborhood quality (Chetty, Hendren, and Katz 2016) and school finance (Biasi 2023), offering the first set of empirical evidence from a demographic perspective on this critical topic.

2. Measures of Intergenerational Mobility

This section describes three measures of intergenerational income mobility. The first measure is the rank–rank slope, which associates child's income rank with parent's income rank in their respective generations. We construct this measure by first comparing each child's/father's lifetime income with that of their peers, to calculate the respective percentile rank at the *national* level, 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, as follows:

$$rank_i = \alpha_0 + \alpha_1 rank_f + \varepsilon_i, \tag{1}$$

where $rank_i$ is the income percentile rank of child i and $rank_f$ is his/her father f's income percentile rank. We control for both the child's and father's demographic variables, including the child's sex, age, and age squared and the father's age and age squared. The coefficient α_1 is the income rank–rank slope. 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 (Chetty et al. 2014a, Chetty and Hendren 2018). A larger rank–rank slope indicates higher income persistence across generations and, therefore, lower intergenerational income mobility.

The rank–rank slope indicates the degree of relative mobility, which measures the difference in outcomes between children from richer and poorer families. We further estimate two measures of absolute income mobility: the expected mean income percentile ranks of children born to fathers at the 25 and 75 percentile ranks of their *national* income distribution. These two estimates separately measure the mobility of children from low-income (e.g., bottom-quartile) and high-income (e.g., top-quartile) families. Specifically, the mean income percentile rank of children born to fathers at the 25 income percentile rank is calculated as follows:

$$income^{25} = \widehat{\alpha_0} + \widehat{\alpha_1} \times 25, \quad (2)$$

where $\widehat{\alpha_0}$ and $\widehat{\alpha_1}$ are the estimates from Equation (1) and $income^{25}$ is the expected mean income percentile rank of children born to fathers at the 25 income percentile rank at the *national* level. A larger estimate of $income^{25}$ indicates a higher mean percentile rank of children from families in the bottom income quartile, suggesting *higher* mobility of children from low-income families.

Similarly, the expected mean income percentile rank of children born to fathers at the 75 income percentile rank is calculated as follows:

$$income^{75} = \widehat{\alpha_0} + \widehat{\alpha_1} \times 75. \quad (3)$$

As discussed previously, $\widehat{\alpha_0}$ and $\widehat{\alpha_1}$ are the estimates from Equation (1). The estimate, $income^{75}$, is the expected mean income percentile rank of children born to fathers at the 75 income percentile rank at the *national* level. A larger estimate of $income^{75}$ indicates a higher mean percentile rank of children born to fathers in the top income quartile, suggesting *lower* mobility of children from high-income families.

When estimating these three measures, three econometric challenges—lifecycle bias, attenuation bias, and selection bias—may arise. Appendix Section 2.2 details the variable construction, econometric challenges, and our proposed empirical strategies to mitigate them.

3. Data and Intergenerational Estimates at Province-cohort level

3.1. Data Sources

We combine data from two nationally representative biannual longitudinal household surveys: the 2010–2018 CFPS and the 2011–2015 CHARLS. The baseline CFPS 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 survey covered 25 provinces, municipalities, and autonomous regions and targeted 16,000 households, with a response rate of 79% (Xie and Hu 2014, Xie and Zhou 2014).[5] The CHARLS was launched by the National School of Development, ISSS, and the Youth League Committee at Peking University. Its national baseline survey, which targeted individuals aged 45 years and above, was launched in 2011. It covered 150 counties in 28 provinces, municipalities, or autonomous regions, including 12,400 households in total (Chen et al. 2017, Zhao et al. 2014). Two follow-up surveys in 2013 and 2015 are also included in our study.

The combined dataset from the CFPS and CHARLS is the best available for studying intergenerational mobility in China, because of its national representativeness,

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[5] Inner Mongolia, Xinjiang, Tibet, Hainan, Ningxia, Qinghai, Hong Kong, Macau, and Taiwan are excluded from the CFPS surveys.

panel structure to facilitate calculating lifetime income and mitigating biases in estimation, and detailed demographic and socioeconomic information of coresiding and non-coresiding family members. Appendix Section 2.1illustrates the details.

The data consist of 22,169 father–child pairs of *Han* ethnicity from 28 provinces or autonomous regions. We restrict our sample to the 1970-1985 birth cohorts to study children in the midlife stage during the survey periods. We exclude fathers above 65 to mitigate the lifecycle bias, as detailed in Appendix Section 2.2.2. Among all father-child pairs, 13,881 ones are from the CFPS and 8,288 pairs are from the CHARLS.

3.2. Variable Construction

The dataset provides comprehensive information on individual demographics and socioeconomic variables, including age, gender, years of schooling, *hukou* status, annual income from wage, farming/self-employment, property, transfers, and others (e.g., gifts in kind), and number of siblings. Income for 2012, 2014, 2016, and 2018 is adjusted by the Consumer Price Index to the 2010 price level. We then average individual income across waves. Combining this average of observed income with demographic information, we compute lifetime income for non-coresiding children/fathers, using Heckman selection model and following the empirical strategies in Fan, Yi, and Zhang (2021). Consistently, we also predict lifetime income for coresiding children and fathers. Appendix Section 2.2.1 details the steps to construct the individual lifetime income. Appendix Table A1 tabulates the summary statistics.

3.3. Sample Construction

We divide the full sample of the 22,169 *Han* father-child pairs into 105 groups by child's birth cohort and province. Specifically, we first divide full sample into five cohorts by child's birth year: 1970–1973, 1974–1976, 1977–1979, 1980–1982, and 1983–1985. This practice should generate 140 groups by the child's birth cohort and province in principle (5 birth cohorts and 28 provinces). However, we drop groups with a sample size of less than 50 father–child pairs, merge Chongqing Municipality—an area that has historically been included in Sichuan Province—with Sichuan, and exclude Shanghai, which is a Special Administrative Municipality directly under the central government. Our analytic sample eventually includes 105 groups based on 5 child's birth cohorts and 21 provinces.

3.4. Intergenerational Estimates at Province-Cohort Level

For each province-cohort group, we estimate the three measures of intergenerational income mobility, as discussed in Section 2. Specifically, we first calculate income percentile rank for child and father separately, at the *national* level and by child's birth cohort. We then regress the child's percentile rank on the father's percentile rank for each group, obtaining the rank-rank slope estimate $\widehat{\alpha_1}$ from Equation (1) at the group level. We also calculate the expected mean percentile ranks of children born to fathers at the 25 and 75 percentile ranks, $income^{25}$ and $income^{75}$ from Equations (2) and (3) respectively. Similarly, we construct three measures of intergenerational mobility in education at the group level for mechanism analysis.

3.5. Summary Statistics at Province-Cohort Level

Panels A-C of Appendix Table A5 present summary statistics for the group-level measures of intergenerational income mobility, intergenerational education mobility, and differential fertility, respectively. The mean of the income rank–rank slope, which is the main dependent variable, is 0.295, with a standard deviation of 0.123. On average, a child's income percentile rank increases by 0.295, following a one-percentile increase in the father's rank.[6] For children from low-income (25 percentile) and high-income (75 percentile) families, the expected mean income percentile ranks are 43.34 and 57.065, respectively.

Differential fertility, as measured by the difference in average number of children between rural and urban households by cohort and province, is our main independent variable. Specifically, for children born in cohort c in province p, the value of this variable equals the average fertility rate of rural children's mothers minus that of urban children's mothers. The mean of this variable is 0.529, indicating that on average rural families have approximately 0.5 more children than their urban counterparts. This is not surprising, as the follow-up policy exemptions of the OCP allowed rural mothers to have a second child if their first one was a girl. In addition, our sample includes children born before the OCP.

Figure 2 displays the trend in intergenerational income mobility measured by the rank–rank slope and the trend of differential fertility across children's birth cohorts. Consistent with the literature (Deng, Gustafsson, and Li 2013, Fan, Yi, and Zhang 2021), the intergenerational income persistence rises, increasing by 27% from 0.25 for the

[6] The mean of the income rank-rank slope estimates is smaller than the one in Fan, Yi, and Zhang (2021). It is because 1) we use an alternative sample composed of *Han* population only, 2) our sample contains fewer provinces than those in Fan, Yi, and Zhang (2021) because of minimal sample size requirement in each province-by-cohort group, and 3) the cohorts in our study are different from those in Fan, Yi, and Zhang (2021). Details are presented in Section 3.2.

1970–1973 cohort to 0.32 for the 1983–1985 cohort. This sharp decrease in intergenerational income mobility is accompanied by a prominent rise in differential fertility, which increases by 32% from 0.44 for the first cohort to 0.58 for the last cohort, in step with the rollout of the OCP across the nation.

4. The Causal Effect of Differential Fertility on Intergenerational Mobility

4.1. Econometric Specification

Our statistical analysis is conducted at the group level. The regression equation is:

$$Y_{pc} = \beta_0 + \beta_1 DiFertility_{pc} + X_{pc}\beta_X + \mu_r + \lambda_c + \varepsilon_{pc}, \quad (4)$$

where Y_{pc} is one of the three measures of intergenerational income mobility for birth cohort c in province p, as defined in Section 2. $DiFertility_{pc}$ is measured by the rural-urban difference in fertility. The vector of control variables, X_{pc}, include a set of socioeconomic variables associated with a child's environment aged between 3 and 12, such as GRP per capita, share of primary industry, number of beds per 10,000 persons, import & export per capita, and sex ratio. We also control for the average share of rural mothers and average exposure to land reform at the group level.[7] We use regional fixed effect (FE), μ_r, to control for unobserved factors affecting intergenerational income mobility that differ across regions but are common to all cohorts.[8] We use cohort FE, λ_c, to control for unobserved time shocks that differ across cohorts but are common to

[7] Panel D of Appendix Table A5 presents summary statistics of control variables. Appendix Section 2.2.4 details the construction of the control variables for each group.

[8] Because of a small sample size, we control for regional instead of provincial fixed effects. We classify three geographic regions. The east region includes Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong; the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the west region includes Inner Mongolia, Guangxi, Sichuan, Yunnan, Shaanxi, and Gansu.

all provinces. The error term, ε_{pc}, captures measurement errors. Bootstrapped standard errors are reported because the sample size is small and dependent variables and main independent variables are calculated or estimated based on the full sample.

We are interested in the coefficient of β_1, which measures the change in intergenerational income mobility when differential fertility increases by 1. We expect β_1 to be positive. As discussed in Appendix Section 1, the OCP induces differential fertility between rural and urban China. Fertility in urban/richer households declines more sharply compared to their rural/poorer counterparts, as the former is more constrained by the OCP. Under child quality-quantity trade-off, the urban/richer parents have less children but invest more human capital in each child (Becker and Lewis, 1973; Becker and Tomes, 1976). Consequently, the intergenerational income persistence (mobility) rises (declines), resulting in a positive β_1.

4.2. Fixed-effects Estimates

Panel A of Table 1 shows the FE estimates from Equation (4). As expected, differential fertility has a positive correlation with intergenerational income persistence, as measured by the rank–rank slope (Column (2)). This estimate is 0.078 and is statistically significant at the 5% level. Interestingly, while there is no statistically significant correlation between differential fertility and the mean percentile rank of children born to poor fathers (Column (3)), we find positive and statistically significant correlation for children born to rich families (Column (4)). With differential fertility increasing by 1, the mean percentile rank of children in rich families rises by 2.475 percentile ranks. The estimate is statistically significant at the 10% level. It implies that the differential fertility between rural and urban China makes children of the rich become richer but has no significant impact on those of the poor.

However, the FE estimates can be biased, because the increase in differential fertility across cohorts may be driven by unobserved preference which may correlate with changes in intergenerational mobility. For example, the urban Chinese may have started to prefer smaller families in tandem with market-oriented and education reforms. Such unobserved changing preference can be positively correlated with both differential fertility and the intergenerational income persistence.[9] To address this endogeneity concern in estimating the effect of differential fertility on intergenerational income mobility, we turn to an instrumental variable estimation.

4.3. Constructing Instrumental Variables

We conduct the instrumental variable estimation by exploring different implementation timing of the OCP across birth cohorts and provinces as a quasi-natural experiment. The policy was initiated in 1979 but implemented in different years across provinces, as discussed in Appendix Section 1. The one-child restriction was followed by a series of exemptions, mainly depending on parents' *hukou* status. Rural families with a first-born daughter can legally have a second child, according to the 1984 policy amendment. Based on this, differential fertility per group is affected by the extent to which the fertility behavior of children's mothers is differentially constrained by the policy between rural and urban areas.

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[9] The intergenerational income persistence is found to be closely and positively linked with the traditional clan culture in having big families and passing down socioeconomic status across generations (Liu 1983).

We calculate the policy exposure of child i's mother, $exposure_{ipc}$, based on (i) the start year of implementing the OCP in province p, $PolicyYear_p$, (ii) the mother's birth year, τ, and (iii) the mother's probability of giving birth at ages 17 to 46—the childbearing period (Guo, Yi, and Zhang 2020):[10]

$$exposure_{ipc} = \sum_{a=17}^{46} ProbBirth_e(a) \cdot I[\tau + a \geq PolicyYear_p], \qquad (5)$$

where c is child i's birth cohort. $ProbBirth_e(a)$ is the probability of a mother with education e giving birth at age a. For ease of interpretation, we standardize $ProbBirth_e(a)$ with a mean 0 and a standard deviation 1. 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 the OCP at age a and 0 otherwise. We calculate $ProbBirth_e(a)$ using the 1% sample of the 1982 Chinese Population Census, which was conducted by the China Bureau of Statistics. Following Guo, Yi, and Zhang (2020), we focus on a restricted sample of mothers born between 1930–1939 to calculate the natural birth rates by education and age, because the OCP primarily affected mothers born after 1940. The product of $ProbBirth_e(a)$ and $I[\tau + a \geq PolicyYear_p]$ measures the effect of the OCP on the probability of giving birth at age a for child i's mother born in year τ. By construction, when the policy was implemented in her province, policy exposure ($exposure_{ipc}$) is 1 if a mother was 16 or younger, and 0 if she was 47 or older. Policy exposure decreases monotonically with the mother's age at the start of the OCP. The decline is expected faster at an age when the probability of giving birth is higher. In

[10] As evident in Figure A2, the probability of giving birth at ages younger than 17 or older than 46 is almost nil.

sum, $exposure_{ipc}$ captures heterogeneous policy treatments of mothers by their birth year, province, and education.

We construct our IV by averaging $exposure_{ipc}$ across children by birth cohort and province.[11] It measures the average exposure of the policy for mothers of all children in the group. Panel E of Appendix Table A5 shows that the mean of the IV is 0.68 and the standard deviation is 0.159, demonstrating substantial variations in the policy exposure across groups. Our IV estimation results are robust to using alternative measure of policy exposure (Appendix Section 3.3).

We introduce a second IV by interacting the average exposure with the share of rural mothers, based on their *hukou* status. We utilize this variable to account for the heterogeneity in the degree of OCP enforcement across groups. According to official documents, the overall degree of OCP enforcement, not just in rural areas, is weaker in regions with a higher share of rural households (Li and Zhang, 2004; Zhang, 2017). Consequently, we anticipate that the policy's effect on differential fertility is less pronounced for groups with a larger share of rural mothers. It is worth noting that we include the share of rural mothers as a control variable in all our regression analyses.

4.4. First-stage Estimates

The first-stage regression of our IV estimation is as follows:

$$DiFertility_{pc} = \gamma_0 + \gamma_1 Exposure_{pc} + \gamma_2 Exposure_{pc} \times RuralMother_{pc}$$
$$+X_{pc}\beta_X + \mu_r + \lambda_c + \varepsilon_{pc}, \qquad (6)$$

[11] Appendix Section 2.2.3 details the steps in constructing the IVs for each group.

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 at the group level. Other variables are the same as in Equation (4). Note that the vector of X_{pc} includes $RuralMother_{pc}$.

Column (1) in Panel B of Table 1 presents the first-stage estimates. The estimated coefficient of policy exposure on differential fertility (γ_1) is positive, which is consistent with our prediction: As the OCP was enforced in urban areas (Li and Zhang 2004), we expect a larger decrease in fertility for urban mothers, and thus an increase in fertility differential between rural and urban areas. Nevertheless, the estimate is not statistically significant at conventional levels. Coefficient of the interaction term, γ_2, is negative and statistically significant. This is consistent with our prediction based on the heterogeneity in the degree of the OCP enforcement. The higher the share of rural households, the weaker the degree of OCP enforcement is, not only in rural areas but also in urban counterparts (Li and Zhang, 2004; Zhang, 2017). In these regions, thus, the decrease in fertility is smaller in urban households, leading to a smaller rural-urban fertility differential, compared to regions with lower share of rural mothers.

The F statistic for the excluded two instruments in the first-stage estimation is 20.783, which mitigates the weak instrument concern (Stock and Yogo 2005). The p-values of Sargan tests on over-identifying restrictions are 0.183, 0.610, and 0.174 respectively, in the specifications using rank-rank slope and mean percentile ranks of children born to fathers at the 25 and 75 percentile ranks as outcome variables. The null hypothesis that both instruments are valid cannot be rejected. Appendix Section 2.2.6 further justifies the assumptions of relevance, independence, and exclusion restriction for the validity of our IV.

4.5. Instrumental Variable Estimates

With the first-stage results, we present our second-stage estimates in Columns (2) – (4) in Panel B of Table 1. The outcome variable is the intergenerational income mobility measured by rank-rank slope, mean percentile rank of children born to fathers at the 25 and 75 percentile ranks, sequentially. With differential fertility increasing by 1, the rank–rank slope increases by 0.133 (Column (2)). The estimate is statistically significant at the 5% level. Given that the estimate of intergenerational income persistence in the first cohort is 0.25, such increase is equivalent to a 53.2% increase compared to the baseline cohort. It indicates that the increasing fertility differential, caused by the OCP, significantly increases intergenerational income persistence. In other words, the intergenerational mobility declines sharply. Comparing this IV estimate with the FE estimate (Column (2) in Panel A), we find that the FE estimate is biased downward.

In addition to the average effect of differential fertility on intergenerational mobility, its impact on children from low-income (e.g., rural) vs. high-income (e.g., urban) families is also intriguing. While differential fertility has no significant effect on the expected mean percentile rank of children born to poor fathers (at the 25 percentile rank; Column (3)), it demonstrates a positive and statistically significant impact on the mean percentile rank of children born to rich fathers (at the 75 percentile rank; Column

(4)). Specifically, with differential fertility rising by 1, the expected mean percentile rank of children born to fathers at the top quartile increases by 9.666. The estimate is statistically significant at the 1% level. The above results are robust to a series of robustness analyses, as detailed in Appendix Section 3. Appendix 4 presents the heterogeneity analysis by child's gender, as the one-and-a-half child policy depends on the first child being a girl in rural areas. We find that the positive effect of differential fertility on intergenerational income persistence is more evident among daughters than sons.

Why does differential fertility decrease intergenerational income mobility? We consider investment in child's human capital to be one important channel. Intuitively, fertility of urban/richer families is more constrained under the OCP than their rural/poorer counterparts, as detailed in Appendix Section 1. With a quality-quantity trade-off, urban parents with less children are more likely to increase human capital investment in each child, raising the child's expected percentile rank in the next generation. As expected, the results presented in Table 2 show that rising differential fertility induced by the OCP increases intergenerational education persistence in China. As fertility differential increases by 1, the IV estimate of the rank–rank slope rises by 0.103 and is statistically significant at the 10% level (Column (1) of Panel B). More discussion on the human capital mechanism is provided in Appendix Section 5.

5. How Much does the OCP Account for the Declining Intergenerational Income Mobility?

To answer this question, we assume that the OCP affects intergenerational income mobility exclusively through differential fertility, and derive the partial effect of the OCP on intergenerational mobility as follows:

$$\frac{\partial intergenerational\ mobility}{\partial OCP} = \frac{\partial intergenerational\ mobility}{\partial differential\ fertility} \times \frac{\partial differential\ fertility}{\partial OCP} \quad (7)$$

Our IV estimate, which measures the causal impact of differential fertility on intergenerational income mobility, quantifies the first term on the right-hand side of Equation (7). The impact of differential fertility on intergenerational income persistence is 0.261 as displayed in Column (1) in Panel A of Appendix Table A7.[12] For the second term, we use existing estimates from the literature to quantify the impact of the OCP on differential fertility. Literature shows that the OCP has increased differential fertility, as measured by rural/urban fertility ratio, by approximately 0.064 (Zhang 2017).

Combining the two terms from our estimate and from that in the literature, we practice a back-of-envelop calculation on the contribution of the OCP to the declining intergenerational income mobility. The increase in the income rank–rank slope induced by the OCP is approximately 0.017 (0.261×0.064). Given that the overall rank–rank slope increases by 0.07 (0.32−0.25 from Figure 2), the OCP accounts for approximately 25% of the decrease in the intergenerational income mobility in China.

6. Conclusion

Using China's OCP as a quasi-natural experiment, we conduct an IV estimation to examine the causal effect of differential fertility on intergenerational income mobility.

[12] We use the estimate derived from our alternative measure of differential fertility, the rural/urban fertility ratio, to be consistent with the measure used in the second term on the right-hand side of Equation (7).

Our results show that the increased differential fertility induced by the OCP enlarges gap in child's human capital investment between rural and urban families and contributes significantly to the declining intergenerational income mobility in China. With fertility difference between rural and urban areas rising by 1, the intergenerational income persistence, as measured by the rank-rank slope, increases significantly by 0.133 (53.2%) from the 1970-1973 to 1983-1985 birth cohort. The effect is driven by the rising mean percentile rank of children born to urban/richer families. Our calculation shows that the OCP contributes to approximately 25% of the declining intergenerational income mobility.

The population control policy may have significant ramifications for Chinese society, not only intragenerationally but also intergenerationally. China relaxed the population control policy, allowing all families to have at most two children from January 2016, and further three children from May 2021. If parents with different socioeconomic status respond to these policies differently, the resulting differential fertility would have long-term intergenerational consequences.

Our findings have policy implications for both developed and developing countries. Population policies, whether aimed at slowing population growth in developing countries or addressing falling birth rates in developed countries, could have varying impacts on families with different socioeconomic status. These differences in impact could result in unexpected intergenerational consequences. Therefore, we call for policy attention to unintended effects of population control policies on changing demographic structure in future generation, in addition to their intended effect on fertility rates.

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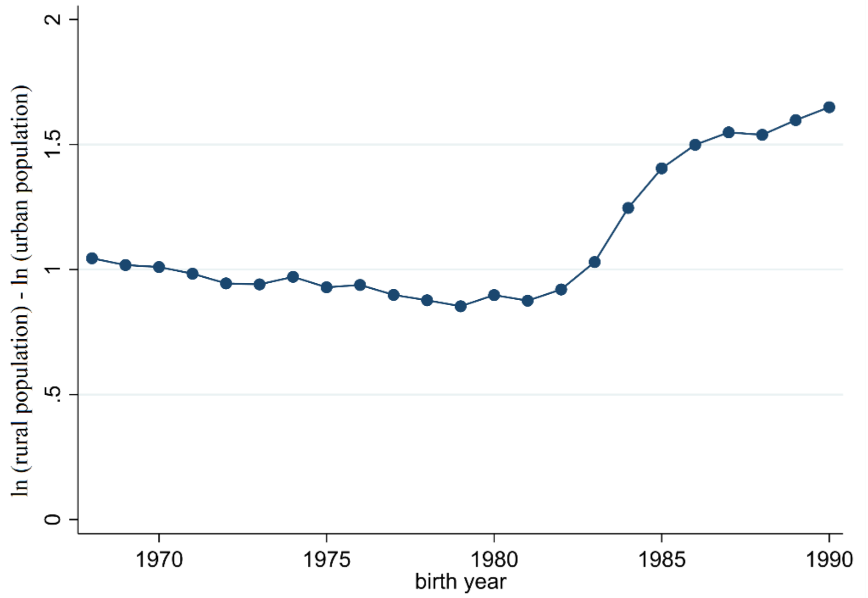

Figure 1a. Differences in cohort sizes between rural and urban China by birth cohort, 1968-1990

Note: Data are from the 1% sample of 2000 Chinese Population Census. The differences are calculated by subtracting logarithm of urban population from logarithm of rural population by birth cohort.

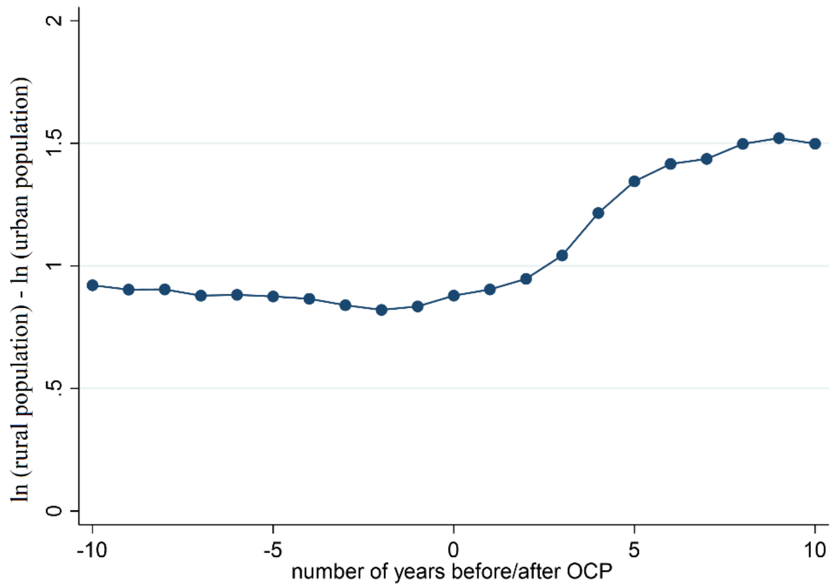

Figure 1b. Differences in cohort sizes between rural and urban China against the OCP adoption years

Note: Data are from the 1% sample of 2000 Chinese Population Census. The x axis indicates the number of years before or after the implementation of the OCP at the provincial level. The y axis shows the differences in cohort sizes between rural and urban population in China. To construct this variable, we separately regress the logarithm of rural and urban population on birth year and province fixed effects, average the regression residuals relative to the OCP adoption years across provinces, and calculate the differences between rural and urban population relative to the OCP adoption years.

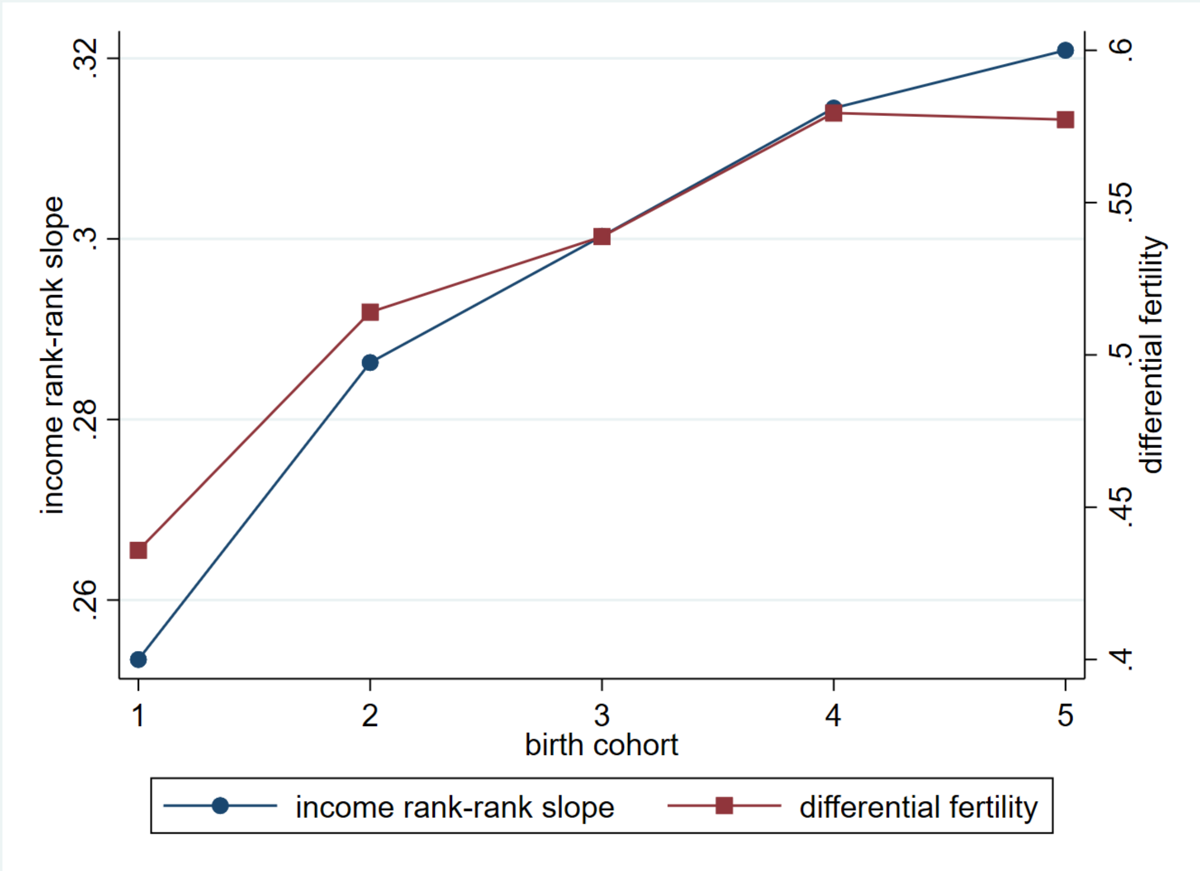

Figure 2. Trends in intergenerational rank-rank slope and differential fertility

Note: The blue line with circles displays the trend in intergenerational income mobility measured by the rank-rank slope, and the red line with squares displays the trend in differential fertility measured by the difference between average number of children of rural mothers and that of urban ones across the child's birth cohorts. We combine two nationally representative biannual longitudinal household surveys: the 2010–2018 CFPS and the 2011–2015 CHARLS. The combined dataset generates a sample of 22,169 father–child pairs. We first divide the sample into five birth cohorts by the child's birth year: 1970–1973, 1974–1976, 1977–1979, 1980–1982, and 1983–1985. We further divide the sample into 105 groups by the child's birth cohort and province. For each group, we estimate the income rank-rank slope and calculate the difference in rural and urban fertility rates. Then, for each child's birth cohort, we separately average the estimates of the income rank-rank slope and the fertility differentials across provinces.

Table 1. Effects of differential fertility on intergenerational income mobility

	Differential fertility	Rank-rank slope	Mean percentile rank of children born to fathers at the 25 percentile rank	Mean percentile rank of children born to fathers at the 75 percentile rank
	(1)	(2)	(3)	(4)
Panel A. FE Estimation Results				
Differential fertility		0.078**	-0.146	2.475*
		(0.031)	(1.635)	(1.326)
R-squared		0.525	0.607	0.377
Panel B. IV Estimation Results				
Differential fertility		0.133**	3.536	9.666***
		(0.054)	(2.318)	(2.716)
Policy exposure of mothers	0.555			
	(1.562)			
Policy exposure of mothers × share of rural mothers	-0.046**			
	(0.018)			
Control variables	YES	YES	YES	YES
Cohort FE	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Observations	105	105	105	105

Note: Data are derived from CFPS (2010–2018), CHARLS (2011–2015), China Compendium of Statistics (1949–2008), and China Compilation of Demographic Data (1949–1985). Panel A reports the FE estimates of differential fertility and intergenerational income mobility. The dependent variables are the rank-rank slope (Column (2)), the expected mean percentile rank of children born to fathers at the 25 percentile rank (Column (3)), and the expected mean percentile rank of children born to fathers at the 75 percentile rank (Column (4)). The explanatory variable of interest is differential fertility. The control variables are share of rural mothers, the policy exposure of mothers to land reform and a set of socioeconomic measures of a child's environment between 3 and 12—gross regional product (GRP) per capita, share of primary industry, number of beds per 10,000 persons, imports and exports per capita, and sex ratio; region FE and cohort FE are also controlled for. Panel B reports the IV estimates of differential fertility and intergenerational income mobility. Column 1 presents first-stage estimation results, where the dependent variable is differential fertility, and the explanatory variables of interest are the policy exposure of mothers and its interaction term with share of rural mothers. The F statistic for the first-stage estimation is 20.783. Columns 2–4 present second-stage estimation results. The corresponding p-value of Sargan statistic is 0.183, 0.610, 0.174, sequentially. Bootstrapped standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Table 2. Effects of differential fertility on intergenerational education mobility

	Rank-rank slope	Mean percentile rank of children born to fathers at the 25 education percentile rank	Mean percentile rank of children born to fathers at the 75 education percentile rank
	(1)	(2)	(3)
Panel A. FE Estimation Results			
Differential fertility	0.073**	-1.416	1.761
	(0.028)	(1.237)	(1.335)
R-squared	0.329	0.525	0.461
Panel B. IV Estimation Results			
Differential fertility	0.103*	2.666	7.828***
	(0.054)	(2.359)	(3.038)
Control variables	YES	YES	YES
Cohort FE	YES	YES	YES
Regional FE	YES	YES	YES
Observations	105	105	105

Note: Data are derived from CFPS (2010–2018), CHARLS (2011–2015), China Compendium of Statistics (1949–2008), and China Compilation of Demographic Data (1949–1985). Panel A reports the FE estimates of the impact of differential fertility on intergenerational education mobility. The dependent variables are the rank-rank slope (Column (1)), expected mean percentile rank of children born to fathers at the 25 percentile rank (Column (2)), and expected mean percentile rank of children born to fathers at the 75 percentile rank (Column (3)). The explanatory variable of interest is differential fertility. The control variables are the same as in Columns (2)–(4) in Panel B of Table 1. Panel B reports the IV estimates of the impact of differential fertility on intergenerational income mobility. The F statistic for the first-stage estimation is 20.783. Bootstrapped standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.