Differential Fertility, Intergenerational Mobility, and Income Inequality: Evidence from China

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Abstract

This study explores the causal effect of differential fertility across income classes on income inequality in the next generation, using China's Great Famine (1959–1961) as a plausible exogenous shock to the post-famine fertility structure and rural–urban population composition. By leveraging extreme weather shocks during the famine as an instrument for famine severity, we find that the famine significantly increased both the rural population share and the Gini coefficient for the post-famine birth cohorts. Further analysis reveals that the increase in rural population share significantly contributes to the rise in income inequality within these cohorts. Employing a difference-in-differences strategy, we compare pre- and post-famine birth cohorts, with famine severity as an instrument for the rural population share in post-famine cohorts. Our results show that the higher rural population share in post-famine cohorts caused by the famine led to a higher Gini coefficient for these cohorts decades later. Mechanism analysis indicates that a higher rural population share decreased the likelihood of rural youths gaining admission to senior high school and college, thereby reducing intergenerational mobility due to increased rural fertility.

Keywords: Great Famine, differential fertility, income inequality, intergenerational mobility

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1. Introduction

As is commonly observed in the modern world, fertility levels vary significantly across countries at different stages of development and among income classes within a country. Poor families typically have more children than wealthy families, and less developed countries tend to have higher fertility rates than developed ones. Figure 1 shows trends in fertility levels across countries by income level from 2000 to 2021. While fertility rates in low-income countries show a persistent decline over time, they remain much higher than those in high-income countries. Similarly, fertility rates differ greatly across income classes within the same country. For instance, Figure 2 illustrates that in developed countries with generally low fertility levels, such as the United States, low-income families tend to have significantly more children than high-income families.

These differential fertility across countries and income classes may have important consequences. For instance, higher fertility among poorer families may perpetuate poverty, as a larger share of the next generation could be trapped in poverty. Additionally, differential fertility patterns can influence human capital investment in the next generation, potentially affecting a society's long-term economic development. Unsurprisingly, this issue has drawn significant attention from both demographers and economists. Several influential studies have theoretically demonstrated that fertility differentials across income classes can substantially impact income distribution and, consequently, a society's economic growth (see Lam, 1986; Chu, 1987; Dietzenbacher, 1989; Chu and Koo, 1990; de la Croix and Doepke, 2003).

However, the issue is highly complicated, and drawing a clear conclusion solely through theoretical analysis is difficult. Additionally, understanding whether and how differential fertility across income classes affects income inequality of the next generation is fundamentally an empirical issue rather than a purely theoretical one. Yet, direct empirical evidence on this topic remains limited. This study aims to provide a rigorous empirical analysis of the impact of differential fertility across income classes on the income inequality of the next generation.

Undoubtedly, such empirical investigations face great challenges. In particular, both differential fertility and income inequality are endogenous and simultaneously influenced by many factors, such as institutions and economic development, making the identification difficult. In this study, we argue that China's rural–urban divide, combined with the exogeneous shock of the Great Famine (1959–1961) on its fertility structure, provides an ideal natural experiment for empirically studying this issue.

Indeed, a significant rural–urban gap exists in China. Urban areas are substantially more developed than rural areas, with urban residents enjoying a much higher level of social welfare over a prolonged period. Urban areas also have far better health and medical facilities, as well as more advanced educational systems, compared to their rural counterparts. Urban families possess more resources to invest in their children. Given the large disparity in income and resources between rural and urban areas, differential fertility across these groups may have a significant impact on income inequality of the country's next generation.

The Great Famine (1959–1961) primarily affected rural areas, significantly impacting China's rural–urban fertility structure and population composition. Over 30 million people died during the famine, most of whom were rural residents (Meng et al., 2015). Although the majority of the prime-age adults survived (Thaxton, 2008), the elderly and young children were heavily affected, with estimates suggesting that over half of the total deaths were among young children (Ashton et al., 1984; Spence, 1991). Consequently, rural fertility rebounded substantially after the famine, reaching a historic peak in 1963. Meanwhile, China's rural–urban fertility ratio also rose sharply and remained at high levels for an extended period.

Our analysis shows that the effect of the famine on the rural–urban fertility ratio lasted for nearly 20 years before gradually diminishing. With the famine as a plausible exogenous shock to China's post-famine fertility structure and rural–urban population composition, we empirically study the effect of such exogenous changes in fertility structure on income inequality in the long term. Frist, we use extreme weather shock during the famine as an instrument for famine severity at the prefectural level. Our findings reveal that the famine significantly increased both the rural population share and the Gini coefficient of the post-famine birth cohorts. We then conduct a comprehensive analysis of the various mechanisms through which the famine affected the long-term income inequality of these cohorts, identifying its effect on their rural population share as a significant contributing factor.

Next, we employ a difference-in-differences (DID) strategy to identify the effect of the increased rural population share among post-famine birth cohorts, caused by the famine, on their Gini coefficient in 2005. Specifically, we select the 1962–1980 birth cohorts, whose population composition was significantly affected by the famine, as the treatment group, and the pre-famine (1950–1956) birth cohorts as the control group. We use famine severity at the prefectural level to instrument the rural population share of the 1962–1980 birth cohorts. The IV estimates within the DID framework provide strong evidence of the effect of population composition on income inequality. The first-stage estimates suggest that the famine significantly increased the rural population share of the post-famine cohorts relative to the pre-famine cohorts. The second-stage estimates indicate that this increased rural population share caused by the famine led to a higher Gini coefficient for these cohorts.

The major concern lies in the validity of using famine severity as an IV for population composition. The exclusion restriction requires that the famine only influences the income inequality of the post-famine birth cohorts through its effect on their population composition. However, given that the famine could impact long-term income inequality through various mechanisms, this condition is unlikely to hold. By analyzing all possible mechanisms, we can incorporate them into our DID framework to assess the IV's validity.

Overall, there are three mechanisms through which the famine could affect income inequality: (1) The famine may have had a long-lasting negative impact on regional characteristics, such as institutions and productivity, leading to higher income inequality among both pre- and post-famine cohorts; (2) The famine may have directly impacted individuals in the pre-famine cohorts who experienced it, particularly rural residents, resulting in higher income inequality for these cohorts; (3) The famine may have induced a significantly higher rural population share of post-famine cohorts compared to pre-famine ones, potentially leading to a higher Gini coefficient for the former.

If population composition did not play a role, or if Mechanism 3 were absent, the famine would induce a higher Gini coefficient for pre-famine cohorts than for post-famine ones. However, our DID estimates indicate that the famine led to higher income inequality of post-famine cohorts—who did not experience the famine—compared to pre-famine cohorts who did. These results suggest that the effect of population composition dominates the direct effects of the famine on the income inequality among pre-famine cohorts. Consequently, these estimates represent a lower bound of the effect of population composition on the income inequality of post-famine cohorts.

Another concern is the potential sample selection issue arising from the famine. Many rural children died during the famine, and the majority were likely from lower-income families within rural areas. Additionally, these lower-income families who lost children during the famine would likely have had more children afterward, leading to higher post-famine rural fertility. However, this potential sample selection may actually strengthen, rather than undermine, our findings. In essence, the fact that rural children from poorer families were more severely impacted by the famine implies that the famine acted as a substantial shock to fertility among the poor, supporting our hypothesis that higher fertility among lower-income families exacerbates income inequality in the subsequent generation.

We perform additional DID regressions using the 1962–1980 and 1981–1985 birth cohorts—whose population composition was and was not affected by the famine, respectively— as the treatment and control groups. The results indicate that, compared to the 1981–1985 birth cohorts, the famine induced a much higher rural population share for the 1962–1980 birth cohorts, which, in turn, led to a higher Gini coefficient for them. Additionally, we conduct a placebo test, using the 1950–1956 and 1981–1985 birth cohorts—both of which had population compositions largely unaffected by the famine—as the treatment and control groups, respectively. The results show that both the first- and second-stage coefficients are close to zero and insignificant. Overall, these findings suggest that the famine significantly increased income inequality among post-famine birth cohorts, with its effects on population composition being one of the potential underlying mechanisms.

We further analyze the mechanisms through which differential fertility or population composition affects income inequality of the next generation. Intuitively, if an increasing new population concentrate in backward rural areas, it may become more difficult for these rural children to acquire limited resources and opportunities critical for their later social success. In other words, a higher share of rural population could worsen these rural children's upward mobility. Consequently, if more rural population were trapped in poverty, the income inequality of the society would increase. We present evidence that a higher rural population share induces a lower probability of these rural children gaining admission to college and senior high school than that of their urban counterparts. That is, if rural areas have a larger share of the total population, it would be more difficult for these rural children to receive higher education and climb up the social ladder.

Our study contributes to the extensive literature on the fundamental causes of income inequality. The determinants of income inequality include technological change (Autor, Levy, and Murnane, 2003; Goldin and Katz, 2008), globalization and immigration (Feenstra and Hanson, 1996; Borjas, 2003), education and human capital (Becker and Tomes, 1979, 1986; Chetty et al., 2014), institutions and policies (Stiglitz, 2012; Piketty, 2014), and fertility and population dynamics (Lam, 1986; Chu and Koo, 1990; de la Croix and Doepke, 2003). Our study focuses on the relationship between fertility, population dynamics, and income inequality, empirically testing the theoretical investigations of this strand of literature. Specifically, we examine the impact of differential fertility across income classes on income inequality and explore the potential mechanisms driving this effect. Our findings also carry significant welfare and policy implications for the global effort to reduce rising income inequality.

Additionally, our findings shed light on the interpretation of the positive correlation between income inequality and intergenerational income persistence reported in the literature (Corak, 2004; Björklund and Jäntti, 2011; Krueger,2012; Fan et al., 2020), the underlying cause of which remains unclear. Intuitively, higher income inequality may lead to lower intergenerational income mobility, or lower social mobility may widen income inequality, or these two factors may interact as both cause and effect. This study introduces another possibility: a more fundamental factor—differential fertility across income classes—positively affects both income inequality and intergenerational income persistence, thereby creating a seemingly positive correlation between the two. This novel evidence provides a new perspective for understanding the relationship between income inequality and intergenerational mobility.

Our findings could also help explain China's ever-increasing income inequality and decreasing intergenerational income mobility. Recent reports indicate that income inequality in China has reached levels much higher than in many developed countries, with a substantial portion of this inequality stemming from regional disparities and the rural–urban divide (Xie and Zhou, 2014; Zhang, 2021). Meanwhile, intergenerational income mobility has been decreasing rapidly, with differences in human capital investment across income classes serving as an important contributing factor (Li et al., 2013; Fan et al., 2020). However, the underlying reasons for these trends remain unclear. Our findings suggest that the widening rural–urban fertility gap, driven by the historical shocks and policies, such as the Great Famine and the two-tier population control policy—which has led to a much higher fertility in rural areas compared to urban areas—may be contributing factors to China's current high income inequality and low intergeneration mobility.

2. Data

We use the 1% samples from the 1990, 2000 censuses, as well as the 2005 mini-census, provided by the Chinese National Bureau of Statistics as our data sets, with the 2005 census serving as our primary dataset. These datasets cover 3,152,818 households (1990), 3,742,658 households (2000), and 996,588 households (2005), with a record for each household. Each record includes information on demographic characteristics, occupation, education levels, income (available in the 2005 mini-census only), ethnicity, household type (rural or urban), and fertility for each individual living in the household. The 2005 census also records the income levels for the labor force, allowing for the calculation of the Gini coefficient.[4]

We primarily focus on the income equality of the 1950–1985 birth cohorts in 2005, who constitute the main labor force (aged 20–55) at that time. We use the 2005 census data to calculate the Gini coefficient at the individual level for these birth cohorts in each prefecture. Specifically, we include all members of the labor force who were working in the prefecture at the time of survey to obtain the Gini coefficient.

The 2005 mini-census is the only census dataset that includes respondents' income information, making it the most representative source available for analyzing recent income distribution in China. The Gini coefficients calculated from the data are 0.496 at the individual level and 0.483 at the family

[4] The variable "income" is derived from question R25 in the 2005 census survey, which asked, "Last month how much money did you make (alternatively, you can divide your annual income by 12)". This question was answered only by individuals who reported working during the week prior to the survey. Consequently, this measure reflects monthly earnings and may not fully capture individuals' income over a longer period. However, this measure is commonly used in the literature to study income inequality in China (e.g., Xie and Zhou, 2014). We follow this practice as the 2005 census is the most representative dataset available for analyzing recent income distribution in China.

level.[5] Xie and Zhou (2014) also use the 2005 mini-census as one of their primary datasets to analyze income inequality in China. They demonstrate that the Gini coefficient derived from the data closely aligns with that reported by Li et al. (2013) from the 2007 survey of the Chinese Household Income Project (CHIP, 2007). Furthermore, they calculate Gini coefficients for China over the past four decades using data from the World Institute for Development Economics Research of the United Nations University, finding that their 2005 estimate is similar to that obtained from the mini-census, which supports the reliability of the 2005 mini-census for studying income inequality during this period.

Following Meng et al. (2015), we use the 1990 census data to identify the rural and urban population sizes for the 1950–1985 birth cohorts and calculate the rural population share for these birth cohorts at the prefectural level, defined as the proportion of the population born in rural areas within each prefecture. We consider respondents' registered residence (*hukou*) in the census year as their birthplace in the 1990 census. However, this information may not be entirely accurate, as hukou statuses can change over time, with rural-born children sometimes acquiring urban hukous later in life. Additionally, rural residents may migrate across provinces and obtain hukous in other cities over the years.

Nevertheless, these factors may not pose significant issues. As noted by Meng et al. (2015), rural populations are defined as households officially registered as agricultural (holding rural hukous), and these designations were assigned in the early 1950s. Moreover, extremely limited mobility occurred from rural to urban households between then and 1990. They also show that, due to strict policies against labor migration, very little migration across regions took place before 1990.[6]

Panel A of Table 1 shows the summary statistics for the main variables at the prefectural level. The mean Gini coefficient for the 1950–1985 birth cohorts in 2005 is approximately 0.403, with a standard deviation of 0.055. For the pre- and post-treatment groups, corresponding to the 1950–1956 and 1962–1980 birth cohorts, the mean Gini coefficients are 0.416 and 0.400, respectively.

Panel A also indicates that the variation in the Gini coefficient across prefectures is relatively modest. However, this does not imply that income inequality is negligible nationwide. In fact, regional disparities are a significant contributor to overall income inequality at the national level. For example, even if the Gini coefficients within both the eastern and western regions are relatively low, substantial

[5] Since we examine the income inequality by birth cohort within a region, and members of the same family may belong to different cohorts, we primarily analyze the Gini coefficient at the individual level. As shown earlier, the Gini coefficients at the individual and family levels derived from the census data are very similar, so this choice should not make a significant difference.

[6] We exclude the 1982 census data in calculating the rural population share for post-famine birth cohorts due to the lack of accurate information on respondents' hukou status and the absence of data for individuals born between 1982 and 1985. Similarly, we do not use the 2000 and 2005 census data, as rural-to-urban and regional migration became more prevalent after 1990, making it challenging to accurately determine the birthplace of those born between 1962 and 1985.

wealth differences between these regions can still result in high income inequality across the entire country.

The mean and standard deviation of the rural population share for the 1950–1985 birth cohorts at the prefectural level are 0.761 and 0.187, respectively, with similar values observed for the 1950–1956 and 1962–1980 birth cohorts. In most prefectures, the rural population is significantly larger than the urban population, though the rural population share varies substantially across different prefectures.

Due to the lack of mortality rate data at the prefectural level during the famine, we employ an alternative measure of famine severity for each prefecture. Following a method similar to that of Meng et al. (2015), we use the 1990 census data to calculate the average rural birth cohort size gap for 1959–1961. This gap reflects to the extent which the size of these birth cohorts diminished during the famine, serving as an indicator of famine severity at the prefectural level. The last row of Panel A shows that the mean ratio of the average rural birth cohort size gap for the 1959–1961 birth cohorts is approximately 0.405, with a standard deviation of 0.168. This indicates that, on average, the rural birth cohort size at the prefectural level decreased by 40% during the famine, with considerable variation observed across prefectures.

We use a dummy variable indicating whether a prefecture experienced rainfall shock during the famine as an instrument for famine severity. The mean value of this variable is 0.374, with a standard deviation of 0.486. Panel B of Table 1 also includes summary statistics pertinent to the DID regressions.

3. China's Great Famine (1959–1961)

China's Great Famine (1959–1961), one of the most severe famines in human history, led to substantial population loss. Yang (2013) estimates that 36 million people perished due to starvation, while an additional 40 million births were prevented. Numerous studies on the Great Famine concur that a sharp decline in food production in 1959, coupled with high government procurement from rural areas, were the primary causes of the famine (Meng et al., 2015). This study primarily investigates the long-term effects of the Great Famine on China's population structure. We propose that the famine serves as an exogenous shock to China's fertility structure, with a significant long-term impact on the rural–urban population composition in the post-famine period.

Rural areas were disproportionately impacted by the famine compared to urban areas, with the majority of deaths occurring among rural residents. While most prime-age adults survived (Thaxton, 2008), the elderly and young children were severely affected, with young children accounting for over half of the total deaths (Ashton et al., 1984; Spence, 1991). Following the end of the famine, rural fertility rebounded significantly, soon reaching a historical peak. Consequently, the fertility gap between rural and urban households widened significantly and remained high over an extended period. In the following sections, we present several figures to illustrate the short- and long-term effects of the famine on post-famine fertility structure and population composition.

Given that the famine was driven by crop failure and excessive government procurement, primarily impacting rural areas, one might assume that major agricultural provinces—those more dependent on food production and with a larger rural population share—would have been the hardest hit. However, this assumption does not hold true.

Figure 3 illustrates the correlation between the rural population share in 1958 (prior to the famine) and famine severity as measured by the average excess mortality rate in rural areas (deaths per 1000 people) during 1959–1961, across all provinces. The figure shows no significant correlation between the pre-famine rural population share and famine severity across provinces. A regression of the 1958 rural population share on the excess mortality rate yields an insignificant coefficient of 0.005 (p-value≈0.15), which is effectively zero. Excess mortality rates vary significantly across provinces. For instance, in provinces with a rural population share exceeding 80%, some show excess mortality rates are as high as 30‰, while others have rates close to zero. These results indicate that famine severity was uncorrelated with the pre-famine rural population share at the provincial level,[7] suggesting that the famine could have acted as an exogenous shock to the population structure in the affected regions.

As previously mentioned, the survival rate of prime-age adults was high during the famine, while the elderly and young children were severely affected. Intuitively, if most prime-age adults survived while many young children died in rural areas during the famine, rural families would be likely to have more children after the famine to compensate for the population loss. Therefore, we anticipate a significant rebound in rural fertility following the famine.

Figure 4 presents the total fertility rate (TFR) for rural and urban areas at the national level from 1950 to 1985, using data from Yao and Yin (1994). The rural TFR experienced a marked rebound after 1961, quickly reaching a peak, while urban fertility also rose significantly shortly after the famine. Existing literature suggests that although urban areas did not suffer extensive fatalities during the famine, urban families delayed their birth plans due to the hardships of that period (Yang, 2013). Consequently, urban fertility saw a notable but temporary rebound, lasting only 1 or 2 years.

In contrast, rural families not only postponed their birth plans but also experienced substantial population losses during the famine. Consequently, the impact of the famine on post-famine rural fertility was more significant and long-lasting. This led to a pronounced widening of the rural–urban

[7] Lin and Yang (2000) show that a higher rural population share was associated with a higher mortality rate at the provincial level during the famine. This result is not surprising, as the rural population was more affected by the famine than the urban population, meaning a higher proportion of rural residents would mechanically increase the overall provincial mortality rate. However, this finding does not contradict our assertion that famine severity in rural areas is uncorrelated with the pre-famine population structure.

fertility gap after the famine. Figure 5 supports this finding: before the famine, rural fertility was only slightly higher than urban fertility, with the rural–urban TFR ratio being just above 1. After the famine, this ratio rose significantly, exceeding 2 and remaining elevated for an extended period.

This lasting impact of the famine on post-famine fertility structure is unsurprising, as rural families needed time to recover from the significant population loss during the famine. Additionally, the trauma of the famine likely motivated rural families to have more children as a precautionary measure against potential future crises.

An alternative hypothesis for the significantly high post-famine rural–urban fertility ratio is that urban areas in China began their demographic transition earlier than rural areas due to higher income levels. However, China's economic development remained stagnant for an extended period before the introduction of the reform and opening-up policy in 1978, and no evidence suggests that economic development was the primary driver of China's demographic transition before 1978. Thus, the substantial increase in the rural–urban fertility ratio observed shortly after the famine is unlikely to have been driven by economic development.

Furthermore, the more stringent population control policies in urban areas may have also contributed to lower urban fertility. However, China only began to implement its population control policy in the early 1970s (Zhang, 2017), whereas the rural–urban fertility ratio rose substantially shortly after the famine, which occurred a decade prior to the policy's implementation. Therefore, China's two-tier population control policy cannot be the primary cause of the high post-famine rural–urban fertility ratio.

We further examine the impact of the famine on rural population growth by comparing growth rates over time across provinces with varying levels of famine severity. Figure 6 illustrates the rural population growth rates for Shaanxi and Anhui Provinces from 1950 to 1998. Shaanxi experienced minimal excess mortality during the famine, whereas Anhui faced extremely high excess mortality. The figure reveals that the rural population growth rates in both provinces rebound significantly after the famine. Notably, Anhui, which endured greater population loss during the famine, exhibited a more pronounced rebound in rural population growth. Before the famine, Anhui's rural population growth rate was generally lower than that of Shaanxi. However, it exceeded Shaanxi's rate shortly after the famine and maintained this higher level for an extended period. It is not surprising that recovery from the severe population loss caused by the famine required considerable time in the most affected provinces.

Given that the famine primarily impacted rural areas while urban areas were minimally affected, it could have increased the post-famine rural population share over a long period. Figure 7 illustrates the correlation between the average excess mortality rate in rural areas during 1959–1961 and the rural population share for the 1962–1985 birth cohorts across all provinces and municipalities. The figure clearly shows a positive correlation between these two variables: provinces where rural areas experienced significant population loss during the famine also had higher post-famine rural population shares. This observation aligns perfectly with our expectations.

4. Great Famine, Differential Fertility, and Income Inequality

We estimate the effect of the rural population share (by birth cohort) on the Gini coefficient for those same birth cohorts several decades later at the prefectural level. Our objective is to explore how the differential fertility between rural and urban households after the famine affected income inequality among the post-famine birth cohorts. In practice, we use the rural population share of the post-famine birth cohorts as a proxy for the fertility differential between rural and urban households. Although there is a close relationship between differential fertility and the population composition of the next generation, a subtle distinction exists between the two concepts. In the Appendix, we demonstrate that under certain scenarios, these two concepts could be equivalent.

4.1 The Effects of the Famine on Differential Fertility and Income Inequality: IV Estimates

In Section 3, we provide suggestive evidence that the famine may have had significant effects on the rural population share and income inequality of the post-famine birth cohorts. We now empirically identify the famine's these potential effects at the prefectural level.

Mortality rate data during the famine at the prefectural level are not available. Meng et al. (2015) use the 1990 census data to calculate the birth cohort size of survivors during the famine within the agricultural population as a proxy for famine severity at the county level. They show that birth cohort size during 1959–1961 is negatively correlated with famine severity, as it reflects the reduced fertility and increased mortality caused by the famine. Furthermore, they argue that this famine severity index has several advantages over using mortality rate data.

Adopting a similar approach, we first extract the rural birth cohort size of each year from 1950 to 1970 for each prefecture using 1990 census data and fit a trend line of the prefecture's rural birth cohort size over this period. We then calculate the gap between the actual and trend values of the rural birth cohort size during the famine (1959–1961). Finally, we obtain the ratio of this gap and the corresponding trend value as a proxy for the famine severity at the prefectural level.[8] For further details, see the Appendix.

[8] We select the period 1950–1970 to fit the fertility trend line because the famine occurred precisely in the middle of this timeframe. Additionally, as previously mentioned, China began implementing its population control policies after 1970, leading to a decline in fertility rates. Therefore, extending the time trend beyond 1970 would introduce the effects of other factors, such as population control

We begin by estimating the following equation to examine the correlation between famine severity and either the rural population share or the Gini coefficient of post-famine birth cohorts at the prefectural level:

$$Y_p = c + \beta FM_p + \delta_2 X_p + \varepsilon_{p2}, \quad (1)$$

where Y_p represents the dependent variable of interest (either the rural population share or the Gini coefficient) for post-famine birth cohorts (1962–1985) in prefecture p, FM_p denotes famine severity, measured by rural birth cohort size gap during the famine in prefecture p, X_p is a vector of prefectural level control, c is a constant term, and ε_{p2} represents the error term. The coefficient β is the parameter of interest.

We include a set of prefectural characteristics in 2005 into the regressions, as these factors may have a direct impact on income inequality at that time. Specifically, we control for characteristics related to regional economic development, including GDP, income per capita,[9] the shares of agricultural and industrial output in GDP, and the proportion of the immigrant population within the total population.[10] Additionally, since population density and social welfare policies can affect income inequality, we include controls for population density and fiscal expenditure per capita in 2005.

Table 2 presents the estimation results. Columns (1)–(3) report the results for the rural population share, while Columns (4)–(6) show the results for the Gini coefficient. These correlations are significant and remain stable, robust, regardless of whether control variables are included or excluded. The results suggest that greater famine severity is associated with a higher rural population share and an increased Gini coefficient among post-famine birth cohorts.

Famine severity is clearly endogenous and correlated with regional characteristics. While a DID framework can absorb these effects through prefecture fixed effects, the cross-sectional OLS estimates presented above are limited to suggesting correlations between famine severity and the variables of interest, rather than establishing causal relationships. To address this issue, we use the climate shock experienced during the famine to instrument for famine severity. As established in the literature, climate disasters played a nonnegligible role in the sharp decline of agricultural productivity during the famine (Kueh, 1995; Yao, 1999; Lin and Yang, 2005). Thus, extreme weather events likely impacted regional grain output and famine severity during 1959–1961. Moreover, since extreme

policies, confounding the analysis. Notably, the rural birth cohort size gap derived from the 1950–1970 period shows a strong correlation with famine severity at the provincial level. This correlation diminishes when the timeframe is extended to include the 1970s and 1980s, thereby confirming the validity of our chosen period for analysis.

[9] Alternatively, we could control for GDP per capita, as it is strongly correlated with income per capita. However, since income per capita is more relevant when examining income inequality, we choose to control for income per capita instead.

[10] The share of immigrant population within the total population is another aspect of population composition that can directly affect the Gini coefficient. It also indicates the attractiveness of a region to migrants, highlighting an important regional characteristic. We will discuss how to address the issues related to migration later.

weather can be viewed as an exogenous shock to agricultural production, it is unlikely to affect the long-term outcomes through mechanisms unrelated to the famine. Further discussions on the validity of using extreme weather as an instrumental variable for famine severity are provided in the Appendix.

Using extreme weather events during 1959–1961 as an instrument variable for famine severity, we examine the impacts of the famine on the rural population share and the income inequality in 2005 of post-famine birth cohorts at the prefectural level. Specifically, we estimate the following 2SLS model:

$$M_p = c_1 + bRainShock_p + \delta_1 X_p + \varepsilon_{p1}, \quad (2)$$

$$Y_p = c_2 + \beta FM_p + \delta_2 X_p + \varepsilon_{p2}, \quad (3)$$

where most variables are the same as in Equation (1). The new variable, $RainShock_p$, is a dummy that equals 1 if prefecture p experienced extreme rainfall shocks during the famine and 0 otherwise. β is the parameter of interest, which aims to capture the causal effects of the famine on either the rural population share or the Gini coefficient of post-famine birth cohorts.

Table 3 report the estimation results. Columns (1)–(4) show the estimated effects of the famine on the rural population share for the1962–1985 birth cohorts. The results indicate that the famine significantly increased the rural population share in the post-famine period. Specifically, the IV estimates in Columns (2)–(4) indicate that a 10% increase in the average rural birth cohort size gap during the famine is associated with an approximately 0.1 increase in the post-famine rural population share, representing a substantial impact.

Similarly, Columns (5)–(8) present the estimates of the famine's effect on the Gini coefficient for the1962–1985 birth cohorts. The findings suggest that the famine had a significant impact on income inequality within these cohorts. In particular, the IV estimate in Column (8) indicates that a 10% increase in the average rural birth cohort size gap during the famine corresponds to an approximately 0.03 increase in the Gini coefficient, signifying a nonnegligible effect on income inequality.

In the regressions above, we use the 1990 census data to calculate the rural population share of each prefecture, based on respondents' hukou status at the time of the census. To calculate the Gini coefficient, we use the 2005 census data, relying on respondents' place of residence and workplace. All current labor force members working in each prefecture are included to derive the 2005 Gini coefficient for that prefecture. However, since individuals born in one prefecture may migrate to others over time, this approach might have limitations. Although migration was uncommon before 1990, there was a steady inflow of migrants from the western and central regions to the more developed eastern regions by 2005. Given that some migrant workers in each prefecture in 2005 may have originated from other areas, this could pose challenges to our strategy. To address this issue, we use information on respondents' migration status from the 2005 census data, as discussed in the Appendix. Our findings remain robust even after fully accounting for potential population migration across regions.

4.2 The Effect of the Famine on Income Inequality: Potential Mechanisms

The findings above indicate that the famine increased both the rural population share and the Gini coefficient of the post-famine birth cohorts. The first effect is relatively straightforward: greater famine severity likely resulted in higher child mortality rates, followed by a significant rebound in fertility after the famine. However, the impact on the Gini coefficient is more complex and may involve multiple influencing mechanisms. This section aims to demonstrate that the increase in the post-famine rural population share could be one of the potential mechanisms underlying the observed relationship between the famine and income inequality.

We begin by examining the dynamics of the famine's impact on the population composition of post-famine birth cohorts. As mentioned earlier, the famine may have had a long-term effect on the rural population share of the post-famine birth cohorts, an effect which could gradually diminish over time. To analyze the dynamics of this impact on the rural population share, we employ a DID strategy. Specifically, we compare the rural population share across prefectures with varying levels of famine severity to examine whether the share in high-severity areas becomes significantly larger than in low-severity areas following the famine. In practice, we estimate the following dynamic version of the DID model:

$$Rshare_{pt} = c + \alpha_p + \gamma_t + \sum_{t=1951}^{1985} b_t(FM_p \times d_{pt}) + \sum_{t=1951}^{1985} \delta_t(X_p \times d_{pt}) + \varepsilon_{pt}, \quad (4)$$

where $Rshare_{pt}$ represents the rural population share of birth cohort *t* in or prefecture *p*, c is a constant, α_p is a prefecture fixed effect, γ_t is a birth cohort fixed effect, FM_p is the rural birth cohort size gap (in terms of ratio) during the famine in prefecture *p*, d_{pt} is a dummy that indicates whether the rural population share of prefecture *p* is for the birth cohort *t* (a birth cohort dummy), *and* X_p is a vector of prefectural level controls.

As previously discussed, we focus on the 1950–1985 birth cohorts for our analysis. In these estimates, we measure the time dimension of exposure to the famine with 35 birth cohort dummies (1951–1985), with the 1950 birth cohort serving as the reference group, which is omitted from the regression. Therefore, each coefficient b_t can be interpreted as an estimate of the effect of the famine on the rural population share for a specific birth cohort.

We estimate Equation (4) and present the b_t coefficients in Figure 8. Each dot on the solid line is the coefficient of the interaction between the birth cohort dummy and famine severity, with the 95-percent confidence interval indicated by the broken lines.

Figure 8 reveals that the estimates for the 1951–1956 birth cohorts are insignificant and close to zero but drop sharply for the 1957 birth cohort, becoming significantly negative. After the famine ends, the estimates increase dramatically, becoming significantly positive and remaining elevated for an extended period. The estimates start to decline after 1974 and eventually diminish to zero for the post-1980 birth cohorts. These results suggest that the famine likely had a long-term effect on post-famine fertility structure and population composition, with this effect gradually fading after 1980.

Although Figure 8 shows that the estimates for the 1951–1956 birth cohorts are close to zero and statistically insignificant, this does not imply that the famine had no effect on the rural population share of these cohorts. As previously discussed, the famine led to the deaths of many young children in rural areas, which could have reduced the rural population share of the pre-famine birth cohorts in affected regions. Given that the 1950 birth cohort serves as the reference group, it is plausible that the rural population share of the 1951–1956 cohorts was affected by the famine to a similar extent as that of the reference cohort. Therefore, the famine may have decreased the rural population share of the 1950–1956 birth cohorts. Consequently, the large positive estimates for the post-famine cohorts indicate that the famine led to a much higher rural population share of these cohorts compared to the pre-famine cohorts.

We now further examine the effects of the famine on the Gini coefficient across different birth cohorts in 2005. To do this, we estimate Equations (2) and (3) for both pre- and post-famine cohorts, with the results presented in Table 4. The findings indicate that the estimates for all cohorts—specifically the 1950–1956, 1962–1967, 1968–1973, 1974–1980, and 1981–1985 birth cohorts—are significantly positive. These results suggest that the famine may have significantly increased the Gini coefficient for all of these cohorts.

The estimate for the 1950–1956 birth cohorts is approximately 0.22, suggesting that a 10% increase in the average rural birth cohort size gap during the famine is associated with an approximately 0.022 increase in the Gini coefficient. In contrast, the estimates for the 1962–1980 birth cohorts are around 0.3, indicating a slightly larger effect of the famine on their Gini coefficient. It is surprising that the famine has a greater impact on the income inequality of post-famine birth cohorts—who did not experience the famine—than on that of pre-famine cohorts who did. To explain this, we need to comprehensively analyze various mechanisms through which the famine influenced the income inequality of the two groups.

Overall, there are three mechanisms through which the famine could affect income inequality: (1) The famine may have had a long-lasting negative impact on regional characteristics, such as institutions and productivity, ultimately hindering the economic development of the affected regions. This could contribute to higher income inequality among both pre- and post-famine cohorts in the long term, with pre-famine cohorts potentially being more affected as they directly experienced the famine; (2) The famine may have had a direct negative impact on individuals in the pre-famine cohorts who experienced the famine, particularly rural residents, leading to higher income inequality for these cohorts; (3) The famine may have induced a much higher rural population share of post-famine cohorts compared to pre-famine ones, potentially leading to a higher Gini coefficient for the former.

Based on the analysis above, if population composition did not play a role, or if Mechanism 3 were absent, the Gini coefficient of the pre-famine cohorts would be expected to be higher than that of the post-famine cohorts, all else being equal. However, since we find that the famine had a greater effect on the Gini coefficient of the post-famine birth cohorts than the pre-famine cohorts, we can infer that Mechanism 3 matters and that the population compositional effect dominates the other direct effects of the famine on the income inequality of the pre-famine cohorts.

Finally, the estimate for the 1981–1985 birth cohorts is smaller but remains significant, indicating that the famine continued to have a significant effect on the Gini coefficient of these cohorts. Since the effect of the famine on the rural population share of these cohorts had already diminished, this suggests that the impact on their income inequality likely operated through other mechanisms, probably Mechanism 1. Therefore, the famine affected the income inequality of different birth cohorts through varying mechanisms, which can help clarify our subsequent IV estimation within the DID framework.

In our analysis above, we primarily use extreme weather during the famine as an IV for famine severity for our identification. However, weather data is only available for 139 prefectures, representing less than half of all prefectures, which limits our analysis. In the Appendix, we provide evidence that these 139 prefectures do not significantly differ from the full sample in most observable characteristics. However, we cannot completely rule out the possibility of sample selection bias arising from unobservable characteristics. Therefore, the findings based on this IV have limitations, and we rely more on our subsequent DID strategy for identification.

4.3 Population Composition and Income Inequality: IV Estimates within a DID Framework

Given that the famine may have induced a much higher rural population share for the post-famine cohorts than the pre-famine cohorts, we can identify the effect of the rural population share on the income inequality of the post-famine cohorts within a DID framework, with the pre- and post-famine birth cohorts as the pre- and post-treatment groups, respectively. Specifically, we use the famine severity as an instrument variable for the post-famine rural population share to estimate the effect of population composition on the income inequality at the prefectural level.

We first need to confirm the validity of this IV. As discussed earlier, the exclusion restriction condition requires that the famine only affects the income inequality of the post-famine birth cohorts through its effect on the population composition of theses cohorts. However, given the various influencing mechanisms analyzed above, this condition is unlikely to hold. Since we have already explored all possible mechanisms through which the Famine could influence the income inequality several decades later, we can incorporate these potential mechanisms into our DID framework to assess the validity of the IV.

As discussed earlier, Mechanism 1 affects both the pre- and post-famine birth cohorts and would contribute to higher income inequality for both groups. Therefore, we can largely control for these effects by including prefecture and birth cohort fixed effects in a DID framework. Furthermore, Mechanism 2 would lead to a higher income inequality of the pre-famine birth cohorts, whereas Mechanism 3 would result in a higher income inequality of the post-famine birth cohorts. Therefore, if the DID estimates show that the income inequality of the post-famine birth cohorts is significantly higher than that of the pre-famine cohorts, indicating that the effect of Mechanism 3 dominates that of Mechanism 2, then these estimates would be a lower bound of the effect of population composition on the income inequality of the post-famine birth cohorts.

In our DID framework, we select the 1962–1980, whose population composition was significantly affected by the famine, as the treatment group, and the 1950–1956 birth cohorts as the control group. Meanwhile, we use famine severity as an instrument for the rural population share of the post-famine birth cohorts. Within this framework, a significant first-stage coefficient suggests that the famine increased the rural population share of the post-famine cohorts relative to the pre-famine cohorts. A significant second-stage coefficient indicates that this higher rural population share caused by the famine led to a higher Gini coefficient for these cohorts. In practice, we estimate the following regressions:

$$Rshare_{pt} = c_1 + \alpha_{1p} + \gamma_{1t} + b(FM_p \times T_t) + \delta_1(X_p \times T_t) + \varepsilon_{pt1}, \quad (5)$$

$$Gini_{pt} = c_2 + \alpha_{2p} + \gamma_{2t} + \beta Rshare_{pt} + \delta_2(X_p \times T_t) + \varepsilon_{pt2}, \quad (6)$$

where $Rshare_{pt}$ is the rural population share of birth cohort *t* in or prefecture p, c_1 (c_2) is a constant, α_{1p} (α_{2p}) is a prefecture fixed effect, γ_{1t} (γ_{2t}) is a birth cohort fixed effect, FM_p is the rural birth cohort size gap (in terms of ratio) during the famine in prefecture p, T_t is a dummy variable that takes the value of 1 if birth cohort *t* belongs to the 1962–1980 birth cohorts, and 0 otherwise, X_p is a vector of prefectural level controls, and $Gini_{pt}$ is the Gini coefficient for birth cohort t in prefecture p in 2005. β is the estimator of interest.

The estimation results are presented in Table 5. Column (1) of Table 5 reports the reduced-form result and shows that the famine severity is significantly correlated with the Gini coefficient for the 1962–1980 birth cohorts in 2005 at the prefectural level. Specifically, an 1% increase in the average rural birth cohort size gap during the famine corresponds to an increase of the Gini coefficient of the post-famine birth cohorts in 2005 by 0.049. Columns (2)–(4) present the IV estimates, which remain robust as control variables are gradually included in the regressions. Column (4) shows that the coefficient of the rural population share is approximately 1.13, which implies that a 0.1 increase in rural population share would increase the Gini coefficient by 0.113, or an increase of 13.5% (0.1/0.74, where 0.74 is the mean of rural population share) in rural population share would increase the Gini coefficient by 28.3% (0.113/0.40, where 0.40 is the mean of the Gini coefficient).

The lower panel shows that the coefficient for the famine severity in the first-stage regression is about 0.04, which indicates that an increase of 10% in the average rural birth cohort size gap would increase the post-famine rural population share by 0.4%, which is a non-negligible impact. Furthermore, the first-stage F statistic is above 20, implying that the instrument is not weak.

One major concern is the potential sample selection issue arising from the famine. Many rural children died during the famine, and the majority were likely from lower-income families within rural areas. Their absence from the pre-famine sample presents a typical case of sample selection. Additionally, these lower-income families who lost children during the famine would likely have had more children afterward, leading to higher post-famine rural fertility. Thus, the observed increase in post-famine fertility in rural areas can also be attributed to higher fertility among these poor families. This sample selection issue in both the pre- and post-famine birth cohorts complicates the interpretation of our results.

However, this potential sample selection may actually strengthen, rather than weaken, our findings. While we broadly categorize families as rural (low-income) and urban (high-income), income disparities still exist within both groups. We argue that higher fertility among poorer families contributes to greater income inequality in the next generation. If the famine disproportionately affected the poorest rural families, and their fertility rebounded significantly afterward, this would have contributed to increased income inequality, which is consistent with our hypothesis. In essence, the fact that rural children from poorer families were more severely impacted by the famine implies that the famine acted as a substantial shock to fertility among the poor, supporting our assertion that higher fertility among low-income families exacerbates income inequality in the following generation.

Furthermore, the birth cohorts we examined above range from 1950 to 1980, naturally raising concerns that these cohorts were born in completely different times and thus may not be comparable. We next restrict our analysis to those birth cohorts who were born shortly before and after the famine to make our identification more convincing. Specifically, we select the 1954–1956 birth cohorts, who were born just before the famine and whose population composition was much less affected by the famine, as the pre-treatment group, and the 1962–1966 birth cohorts, who were born shortly after the famine and whose population composition was considerable affected by the famine, as the post-treatment group. In this way, we could avoid the potential confounders such as population control policies implemented after 1970, and the pre- and post-treatment groups are also more comparable.

Intuitively, the income inequality of the 1954–1956 birth cohorts who were directly exposed to the Famine should be higher than that of the post-Famine 1962–1966 birth cohorts if differential fertility does not matter. However, if we find that the opposite is true, we could deduce that the population compositional effect dominates the other direct effects of the Famine on the income inequality of the pre-Famine birth cohorts.

Table 6 reports the corresponding estimate results for this restricted sample. The estimates are slightly larger than those presented in Table 5 and are always significant at the 1% level. Such results indicate that the famine induced a higher rural population share of the post-famine birth cohorts, and as a higher share of population concentrate in rural areas, the income inequality of these cohorts increases accordingly.

In the Appendix, we present additional empirical results to examine the effects of the famine on the income inequality in the long term. We first perform DID regressions similar to those in Table 5, using the 1962–1980 and 1981–1985 birth cohorts—whose population composition was and was not affected by the famine, respectively— as the treatment and control groups. We find that, compared to the 1981–1985 birth cohorts, the famine induced a much higher rural population share for the 1962–1980 birth cohorts, which, in turn, led to a higher Gini coefficient for them.

To further validate these findings, we conduct a placebo test, using the 1950–1956 and 1981–1985 birth cohorts—both of which had population compositions largely unaffected by the famine—as the treatment and control groups, respectively. The results show that both the first- and second-stage coefficients are close to zero and insignificant. These results further confirm that population composition could be an important mechanism through which the famine has affected long-term income inequality. For more detailed results and discussions, please refer to the Appendix.

To further verify the validity of famine severity as an IV for the post-famine fertility structure, we introduce an additional IV to perform an overidentification test. As noted in the literature, China's population control policy is more strictly enforced in urban areas than in rural areas, leading to a significantly higher rural fertility rate (Zhang, 2017; Wang and Zhang, 2018). Therefore, we use the implementation intensity of the population control policy as another IV for China's rural–urban fertility structure or population composition. This policy serves as a valid IV because it directly affects fertility and is unlikely to influence the income inequality of affected cohorts through channels other than fertility, such as institutions and regional productivity several decades later. The results in the Appendix confirm that the overidentification test was passed, further supporting the validity of the IV.

5. Potential Mechanisms: Further Investigation

5.1 Theoretical Discussion

Chu and Koo (1990) prove that under three assumptions, a reduction in the reproductive rate of the poor will decrease the proportion of the poor and lead to a conditional stochastic dominance improvement in income distribution in the steady state and all the transition periods and vice versa. This section discusses whether these assumptions hold in the scenario of China's rural–urban divide.

Assumption 1 states that the lower income group experiences a faster natural increase rate, which is evidently true in China. This study divides the Chinese population into two groups: rural (low-income) and urban (high-income). As commonly observed, rural fertility has been consistently higher than urban fertility in China.

Assumption 2 concerns the mobility among the rich and poor and states that if a child from a poor family and a child from a rich family both fall into the poorest class, the child from the poor family is more likely to be poorer than the child from the rich family. Intuitively, if children from rich families become even poorer than children from poor families, then, a lower fertility of the rich (or a higher fertility of the poor) would reduce the number of poorest people and further decrease the income inequality of the next generation. Therefore, this assumption is necessary to reach the conclusion that a higher fertility of the poor increases rather than decreases income inequality.

In China, while both rural and urban children can end up in either the poor or rich class as they grow up, rural children are more likely to fall into the poor class compared to their urban counterparts. Given that China's income inequality is predominantly driven by the substantial rural–urban income gap, with the poorest populations concentrated in remote and underdeveloped rural areas, Assumption 2 likely holds true. Although some urban children may also fall into the poor class, their circumstances are generally better than those of rural children from remote, mountainous regions whose parents often live in persistent poverty.

Assumption 3 states that an increase in the fertility of the poor results in their children having a higher conditional probability of remaining poorer. This implies that higher fertility among the poor diminishes the upward mobility of their children. This assumption is particularly critical, as it highlights the key mechanism by which differential fertility across income classes affects income inequality of the next generation. The following sections will explore and empirically test the validity of this assumption in the context of China.

Intuitively, if an increasing new population concentrate in backward rural areas, it may become more difficult for rural children to acquire limited resources and opportunities critical for their later social success. Previous studies have shown that the tradeoff between the number of children and average child quality is more evident for rural families who face severe resource constraints, whereas such a tradeoff relationship diminishes or even vanishes in urban China (Li et al., 2008; Rosenzweig and Zhang, 2009). Thus, as a larger proportion of the new population concentrate in rural areas, rural children may become even less competitive than urban ones. Consequently, it would be more difficult for rural children to gain access to scarce resources (e.g., higher education opportunities) and subsequently get out of poverty and climb up the social ladder. Therefore, intergenerational mobility will also decrease correspondingly.

5.2 Evidence from the National College Entrance Exam

In contemporary China, receiving a college education is an extremely important opportunity and an ideal way of achieving social success for most youths, particularly for rural children, who generally lack other opportunities to ascend the social ladder. From 1977, rural and urban high school students have all taken the National College Entrance Exam (NCEE, or *gaokao* in Chinese) and competed for the limited quota of college admissions. Therefore, the NCEE outcomes can perfectly measure the rural–urban gap in the quality of basic education (elementary and high school) and serve as a reliable indicator of social mobility among rural and urban children.

The 2000 census data contains rich information on all enrolled college students in that census year. In the census questionnaire, questions R9 and R10 ask respondents when they moved to their current residence and where they migrated from, and question R11 further inquires about the type of their original residence, which can be used to identify their hukou type before college admission. Given that high school graduates can only take the NCEE in their hometowns where their hukous are registered, most college students took the NCEE in their hometowns and then migrated to the city where their colleges are located. Thus, we can accurately identify all college students' hometowns and hukou types based on the information from questions R9–11. We exclude college graduates from our analysis, as many of them migrated to other cities after graduation, making it difficult to identify their hometowns and original hukou types, especially for those who graduated many years ago.

These college students were typically 18–21 years old in the census year. That is, the majority of them belonged to the 1979–1982 birth cohorts in the 2000 census. As discussed earlier, given that migration was not common in 1990, we can obtain the rural and urban birth cohort size for each year of 1979–1982 and for all provinces from the 1990 census data. Furthermore, we can obtain the number of college students of these birth cohort (rural and urban) for all provinces from the 2000 census data, based on which we can calculate the probability of rural and urban youths being in college for each birth cohort at the provincial level and further calculate the rural–urban ratio of this probability. Such a rural–urban ratio measures the relative difficulty of gaining admission to college for rural and urban youths. We further combine this data set with the rural population share for these same cohorts (the 1979–1982 birth cohorts) obtained from the 1990 census and eventually obtain a panel for all the provinces.

With this panel data set, we examine whether a higher rural population share is associated with a lower rural–urban ratio of college admission probability. Specifically, we estimate the following two-way fixed-effects model:

$$\mathrm{Ruratio}_{\mathrm{pt}} = \mathrm{c} + \alpha_{\mathrm{p}} + \gamma_{\mathrm{t}} + \beta \mathrm{Rshare}_{\mathrm{pt}} + \varepsilon_{\mathrm{pt}}, \quad (6)$$

where $Ruratio_{pt}$ is the rural–urban ratio of the probability of gaining admission to colleges for birth cohort *t* in province *p*, *c* is a constant, α_p and γ_t represent province and birth cohort fixed effects, respectively, $Rshare_{pt}$ is the rural population share for birth cohort *t* in province *p*, and ε_{pt} is the disturbance term.

Column (1) of Table 7 reports the fixed-effects estimates of the effect of the rural population share on the rural–urban ratio of college admission probability (for youths aged 18–21). The coefficient of rural population share is approximately -0.51, significant at the 5% level. This suggests that a 1% increase in rural population share reduces the rural–urban ratio by 0.0051, or by 3% in percentage (considering the mean ratio of 0.17), indicating a substantial impact.

All 18–21-year-old youths are included in our analysis, as most college students belonged to these age cohorts. However, this approach may not be perfectly accurate. Some 18–21-year-olds may still be in high school and have not yet taken the NCEE, while others may have already graduated from college. Excluding these individuals could lead to underestimating the probability of gaining admission to college for each birth cohort. To address potential bias, we made the following adjustments:

1. Graduated Individuals: Some 18–21-year-olds had already graduated by the 2000 census and may have moved to other cities. However, they represented less than 2% of this group, so excluding them should not significantly affect results.
2. High School Students: We identified 18–21-year-olds still in high school and estimated their likelihood of future college admission. This involved calculating the ratio of college to high school students in each province and multiplying it by the number of high school students to project the number of potential college entrants.

Column (4) of Table 7 presents the FE results with these adjustments. The coefficient remains consistent with Column (1) and is significant at the 1% level, confirming the robustness of the findings.

Earlier, we show that the effect of the famine on the post-famine population composition diminishes over time, with estimates becoming insignificant for the post-1980 birth cohorts. Therefore, we can adopt a similar DID strategy to estimate the effect of rural population share on the rural–urban college admission ratio, with the 1979–1980 birth cohorts as the treatment group (affected by the famine) and the 1981–1982 birth cohorts as the control group.

Specifically, we estimate the following equations:

$$Rshare_{pt} = c_1 + \alpha_{1p} + \gamma_{1t} + b(FM_p \times T_t) + \delta_1(X_p \times T_t) + \varepsilon_{pt1}, \qquad (5')$$

$$Ruratio_{pt} = c_2 + \alpha_{2p} + \gamma_{2t} + \beta Rshare_{pt} + \delta_2\left(X_p \times T_t\right) + \varepsilon_{pt2}. \qquad (6')$$

These equations are similar to Equations (5) and (6), with the key difference being that the dependent variable in the second-stage regression is $Ruratio_{pt}$ (the rural–urban ratio of college admission probability for birth cohort *t* in province *p*) rather than $Gini_{pt}$ (the Gini coefficient for birth cohort *t* in province *p* in 2005). X_p is a vector of provincial-level characteristics in 2000, similar to those in Equations (5) and (6), and T_t is a dummy variable indicating whether birth cohort *t* belongs to the earlier (1979–1980) birth cohorts.

Columns (2) and (3) of Table 7 report the benchmark DID estimation results. Column (2) shows the reduced-form result, demonstrating that the instrument (the average rural excess mortality rate during 1959–1961) is negatively correlated with the rural–urban ratio of college admission probability for the 1979–1980 birth cohorts in 2000. This implies that provinces more severely affected by the famine faced greater challenges in college admission for rural children in the earlier post-famine birth cohorts. Column (3) presents the IV estimate, where the coefficient is double that of the FE estimate in Column (1).

Columns (5) and (6) report the DID estimation results incorporating the college admission adjustment. The coefficients remain consistent with those in the benchmark results, confirming the robustness of our findings.

5.3 Evidence from the Senior High School Entrance Examination

We now further examine the effect of rural population share on the rural–urban ratio of the probability of gaining admission to senior high school. Attending senior high school is an essential step before taking the NCEE and seeking college admission. Similar to the NCEE, rural and urban junior high school graduates took the Senior High School Entrance Examination (SHSEE), which, while less competitive than the NCEE, was still rigorous in the 1990s. We identify senior high school students and their information, such as hometown and hukou status, from the 2000 census data. These students were typically 15–18-year-old at the time of the census, meaning most belonged to the 1982–1985 birth cohorts.

We obtain the rural and urban birth cohort size for each year of 1982–1985 from the 1990 census data and the number of senior high school students for each birth cohort from the 2000 census data. This allows us to calculate the probability of rural and urban youths being in senior high school and derive the rural–urban ratio at the provincial level. We then combine this dataset with the rural population share for these cohorts to create a panel for all provinces.

We estimate Equation (6) using this data, where the dependent variable $Ruratio_{pt}$ is the rural–urban ratio of the probability of gaining admission to senior high school for birth cohort t in province *p*. Column (1) of Table 8 shows that the FE estimate of the coefficient of rural population share is approximately -1.5, significant at the 5% level. This indicates that a 1% increase in the rural population share reduces the ratio by 0.015, or by 5% in percentage terms, given the mean ratio of approximately 0.3).

To address potential biases, such as some youths still being in junior high school or having already graduated from senior high school, we identify 15–18-year-old respondents who had already graduated and included them in the senior high school sample. We also calculate the expected number of students still preparing for the SHSEE and included them in the sample. These adjustments provide a more reliable indicator of the rural–urban ratio of senior high school admission probability.

Column (4) of Table 5 reports the FE results after these adjustments, with the coefficient of rural population share at approximately -1.1, significant at the 1% level. The suggests that a 1% increase in rural population share reduces the ratio by 0.011, or by 3% in percentage terms, with an adjusted mean ratio of 0.35.

As discussed earlier, China's one-child policy (OCP) was more strictly implemented in urban areas than in rural ones. Such a two-tier population control policy may also induce a much higher rural fertility than the urban one. Therefore, we can use the OCP as an exogeneous shock on China's post-1980 fertility structure and population composition to identify the effect of rural population share on income inequality several decades later. Specifically, we use the implementation intensity of the OCP to instrument for the rural population share of the 1982–1985 birth cohorts at the provincial level to identify the effect of such plausible exogeneous variations in the rural population share on the rural–urban ratio of the probability of gaining admission to senior high school.

In practice, we use the fines due to the breach of the OCP to measure the implementation intensity of the policy at the provincial level. Under the OCP, households who exceed their fertility limit are forced to pay a fine (usually several years of household income) and are subject to a variety of other monetary punishments, such as the seizure of property and forced dismissal from government employment (Ebenstein, 2010). Such punishments are generally much more effective in urban areas than in rural ones. As discussed in Zhang (2017), rural residents received few benefits from the government; thus, they had nothing or little to lose, and the penalty (e.g., a fine) is typically ineffective because many rural families are too poor to pay them. Consequently, even if rural and urban households face the same fines, they impacts were different.[11] Intuitively, a higher fine may dramatically reduce urban fertility but only mildly cut down rural fertility, leading to a higher rural–urban fertility ratio or rural population share.

We estimate the following fixed-effects model：

$$Rshare_{pt} = c_1 + \alpha_{1p} + \gamma_{1t} + bFine_{pt} + \varphi_1 \mathrm{R}_{pt} + \varepsilon_{pt1}, \tag{5''}$$

$$Ruratio_{pt} = c_2 + \alpha_{2p} + \gamma_{2t} + \beta Rshare_{pt} + \varphi_2 \mathrm{R}_{pt} + \varepsilon_{pt2}, \tag{6''}$$

where $Fine_{pt}$ is the fine as measured in years of household income of province p in year t (1982–1985), and other variables are similar to those in Equations $(5')$ and $(6')$.

The fines in a province could be correlated with the provincial characteristics and may thus be endogenous. However, we have already controlled the province fixed effects in the above FE model, thereby alleviating this problem to a large extent.

Column (3) of Table 8 shows that the IV estimate is larger than the FE estimate in Column (1), significant at the 5% level. Column (6) of reports the IV estimate results with senior high school admission adjustment, with a coefficient larger than the corresponding FE estimate. Although the coefficients obtained from adjusted identifications are smaller than those in the benchmark regressions, they are more precisely estimated with much smaller standard errors.

Tables 7 and 8 suggest that a higher rural population share reduces the rural–urban ratios of college and senior high school admission probability at the provincial level. This implies that a greater

[11] Rural and urban families faced the same fines as measured by years of household income within each province. However, given that urban household income was much higher than the urban one, urban families generally paid a higher fine in absolute amount than rural families.

concentration of new population in rural areas hinders rural youths' educational opportunities, contributing to future income inequality by reducing intergenerational mobility.

To sum up, the comprehensive evidence presented above indicates that the plausible exogeneous shock of the Great Famine (1959–1961) on the post-famine fertility structure resulted in a higher rural population share for the 1962–1980 birth cohorts and further led to a higher Gini coefficient for these cohorts in 2005. Furthermore, as a larger share of the population concentrate in backward rural areas, the probability of gaining admission to senior high school and college for them decreased. These findings explain the mechanism through which differential fertility affects income inequality in the next generation: higher fertility of the poor reduces the upward mobility of their children.

6. Conclusions

China has created an economic growth miracle since implementing of the reform and open policy in 1978. Meanwhile, income inequality in China has also increased substantially, with the Gini coefficient remaining high after 2000. Numerous studies have explored the reasons for this high income inequality and proposed solutions to reduce it, but no consensus has been reached.

In this study, we show that China's Great Famine (1959–1961) has a long-lasting effect on the rural–urban fertility ratio, leading to a higher concentration of the new population in rural areas and significantly increased income inequality. Using famine severity as an instrument for post-famine rural–urban population composition, we find that a higher rural population share led to a higher Gini coefficient decades later. This finding is the first empirical evidence of the causal effect of differential fertility across income classes on the income inequality of the next generation.

The literature indicates that China's two-tier population control policy significantly increased the rural–urban fertility ratio. Our study suggests that this increase in the rural population share heightened income inequality at the national level. Therefore, China's high income inequality may be partially attributed to the Great Famine and the subsequent two-tier population control policy, both of which contributed to a higher concentration of the population in rural areas.

We also provide evidence that differential fertility across the rural–urban divide in China exacerbates income inequality by limiting social mobility for the next generation. The rural–urban divide and the hukou system, perpetuate inequality in opportunities between rural and urban children. A larger share of rural children intensifies this disparity, reducing their chances of upward mobility and escaping poverty. In other countries, while such a stark rural–urban divide may not exist, an invisible gap between the wealthy and the poor similarly creates opportunity inequality among children from diverse backgrounds. The most effective way to mitigate the adverse effects of differential fertility is to ensure equal access to critical resources, such as education and employment, regardless of family background. Achieving this remains a significant challenge for both policymakers and scholars.

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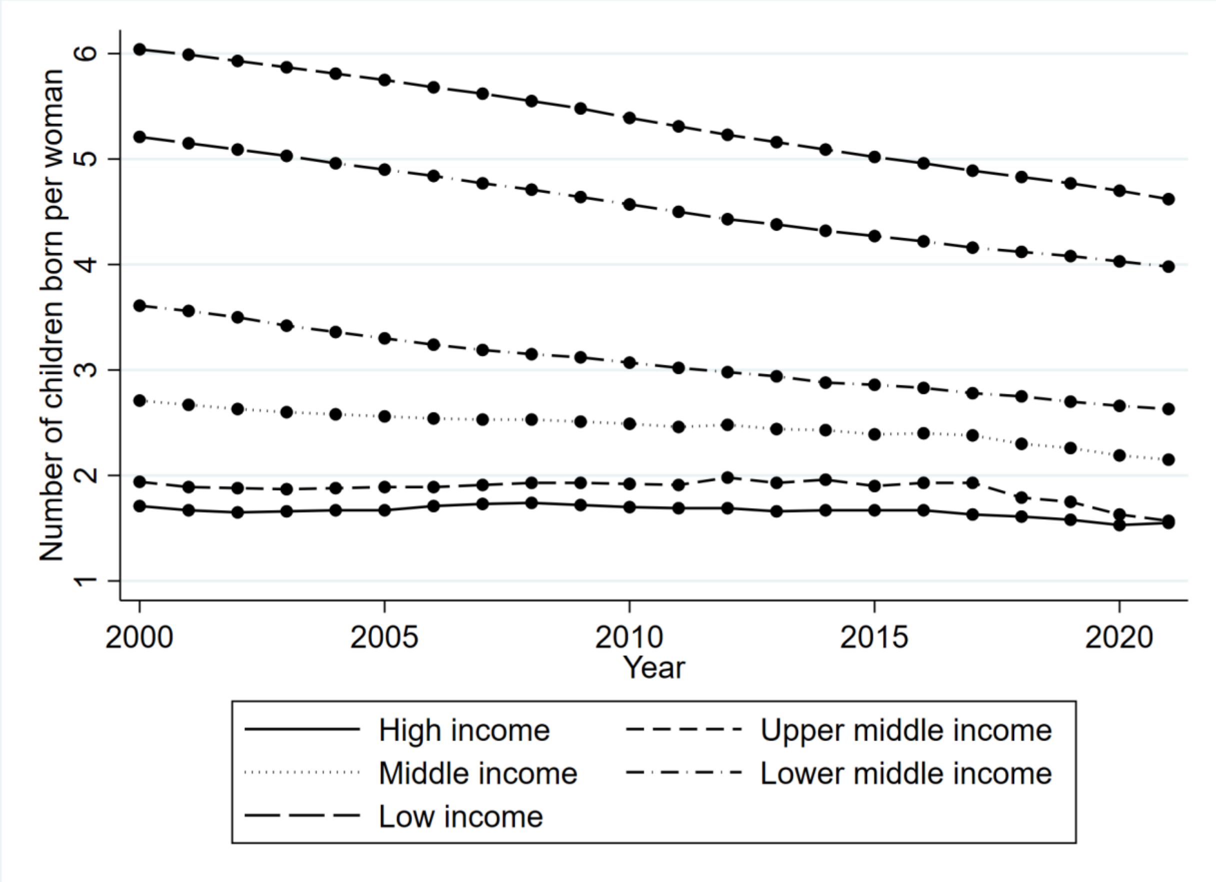
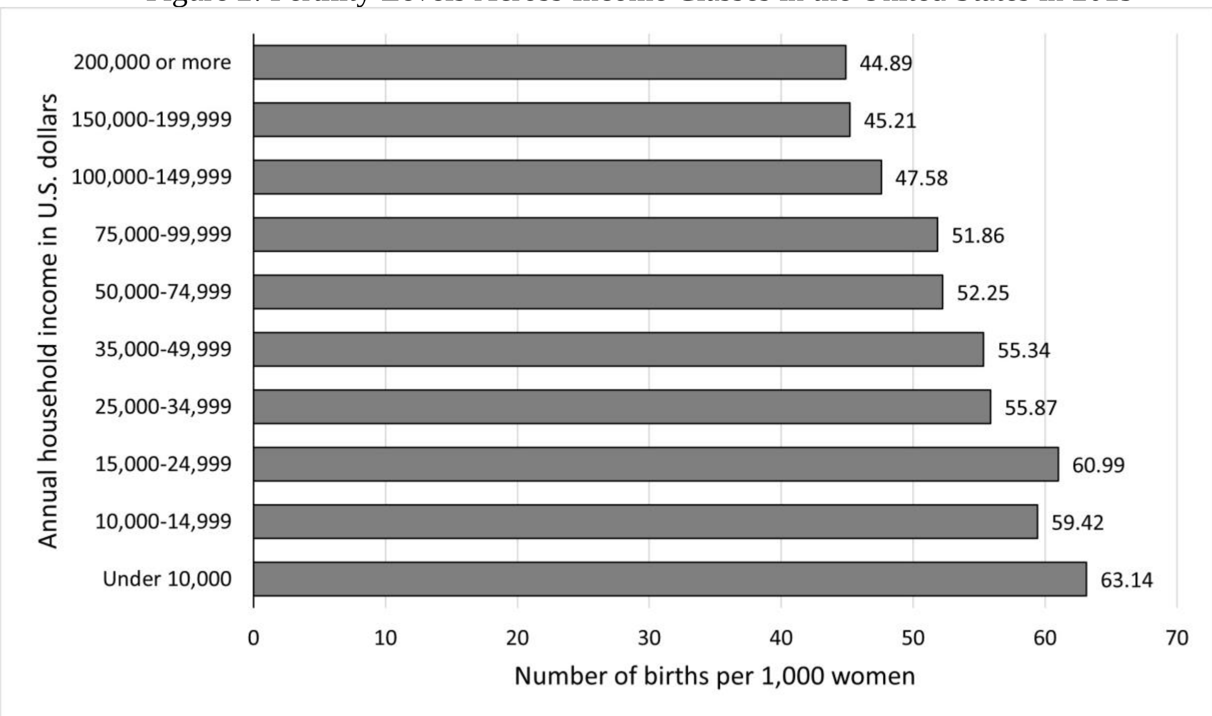
Figure 1: Trends in Fertility Levels Across Countries by Income Level, 2000–2021



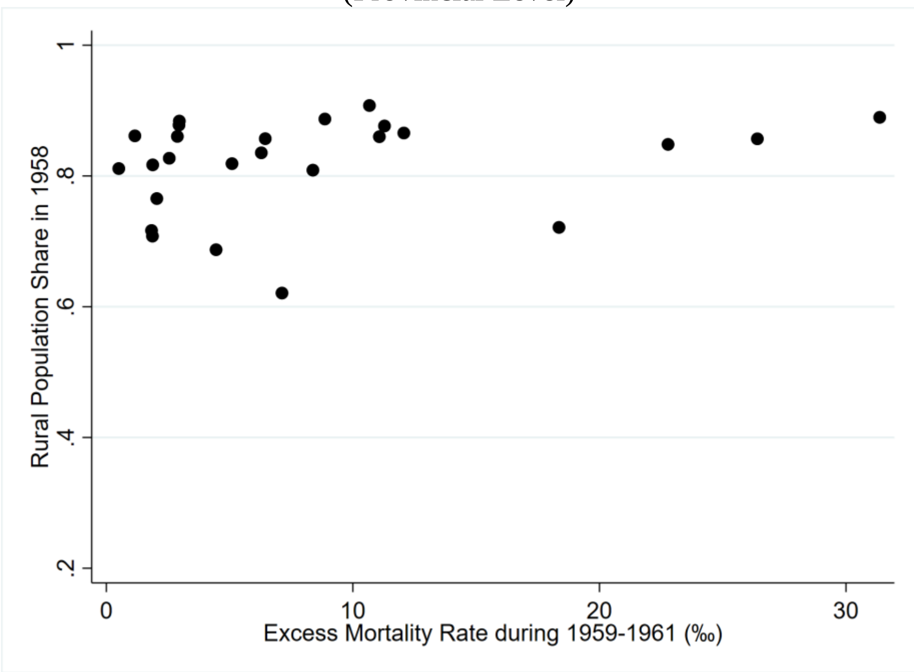
Source: United Nations

Figure 2: Fertility Levels Across Income Classes in the United States in 2019



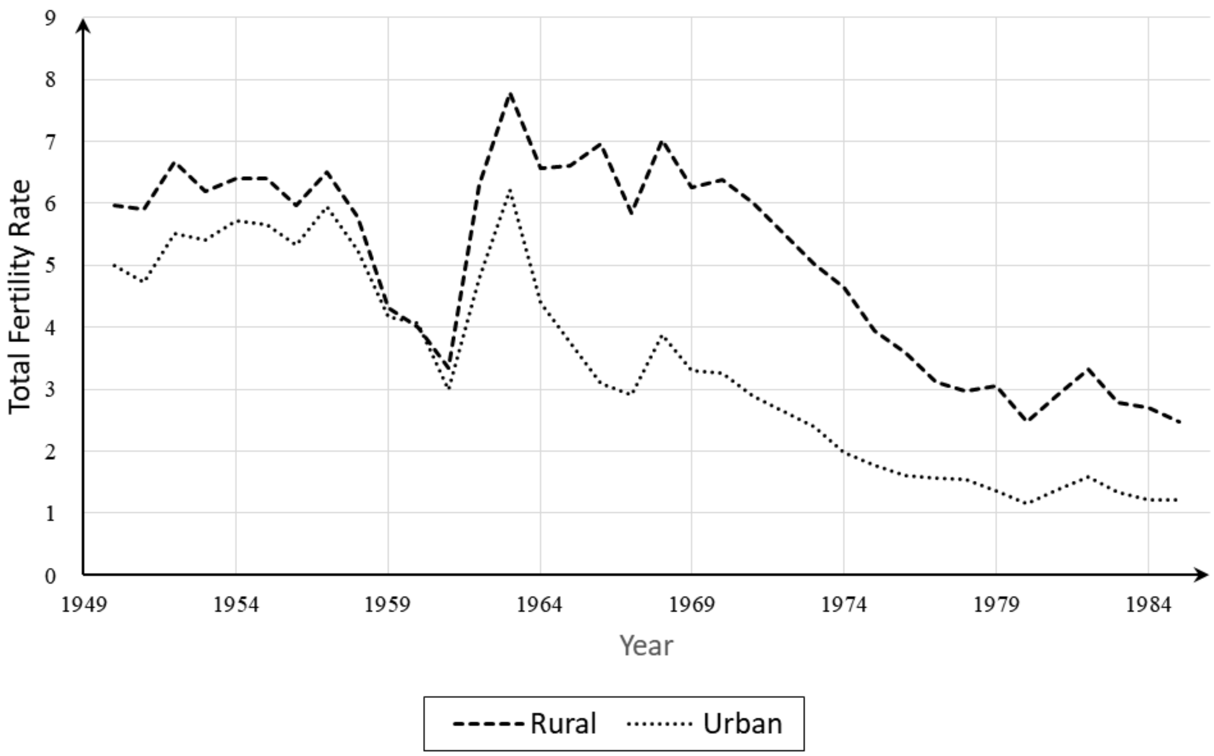
Source: U.S. Census Bureau

Figure 3: Rural Population Share in 1958 and Average Rural Excess Mortality Rate in 1959–1961 (Provincial Level)



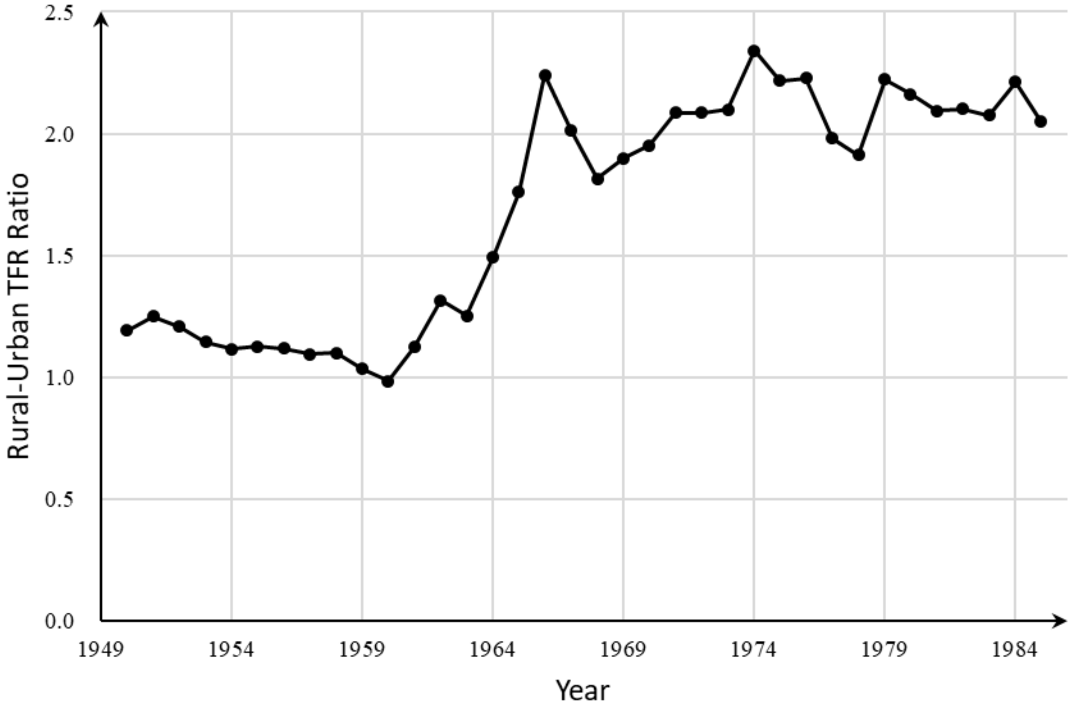
Source: Meng and Qian (2015)

Figure 4: Rural and Urban Total Fertility Rates (National Level)



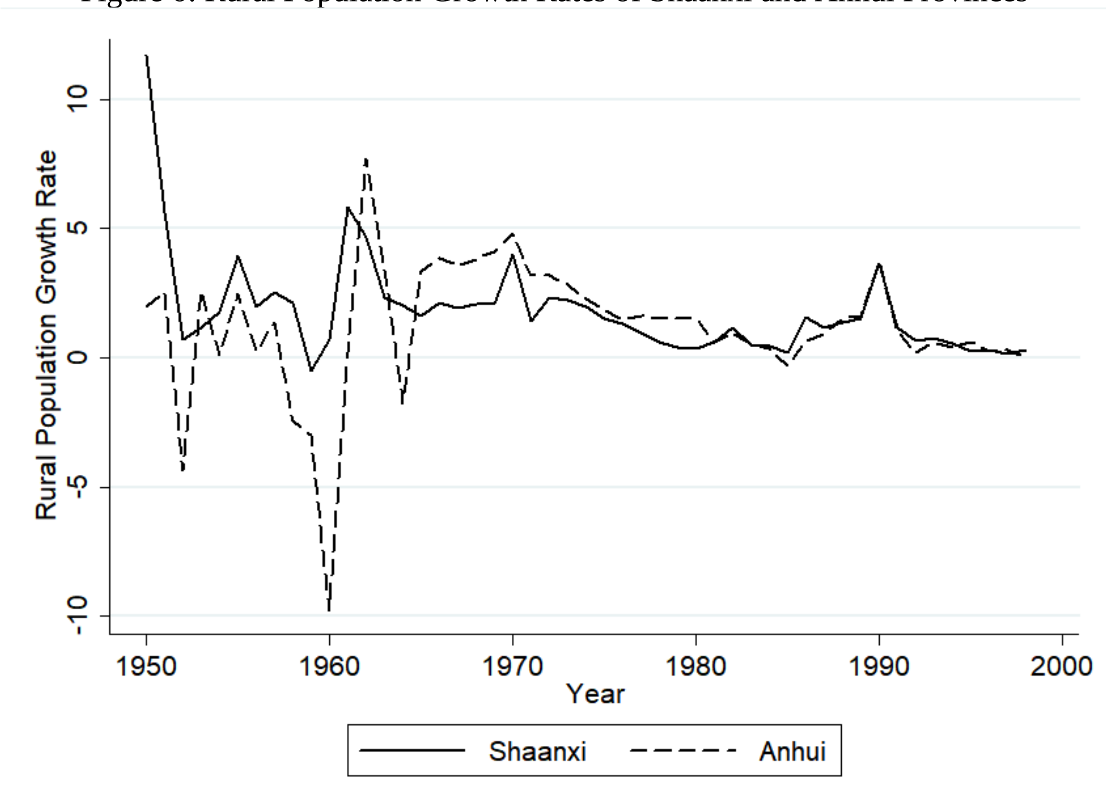
Source: Yao and Yin (1994).

Figure 5: Rural–Urban TFR Ratio (National Level)



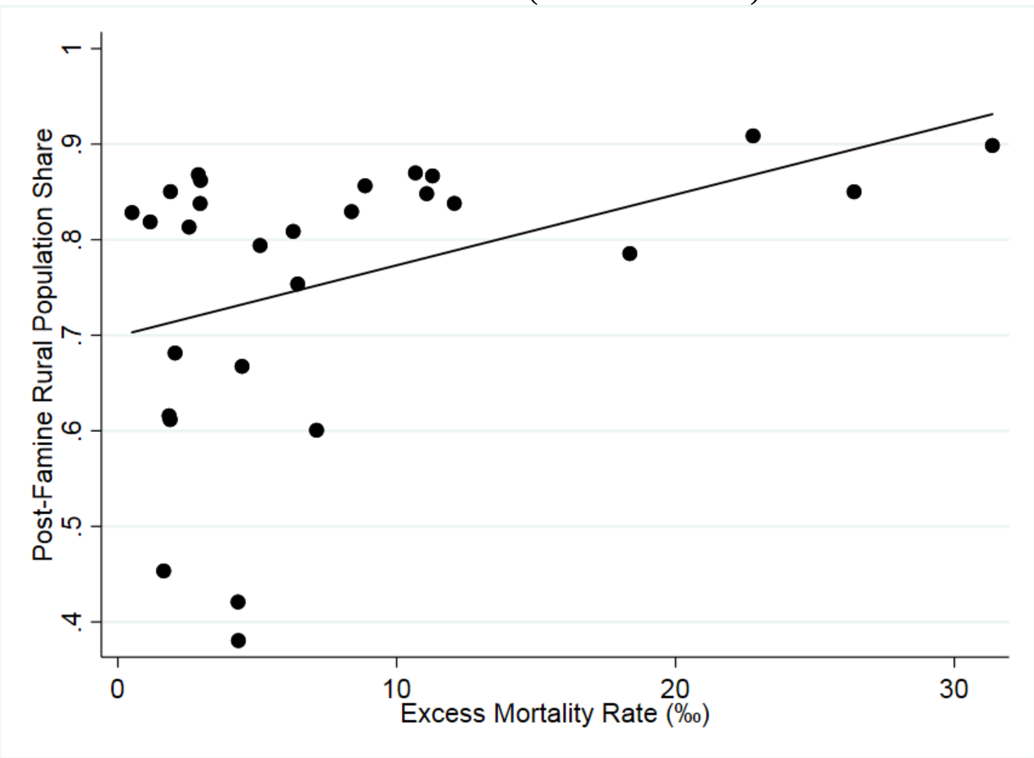
Source: Yao and Yin (1994)

Figure 6: Rural Population Growth Rates of Shaanxi and Anhui Provinces



Source: Meng and Qian (2015)

Figure 7: Rural Excess Mortality Rate during 1959–1961 and Rural Population Share for the 1962–1985 Birth Cohorts (Provincial Level)



Source: Meng and Qian (2015)

Figure 8: Coefficients of the Interactions Famine Severity×Birth Cohort (1951–1985) in Equation (4) (Prefectural Level)

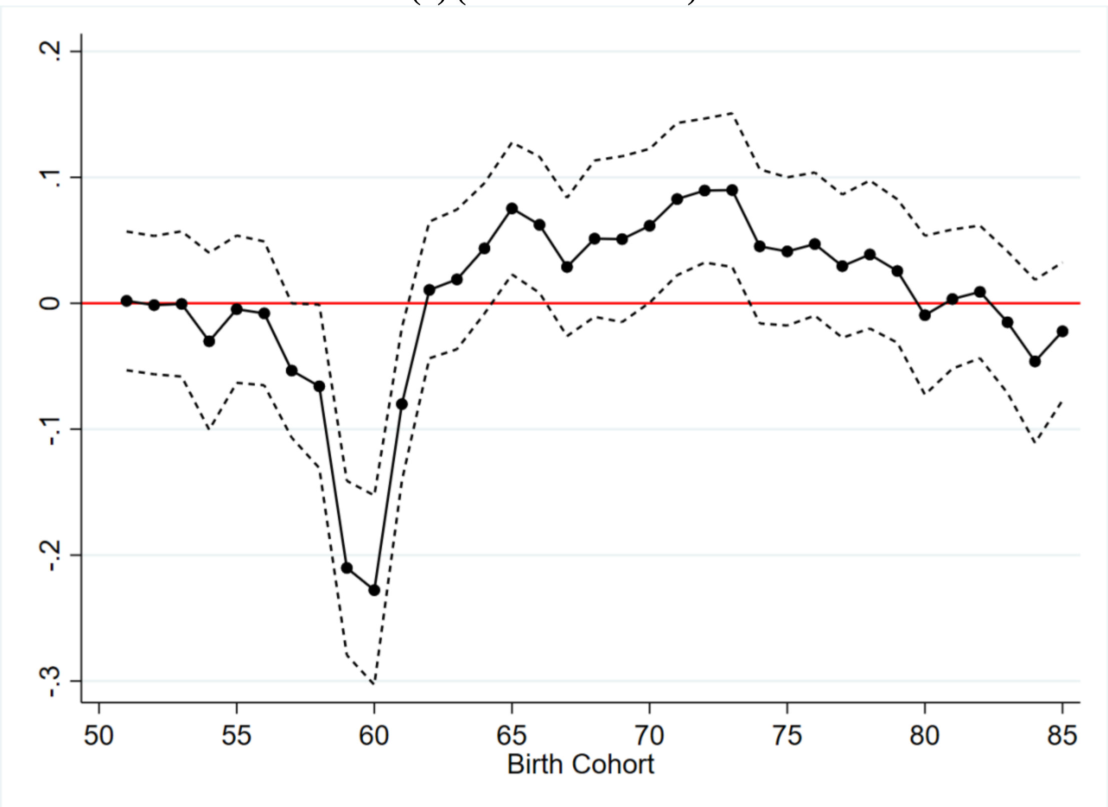


Table 1: Summary Statistics

Variables	Definition	Obs.	Mean	S.D.
	A. Prefectural Level			
1950-1985 Birth Cohorts				
Gini	Gini coefficients	291	0.403	0.055
Rshare	Rural population share	291	0.761	0.187
1950-1956 Birth Cohorts				
Gini	Gini coefficients	291	0.416	0.056
Rshare	Rural population share	291	0.737	0.198
1962-1980 Birth Cohorts				
Gini	Gini coefficients	291	0.400	0.057
Rshare	Rural population share	291	0.765	0.184
Famine Severity				
Rural Birth cohort size gap	Average rural birth cohort size gap during 1959–1961	291	0.405	0.168
Climate Shock				
Rainfall Shock	Whether there was a rainfall shock during 1959–1961	139	0.374	0.486
	B. Difference-in-Difference Regressions			
1950-1985 Birth Cohorts				
Gini	Gini coefficients	7,776	0.385	0.072
Rshare	Rural population share	7,776	0.745	0.195
1950-1956 Birth Cohorts				
Gini	Gini coefficients	1,547	0.399	0.074
Rshare	Rural population share during	1,547	0.718	0.207
1962-1980 Birth Cohorts				
Gini	Gini coefficients	4,199	0.388	0.067
Rshare	Rural population share	4,199	0.753	0.194

Table 2: The Correlation between Famine Severity and the Rural Population Share and the Gini Coefficient of Post-Famine Birth Cohorts

	Rural Population Share			Gini Coefficient		
	(1)	(2)	(3)	(4)	(5)	(6)
Famine Severity	**0.372*** **	**0.295*** **	**0.319*** **	**0.036* **	**0.032* **	**0.037** **
	(0.062)	(0.062)	(0.066)	(0.020)	(0.018)	(0.019)
GDP		0.016	0.017		-0.001	0.000
		(0.019)	(0.019)		(0.005)	(0.005)
Income		-0.032	-0.052		-0.110***	-0.117***
		(0.043)	(0.047)		(0.015)	(0.015)
Expenditure		-0.114***	-0.165***		0.038***	0.027***
		(0.028)	(0.036)		(0.008)	(0.010)
Density		-0.011	-0.018		-0.003	-0.007*
		(0.014)	(0.016)		(0.004)	(0.004)
Immigrant			0.362***			0.005
			(0.106)			(0.045)
Primary			-0.072			-0.210***
			(0.379)			(0.037)
Secondary			0.032			-0.145***
			(0.187)			(0.030)
Observations	291	291	291	291	291	291
R-squared	0.117	0.255	0.276	0.011	0.329	0.388

Notes: This table examines the correlations between famine severity and the rural population share and the Gini coefficient of post-famine birth cohorts (the 1962–1985 birth cohorts). Specifically, it presents estimates of the coefficient β from Equation (1). The dependent variables are the rural population share and the Gini coefficient for the1962–1985 birth cohorts, respectively. Control variables include a set of prefectural level characteristics in 2005, such as GDP, income per capita (Income), fiscal expenditure per capita (Expenditure), population density (Density), immigrant share of the total population (Immigrant), and the shares of agricultural and industrial output in GDP (Primary and Secondary).

Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 3: IV Estimates of the Effect of the Famine on the Rural Population Share and the Gini Coefficient

	Rural Population Share				Gini Coefficient			
	RF	IV	IV	IV	RF	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Famine Severity		**1.006*****	**0.963*****	**0.891*****		**0.041**	**0.250*****	**0.261*****
		(0.211)	(0.228)	(0.196)		(0.066)	(0.078)	(0.068)
		First Stage				First Stage		
Rainfall Shock	-0.158***	-0.161***	-0.169***	-0.178***	-0.046***	-0.161***	-0.169***	-0.178***
	(0.037)	(0.025)	(0.028)	(0.026)	(0.011)	(0.025)	(0.028)	(0.026)
GDP	0.002		0.028	0.029	-0.004		0.003	0.004
	(0.021)		(0.031)	(0.026)	(0.007)		(0.010)	(0.009)
Income	-0.057		0.084	0.033	-0.120***		-0.071***	-0.094***
	(0.066)		(0.067)	(0.062)	(0.019)		(0.021)	(0.020)
Expenditure	-0.078		-0.117**	-0.195***	0.028*		0.031**	-0.006
	(0.052)		(0.049)	(0.048)	(0.015)		(0.014)	(0.019)
Density	-0.014		-0.060**	-0.050*	-0.015		-0.022**	-0.026**
	(0.030)		(0.030)	(0.030)	(0.009)		(0.010)	(0.010)
Immigrant	0.317			1.062***	0.020			0.238**
	(0.195)			(0.269)	(0.054)			(0.115)
Primary	0.071			0.234	-0.323***			-0.275**
	(0.300)			(0.312)	(0.084)			(0.108)
Secondary	-0.062			-0.022	-0.192***			-0.180**
	(0.184)			(0.216)	(0.054)			(0.071)
K-P F statistic		42.857	35.396	46.144		42.857	35.396	46.144
Observations	139	139	139	139	139	139	139	139

Notes: This table reports the IV estimates of the famine's effect on the rural population share and the Gini coefficient of post-famine birth cohorts (the 1962–1985 birth cohorts). Specifically, it presents estimates of the coefficients from Equations (2) and (3). The dependent variables are the rural population share and the Gini coefficient for the1962–1985 birth cohorts, respectively. The control variables are the same as those in Table 2. The table includes both reduced form (RF) and IV estimation results.
Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4: IV Estimates of the Effect of the Famine on the Gini Coefficient, by Birth Cohort

	1950–1956		1962–1967		1968–1973		1974–1980		1981–1985	
	RF	IV	RF	IV	RF	IV	RF	IV	RF	IV
		(3)								
Famine Severity		0.222***		0.303***		0.294***		0.256***		0.207***
		(0.079)		(0.079)		(0.086)		(0.073)		(0.074)
		1st Stage		1st Stage		1st Stage		1st Stage		1st Stage
Rainfall Shock	-0.038***	-0.173***	-0.052***	-0.173***	-0.051***	-0.173***	-0.044***	-0.173***	-0.036***	-0.173***
	(0.011)	(0.028)	(0.012)	(0.028)	(0.013)	(0.028)	(0.011)	(0.028)	(0.011)	(0.028)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
K-P F statistic		39.093		39.093		39.093		39.093		39.093
Observations	139	139	139	139	139	139	139	139	139	139

Notes: This table presents the IV estimates of the famine's effect on the Gini coefficient for various birth cohort groups: 1950–1956, 1962–1967, 1968–1973, 1974–1980, and 1981–1985. The control variables are the same as those in Table 2. The table includes both reduced form (RF) and IV estimation results.
Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: DID Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1980 Birth Cohorts

	Dependent variable: Gini Coefficient			
	RF	IV	IV	IV
	(1)	(2)	(3)	(4)
Rshare		**1.490*** **	**1.131*** **	**1.126*** **
		(0.358)	(0.294)	(0.308)
		First Stage		
Famine Severity× T_t	**0.049*** **	**0.042*** **	**0.046*** **	**0.043*** **
	(0.009)	(0.008)	(0.009)	(0.009)
GDP× T_t	0.002		0.003	0.004
	(0.003)		(0.004)	(0.004)
Income× T_t	-0.060***		-0.057***	-0.060***
	(0.008)		(0.010)	(0.011)
Expenditure× T_t	0.018***		-0.010	-0.006
	(0.005)		(0.008)	(0.009)
Density× T_t	-0.003		-0.013***	-0.009**
	(0.002)		(0.004)	(0.004)
Immigrant× T_t	-0.014			0.073*
	(0.023)			(0.039)
Primary× T_t	0.057**			0.210***
	(0.026)			(0.054)
Secondary× T_t	-0.016			0.133***
	(0.018)			(0.050)
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Kleibergen-Paap F statistic		28.841	28.108	25.303
Observations	7306	7306	7306	7306

Notes: This table reports the DID estimates of the effect of the rural population share on the Gini coefficient for the 1962–1980 birth cohorts, using the 1950–1956 birth cohorts as the control group and the 1962–1980 birth cohorts as the treatment group. Specifically, it presents estimates of the coefficients from Equations (5) and (6). The control variables are the same as those in Table 2. The table includes both reduced form (RF) and IV estimation results.
Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 6: DID Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1966 Birth Cohorts

	Dependent variable: Gini Coefficient			
	RF	IV	IV	IV
	(1)	(2)	(3)	(4)
Rshare		**1.716*****	**1.315*****	**1.287*****
		(0.588)	(0.494)	(0.484)
		First Stage		
Famine Severity$\times T_t$	**0.056*****	**0.036*****	**0.043*****	**0.044*****
	(0.013)	(0.010)	(0.014)	(0.014)
GDP$\times T_t$	0.005		0.003	0.001
	(0.004)		(0.006)	(0.006)
Income$\times T_t$	-0.049***		-0.079***	-0.078***
	(0.012)		(0.020)	(0.021)
Expenditure$\times T_t$	0.015**		0.017	0.021*
	(0.008)		(0.010)	(0.011)
Density$\times T_t$	-0.002		-0.005	-0.004
	(0.003)		(0.006)	(0.007)
Immigrant$\times T_t$	-0.009			-0.005
	(0.029)			(0.042)
Primary$\times T_t$	-0.000			0.117*
	(0.044)			(0.068)
Secondary$\times T_t$	-0.018			0.137*
	(0.028)			(0.077)
Prefecture FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Kleibergen-Paap F statistic		12.243	10.252	10.436
Observations	2288	2288	2288	2288

Notes: This table reports the DID estimates of the effect of the rural population share on the Gini coefficient for the 1962–1966 birth cohorts, using the 1954–1956 birth cohorts as the control group and the 1962–1966 birth cohorts as the treatment group. Specifically, it presents estimates of the coefficients from Equations (5) and (6). The control variables are the same as those in Table 2. The table includes both reduced form (RF) and IV estimation results.

Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7: FE and DID Estimates of the Effect of Rural Population Share on the Rural–Urban Ratio of College Admission Probability (Provincial Level)

	A. Benchmark results			B. College admission adjustment		
	FE	RF	IV	FE	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Rshare	-0.512**		-1.113***	-0.566***		-0.761**
	(0.190)		(0.373)	(0.156)		(0.349)
Excess Mortality Rate× T_t		-0.019**			-0.013**	
		(0.007)			(0.006)	
			1st Stage			1st Stage
Excess Mortality Rate× T_t			0.017***			0.017***
			(0.003)			(0.003)
Birth Cohort FE	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y
First-Stage F statistic			17.27			17.27
Observations	112	112	112	112	112	112

Notes: The dependent variable is the rural–urban ratio of college admission probability for 18–21-year-old youths, and the independent variable is the rural population share for these same birth cohorts. In the FE model we control the rural share of women of childbearing age for each of the 1979–1982 birth cohorts. In the DID model we further control the rural population share, agricultural productivity in 1958, and income per capita, GDP, agricultural and industrial output shares in GDP, migrant population share in total population, population density, and unemployment insurance participation rate in 2000. Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8: FE and IV Estimates of the Effect of Rural Population Share on the Rural–Urban Ratio of Senior High School Admission Probability

	A. Benchmark results			B. High school admission adjustment		
	FE	RF	IV	FE	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Rshare	-1.501**		-4.430**	-1.134***		-3.450***
	(0.589)		(1.881)	(0.381)		(1.201)
Fine		-0.107*			-0.084	
		(0.061)			(0.053)	
			1st Stage			1st Stage
Fines			0.024			0.024
			(0.019)			(0.019)
Birth Cohort FE	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y
First-Stage F Statistic			10.73			10.73
Observations	120	120	120	120	120	120

Notes: The dependent variable is the rural–urban ratio of senior high school admission probability for 15–18-year-old youths, and the independent variable is the rural population share for the same birth cohorts. We control the rural share of childbearing-age women for each of the 1982–1985 birth cohorts in all regressions. The data on the fines is sourced from Ebenstein (2010).

Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.