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1. Introduction

Urbanization and demographic transition interact with each other (Sato and Yamamoto 2005, Sato 2007). Beyond conventional rural-urban migration, demographic factors, such as internal urban population growth, are identified to explain for rapid urbanization especially for developing countries (Jedwab, Christiaensen, and Gindelsky 2017). Using the staggered rollout of China's OCP across province and cohort as a quasi-natural experiment, we provide the first set of empirical evidence on the impact of differential fertility between urban/richer and rural/poorer families on intergenerational economic mobility—a measure of economic opportunity based on parents' socioeconomic status, to shed light on future urban-rural inequality.

Alongside the Industrial Revolution, the classical positive correlation between parental socioeconomic status and fertility has turned into negative. It implies that higher socioeconomic status is now associated with lower fertility rates (Bar and Leukhina 2010, Vogl 2016). During the Malthusian era, wealthier parents had higher fertility rates than their poorer counterparts, because of softer budget constraints and lower mortality rates. However, during the demographic transition to the modern era, this fertility differential reversed as parents with higher earnings faced greater opportunity costs in raising children. Consequently, more children were born to poorer families.

This reversal has significant implications for the transmission of inequality across generations and future urban-rural disparity. Under a child quality-quantity trade-off mechanism, children born to poorer families have less human capital and lower lifetime income compared to their counterparts from wealthier backgrounds (Lam 1986, De La Croix and Doepke 2003, Doepke 2004). The changing landscape of differential fertility alters income distribution in future and reduces economic opportunities for children born to disadvantaged rural families, leading to a decline in intergenerational mobility (Chu and Koo 1990, Vogl 2016).

This paper seeks to evaluate the causal impact of differential fertility on intergenerational income mobility. Combining two nationally representative longitudinal household surveys, the China Family Panel Studies (CFPS) 2010–2018 and the China Health and Retirement Longitudinal Study (CHARLS) 2011–2015, we create a robust dataset for studying intergenerational income mobility. Both datasets are longitudinal with national representativeness in the baseline survey, covering urban and rural areas in 25 and 28 out of 34 provinces, municipalities, or autonomous regions. They have detailed information on family relationship for coresiding and non-coresiding family members. The distributions of demographic and socioeconomic variables—such as age, sex, and years of schooling—in the two surveys are consistent with those from the population census.

We construct father-child pairs from both CFPS and CHARLS datasets. To account for potential lifecycle, attenuation, and/or selection biases, we construct lifetime income for both coresiding and non-coresiding children and fathers using income derived from CFPS and the Heckman selection model. To have sufficient variations at the province-cohort level, we supplement the father-child pairs from CFPS with the pairs constructed from the CHARLS dataset.[4] We divide the full sample of 22,169 father-child pairs into 105 groups based on 5 child's birth cohorts and 21 provinces, to estimate the impact of differential fertility between rural and urban China on three measures of intergenerational income mobility, namely, rank-rank slope (measuring the correlation between children's and fathers' income ranks), the expected income percentile ranks of children born to fathers at the 25 and 75 percentiles.

Two main challenges stand out: first, the shift in differential fertility during the demographic transition may confound with changes in unobserved socioeconomic factors, which can potentially correlate with intergenerational mobility. 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) estimation on the impact of fertility 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 staggered rollout of the OCP across province and birth cohort as a quasi-natural experiment. The induced differential fertility between urban and rural China is used 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

[4] Appendix Section 2.2 details the imputation of lifetime income and the econometric challenges. Since the income measure for non-resident children of main respondents available from CHARLS is a self-reported income bracket measure from the old-aged parents, we adopt the income information from CFPS only due to the data limitation.

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 (Li and Zhang 2009). Conversely, for rural/poorer residents, who often relied more on family farm work and had less access to old-age pensions, would demand more children even in the case without the OCP and thus demonstrate stronger resistance to the policy. 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).[5] Figures 1a and 1b visually demonstrate this rural-urban disparity in fertility, showing a significant widening in the fertility differential following the OCP's launch.

Regarding the second challenge of generating reliable estimates of intergenerational income mobility, we carefully construct three measures: the rank-rank slope, the expected income percentile ranks of children born to fathers at the 25 and 75 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.

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

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 differential fertility, 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 plausibly exogeneous top-down political decisions and enforcement, minimizes concerns on potential confounding factors.

Our first-stage estimation confirms that the OCP effectively increases differential fertility between rural and urban areas, particularly in groups with larger share of urban residents. Moving to the second stage, our results indicate a significant and negative effect of differential fertility on intergenerational income 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 estimate. This decline in intergenerational income mobility is primarily driven by increased mean percentile ranks for children born to higher-income urban families, with daughters experiencing this effect more pronouncedly than sons. These findings remain robust across a battery of robustness checks.

To examine 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 (75 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 to advancing the understanding of differential fertility, intergenerational mobility, and urban-rural inequality. Prior studies have theorized the impact of flipped differential fertility on human capital and intergenerational mobility (Lam 1986, Chu 1987, Chu and Koo 1990, De La Croix and Doepke 2003, Doepke 2004, Vogl 2016). Our work provides the first *empirical* evidence on this causal impact, in the context of urban-rural differential fertility under China's OCP. Our findings consolidate earlier theoretical predictions.

Further, we contribute to the burgeoning literature on economic opportunity and intergenerational mobility by studying a developing country, unlike the majority of early studies from developed world (Solon 1992, Mazumder 2005, Corak 2013, Chetty, Hendren, Kline, and Saez 2014, Chetty, Hendren, Kline, Saez, et al. 2014, Chetty et al. 2017). Moreover, we extend existing research on the determinants of intergenerational mobility focusing on child neighborhood quality (Chetty, Hendren, and Katz 2016) and school finance (Biasi 2023), by offering the first set of empirical evidence from a demographic perspective.

Last, our results advance understanding in the interrelation between urban-rural disparity and demographic transition. Literature discusses the agglomeration economies and congestion diseconomies of population concentration on urbanization

(Sato and Yamamoto 2005, Sato 2007). Jedwab, Christiaensen, and Gindelsky (2017) explicitly propose an urban push effect (i.e., internal urban population growth), providing additional insight for rapid urbanization without growth in developing countries. We use the OCP context to document the impact of differential fertility between urban and rural China on income inequality for the next generation. With more children born to rural parents and rising intergenerational stagnancy in economic status in urban area, the population-driven rural push effect may be offset by declining economic opportunities in urban area. The trend of urbanization in future China is thus an open question, demanding new avenues of research (Glaeser and Henderson 2017).

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 imputed 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 at the group level, as follows:

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

where $rank_{ipc}$ is the income percentile rank of child i in province p and birth cohort c and $rank_{fpc}$ 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 in

2010 (the baseline survey wave of CFPS), and age squared and the father's age in 2010 and age squared. The coefficient α_{1pc} is the estimate of income rank–rank slope for province p and birth cohort c. 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, Hendren, Kline, and Saez 2014, 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:

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

where $\widehat{\alpha_{0pc}}$ and $\widehat{\alpha_{1pc}}$ are the estimates from Equation (1) and $\widehat{rank}_{pc}^{25}$ 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 $\widehat{rank}_{pc}^{25}$ 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:

$$\widehat{rank}_{pc}^{75} = \widehat{\alpha_{0pc}} + \widehat{\alpha_{1pc}} \times 75. \tag{3}$$

The estimate, $\widehat{rank}_{pc}^{75}$, 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 $\widehat{rank}_{pc}^{75}$ 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.

We are aware that three econometric challenges—lifecycle bias, attenuation bias, and selection bias—may arise when estimating the three measures. Appendix Section 2.2 details the 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 biannual longitudinal household surveys: the 2010–2018 CFPS and the 2011–2015 CHARLS. Among the existing dataset, the CFPS and the CHARLS are the most nationally representative during the sample period, particularly for children between 1970 and 1985.[6] 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

[6] However, neither dataset is representative of all provinces. We acknowledge and discuss this data limitation in Section 6. We choose to combine these datasets because, compared to other available datasets, the combined dataset offers the best national representativeness by far.

households, with a response rate of 79% (Xie and Hu 2014). 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.[7]

The combined dataset from the CFPS and CHARLS is the best available for studying intergenerational mobility in China, because of complete family relationship, national representativeness, 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. Specifically, we adopt the CFPS data to construct father-child pairs and conduct the Heckman selection model to address missing income data and impute lifetime income for both children and fathers of the full sample, using its detailed family relationship, reliable income records in longitudinal surveys, and information on demographics. Although the CFPS is nationally representative and has a large sample size overall, its sample size at the group (province-cohort) level is insufficient to ensure statistical power. We thus expand the father-child pairs from the CHARLS dataset, to achieve sufficient sample size at the province-cohort level. Appendix Section 2.1 illustrates the details.

3.2. Imputed Lifetime Income

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

While both the CFPS and the CHARLS are nationally representative surveys with large sample sizes and comprehensive information on demographics (including age, gender, years of schooling, *hukou* status, residence, etc.), their income data differ significantly in scope and quality. Specifically, each wave of the CFPS provides the high-quality and detailed income information, including wage, farming/self-employment, property, transfers, and others (e.g., gifts in kind), across all adult age groups in China, enabling direct calculation of observed income. Income for 2012, 2014, 2016, and 2018 is adjusted to the 2010 price level using the Consumer Price Index (CPI). Observed lifetime income is then calculated by averaging individual income across waves in the CFPS. By contrast, the CHARLS surveys individuals aged 45 or above, with over 75% of respondents aged 60 or above. Its income data primarily reflect retirement income, pensions, or transfers, which poorly represent earnings during prime working years. Moreover, the income measure for non-resident children of main respondents available from CHARLS is a self-reported income bracket measure (i.e., reported by the old-aged parents). These limitations make the CHARLS unsuitable for calculating observed income for children or fathers (typically working-age adults).

To address missing income data and impute lifetime income for both children and fathers of the full sample, we apply the Heckman selection model following Fan, Yi, and Zhang (2021). First, we estimate the Probit model using only the CFPS sample of children with and without observed lifetime income:

$$I_i = \alpha_0 + \alpha_z z_i + X_i \alpha_X + \varepsilon_i, \tag{4}$$

where I_i is a dummy variable equal to 1 if the information on child i's observed lifetime 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, years of schooling, age, age squared, age cubed, and full interactions with *hukou* status and coastal dummy, and cohorts. We use the number of siblings the child has, z, as the excludable variable to address the selection problem due to missing income. Using the estimates of Equation (4), we calculate the inverse Mills ratio, λ_i, for children from both the CFPS and the CHARLS.

Second, we estimate the income equation using only the CFPS sample of children with observed lifetime income, with the inverse Mills ratio, λ_i, as a control:

$$inc_i = \beta_0 + \beta_\lambda \lambda_i + X_i \beta_X + \varepsilon_i, \quad (5)$$

where inc is the logarithm of the child's observed lifetime income and X is the same as in Equation (4). The lifetime income is calculated by averaging individual income across waves in the CFPS. Note that although Equation (4) is estimated using the full CFPS sample, Equation (5) can only be estimated using the CFPS sample with observed lifetime income; and the variable z is included in Equation (4) but not Equation (5). Based on the estimates of Equation (5), we impute lifetime income for all children from the CFPS and the CHARLS.[8] We apply a similar procedure to impute lifetime income for fathers of the full sample. Appendix Section 2.2 details the steps to impute individual lifetime income and the strategies to overcome econometric challenges. Appendix Table A1 tabulates the summary statistics.

[8] We acknowledge the existence of rural-to-urban and cross-province migration during the sample period in China. However, we use imputed lifetime income for family members at home and migrating out, and the CFPS and CHARLS record basic demographics for both types of family members to conduct such practice. Thus, the impact of migration, if any, is likely non-material in our context.

3.3. Sample Construction

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[9]. Among all father-child pairs, 13,881 ones are from the CFPS and 8,288 pairs are from the CHARLS.

We divide the full sample of the 22,169 *Han* father-child pairs into 105 groups by child's birth cohort and province.[10] 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

[9] We drop father-child pairs with parents aged 65 and above in 2010 because the official retirement age for most men in China during the sample period is 60 years old. For those in managerial or technical roles, several years' extension can be granted. It is likely to have severe sample selection among those who remain working and have income reported above 65. To address the concern that we may exclude some dads who had kids at an older age in this setting, we conduct an additional robustness check by relaxing the fathers' age to 70 years old.

[10] Our analysis focuses on the *Han* population, which constitutes approximately 85–87% of China's total population. We exclude ethnic minorities from the study because they were exempt from the OCP regulations, resulting in negligible rural-urban differentials in fertility behavior. For instance, while *Han* women in urban areas were strictly limited to one child under the OCP, minority women—even in urban regions—were typically permitted to have two or more children (Zhang 2017).

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 $\widehat{\alpha_{1pc}}$ 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, $\widehat{rank}_{pc}^{25}$ and $\widehat{rank}_{pc}^{75}$ 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 and C of Appendix Table A4 present summary statistics for the group-level measures of intergenerational income 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.[11] 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. We derive this variable from the full sample of father-child pairs from both the CFPS and the CHARLS. Specifically, for children born in cohort c in province p,

[11] 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 3.3.

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 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 tandem 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 by province and cohort, such as GRP per capita, share of primary industry, number of beds per 10,000 persons, import & export per capita, and sex ratio, derived from the China Compendium of Statistics (1949–2008). We also control for the average share of rural mothers and average exposure to land reform at the group level (Almond, Li, and Zhang 2019).[12] 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.[13] We use cohort FE, λ_c, to control for unobserved temporal or policy shocks that differ across cohorts but are common to 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,

[12] Panel D of Appendix Table A4 presents summary statistics of control variables. Appendix Section 2.2.5 details the construction of the control variables for each group.

[13] 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.

Becker and Tomes 1986). 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 income 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.[14] To address this endogeneity concern in estimating the effect of differential fertility on intergenerational

[14] 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).

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.

We calculate the policy exposure of child i's mother, $exposure_{iepc}$, based on (i) the start year of implementing the OCP in province p, $PolicyYear_p$, (ii) the mother's birth year, τ, (iii) the mother's educational category, *e*, and (iv) the mother's probability of giving birth at ages 17 to 46—the childbearing period (Guo, Yi, and Zhang 2020):[15]

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

where c is child i's birth cohort. $ProbBirth_e(a)$ is the probability of a mother in educational category 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, $I\left[\tau + a \geq PolicyYear_p\right]$, is equal to 1 if child i's mother born in year τ and

[15] we use the *hukou* province of adult children to construct the IV. As evident in Figure A2, the probability of giving birth at ages younger than 17 or older than 46 is almost nil.

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 educational category (illiterate or semiliterate, primary school, junior-middle, senior-middle, and undergraduate or college graduate) 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 ($exposure_{iepc}$) 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 sum, $exposure_{iepc}$ captures heterogeneous policy treatments of mothers by their birth year, province, and education.

We construct our IV by averaging $exposure_{iepc}$ across children by birth cohort and province.[16] It measures the average exposure of the policy for mothers of all children in the group. Panel E of Appendix Table A4 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 alternative measure of policy exposure. Details are presented in Appendix Section 3.3.

[16] Appendix Section 2.2.4 details the steps in constructing the IVs for each group.

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:

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

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 differential fertility 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 within a province (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 validity of our IVs relies on the assumptions of relevance, independence, and exclusion restriction. The first-stage results explicitly show a significant relationship between the IVs and differential fertility. Institutionally, the staggered rollout of the OCP across provinces and years is likely exogenous, as the timing of policy implementation depends on the Communist Party’s top-down political decision and enforcement (Huang 2021). As illustrated in Appendix Figure A1, there is no evident geographic clustering, which is consistent with the independence assumption. Literature has also extensively used this cross-regional variation in policy enforcement as an exogenous shock to identify the OCP effect on fertility and gender imbalance (Zhang 2017). First, to further address potential concern that concurrent policies during China’s transitional period—such as land reform—may confound the OCP effect on intergenerational mobility, we explicitly control the policy exposure of the land reform by cohort and province in Equation (4). Second, to examine the assumption of exclusion restriction (i.e., the OCP affects intergenerational mobility mainly through the fertility channel), we control plausibly alternative channels, such as sex ratio and agricultural production of rural families. Third, to eliminate the effect of regional economic development and population growth on policy implementation, we control a series of socioeconomic variables. Specifically, we include population growth and public education expenditure at the province-cohort level on top of other macroeconomic controls in a robustness check. Results will be discussed in the next section.

To further justify our IV strategy, we conduct an event study using the 1% sample of the 2000 population census, to estimate the temporal effect of the OCP on differential fertility in rural versus urban China. Results are presented in Figure 1b, with the OCP adoption years across provinces benchmarked as Year 0. Specifically, we regress the logarithm of rural and urban population separately on birth year and province fixed effects. We then average the regression residuals by the OCP adoption years. After that, we plot the differences of residuals between rural and urban areas relative to the OCP adoption years. While the rural-urban differences in cohort sizes are stable before the OCP adoption, the post-treatment differences display a clear increasing trend. It echoes the enlarging differential fertility induced by the OCP, as documented in Appendix Section 1. Again, empirical evidence supports our IV.[17]

The F statistic for the two excluded instruments in the first-stage estimation is 20.783, which largely 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

[17] One potential threat in our context is the inter-temporal correlation in OCP exposure. In particular, provinces that implemented the OCP earlier may tend to enforce the policy more strictly in subsequent years. This could trigger the threat that if the timing of the OCP rollout correlates with subsequent temporal changes in OCP enforcement within the same province. If this is the case, the common trend hypothesis could be violated. Guo et al. (2024) discuss this concern carefully and show that this threat, if exists, is subtle.

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.

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 differential fertility, 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 toward 0, as the FE estimation exacerbates the attenuation bias. Its magnitude is around one-quarter to one-half of the IV one. The unobserved factor, such as the culture of family clan in specific regions in China (Liu 1983), likely negatively correlates with differential fertility but positively associates with the intergenerational income persistence.

In addition to the average effect of differential fertility on intergenerational income 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. As the expected rank of children born to fathers at the top and bottom quarter percentile rank is a linear combination of the average effect estimate $\widehat{\alpha_{1pc}}$ and the estimated intercept $\widehat{\alpha_{0pc}}$ from the rank-rank Eq. (1), a linear relationship appears, yielding 3.325 (i.e., 0.133 * 25) and 9.975 (i.e., 0.133 * 75) for the 25 and 75 percentile rank under this calculation, respectively. The two values are very close to the point estimates of 3.536 and 9.666, respectively. Indeed, the difference between corresponding calculated value and estimate is not statistically significant. A potential concern of non-linearity is mitigated, and our construction of intergenerational mobility measures is further validated.

The results above are robust to a series of robustness analyses, such as using alternative measure of the IV highlighting the different birth probability of rural and urban mothers with given educational attainment, controlling population growth and public education expenditure to eliminate the impact of the OCP on economic prospects, using alternative measure of age, and using enlarged father-child sample with fathers aged below 70. Details of these analyses are provided 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.

4.6. Human Capital Mechanism

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 differential fertility 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:

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

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 A5.[18] 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. Discussion and 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. 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

[18] 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).

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.

Population control policy has significant ramifications for Chinese society, not only intragenerationally but also intergenerationally. China relaxed the population control policy, allowing couples with at least one from a single-child family to have two children in 2014 and a universal Two-Child Policy from January 2016 (Meng, Peng, and Zhou 2023). The policy further extends to three children in May 2021. If parents with different socioeconomic status (e.g., urban/richer vs. rural/poorer) respond differently to these policies, the subsequent enlarging differential fertility would have long-term intergenerational implications on urban-rural inequality. The disproportionally increased rural population may exaggerate the *rural push* (Jedwab, Christiaensen, and Gindelsky 2017), though the declining economic opportunities in urban area may hinder the process of urbanization in future China. Future studies are warranted along this direction with increasing volume of data at granular levels.

Using effective public policies to improve economic opportunities is of major concerns of governments, especially regarding children born to disadvantaged families (Piketty 2000, Corak 2013, Chetty et al. 2017). Our findings can 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. Such differential impact could result in unexpected intergenerational consequences not only on changing demographic structure but also urban-rural disparity in future. We call for policy attention to unintended effects of population control policies, in addition to their intended effect on fertility rates. Additionally, we acknowledge that the external validity of our findings may be limited as neither the CFPS nor the CHARLS is fully representative at the province level. However, we emphasize that our measures of intergenerational income mobility and measure of differential fertility are constructed at the same group level using the same datasets. This alignment ensures the internal validity of our empirical analyses. We view this as an important caveat rather than a fatal flaw: while our results may not generalize to populations or contexts beyond those captured by the CFPS and the CHARLS, the relationships we identify remain rigorously identified within the studied groups. Nevertheless, we explicitly highlight the need for future research to test the generalizability of our findings across broader populations and institutional contexts, particularly using datasets with enhanced granularity and representativeness.

REFERENCES

Almond, Douglas, Hongbin Li, and Shuang Zhang. 2019. "Land Reform and Sex Selection in China." *Journal of Political Economy* 127 (2):560-585.

Almond, Douglas, Hongbin Li, and Shuang Zhang. 2019. "Land reform and sex selection in China." *Journal of Political Economy* 127 (2):560-585.

Bar, Michael, and Oksana Leukhina. 2010. "Demographic transition and industrial revolution: A macroeconomic investigation." *Review of Economic Dynamics* 13 (2):424-451.

Becker, Gary S, and H Gregg Lewis. 1973. "On the interaction between the quantity and quality of children." *Journal of Political Economy* 81 (2, Part 2):S279-S288.

Becker, Gary S, and Nigel Tomes. 1986. "Human capital and the rise and fall of families." *Journal of Labor Economics* 4 (3):S1-S39.

Biasi, Barbara. 2023. "School finance equalization increases intergenerational Mobility." *Journal of Labor Economics* 41 (1):1-38.

Chen, Xinxin, James Smith, John Strauss, Yafeng Wang, and Yaohui Zhao. 2017. "China Health and Retirement Longitudinal Study (CHARLS)." In *Encyclopedia of Geropsychology*, edited by Nancy A. Pachana, 463-469. Singapore: Springer Singapore.

Chetty, Raj, David Grusky, Maximilian Hell, Nathaniel Hendren, Robert Manduca, and Jimmy Narang. 2017. "The fading American dream: Trends in absolute income mobility since 1940." *Science* 356 (6336):398-406.

Chetty, Raj, and Nathaniel Hendren. 2018. "The impacts of neighborhoods on intergenerational mobility II: County-level estimates." *The Quarterly Journal of Economics* 133 (3):1163-1228.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment." *American Economic Review* 106 (4):855-902.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the land of opportunity? The geography of intergenerational mobility in the United States." *The Quarterly Journal of Economics* 129 (4):1553-1623.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner. 2014. "Is the United States still a land of opportunity? Recent trends in intergenerational mobility." *American Economic Review* 104 (5):141-147.

Chu, CY Cyrus. 1987. "The dynamics of population growth, differential fertility, and inequality: Note." *American Economic Review* 77:1054-1056.

Chu, CY Cyrus, and Hui-Wen Koo. 1990. "Intergenerational income-group mobility and differential fertility." *American Economic Review* 80 (5):1125-1138.

Corak, Miles. 2013. "Income inequality, equality of opportunity, and intergenerational mobility." *Journal of Economic Perspectives* 27 (3):79-102.

De La Croix, David, and Matthias Doepke. 2003. "Inequality and growth: Why differential fertility matters." *American Economic Review* 93 (4):1091-1113.

Deng, Quheng, Björn Gustafsson, and Shi Li. 2013. "Intergenerational income persistence in urban China." *Review of Income and Wealth* 59 (3):416-436.

Doepke, Matthias. 2004. "Accounting for fertility decline during the transition to growth." *Journal of Economic Growth* 9 (3):347-383.

Ebenstein, Avraham. 2010. "The “missing girls” of China and the unintended consequences of

the one child policy." *Journal of Human Resources* 45 (1):87-115.
Ebenstein, Avraham. 2011. "Estimating a dynamic model of sex selection in China." *Demography* 48 (2):783-811.
Ebenstein, Avraham. 2014. "Fertility and population in developing countries." *Encyclopedia of Health Economics* 2 (2):300-308.
Fan, Yi, Junjian Yi, and Junsen Zhang. 2021. "Rising intergenerational income persistence in China." *American Economic Journal: Economic Policy* 13 (1):202-230.
Glaeser, Edward, and J Vernon Henderson. 2017. "Urban economics for the developing World: An introduction." *Journal of Urban Economics* 98:1-5.
Guo, Rufei, Lin Lin, Junjian Yi, and Hanyu Zhu. 2024. "Intergenerational Impact of Birth-Control Policies on Fertility: The Role of Norms." 7th Renmin University-GLO Annual Conference, Beijing.
Guo, Rufei, Junjian Yi, and Junsen Zhang. 2020. "Rationed fertility: Theory and evidence." http://www.junjianyi.net/uploads/4/4/9/5/44956225/rationedfertility.pdf.
Huang, Yue. 2021. "Family Size and Children's Education: Evidence from the one-child policy in China." *Population Research and Policy Review*:1-26.
Jedwab, Remi, Luc Christiaensen, and Marina Gindelsky. 2017. "Demography, urbanization and development: Rural push, urban pull and… urban push?" *Journal of Urban Economics* 98:6-16.
Lam, David. 1986. "The dynamics of population growth, differential fertility, and inequality." *American Economic Review* 76 (5):1103-1116.
Li, Hongbin, and Junsen Zhang. 2004. "Fines, limited liability and fertility." https://www.cuhk.edu.hk/eco/staff/jszhang/Fines_Fertility_Zhang.pdf.
Li, Hongbin, and Junsen Zhang. 2009. "Testing the external effect of household behavior: The case of the demand for children." *Journal of Human Resources* 44 (4):890-915.
Liu, Xiuming. 1983. "The family clan system is an important reason for the long-term continuation of Chinese feudal society." *Academic Monthly Chinese Journal of Philosophy and Social Sciences / Xueshuyuekan* (2):63-68.
Mazumder, Bhashkar. 2005. "Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data." *Review of Economics and Statistics* 87 (2):235-255.
McElroy, Marjorie, and Dennis Tao Yang. 2000. "Carrots and sticks: fertility effects of China's population policies." *American Economic Review* 90 (2):389-392.
Nybom, Martin, and Jan Stuhler. 2017. "Biases in standard measures of intergenerational income dependence." *Journal of Human Resources* 52 (3):800-825.
Piketty, Thomas. 2000. "Theories of persistent inequality and intergenerational mobility." In *Handbook of income distribution*, 429-476.
Sato, Yasuhiro. 2007. "Economic geography, fertility and migration." *Journal of Urban Economics* 61 (2):372-387.
Sato, Yasuhiro, and Kazuhiro Yamamoto. 2005. "Population concentration, urbanization, and demographic transition." *Journal of Urban Economics* 58 (1):45-61.
Solon, Gary. 1989. "Biases in the estimation of intergenerational earnings correlations." *Review of Economics and Statistics* 71 (1):172-174.
Solon, Gary. 1992. "Intergenerational income mobility in the United States." *American*

Economic Review 82 (3):393-408.

Stock, James H, and Motohiro Yogo. 2005. "Testing for weak instruments in linear IV regression." *Identification and Inference for Econometric Models: A Festschrift in Honor of Thomas J. Rothenberg, D. W. K. Andrews and J. H. Stock (eds.). Cambridge, UK: Cambridge University Press* 80 (4.2):1.

Vogl, Tom S 2016. "Differential fertility, human capital, and development." *The Review of Economic Studies* 83 (1):365-401.

Xie, Yu, and Jingwei Hu. 2014. "An introduction to the China Family Panel Studies (CFPS)." *Chinese Sociological Review* 47 (1):3-29.

Zhang, Junsen. 2017. "The evolution of China's one-child policy and its effects on family outcomes." *Journal of Economic Perspectives* 31 (1):141-160.

Zhao, Yaohui, Yisong Hu, James P Smith, Strauss John, and Gonghuan Yang. 2014. "Cohort profile: The China Health and Retirement Longitudinal Study (CHARLS)." *International Journal of Epidemiology* 43 (1):61-68.

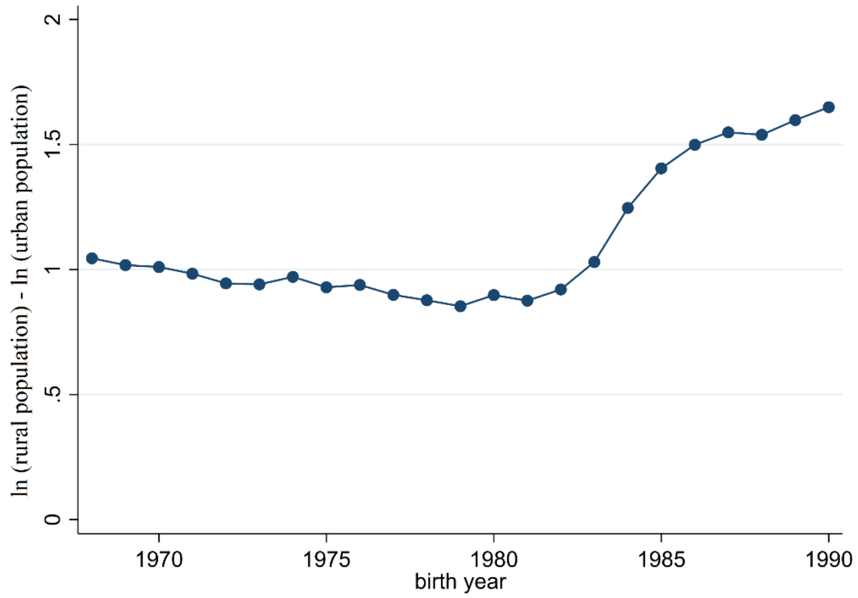

Figure 1a. Differences in cohort sizes between rural and urban China by birth cohort, 1968-1990

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.

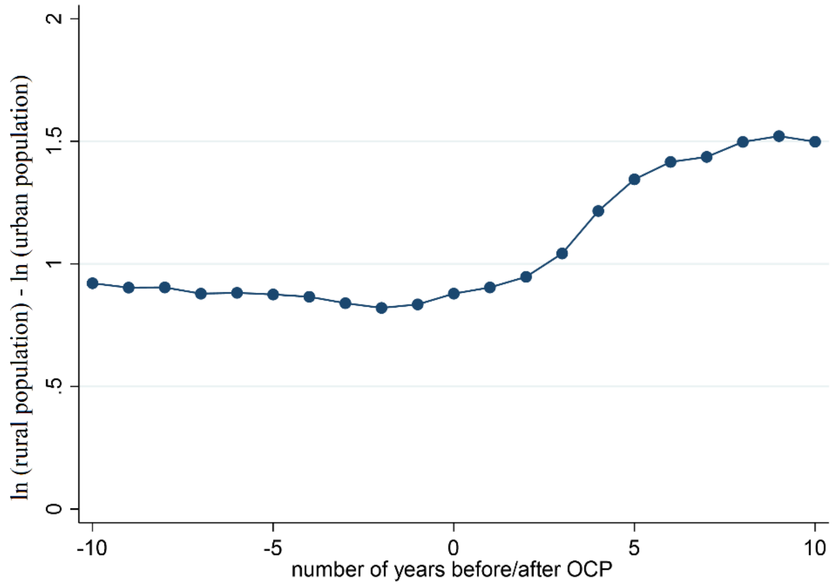

Figure 1b. Differences in cohort sizes between rural and urban China against the OCP adoption years

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.

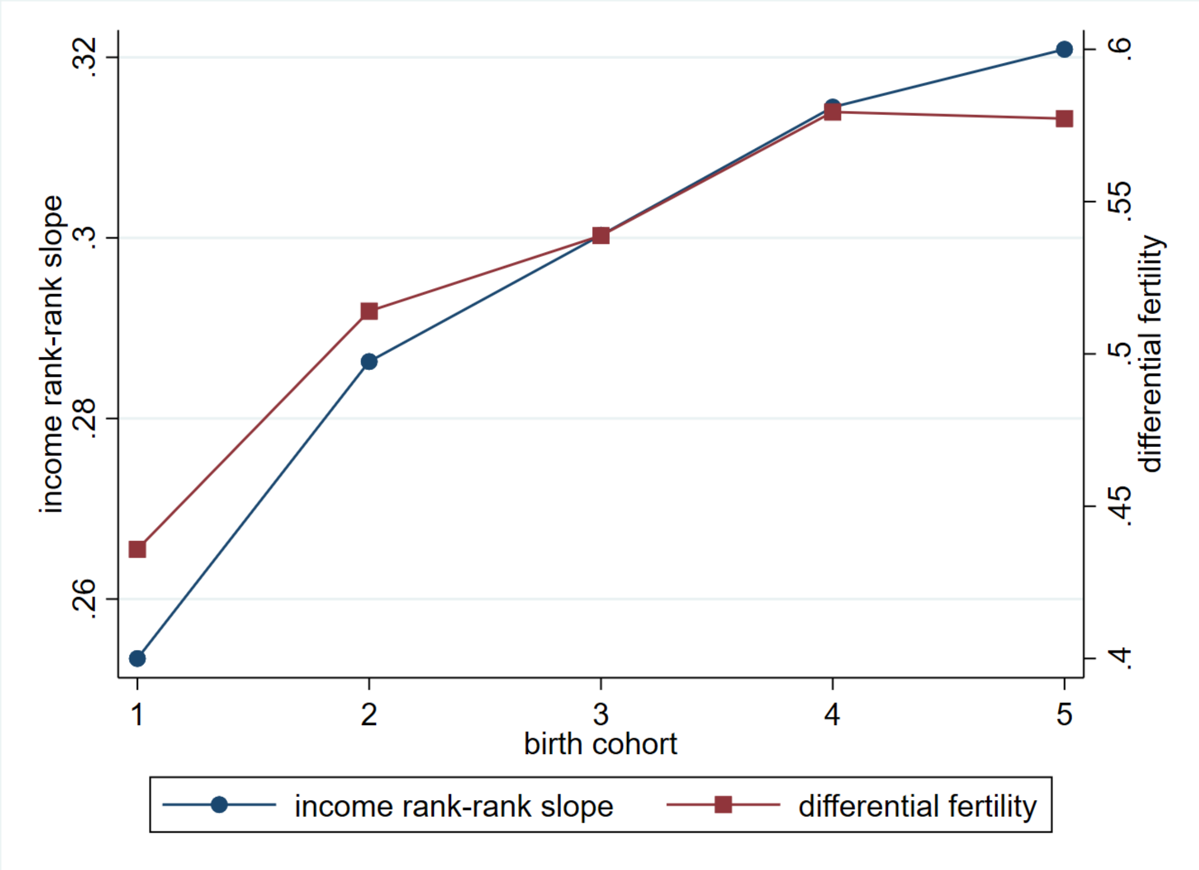

Figure 2. Trends in intergenerational rank-rank slope and differential fertility

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 differential fertility 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), and China Compendium of Statistics (1949–2008). 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), and China Compendium of Statistics (1949–2008). 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.

Differential Fertility and Economic Opportunity:

Evidence from China's One-Child Policy

Online Appendix

Yewen Yu Yi Fan Junjian Yi

1. The One-Child Policy and Differential Fertility in China

China initiated the population control policies in 1979. As one of the most extreme forms of birth control in recorded history, they consisted of extensive propaganda, regulations, incentives, and sanctions with monetary and employment penalties (Chu 1987; Cooney, Wei, and Powers 1991). The bundle of population control policies is popularly and collectively known as the one-child policy. The actual implementation of the OCP, nevertheless, varies in timing across provinces and cohorts, by ethnicity groups, and by rural vs. urban areas. For instance, the implementation time of the OCP differs across provinces, depending on the Communist Party's political decision and enforcement (Huang 2021). Figure A1 visualizes the staggered rollout of the OCP across provinces. In addition, enforcement of the OCP is much stricter among *Han* ethnicities while ethnic minorities can be exempted from some regulations (Zhang 2017). In our analysis, we restrict to the *Han* population, which covers approximately 85%-87% of the China's total population.

We focus on fertility differential between rural and urban China, to mimic the differential fertility between poor and rich families in post Industrial Revolution era. In China's context, the coercive means instituted by local governments to enforce the OCP are more realistic threats for urban/rich families than the rural/poor counterparts, such as economic fines and employment penalties for above-quota births. Many rural households, especially those living below the poverty line, are too poor to pay for the fines. As documented (Chu 1987; Cooney, Wei, and Powers 1991), the fines are equivalent to a considerable proportion of monthly salaries and are too onerous a burden for rural/poor families. Conversely, the urban/rich families' fertility choices are more constrained by the monetary penalties. Evidence shows that fertility of the poor does not vary much with the imposition of fines, whereas the effect of fines on the fertility of the rich is significantly negative (Li and Zhang 2004).

Similarly, the employment penalties, such as demotion/dismissal in a state-owned enterprise or withdrawal of the children's right to go to school, are more realistic threats for urban residents. It is because most urban residents in the 1980s-1990s were employed in the public sector or state-owned enterprises. By contrast, the policy had a smaller effect on rural residents, a majority of whom worked in farms during the study period and received fewer benefits from the government.

Nevertheless, the policy's purportedly utopian goal of restricting each family to one child had never been achieved. Even after it was officially written into the Constitution in 1982, the

OCP encountered serious resistance despite the set of propaganda, regulations, incentives, and sanctions, especially in rural China. Many rural families, particularly those with only one female child, strongly resisted the policy for practical and cultural reasons. Rural parents relied heavily on their male children to carry out the labor-intensive farm work, provide them old-age support, and carry on the family name as son preference remained prevailing.

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. By contrast, the strict one-child restriction remained in force in urban areas. This conditional two-child policy was rolled out across most provinces over the following few years. China's population control policy, therefore, was technically a one-and-a-half child policy.

In sum, violating the OCP policy is costlier for urban/rich residents. They thus have fewer children compared to their rural/poor counterparts. Figure 1b in the text illustrates the rural-urban differences in cohort sizes relative to the OCP adoption years across provinces. While the differences remain constant before the OCP adoption, it increases sharply afterwards. Wang and Zhang (2018) document that this two-tier OCP has significantly enlarged the differential fertility between urban and rural areas, as the former are more bound under the policy. Indeed, the population gap between rural and urban China almost triples from 5.8 million in the 1979 cohort to 15.1 million in the 1990 cohort, as shown in Figure 1a in the text.

2. Data

2.1. Data Sources and Sample Construction

Our main data are drawn from the CFPS and the CHARLS. Specifically, for the 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 the CHARLS, we focus on the national baseline survey, which was carried out in 2011, and the follow-up surveys in 2013 and 2015.

The combined dataset from the CFPS and CHARLS is the best available for studying intergenerational mobility in China for three reasons. First, both the CFPS and CHARLS samples are nationally representative. The two surveys separately cover urban and rural areas in 25 and 28 out of 34 provinces, municipalities, or autonomous regions. The distributions of demographic and socioeconomic variables—such as age, sex, and years of schooling—in the two surveys are consistent with those from the population census.

Second, the panel structure of the CFPS facilitates the calculation of lifetime income and addresses the lifecycle bias and attenuation bias in estimating intergenerational mobility, as discussed in Section 2.2.2. The individuals are tracked across waves. Each wave of the CFPS collects information on individual income from the previous year. The solid technical support and cross-validation mechanism employed by the CFPS ensure the reliability of the income information. We impute lifetime income based on Heckman selection model by exploiting the income information across the five waves of CFPS to generate a reliable measure of intergenerational income mobility.[1]

Third, the two surveys uniquely collect a comprehensive set of demographic and

[1] The CHARLS surveys individuals aged 45 or above, with over 75% of respondents aged 60 or above. Its income data primarily reflect retirement income, pensions, or transfers, which poorly represent earnings during prime working years, making CHARLS unsuitable for calculating observed income for children or fathers (typically working-age adults).

socioeconomic information regarding all family members and their non-coresiding spouses, parents, children, and siblings. This survey design helps us address selection bias in estimating intergenerational mobility using household survey data, especially during China's rapid economic transition period with increasing migration between rural and urban areas and across provinces. We use the father-child pairs constructed from the CHARLS dataset to expand the pairs derived from the CFPS data, so we can get sufficient sample to conduct analysis at the province-cohort level. Below, we detail the steps to construct our analytic sample using the combined dataset.

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 the 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 1970 to exclude the influence of the Cultural Revolution on education and intergenerational income mobility (Meng and Gregory 2002; Meng and Zhao 2021). 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. (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, Guizhou, and Xinjiang due to limited sample sizes.

The full sample consists of 22,169 father–child pairs of *Han* ethnicity with children from 21 provinces and autonomous regions. 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 (Wooldridge 2010). 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, older children possess different characteristics from their younger siblings. 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 impute lifetime income for both children and fathers, which we discuss in Section 2.2.1.

Step 2 Divide the full sample of father–child pairs into 105 groups according to the child's birth cohort and province.

We first divide this full sample into five cohorts according to the child's birth year: 1970–1973, 1974–1976, 1977–1979, 1980–1982, and 1983–1985. We further divide the sample into 105 groups according to the child's birth cohort and province, as shown in Table A2.

2.2. Variable Construction

2.2.1. Three Measures of Intergenerational Income Mobility

Following Fan, Yi, and Zhang (2021), 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 intergenerational elasticity (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. The rank–rank slope provides a measure of relative mobility, which measures the difference in outcomes between children from top and bottom income families. 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 25 and 75 percentile ranks of the *national* income distribution of fathers. These two estimates measure the mobility of children from low-income (e.g., bottom-quartile) and high-income (e.g., high-quartile) families, respectively. Estimating intergenerational income mobility is difficult because of the conventional lifecycle bias, attenuation bias, and selection bias. We detail the construction of these three measures below to overcome the three biases.

A. Intergenerational Income Rank–Rank Slope

Step 1 Impute lifetime income for both children and fathers.

First, we calculate observed income for both children and fathers from the CFPS. 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. By contrast, the CHARLS surveys individuals aged 45 or above, with over 75% of respondents aged 60 or above. Its income data primarily reflect retirement income, pensions, or transfers, which poorly represent earnings during prime working years. Moreover, the income measure for non-resident children of main respondents available from CHARLS is a self-reported income bracket measure (that is, reported by the old-aged parents). These limitations make the CHARLS unsuitable for calculating observed income for children or fathers (typically working-age adults).

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

$$I_i = \alpha_0 + \alpha_z z_i + X_i \alpha_X + \varepsilon_i, \tag{A1}$$

where I_i is a dummy variable equal to 1 if the information on child i's observed lifetime 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, years of schooling, age, age squared, age cubed, and full interactions with *hukou* status and coastal dummy, and cohorts. Educational attainment is a key predictor of lifetime income measured by schooling years. In this study, we use the age measured 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 A3 reports the estimates of Equation (A1) for children. Using the estimates of Equation (A1) for the CFPS sample of children, we calculate the inverse Mills ratio, λ_i, for children from both the CFPS and the CHARLS.

Third, we estimate the following income equation using only the CFPS sample of children with observed lifetime income to correct for selection bias, with the inverse Mills ratio, λ_i, as a control. Note that although Equation (A1) is estimated using the full CFPS sample, Equation (A2) below can only be estimated using the CFPS sample with observed income:

$$inc_i = \beta_0 + \beta_\lambda \lambda_i + X_i \beta_X + \varepsilon_i, \tag{A2}$$

where inc is the logarithm of the child's observed lifetime income and X is the same as in Equation (A1). 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 the full interactions of education with *hukou* status and costal dummies in X_i in Equation (A2). Column (3) in Table A3 presents the estimates of Equation (A2), correcting for selection bias for children. The R-squared in column (3) is 0.259.

The variable z, the number of siblings the child has, is included in Equation (A1) but not Equation (A2). 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 (Guo, Yi, and Zhang 2017). 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 A3.

Fourth, based on the estimates of Equation (A2), we impute lifetime income for all children from the CFPS and the CHARLS using individual characteristics X_i, the calculated inverse Mills ratio λ_i, and the estimated coefficients β_0, β_λ, and β_X. We use the CFPS sample to estimate Equations (A1) and (A2) because the quality of income information recorded in the CFPS is better than that in the CHARLS (Xie and Zhang 2019).

We apply a similar procedure to impute lifetime income for fathers of the full sample. Here, z is the number of children. Column (2) in Table A3 reports the estimates of Equation (A1) for fathers of the CFPS sample. Column (4) in Table A3 presents the estimates of Equation (A2), correcting for selection bias for fathers. The R-squared in column (4) is 0.167. Table A1 summarizes the imputed lifetime income for children and fathers.

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

Using imputed 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:

$$rank_{ipc} = \alpha_{0pc} + \alpha_{1pc} rank_{fpc} + \varepsilon_{ipc}, \tag{A3}$$

where $rank_{ipc}$ is the income percentile rank of child i in birth cohort c and province p

and $rank_{fpc}$ 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 gender, age, and age squared and the 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.

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

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

We calculate the mean income percentile rank of children born to fathers at the 25 income percentile rank as follows:

$$\widehat{rank}_{pc}^{25} = \widehat{\alpha_{0pc}} + \widehat{\alpha_{1pc}} \times 25, \tag{A4}$$

where $\widehat{\alpha_{0pc}}$ and $\widehat{\alpha_{1pc}}$ are estimates from Equation (A3) and $\widehat{rank}_{pc}^{25}$ is the mean income percentile rank of children born to fathers at the 25 income percentile rank at the *national* level for birth cohort c in province p.

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

We calculate the mean income percentile rank of children born to fathers at the 75 income percentile rank as follows:

$$\widehat{rank}_{pc}^{75} = \widehat{\alpha_{0pc}} + \widehat{\alpha_{1pc}} \times 75. \tag{A5}$$

Similarly, $\widehat{\alpha_{0pc}}$ and $\widehat{\alpha_{1pc}}$ are estimates from Equation (A3). The estimate, $\widehat{rank}_{pc}^{75}$, is the mean income percentile rank of children born to fathers at the 75 income percentile rank at the *national* level for birth cohort c in province p.

2.2.2. Econometric Challenges

Three econometric challenges are associated with using household survey data to estimate intergenerational income mobility, namely, lifecycle bias, attenuation bias, and selection bias (Chetty, Hendren, Kline, and Saez 2014; Chetty, Hendren, Kline, Saez, et al. 2014). Active literature from developed countries uses administrative data, especially the tax records, to track full information on lifetime income (Chetty, Hendren, Kline, and Saez 2014; Chetty, Hendren, Kline, Saez, et al. 2014; Chetty and Hendren 2018). In developing countries such as China, nevertheless, the tax system is less capable to provide reliable income information for intergenerational studies. We thus use household surveys as our main data sources. To address the three biases in estimating intergenerational income mobility, especially using survey data, Fan, Yi, and Zhang (2021) design a series of econometric procedures in China's context. In this paper, we follow their work to generate reliable estimates on intergenerational income mobility and take one step further, by linking intergenerational mobility with differential fertility. We briefly summarize the econometric challenges and procedures to mitigate them below.

The lifecycle bias, which is the most intensively discussed bias in the intergenerational literature, arises when using the current earnings of children— especially in early life stages— as a proxy variable for lifetime income to estimate intergenerational income mobility (Solon 1989; Nybom and Stuhler 2017). However, earnings at the early stage of life cycle systematically differ from lifetime earnings. The estimate of intergenerational mobility would be biased if using current earnings. To mitigate this lifecycle bias, we first restrict children in our estimation sample to be in the midlife stage and exclude fathers in the late adulthood who are most likely retired. Nybom and Stuhler (2017) show that income measured at the mid-to-late life stage is subject least to lifecycle bias. We then adopt intergenerational rank-rank correlation as the main measure, which is the most robust to the age at which income is measured (Nybom and Stuhler 2017). In addition, we use predicted lifetime income for both children and parents when calculating the income ranks. Finally, we include age polynomials for children and parents explicitly when estimating intergenerational rank-rank correlation using Equation (A3).

The second bias is attenuation bias, which arises when using income from specific survey year(s). Such measure may not be a proper proxy of lifetime income, as it contains transitory shock and measurement errors from specific survey waves (Mazumder 2005; Solon 2002). To address this attenuation bias, we take an average of income across five survey waves of CFPS, a nationally representative longitudinal survey. Further, we extend to a larger sample by including father-child pairs from CHARLS, another longitudinal household survey in China. In addition, Nybom and Stuhler (2017) demonstrate that the intergenerational rank-rank correlation subject least to the attenuation bias. We thus adopt this rank measure to further mitigate the concern on attenuation bias. Finally, we predict lifetime income for both fathers and children, instead of observed income from specific survey waves, which again reduces attenuation bias.

Last, household surveys, which interview individuals either living in the households or those maintaining close economic relationships with the households, are subject to two sources of selection bias. The first is coresidence bias. Individuals are self-selected to stay at parents' home or set up own families. For instance, married children usually leave parents' households and start own families. The second selection bias arises from temporary migration. Household surveys usually do not track the income information of temporary migrants. This source of selection bias can be severe during China's market reform with increasing rural-to-urban and cross-province migration. To address selection bias, we apply the Heckman selection model and predict lifetime income for both non-coresiding and coresiding children and fathers.

Although the econometric strategies to address the challenges of estimating intergenerational mobility follow Fan, Yi, and Zhang (2021), this paper examines a different research question. Using the OCP as a quasi-natural experiment, we aim to identify the effect of differential fertility on intergenerational income mobility. We construct an enlarged sample from two household survey datasets to estimate the intergenerational income mobility at province-by-cohort level.

2.2.3. 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 of 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 25 and 75 education percentile ranks. These two estimates measure the mobility of children from low-education (e.g., bottom-quartile) and high-education (e.g., high-quartile) families, respectively. We detail the construction of these three measures below.

A. Intergenerational Education Rank–Rank Slope

Step 1 Calculate each child's (father's) education percentile rank based on his/her position in the *national* distribution of children's (fathers') education by the child's cohort (Xie and Zhang 2019).

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

Third, we adjust the cumulative percentages of children (fathers) by taking the midpoint percentile at each education level to get the education percentile rank for each child (father) given that the education category is discrete (Xie and Zhang 2019).

Step 2 Estimate the education rank–rank slope as in Step 3 in Section 2.2.1.

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

We calculate the mean education percentile rank of children born to fathers at the 25 education percentile rank as discussed in Section 2.2.1.

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

We calculate the mean education percentile rank of children born to fathers at the 75 education percentile rank as discussed in Section 2.2.1.

2.2.4. Instrumental Variables

Based on the fact that the OCP, initiated in 1979 but implemented at different timeline across provinces, was followed by a series of exemptions from the strict one-child restriction depending on the spouses' *hukou* status, fertility in a group depends on the mothers' policy exposure during their childbearing years and the share of rural mothers. We thus use the policy exposure of mothers, share of rural mothers, and their interaction as instrumental variables (IVs) and detail the steps for constructing the variable of the policy exposure of mothers below.

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, Yi, and Zhang (2020), we focus on a restricted sample of mothers born in 1930–1939, because the OCP 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, $probbirth_e(a)$. Figure A2 displays the probability of giving birth against mother's age. Because the probability of giving birth at ages younger than 17 or older than 46 is almost nil, 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, $\sum_{a=17}^{46} probbirth_e(a) \geq 1$. Thus, we standardize the probability below:

$$ProbBirth_e(a) = \frac{probbirth_e(a)}{\sum_{a=17}^{46} probbirth_e(a)}. \quad \text{(A6)}$$

Step 2 Calculate the policy exposure of child i's mother at a 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 age a, $ProbBirth_e(a)$ (Chen and Fang 2021; Guo, Yi, and Zhang 2020).

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. 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. For example, this policy was implemented in 1980 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 $I[1965 + 20 \geq 1980] = 1$. 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(= $I[1965 + 20 \geq 1980]$)—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, $exposure_{iepc}$, conditional on the child's cohort *c*, province *p*, and mother's educational category *e*, by summing the policy exposures between 17 and 46 years old according to Equation (5) in the text.

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

2.2.5. 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 between 3 and 12. Specifically, the socioeconomic measures are gross regional product (GRP) per capita, number of beds per 10,000 persons, share of primary industry, import & export per capita, and sex ratio. We also control the group-level average share of rural mothers and average exposure to land reform. Data on the socioeconomic measures of a child's environment between 3 and 12 are drawn from the China Compendium of Statistics 1949–2008 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 between 3 and 12.

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

$$GRP\ per\ capita_{ipy} = \frac{\sum_{t=2}^{11} GRP\ per\ capita_{p,y+t}}{10}. \quad \text{(A7)}$$

Step 2 For each group, the variable of GRP per capita is the average value of

$GRP\ \ per\ \ capita_{ipy}$ across all children within the group.

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

The steps of constructing exposure to land reform at the cohort-province level are as follows:

Step 1 Calculate the policy exposure of child i's mother at a to land reform based on (i) the start year of implementing the land reform in province p, $PolicyYear_p$, (ii) the mother's birth year, τ, and (iii) the mother's probability of giving birth at age a, $ProbBirth_e(a)$.

Step 2 Calculate the total policy exposure of child i's mother to land reform, $exposureland_{ipc}$, by summing the policy exposures between 17 and 46 years old according to Equation (5) in the text.

Step 3 For each group, calculate the variable of mothers' policy exposure to land reform, $ExposureLand_{pc}$, by averaging the value $exposureland_{ipc}$ across all children within the group.

3. Robustness Analyses

3.1. Alternative Measure of Differential Fertility

Differential fertility is our independent variable, which is measured by the rural-urban fertility difference in our main text. We consider an alternative measure of differential fertility, rural/urban fertility ratio, which is also widely used in the literature (Wang and Zhang 2018).

3.2. 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 (Gould, Lavy, and Paserman 2011). 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—ages 3 to 9. We use the variable of GRP per capita to illustrate the procedures used to construct the socioeconomic measures of a child's environment ages 3 to 9. We first calculate the value of GRP per capita for child i born in year y and province p according to Equation (A8), which is similar to Equation (A7). We then do the same step as Step 2 in Section 2.2.5:

$$GRP\ \ per\ \ capita_{ipy} = \frac{\sum_{t=0}^{8} GRP\ \ per\ \ capita_{p,y+t}}{9}. \tag{A8}$$

3.3. Alternative Measure of the IV

The variable of the policy exposure of mothers—the effects of the OCP 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.

Besides, the standard probability of giving birth at a given educational level differs between rural and urban mothers. We use the 1% Sample of the 1982 Chinese Population Census to calculate different birth probability of rural and urban mothers. Because the 1982 census does not contain individual *hukou* status, we define a family as rural if the household head was employed in an agricultural sector (Guo, Yi, and Zhang 2020). We use the calculated average policy exposure of mothers as the new IV. The steps are similar as detailed in Section

2.2.4.

3.4. Alternative Definition of Birth Cohorts

The full sample is divided into five cohorts according to the child's birth year: 1970–1973, 1974–1976, 1977–1979, 1980–1982, and 1983–1985. However, the time span for the 1970–1973 cohort contains less individuals than that for other cohorts. To address this concern, we further expand the first cohort to birth years between 1968 and 1973.

3.5. Additional Control Variables

There could be channels other than differential fertility that the IV would work through, such as worsening income prospects due to the reduced labor by the OCP. To mitigate the concern on the impact of the OCP on economic prospects, we conduct an additional robustness check controlling for population growth and public education expenditure. Specifically, the measure of public education expenditure is the proportion of culture, education, science and public health expenses to the general budgetary expenditure.

3.6. Alternative Measure of Age

The age in 2010—the baseline survey wave of CFPS—is used for measuring the age of child/father. We conduct a robustness check by using the average age of individuals with income records as an alternative measure of age.

3.7. Additional Father-child Pairs

Father-child pairs with parents aged 65 and above in 2010 are dropped, because the official retirement age for most men in China during the sample period is 60 years old, with several years' extension for those in managerial or technical roles. It is likely to have a high sample selection among those who remain working and having income report above 65. To address the concern that we may exclude some dads who had kids at an older age by practicing the cutoff at 65 years old, we conduct an additional robustness check by relaxing the fathers' age to 70 years old.

3.8. Alternative Definition of Region

Due to the small sample size, we divide the provinces into 8 regions according to the classification of Development Research Center of the State Council (Yang et al. 2018). We include fixed effects at this granular level, rather than the broadly classified three regions.

Table A5 presents the IV estimates for intergenerational income mobility. 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 income mobility in China—are robust.

4. Heterogeneity Analyses

Since the one-and-a-half child policy depends on the first child being a girl in rural areas, we further investigate the effect of differential fertility on intergenerational income mobility by gender. We present results by sons versus daughters separately in Table A6. We find that the positive (negative) effect of differential fertility on intergenerational income persistence (mobility) is more evident for daughters than sons. Specifically, with differential fertility rising by 1, the persistence of income across generations increases for both sons (0.160) and daughters (0.200), though only statistically significant for the latter. Consistent with the main finding, the effect is driven by the increasing percentile rank of children born to urban/rich fathers, though the magnitude is almost twice as large for daughters as for sons. A one-unit rise in the differential fertility causes the expected rank of sons born to the high-income families to increase by 11.265. The corresponding estimate for daughters is as high as 20.462. Both estimates are statistically significant at conventional levels of significance. Possibly, with the prevailing son preference in China, parents prioritize human capital investment in sons. The effect of fertility on human capital investment for girls is thus more sensitive to parental education or household wealth that that for boys. More discussion on the human capital mechanism will be presented in the next section.

To sum up, we conclude that the rising differential fertility, caused by the OCP, significantly increases intergenerational income persistence in China. Such effect is driven by an increase in the expected mean percentile rank of children born to the urban/rich families and is more evident among daughters than sons.

5. The Human Capital Mechanism: Differential Fertility and Intergenerational Education Mobility

Why does differential fertility decrease intergenerational income mobility? We consider investment in child's human capital to be one important channel. As discussed in Wang and Zhang (2018) and illustrated in Figures 1a and 1b in the text, the OCP induces fertility differentials between rural/poor and urban/rich areas(Wang and Zhang 2018). With less children, the urban/rich parents likely invest more in each child's human capital under a quality-quantity trade-off, compared to their rural/poor counterparts (Becker and Lewis 1973; Becker and Tomes 1986). Indeed, Wang and Zhang (2018) find that fertility differential between rural/poor and urban/rich areas induced by OCP raises the gap in child's human capital investment between the two areas. Since human capital is a significant factor in determining earnings, the income disparity persists into the next generation. In other words, the intergenerational income mobility declines.

5.1. Fixed Effect Estimate

We also use Equation (4) in the text to examine this human capital mechanism by investigating 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. Panel A of Table 2 in the text reports the FE estimation results for intergenerational education mobility. This model produces a reasonable fit to the data, scoring R-squared over 0.32 across three columns. Column 1, in which the dependent variable is the rank–rank slope, shows that the estimated coefficient before differential fertility is 0.073, which is statistically significant at the 5% level. The estimate implies that as differential fertility increases by 1, the rank–rank slope increases by 0.073. 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 25 percentile rank as the dependent variable in column 2. The FE estimated coefficient before differential fertility is -1.416, 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 75 percentile rank, shows that the estimated coefficient before fertility is 1.761 and statistically insignificant. All results are similar to those in Panel A of Table 1 in the text and suggest a similar pattern for intergenerational education mobility using three corresponding measures for education.

5.2. Instrumental Variable Estimate

FE estimates are subject to omitted variable bias, because the increase in differential 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 differential fertility and intergenerational income mobility embodied in Equation (4) in the text cannot be interpreted as a causal relationship. To overcome this issue, we employ the staggered rollout of the OCP across cohorts and provinces to isolate the impact of the OCP on intergenerational mobility through the differential fertility channel.

5.2.1. Second-Stage Estimation Results

The first-stage results are the same as presented in column 1 in Panel B of Table 1 in the text. Columns 1–3 in Panel B of Table 2 in the text report the second-stage regression results for intergenerational education mobility. Column 1, in which the dependent variable is the rank–rank slope, shows that the estimated coefficient before differential fertility is 0.103, which is statistically significant at the 10% level. The estimate implies that as differential fertility increases by 1 as a result of the OCP, the rank–rank slope increases by 0.103. As expected, this suggests that the increase in differential fertility induced by the OCP has reduced intergenerational education mobility in China. Again, this IV estimate is larger than the corresponding FE estimate (Column (1) of Panel A), consistently with our main finding on income mobility. Column 2, in which the dependent variable is the mean percentile rank of children born to fathers at the 25 percentile rank, shows that the estimated coefficient before differential fertility is 2.666, 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 75 percentile rank, shows that the estimated coefficient before differential fertility is 7.828 and is statistically significant at the 1% level. This implies that as differential fertility increases by 1, the mean percentile rank of children born to fathers at the 75 percentile rank increases by 7.828. Comparing column 2 with column 3, we conclude that the negative effect of differential fertility on intergenerational education mobility is driven by the persistence in the top ranks of children born to high-income families.

The results are consistent with those presented in columns 1–3 of Panel B in Table 1 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.

Our results remain stable under a battery of robustness analyses, as specified in Section 3. Table A7 presents estimates from those robustness checks. Consistent with the income mobility pattern, the heterogeneity mobility analysis result shows that the education pattern is again more evident for daughters than sons (Table A8).

REFERENCES

Becker, Gary S, and H Gregg Lewis. 1973. "On the interaction between the quantity and quality of children." *Journal of Political Economy* 81 (2, Part 2):S279-S288.

Becker, Gary S, and Nigel Tomes. 1986. "Human capital and the rise and fall of families." *Journal of Labor Economics* 4 (3):S1-S39.

Chen, Yi, and Hanming Fang. 2021. "The long-term consequences of having fewer children in old age: Evidence from China’s “later, longer, fewer” campaign." *Journal of Development Economics* 151:102664.

Chetty, Raj, and Nathaniel Hendren. 2018. "The impacts of neighborhoods on intergenerational mobility II: County-level estimates." *The Quarterly Journal of Economics* 133 (3):1163-1228.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the land of opportunity? The geography of intergenerational mobility in the United States." *The Quarterly Journal of Economics* 129 (4):1553-1623.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner. 2014. "Is the United States still a land of opportunity? Recent trends in intergenerational mobility." *American Economic Review* 104 (5):141-147.

Chu, CY Cyrus. 1987. "The dynamics of population growth, differential fertility, and inequality: Note." *American Economic Review* 77:1054-1056.

Cooney, Rosemary Santana, Jin Wei, and Mary G Powers. 1991. "The one child certificate in Hebei province, China: Acceptance and consequence, 1979–1988." *Population Research and Policy Review* 10 (2):137-155.

Fan, Yi, Junjian Yi, and Junsen Zhang. 2021. "Rising intergenerational income persistence in China." *American Economic Journal: Economic Policy* 13 (1):202-230.

Gould, Eric D, Victor Lavy, and M Daniele Paserman. 2011. "Sixty years after the magic carpet ride: The long-run effect of the early childhood environment on social and economic outcomes." *The Review of Economic Studies* 78 (3):938-973.

Guo, Rufei, Junjian Yi, and Junsen Zhang. 2017. "Family size, birth order, and tests of the quantity–quality model." *Journal of Comparative Economics* 45 (2):219-224.

Guo, Rufei, Junjian Yi, and Junsen Zhang. 2020. "Rationed fertility: Theory and evidence." *http://www.junjianyi.net/uploads/4/4/9/5/44956225/rationedfertility.pdf*.

Huang, Yue. 2021. "Family Size and Children’s Education: Evidence from the one-child policy in China." *Population Research and Policy Review*:1-26.

Li, Hongbin, and Junsen Zhang. 2004. "Fines, limited liability and fertility." *https://www.cuhk.edu.hk/eco/staff/jszhang/Fines_Fertility_Zhang.pdf*.

Mazumder, Bhashkar. 2005. "Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data." *Review of Economics and Statistics* 87 (2):235-255.

Meng, Xin, and Robert G Gregory. 2002. "The impact of interrupted education on subsequent educational attainment: A cost of the Chinese Cultural Revolution." *Economic Development and Cultural Change* 50 (4):935-959.

Meng, Xin, and Guochang Zhao. 2021. "The long shadow of a large scale education interruption: The intergenerational effect." *Labour Economics* 71:102008.

Nybom, Martin, and Jan Stuhler. 2017. "Biases in standard measures of intergenerational income dependence." *Journal of Human Resources* 52 (3):800-825.

Solon, Gary. 1989. "Biases in the estimation of intergenerational earnings correlations." *Review of Economics and Statistics* 71 (1):172-174.

Solon, Gary. 2002. "Cross-country differences in intergenerational earnings mobility." *Journal of Economic Perspectives* 16 (3):59-66.

Wang, Xuebo, and Junsen Zhang. 2018. "Beyond the quantity–quality tradeoff: Population control policy and human capital investment." *Journal of Development Economics* 135:222-234.

Wooldridge, Jeffrey M. 2010. *Econometric analysis of cross section and panel data*: MIT press.

Xie, Yu, and Chunni Zhang. 2019. "The long-term impact of the Communist Revolution on social stratification in contemporary China." *Proceedings of the National Academy of Sciences* 116 (39):19392-19397.

Yang, Minghai, Hongxia Zhang, Ya'nan Sun, and Qianqian Li. 2018. "The study of the science and technology innovation ability in eight comprehensive economic areas of China (in Chinese)." *The Journal of Quantitative & Technical Economics* (4):3-19.

Zhang, Junsen. 2017. "The evolution of China's one-child policy and its effects on family outcomes." *Journal of Economic Perspectives* 31 (1):141-160.

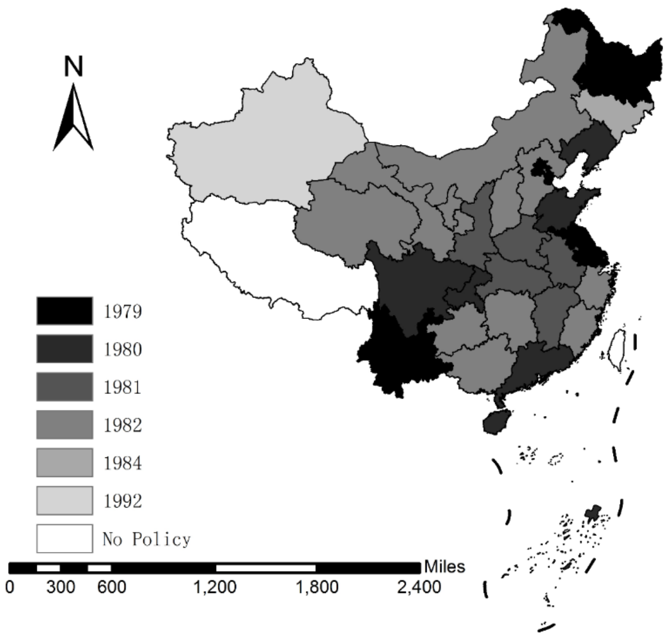

Figure A1. The rollout of China's one-child policy across provinces
Note: This figure visualizes the staggered rollout of China's one-child policy across provinces from Huang (2021). The darker the color, the earlier the policy is implemented.

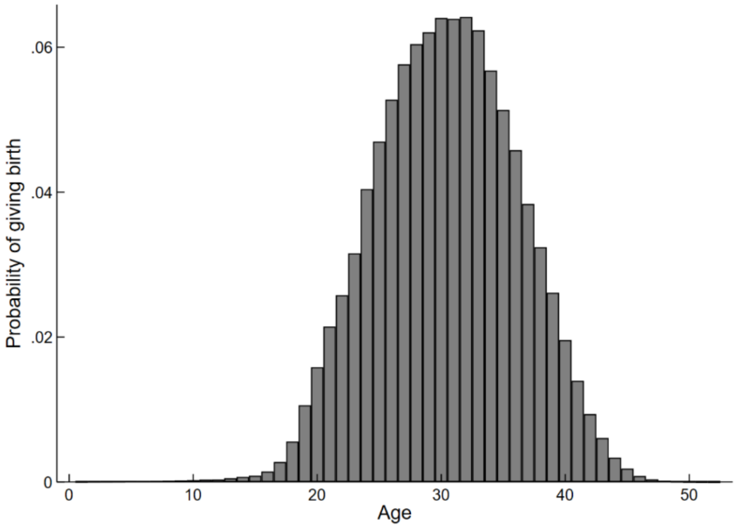

Figure A2. Probability of Giving Birth against Mother's Age
Note: Data are from the 1% Sample of the 1982 Chinese Population Census. The probability of giving birth against mother's age is defined as an aggregate probability of the entire sample.

Table A1. Summary statistics for the full sample at the Individual Level

Variable	Observations	Mean	SD
Panel A. Children			
Age	22,169	31.299	4.264
Hukou status (rural = 1)	22,169	0.722	0.448
Coast (coastal region = 1)	22,169	0.341	0.474
Schooling years	22,169	8.769	4.234
Number of siblings	22,169	1.855	1.179
Gender (male = 1)	22,169	0.492	0.5
Imputed lifetime income (in log form)	22,169	9.808	0.37
Panel B. Fathers			
Age	22,169	57.733	4.387
Hukou status (rural = 1)	22,169	0.738	0.44
Coast (coastal region = 1)	22,169	0.341	0.474
Schooling years	22,169	5.907	4.353
Imputed lifetime income (in log form)	22,169	9.408	0.295

Note: The combined dataset from the CFPS (2010–2018) and the CHARLS (2011–2015) generates a sample with 22,169 father–child pairs with children born between 1970 and 1985 from the remaining 21 provinces and autonomous regions in China; 13,881 pairs are from the CFPS and 8,288 are from the CHARLS.

Table A2. Tabulation of the sample size by the child's birth cohort and province

	Birth cohort					
Province	1	2	3	4	5	Total
Anhui	128	160	173	200	183	844
Fujian	71	114	126	147	173	631
Gansu	352	360	405	487	520	2,124
Guangdong	184	241	379	519	511	1,834
Guangxi	52	77	114	156	172	571
Hebei	200	191	255	340	315	1,301
Heilongjiang	129	177	199	184	151	840
Henan	404	452	531	653	618	2,658
Hubei	64	85	136	126	143	554
Hunan	116	162	165	205	197	845
Inner Mongolia	79	90	107	153	132	561
Jiangsu	79	113	135	140	134	601
Jiangxi	109	165	202	185	198	859
Jilin	121	108	132	130	101	592
Liaoning	238	258	330	347	244	1,417
Shandong	175	231	285	325	298	1,314
Shannxi	121	120	122	127	188	678
Shanxi	172	206	217	275	308	1,178
Sichuan	275	293	242	312	265	1,387
Yunnan	123	188	217	179	207	914
Zhejiang	80	89	107	102	88	466
Total	3,272	3,880	4,579	5,292	5,146	22,169

Note: Data source: the CFPS (2010–2018) and the CHARLS (2011–2015). 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: 1970–1973, 1974–1976, 1977–1979, 1980–1982, and 1983–1985. We further divide the full sample into 105 groups by the child's birth cohort and province.

Table A3. Estimation results of the Heckman selection model

Outcome Variable:	With observed income (=1)		Ln (observed income)	
	Probit		OLS	
	(1)	(2)	(3)	(4)
	Children	Fathers	Children	Fathers
Number of siblings	-0.275***	-0.462***		
	(0.012)	(0.019)		
Inverse Mills Ratio (λ)			-0.041	-0.051
			(0.047)	(0.048)
Child birth cohort (= 2)	-0.135*	0.246***	0.010	-0.270**
	(0.077)	(0.088)	(0.066)	(0.114)
= 3	-0.287**	0.328***	0.042	-0.196*
	(0.123)	(0.085)	(0.104)	(0.109)
= 4	-0.447***	0.533***	0.085	-0.265**
	(0.167)	(0.085)	(0.141)	(0.110)
= 5	-0.373*	0.846***	0.077	-0.254**
	(0.192)	(0.087)	(0.160)	(0.112)
Schooling years	0.023***	0.011	0.050***	0.051***
	(0.008)	(0.010)	(0.007)	(0.010)
Hukou	-26.659*	43.852	-0.031	-63.630
	(15.016)	(78.130)	(12.658)	(95.541)
Schooling years * *hukou*	-0.021**	-0.001	-0.002	-0.038***
	(0.009)	(0.012)	(0.008)	(0.011)
Coast	-35.158*	233.233*	7.449	-124.053
	(20.539)	(127.191)	(17.651)	(144.879)
Schooling years * coast	0.016	-0.023	0.002	-0.020
	(0.012)	(0.016)	(0.011)	(0.014)
Hukou * coast	17.339	-281.434**	-15.821	191.818
	(24.689)	(137.576)	(20.559)	(157.774)
Schooling years * *hukou* * coast	-0.024	0.009	0.010	0.004
	(0.015)	(0.018)	(0.013)	(0.017)
Gender	0.185***		0.282***	
	(0.055)		(0.047)	
Gender * *hukou*	0.382***		0.232***	
	(0.066)		(0.058)	
Gender * coast	0.055		0.151**	
	(0.087)		(0.075)	
Gender * *hukou* * coast	-0.172		-0.173*	
	(0.107)		(0.090)	
Age	-1.602	-2.841	-0.313	-1.232
	(1.389)	(3.912)	(1.179)	(4.908)
Age * *hukou*	2.624*	-2.351	0.072	3.446
	(1.431)	(4.286)	(1.213)	(5.296)
Age * coast	3.387*	-12.906*	-0.567	6.879
	(1.958)	(6.938)	(1.690)	(7.973)
Age * *hukou* * coast	-1.571	15.556**	1.301	-10.755
	(2.353)	(7.522)	(1.967)	(8.708)
Age squared/100	5.073	5.794	1.106	1.889
	(4.371)	(7.112)	(3.737)	(9.019)
Age squared/100 * *hukou*	-8.442*	4.181	-0.493	-6.149
	(4.501)	(7.808)	(3.836)	(9.753)
Age squared/100 * coast	-10.851*	23.666*	1.302	-12.609
	(6.162)	(12.576)	(5.341)	(14.581)

Age squared/100 * *hukou* * coast	4.839	-28.472**	-3.457	19.995
	(7.404)	(13.663)	(6.211)	(15.971)
Age cubed/1000	-0.543	-0.390	-0.129	-0.092
	(0.453)	(0.429)	(0.390)	(0.551)
Age cubed/1000 * *hukou*	0.895*	-0.246	0.078	0.361
	(0.467)	(0.472)	(0.400)	(0.597)
Age cubed/1000 * coast	1.146*	-1.437*	-0.082	0.766
	(0.640)	(0.757)	(0.557)	(0.886)
Age cubed/1000 * *hukou* * coast	-0.493	1.726**	0.294	-1.234
	(0.769)	(0.825)	(0.648)	(0.973)
Constant	16.704	44.824	12.210	35.512
	(14.505)	(71.486)	(12.220)	(88.741)
Observations	13,881	13,881	3,548	1,553
R-squared			0.259	0.167

Note: Data source: the CFPS (2010–2018) and the CHARLS (2011–2015). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ for two-sided t tests.

Table A4. Summary statistics for variables at the province-cohort level

Variable	Mean	SD
Panel A. Intergenerational Income Mobility		
Income rank-rank slope	0.295	0.123
Mean income percentile rank of children born to fathers at the 25 income percentile rank	43.34	8.313
Mean income percentile rank of children born to fathers at the 75 income percentile rank	57.065	5.633
Panel B. Intergenerational Education Mobility		
Education rank-rank slope	0.337	0.106
Mean education percentile rank of children born to fathers at the 25 education percentile rank	42.187	6.416
Mean education percentile rank of children born to fathers at the 75 education percentile rank	58.958	6.653
Panel C. Main Independent Variable		
Differential fertility (difference in average number of children between rural and urban areas)	0.529	0.357
Panel D. Control Variables		
Logarithm of GRP per capita	6.362	0.455
Share of primary industry	32.347	8.22
Number of beds per 10,000 persons	22.203	7.972
Imports and exports per capita	60.697	91.645
Sex ratio	0.515	0.005
Policy exposure of mothers to land reform	0.782	0.21
Share of rural mothers (percentage points)	75.466	12.24
Panel E. Instrumental Variable		
Policy exposure of mothers to OCP	0.68	0.159

Note: Data are derived from the CFPS (2010–2018), CHARLS (2011–2015) and China Compendium of Statistics (1949–2008). Number of observations: 105.

Table A5. Robustness analyses

	(1)	(2)	(3)
	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
Panel A. Alternative Measure of Differential Fertility: Rural/Urban fertility ratio			
Differential fertility	0.261**	6.958	19.014***
	(0.104)	(4.645)	(5.287)
Panel B. Alternative Socioeconomic Measures of a Child's Early Environment: Ages 3–9			
Differential fertility	0.122**	4.160	9.854***
	(0.051)	(2.437)	(2.821)
Panel C. Alternative Measure of IV: Unstandardized Probability of Giving Birth			
Differential fertility	0.122**	2.330	8.043***
	(0.055)	(2.404)	(2.421)
Panel D. Alternative Measure of IV: Different Natural Fertility of Rural Mothers and Urban Mothers			
Differential fertility	0.156***	4.917*	11.836***
	(0.053)	(2.712)	(3.189)
Panel E. Alternative Definition of the First Cohort: Children Born between 1968 and 1973			
Differential fertility	0.119**	2.885	8.310***
	(0.049)	(2.227)	(2.428)
Panel F. Alternative Control Variables: Population Growth and Public Education Expenditure			
Differential fertility	0.133**	3.727	9.872***
	(0.054)	(2.420)	(2.980)
Panel G. Alternative Measure of Age: Average Age of Individuals with Income Records			
Differential fertility	0.104**	2.791	7.667***
	(0.050)	(1.722)	(2.548)
Panel H. Additional Father-child Pairs: Relaxing the Fathers' Age to 70 Years Old			
Differential fertility	0.168**	1.577	9.062***
	(0.078)	(2.870)	(2.903)
Panel I. Alternative Definition of Region: Divide the Provinces into 8 Regions			
Differential fertility	0.167**	0.928	8.222**
	(0.065)	(4.092)	(3.415)
Control variables	YES	YES	YES
Cohort FE	YES	YES	YES
Regional FE	YES	YES	YES
Observations	105	105	105

Note: The F statistics for the first-stage estimations in Panels A–I are 24.077, 20.536, 18.489, 27.323, 21.051, 20.384, 20.783, 16.661, and 13.603, respectively. Bootstrapped standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Table A6. Effect of differential fertility on intergenerational income mobility by gender

	(1)	(2)	(3)
	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
		Panel A. Sons	
Differential fertility	0.160	6.193	11.265**
	(0.100)	(6.151)	(5.665)
		Panel B. Daughters	
Differential fertility	0.200**	8.786	20.462***
	(0.091)	(7.281)	(6.996)
Control variables	YES	YES	YES
Cohort FE	YES	YES	YES
Regional FE	YES	YES	YES
Observations	100	100	100

Note: Bootstrapped standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 for two-sided t tests.

Table A7. Robustness analyses: Differential fertility and intergenerational education mobility

	(1)	(2)	(3)
	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
Panel A. Alternative Measure of Differential Fertility: Rural/Urban fertility ratio			
Differential fertility	0.203*	5.298	15.479**
	(0.104)	(4.875)	(6.108)
Panel B. Alternative Socioeconomic Measures of a Child's Early Environment: Ages 3–9			
Differential fertility	0.106*	2.421	7.760***
	(0.055)	(2.421)	(3.022)
Panel C. Alternative Measure of IV: Unstandardized Probability of Giving Birth			
Differential fertility	0.099*	1.415	6.470**
	(0.058)	(2.202)	(2.915)
Panel D. Alternative Measure of IV: Different Natural Fertility of Rural Mothers and Urban Mothers			
Differential fertility	0.142**	4.445	11.441***
	(0.059)	(3.082)	(3.975)
Panel E. Alternative Definition of the First Cohort: Children Born between 1968 and 1973			
Differential fertility	0.104**	1.997	7.187**
	(0.052)	(2.192)	(2.804)
Panel F. Alternative Control Variables: Population Growth and Public Education Expenditure			
Differential fertility	0.104*	2.816	8.010**
	(0.055)	(2.552)	(3.555)
Panel G. Alternative Measure of Age: Average Age of Individuals with Income Records			
Differential fertility	0.106*	2.579	7.667**
	(0.058)	(2.395)	(3.182)
Panel H. Additional Father-child Pairs: Relaxing the Fathers' Age to 70 Years Old			
Differential fertility	0.126**	0.007	5.964**
	(0.061)	(2.602)	(2.796)
Panel I. Alternative Definition of Region: Divide the Provinces into 8 Regions			
Differential fertility	0.146**	-0.337	6.796*
	(0.071)	(2.867)	(3.509)
Control variables	YES	YES	YES
Cohort FE	YES	YES	YES
Regional FE	YES	YES	YES
Observations	105	105	105

Note: Bootstrapped standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ for two-sided t tests.

Table A8. Effect of differential fertility on intergenerational education mobility by gender

	(1)	(2)	(3)
	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
		Panel A. Sons	
Differential fertility	0.102	4.385	9.168*
	(0.115)	(5.827)	(5.081)
		Panel B. Daughters	
Differential fertility	0.214	12.745	24.079**
	(0.141)	(9.357)	(9.610)
Control variables	YES	YES	YES
Cohort FE	YES	YES	YES
Regional FE	YES	YES	YES
Observations	100	100	100

Note: Bootstrapped standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ for two-sided t tests.