Who Is Born Matters: The Demographic Origins of Inequality

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Abstract

Why does inequality persist across generations? We propose a demographic channel: inequality depends not only on how opportunities are allocated within cohorts, but also on the socioeconomic composition of cohorts themselves. We identify this mechanism by exploiting one of the largest demographic shocks in modern history—China's Great Famine of 1959–1961. Following severe rural mortality, fertility rebounded sharply in the countryside, substantially raising the rural share of cohorts born after the famine. Combining spatial variation in famine severity with a prefecture-by-cohort difference-in-differences framework, we instrument for cohort-level rural population shares and estimate their effect on income inequality decades later. We find that cohorts with larger famine-induced increases in rural population share exhibit significantly higher inequality in adulthood. Event-study estimates reveal that these effects emerge sharply for post-famine cohorts and closely track changes in population composition over time. We further show that a larger rural population share reduces intergenerational mobility: larger rural cohorts faced intensified competition for scarce resources, reducing college and senior high school access for rural children and limiting upward mobility. Our findings demonstrate that demographic shocks can generate persistent distributional consequences by altering the socioeconomic composition of birth cohorts, establishing population composition as an important channel underlying long-run inequality and intergenerational mobility.

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1. Introduction

Why does income inequality persist across generations? Existing research emphasizes the intergenerational transmission of human capital, technological change, institutions, and public policy (e.g., Becker and Tomes, 1979, 1986; Goldin and Katz, 2008; Chetty et al., 2014; Piketty, 2014). These explanations share a common feature: they focus on how opportunities and resources are allocated among individuals within a generation. Much less attention has been paid to a more fundamental question: can inequality also persist because the socioeconomic composition of successive generations changes over time? Put differently, inequality may depend not only on how opportunities are distributed, but also on who is born.

This demographic channel has important implications for understanding persistent inequality. If children born into different socioeconomic backgrounds face systematically different opportunities, then changes in the relative size of these groups may alter the distribution of income in subsequent generations even absent institutional change. This mechanism is potentially important because differential fertility across socioeconomic groups is both pervasive and persistent. Throughout history and across countries, poorer households have exhibited systematically higher fertility rates (Dribe et al., 2014). Although fertility is primarily a private household decision rather than a direct target of public policy, it responds to economic conditions and may adjust differently across socioeconomic groups.

This asymmetry has become particularly salient in recent decades. Rapid technological progress and economic development have triggered substantial fertility declines globally (Galor and Weil, 2000; Guinnane, 2011), yet these declines have occurred earlier and more rapidly among higher socioeconomic groups than among lower socioeconomic groups (Dribe et al., 2014). As a result, fertility differentials across income classes have actually widened during this demographic transition, potentially exacerbating inequality. These changes alter the relative size of socioeconomic groups across generations and may thereby contribute to the persistence—or even intensification—of income inequality.

A long theoretical literature suggests differential fertility across income classes may reshape population composition and influence the distribution of human capital, economic opportunities, and income (Lam 1986; Chu 1987; Chu and Koo 1990; de la Croix and Doepke 2003). Yet due to substantial identification challenges, direct micro-level evidence remains limited. Whether—and, if so, how and to what extent—fertility differentials shape long-run income inequality therefore remains an open empirical question.

This paper identifies the causal effect of population composition on long-run inequality by exploiting one of the largest demographic shocks in modern history—China's Great Famine of 1959–1961. The famine disproportionately affected rural populations and was followed by a dramatic fertility rebound in rural areas, substantially increasing the rural share of post-famine birth cohorts in affected regions. We exploit spatial variation in famine severity to generate plausibly exogenous variation in cohort composition and examine whether cohorts with a larger share of individuals born into disadvantaged rural households subsequently experienced greater income inequality decades later.

China provides an ideal setting for two reasons. First, the socioeconomic divide between rural and urban populations has historically been large and persistent. Urban households enjoyed substantially better access to education, healthcare, social welfare, and labor-market opportunities, enabling them to invest more heavily in their children's human capital. Second, the Great Famine created an unusually large shock to demographic structure. More than 30 million people died, the vast majority were rural residents (Meng et al., 2015). Mortality was concentrated among the elderly and young children, whereas most prime-age adults survived (Ashton et al., 1984; Spence, 1991; Thaxton, 2008). Following the famine, rural fertility rebounded sharply, reaching historical highs in the early 1960s. The rural–urban fertility ratio, which had been only slightly above one before the famine, more than doubled and remained elevated for an extended period. These demographic responses substantially altered the socioeconomic composition of post-famine birth cohorts.

Using census microdata, we first document that regions more severely affected by the famine experienced larger increases in the rural share of post-famine birth cohorts. These same regions subsequently exhibited significantly higher levels of income inequality among those cohorts several decades later. To establish causality, we combine a prefecture-by-cohort difference-in-differences framework with an instrumental-variable strategy that uses local famine severity to instrument for cohort-level rural population shares. Specifically, we compare cohorts born after the famine (1962–1980) with cohorts born before the famine (1950–1956), exploiting variation in famine intensity across prefectures.

Our estimates indicate that famine-induced increases in the rural population share led to significantly higher income inequality in adulthood. The first-stage results show that more severe famine exposure generated larger increases in the rural share of post-famine cohorts. The second-stage estimates demonstrate that these compositional changes substantially increased cohort-level Gini coefficients measured decades later.

A major concern is that famine exposure may affect inequality through channels other than demographic composition. For example, the famine may have directly affected the health, education,

and labor-market outcomes of individuals who experienced it during childhood. Alternatively, it may have generated indirect persistence effects by altering regional institutions, productivity, private economic decisions, or broader economic development. Rather than assuming away these possibilities, we explicitly examine their empirical implications.

Direct exposure effects should be concentrated among pre-famine cohorts that experienced the famine. Indirect persistence effects, by contrast, should affect both pre- and post-famine cohorts within a region and, if anything, be stronger among pre-famine cohorts directly exposed to the famine. The demographic-composition channel instead predicts stronger effects among post-famine cohorts whose population structure was altered by the famine. Consistent with this prediction, we find that famine severity has substantially larger effects on inequality among post-famine cohorts than among pre-famine cohorts. This pattern is difficult to attribute to direct exposure or persistent regional effects alone and points to an important role for changes in population composition.

We further show that the effects of famine severity on cohort composition and income inequality closely track each other over time. Event-study estimates indicate that the estimated effects on both outcomes rise sharply among post-famine cohorts, remain elevated for an extended period, and gradually attenuate among later cohorts. This close correspondence is difficult to reconcile with explanations based solely on direct exposure or indirect persistence effects. Instead, it is consistent with a demographic-composition channel through which the famine reshaped the socioeconomic structure of birth cohorts, with persistent consequences for inequality.

We next investigate mechanisms linking population composition to inequality. A larger rural share implies that more individuals are born into environments characterized by lower incomes and more limited educational resources. As competition for scarce educational opportunities intensifies, rural children face reduced prospects for upward mobility. Consistent with this mechanism, we find that larger rural cohorts experienced lower probabilities of admission to senior high schools and colleges relative to their urban counterparts. These results suggest that demographic composition affects inequality partly through its influence on educational attainment and intergenerational mobility.

Although our study focuses on China, where a pronounced rural-urban divide perpetuates inequality in opportunities between rural and urban children, the findings have broader relevance. In other countries, even absent such a stark rural–urban split, gaps between wealthy and poor households similarly generate unequal opportunities for children from different backgrounds. Thus, the implications of our analysis extend beyond China's specific institutional context: while the rural-urban divide is particularly salient in China, analogous cleavages based on race, caste, or other

socioeconomic characteristics are common in many countries with differential fertility and persistent inequality.

This paper contributes to several strands of the literature. First, it contributes to research on the fundamental determinants of income inequality. Existing studies emphasize technological change, globalization, education, institutions, and demographic forces (Autor, Levy, and Murnane, 2003; Goldin and Katz, 2008; Feenstra and Hanson, 1996; Borjas, 2003; Becker and Tomes, 1979, 1986; Chetty et al., 2014; Stiglitz, 2012; Piketty, 2014; Lam, 1986; Chu and Koo, 1990; de la Croix and Doepke, 2003). We identify population composition as a critical but understudied mechanism. Our key insight is that inequality depends not only on how opportunities are allocated within cohorts, but also on the socioeconomic composition of cohorts themselves. By showing that demographic shocks can durably reshape cohort composition and thereby influence the distribution of income, we offer a new perspective on the persistence of income inequality.

Second, our study contributes to the literature on the relationship between income inequality and intergenerational income persistence (Corak, 2004; Björklund and Jäntti, 2011; Krueger, 2012; Fan et al., 2020). While prior work documents a strong positive correlation between the two, the underlying cause remains unclear. We propose that differential fertility and resulting changes in cohort composition may constitute a common underlying force driving both higher inequality and lower mobility.

Finally, our findings shed light on the demographic origins of inequality in contemporary China. While existing work emphasizes regional inequality, educational disparities, and institutional barriers (Xie and Zhou, 2014; Fan et al., 2020; Zhang, 2021), our results highlight an additional demographic channel: fertility differentials across socioeconomic groups. More broadly, the findings underscore a simple but powerful insight: inequality is shaped not only by how resources are allocated within a generation, but also by who constitutes that generation.

2. China's Great Famine (1959–1961)

China's Great Famine (1959–1961) generated one of the largest demographic shocks of the twentieth century. Existing estimates suggest that the famine caused approximately 36 million excess deaths and prevented an additional 40 million births (Yang, 2013). While the famine is primarily known for its catastrophic mortality consequences, it also produced profound and lasting changes in fertility patterns. Following the famine, fertility rebounded sharply, particularly in rural areas, substantially altering the socioeconomic composition of subsequent birth cohorts. This paper exploits these demographic changes to examine how shifts in population composition affect long-run income

inequality. We argue that the famine provides a large shock to cohort composition, generating substantial variation in the rural–urban composition of post-famine birth cohorts across regions.

Figure 1 provides preliminary evidence on the relationship between famine severity and pre-famine population composition. One might expect regions with larger rural populations and greater dependence on agriculture to have experienced more severe famine conditions. However, the figure reveals little systematic relationship between the 1958 rural population share and famine severity, measured by excess rural mortality during 1959–1961. Provinces with similarly high rural population shares experienced markedly different mortality outcomes during the famine. Although this evidence is purely descriptive and does not establish exogeneity, it suggests that subsequent demographic changes were not mechanically driven by pre-existing differences in rural population composition.

The famine disproportionately affected rural areas, where most excess deaths occurred. Mortality was concentrated among the elderly and young children, while the majority of prime-age adults survived (Ashton et al. 1984; Spence 1991; Thaxton 2008). Following the famine, fertility rebounded sharply, especially in rural areas. As a result, the rural–urban fertility differential widened substantially and remained elevated for an extended period. The remainder of this section documents how this fertility response translated into persistent changes in cohort composition.

Figure 2 illustrates the total fertility rate (TFR) in rural and urban China between 1950 to 1985. Rural TFR surged after 1961, peaking rapidly, while urban fertility also rose significantly shortly after the famine. 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 after the famine, lasting only 1 or 2 years. In contrast, rural families, facing both delayed births and substantial losses, exhibited a more pronounced and sustained fertility rebound, significantly widening the rural–urban fertility gap.

Figure 3 illustrates this shift more directly by plotting the rural–urban fertility ratio over time. Before the famine, rural fertility exceeded urban fertility only modestly. Following the famine, however, the ratio more than doubled and remained elevated for many years. The persistence of this change suggests that the famine altered not only short-run fertility behavior but also the demographic composition of subsequent birth cohorts.

Alternative explanations are unlikely to account for the timing of this shift. China's demographic transition accelerated only after the onset of economic reforms in the late 1970s, while the two-tier population control policy was introduced in the early 1970s. In contrast, the sharp increase in the rural–urban fertility differential emerged immediately after the famine. The timing is therefore consistent with the famine being the primary force behind the observed change in fertility patterns.

The fertility rebound documented above translated into persistent differences in population growth across regions. Figure 4 compares the evolution of rural population growth in Anhui and Shaanxi, two provinces that experienced markedly different levels of famine severity. Although both provinces experienced post-famine recovery, the rebound was substantially stronger and more persistent in Anhui, where famine-induced population losses were considerably larger. The figure illustrates the dynamic mechanism through which severe famine exposure generated sustained increases in the size of subsequent rural cohorts.

These demographic adjustments ultimately altered the composition of post-famine birth cohorts. Figure 5 plots famine severity against the rural population share of the 1962–1985 birth cohorts across provinces and municipalities. Regions that experienced more severe rural population losses during the famine subsequently exhibited larger rural population shares among post-famine cohorts. This pattern is consistent with the hypothesis that stronger fertility recovery in heavily affected rural areas generated persistent changes in cohort composition. Together, Figures 2–5 suggest that the famine not only affected contemporaneous population outcomes but also reshaped the socioeconomic composition of subsequent generations.

3. 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, ethnicity, household type (rural or urban), and fertility all individual within the household. The 2005 census uniquely includes income data for the labor force, allowing for the calculation of the Gini coefficient.[4]

We focus on the income equality of the 1950–1985 birth cohorts in 2005, representing 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 cohorts in each prefecture, including all labor force members working in the prefecture at the time of survey. The calculated Gini coefficients are 0.496 at the individual level and 0.483 at the household level.[5] Xie and Zhou (2014) also use the 2005 mini-census as one of their

[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 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.

[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.

primary datasets to analyze income inequality, finding that its Gini coefficient aligns closely with that reported by Li et al. (2013) from the 2007 Chinese Household Income Project (CHIP) survey. Additionally, their calculations using data from the World Institute for Development Economics Research (UNU-WIDER) confirm that the 2005 mini-census estimate is consistent with other sources, supporting its reliability for studying income inequality during this period.

Following Meng et al. (2015), we use the 1990 census to estimate 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. We use respondents' registered residence (*hukou*) in the 1990 census as a proxy for birthplace. However, this measure may have limitations, as hukou statuses can change over time, with some rural-born individuals acquiring urban hukous in life or migrating across regions. Despite these concerns, Meng et al. (2015) note that rural populations are defined as households officially registered as agricultural (holding rural hukous), assigned in the early 1950s, and that strict policies significantly limited rural-to-urban mobility and inter-regional migration before 1990, minimizing potential biases.[6]

Panel A of Table 1 presents summary statistics for key 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. Note that the variation in Gini coefficients across prefectures is modest. However, this does not imply that income inequality is negligible nationwide. In fact, regional disparities significantly contribute to national income inequality. For instance, even if the Gini coefficients within both the eastern and western regions are low, substantial wealth differences between these regions can still drive high national income inequality.

The rural population share for the 1950–1985 birth cohorts has a mean of 0.761 and a standard deviation of 0.187, with similar values for the 1950–1956 and 1962–1980 cohorts. In most prefectures, the rural population significantly outnumbers the urban population, though the rural share varies considerably across prefectures.

Due to the lack of prefectural-level mortality data during the famine, we follow Meng et al. (2015) and use the 1990 census to calculate the average rural birth cohort size gap for 1959–1961 as a proxy for famine severity. This gap reflects the extent to which these birth cohorts were reduced during the famine. The last row of Panel A shows a mean rural birth cohort size gap of 0.405, with a standard deviation of 0.168, indicating that rural birth cohorts decreased by approximately 40% on average

[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.

during the famine, with significant variation across prefectures. Panel B of Table 1 provides additional summary statistics relevant to the DID regressions.

4. Great Famine, Population Composition, and Income Inequality

We estimate how fertility differentials across socioeconomic groups affect income inequality in the next generation. In China, the relevant differential is between rural and urban households, which historically occupied markedly different positions in the socioeconomic hierarchy and faced unequal access to education, public services, and labor markets.

The famine generated a large, persistent increase in rural relative to urban fertility. As documented in Section 2, the post-famine fertility rebound was substantially stronger in rural areas, raising the rural share of subsequent birth cohorts and altering their socioeconomic composition.

Conceptually, differential fertility influences inequality by changing the composition of the next generation. What matters for future inequality is not fertility per se, but whether fertility differentials increase or decrease the relative size of groups that differ in economic opportunities and outcomes. We therefore focus on cohort composition as the key mechanism linking differential fertility to long-run inequality.

We use each cohort's rural population share as our measure of composition. Although differential fertility and population composition are conceptually distinct, they are closely related. As shown in Appendix S2, the rural population share is a monotonic function of the rural–urban fertility ratio, conditional on the relative number of women of childbearing age in each sector. Under this condition, changes in cohort composition provide a sufficient statistic for changes in differential fertility.

Our empirical strategy thus focuses on the causal effect of cohort composition on long-run income inequality. We interpret variation in cohort composition as arising from famine-induced changes in rural–urban fertility differentials and estimate whether cohorts containing a larger share of individuals born into disadvantaged rural households subsequently experienced higher levels of inequality.

4.1 Suggestive Cross-Sectional Evidence

Before turning to our main identification strategy, we present suggestive evidence on the long-run relationship between famine exposure, demographic composition, and income inequality.

Following Meng et al. (2015), we construct a prefecture-level measure of famine severity using deviations in rural birth cohort size during the famine years (1959–1961) from their long-run trends. Areas experiencing larger declines in cohort size are interpreted as having suffered more severe famine shocks. Details of the construction are provided in Appendix S3.

We first examine whether prefectures more severely affected by the famine subsequently exhibited different demographic and distributional outcomes. Table S1 reports a strong positive relationship between famine severity and the rural population share of post-famine birth cohorts. More severely affected prefectures also display significantly higher Gini coefficients among these cohorts several decades later. These correlations remain robust to the inclusion of a wide range of controls.

Because famine severity may itself be correlated with local characteristics, we further instrument it using prefecture-level exposure to extreme weather shocks during 1959–1961. The IV estimates, reported in Table S2, yield similar conclusions. Prefectures more heavily exposed to the famine experienced larger increases in the rural share of post-famine cohorts and higher levels of subsequent income inequality.

Taken together, these results suggest that the famine generated persistent changes in population composition and that these demographic changes were associated with higher income inequality in later decades. While these cross-sectional patterns are not sufficient to establish causality, they provide preliminary evidence consistent with the hypothesis that famine-induced shifts in population composition contributed to the distributional outcomes of post-famine cohorts.

4.2 IV Estimates within a DID Framework

The cross-sectional evidence suggests that the famine increased both the rural population share and the Gini coefficient among post-famine birth cohorts. The increase in the rural population share is relatively straightforward: more severe famine exposure caused disproportionately higher child mortality in rural areas, followed by a substantial rural fertility rebound, raising the rural–urban fertility ratio and altering cohort composition. The effect on the Gini coefficient is more complex and may operate through multiple channels, which we discuss in detail below.

In this section, we exploit the famine-induced shift in cohort composition to identify the causal effect of rural population share on later cohort inequality. Our design combines a DID comparison of pre- and post-famine cohorts with an instrument for post-famine rural share. The key idea is that heterogeneous famine severity generates exogenous, prefecture-level variation in the rural share of cohorts born after the famine relative to those born before it; we use this variation to estimate how changes in cohort composition affect the Gini coefficient decades later.

We begin by examining the dynamics of the famine's impact on the population composition of post-famine birth cohorts. As noted, the famine may have had a long-term effect on the rural population share of the post-famine cohorts, which could gradually diminish over time. To analyze these dynamics, 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 after the famine. In practice, we estimate the following dynamic DID model:

$$Rshare_{pt} = c + \alpha_p + \gamma_t + \sum_{t=1951}^{1985} b_t(FM_p \times d_{pt}) + \sum_{t=1951}^{1985} \delta_t(X_p \times d_{pt}) + \varepsilon_{pt}, \quad (1)$$

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 prefecture-level controls.

We focus on the 1950–1985 birth cohorts. We include 35 birth cohort dummies (1951–1985), with the 1950 cohort as the omitted reference group. Each coefficient (b_t) can therefore be interpreted as the effect of famine on the rural population share for cohort (*t*).

We estimate Equation (1) and plot the b_t coefficients in Figure 6. The estimates for the 1951–1956 birth cohorts are near zero and statistically insignificant, then fall sharply for the 1957 cohort and become significantly negative. After the famine ends, the estimates increase dramatically, turn significantly positive, and remain elevated for an extended period. They begin to decline after the mid-1970s and eventually diminish to zero for birth cohorts after 1980. These dynamics indicate a persistent, cohort-specific compositional effect of the famine that gradually fades over time.

Note that near-zero coefficients for the 1951–1956 cohorts (with the 1950 cohort as the reference) do not imply the famine had no demographic impact on those cohorts. Rather, they indicate that the 1951–1956 cohorts' rural shares shifted similarly to the 1950 cohort. Prior studies show that famine-induced excess deaths were concentrated among very young children—especially infants under one—and substantially smaller for those older than five (Peng, 1987; Song, 2013). Most members of the 1950–1956 cohorts were beyond infancy during the famine, so direct mortality exposure for these cohorts was likely limited. By contrast, the substantially positive estimates for post-famine cohorts point to a pronounced increase in their rural population share relative to pre-famine cohorts, consistent with compositional consequence of the famine. Thus, while direct mortality effects on the 1950–1956 cohorts appear limited, larger compositional shifts are concentrated among cohorts born after the famine. Accordingly, the 1950–1956 cohorts constitute a reasonable control group for post-famine cohorts.

We thus implement a two-stage IV within a DID framework, using the 1950–1956 cohorts as the control group and the 1962–1980 cohorts as the treatment group. The first stage estimates how famine severity differentially shifted cohort rural shares for treated cohorts:

$$Rshare_{pt} = c_1 + \alpha_{1p} + \gamma_{1t} + b(FM_p \times Post_t) + \delta_1(X_p \times Post_t) + \varepsilon_{pt1}, \quad (2)$$

and the second stage links the (instrumented) rural share to cohort Gini in 2005:

$$Gini_{pt} = c_2 + \alpha_{2p} + \gamma_{2t} + \beta Rshare_{pt} + \delta_2\left(X_p \times Post_t\right) + \varepsilon_{pt2}, \quad (3)$$

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 famine severity (rural birth cohort size gap during the famine) in prefecture p; $Post_t$ is a dummy variable equal to 1 for the 1962–1980 birth cohorts (treatment group) and 0 for the 1950–1956 birth cohorts (control group); 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. The parameter b identifies the first stage; β is the parameter of interest.

Within this DID framework, a significant first stage (b) establishes that greater famine severity led to relatively larger rural shares for post-famine cohorts. A significant second stage (β) implies that the famine-driven increase in rural share raised cohort Gini.

Estimation results are reported in Table 2. Column (1) presents the reduced-form result and shows that famine severity is significantly correlated with the Gini coefficient for the 1962–1980 birth cohorts in 2005 at the prefectural level. Quantitatively, a 1% increase in the average rural birth cohort size gap during the famine is associated with an increase of 0.049 in the Gini coefficient of the post-famine birth cohorts in 2005. Columns (2)–(3) report the IV estimates, which remain robust as control variables are included. Column (3) shows that the coefficient on the rural population share is approximately 1.13, which implies that a 0.01 increase in rural population share is associated with a 0.0113 increase in the Gini coefficient.

The lower panel reports the first-stage results. The coefficient on famine severity in the first stage is about 0.04, indicating that a 1% increase in famine severity is associated with a 0.4% increase in the post-famine rural population share. Moreover, the first-stage F-statistic exceeds 20, suggesting that the instrument is not weak.

In the regressions above, we use the 1990 census to compute the rural population share in each prefecture, based on respondents' hukou status in 1990. To construct the Gini coefficient, we use the 2005 census, relying on respondents' place of residence and workplace. All current labor force members working in a prefecture are included in the calculation of that prefecture's 2005 Gini coefficient. Because individuals born in one prefecture may migrate to another, this approach may be affected by migration. Although migration was limited before 1990 (Meng et al., 2015), there was a substantial inflow of migrants from western and central regions into more developed eastern regions

by 2005. The presence of migrants in each prefecture in 2005 therefore poses a potential challenge to our empirical strategy.

To address this concern, we use information on migration status from the 2005 census. The results remain robust after fully accounting for potential migration across regions. Additional details are provided in Appendix S5.

4.3 Identification: How Does Famine Severity Affect Inequality?

A central concern is whether famine severity satisfies the exclusion restriction required for our instrumental-variable strategy. Specifically, famine severity may affect long-run income inequality through channels other than cohort population composition. Rather than assuming away these possibilities, we examine the main alternative mechanisms and their empirical implications.

We distinguish three channels through which the famine could affect income inequality decades later. The first is the **population compositional effect**, which is the mechanism of interest. The second is a **direct exposure effect**, whereby individuals who experienced the famine in early life suffered persistent adverse consequences. The third is an **indirect persistence effect,** whereby the famine permanently altered local institutions, economic conditions, or private decision-making, with consequences for subsequent generations.

The population compositional channel operates through changes in fertility and mortality. The famine disproportionately affected rural households and caused substantial mortality among young children. After the famine, fertility rebounded sharply in rural areas, dramatically raising the rural–urban fertility ratio. As a result, the rural population share of post-famine birth cohorts increased. Because rural children generally faced poorer educational opportunities and lower expected earnings than urban children, this shift in cohort composition could increase income inequality in subsequent generations.

The direct exposure channel makes a different prediction. Individuals born before the famine were directly exposed to famine conditions during childhood and may have suffered lasting disadvantages in health, human capital accumulation, and labor-market outcomes. Such effects were likely most pronounced among rural residents and could therefore have widened rural–urban disparities within the cohorts that experienced the famine. If direct exposure were the dominant mechanism, we would consequently expect the effects of famine severity on inequality to be concentrated among pre-famine cohorts rather than among cohorts born after the famine.

The indirect persistence channel is broader. The famine may have generated persistent changes in local institutions, public finances, productivity, infrastructure, or private economic behavior. Such changes could potentially increase inequality many decades later, particularly if they

disproportionately affected rural areas. However, because these regional shocks operate through local economic conditions rather than through the circumstances of particular birth cohorts, they do not naturally predict substantially larger effects among post-famine cohorts than among pre-famine cohorts living in the same prefecture. If anything, pre-famine cohorts directly exposed to the famine may bear additional consequences of the shock. Persistent regional effects alone therefore cannot readily account for a substantially stronger relationship between famine severity and inequality among post-famine cohorts.

These alternative mechanisms thus generate distinct cohort-level predictions. Direct exposure effects predict larger effects among pre-famine cohorts, while a purely regional persistence mechanism does not naturally predict a sharp increase in effects among post-famine cohorts. In contrast, the population compositional channel predicts the largest effects among post-famine cohorts, whose socioeconomic composition was reshaped by the post-famine fertility rebound. The relative magnitude of the effects across cohorts therefore provides a direct test of the mechanism underlying the IV relationship.

Our estimates strongly support the compositional prediction. The effects of famine severity on income inequality are substantially larger among post-famine cohorts than among cohorts directly exposed to the famine. This pattern is difficult to reconcile with a dominant direct-exposure mechanism, which should primarily affect pre-famine cohorts, and does not naturally follow from persistent regional effects, which are not inherently cohort-specific. Instead, the cohort pattern points to demographic composition as an important channel linking famine severity to long-run inequality.

We next examine whether the dynamic evolution of cohort composition and income inequality follows the same pattern. Specifically, we estimate Equation (1) separately using the rural population share and the cohort Gini coefficient as outcome variables and plot the resulting coefficients in Figure 7. For the pre-famine cohorts (1951–1956, corresponding to -6 to -1 in the figure), the estimated effects on both outcomes are small and statistically insignificant. For the post-famine cohorts (1962–1985, corresponding to 0 to 23), the coefficients increase sharply, remain positive for an extended period, and gradually decline for cohorts born after 1980.

Most importantly, the two series closely track each other over time. Cohorts for which famine severity generates larger increases in rural population shares are also those for which it generates larger increases in income inequality. Both effects rise sharply among cohorts born immediately after the famine, remain elevated for many years, and gradually fade among later cohorts. This temporal alignment provides additional evidence consistent with demographic composition as the mechanism transmitting famine severity into long-run inequality.

A potential concern is that the birth cohorts examined above (1950 to 1980) span substantially different periods and may therefore differ for reasons unrelated to the famine. To address this concern, we restrict attention to cohorts born immediately before and after the famine, defining the 1954–1956 birth cohorts as the pre-famine group and the 1962–1966 birth cohorts as the post-famine group. Because these cohorts were born relatively close in time, this comparison reduces concerns about secular changes and limits potential confounding from later demographic policies. Table 3 reports the corresponding DID estimates. The results are quantitatively similar to, and slightly larger than, those reported in Table 2. The first-stage estimates confirm that famine severity increased the rural population share of post-famine cohorts, while the second-stage estimates show that these compositional changes significantly increased cohort-level income inequality.

Appendix S7 provides additional supporting evidence. First, we compare the 1962–1980 cohorts with the 1981–1985 cohorts, whose population composition was largely unaffected by the famine. Consistent with our main results, famine severity predicts larger rural population shares and higher income inequality among the earlier cohorts. Second, we conduct a placebo exercise comparing the 1950–1956 and 1981–1985 cohorts, neither of which experienced substantial famine-induced compositional changes. In this comparison, both the first-stage and second-stage estimates are small and statistically insignificant. These findings further support the interpretation that cohort composition is an important channel through which famine severity affected long-run inequality.

Finally, it is important to clarify the role of mortality and fertility in generating the observed changes in cohort composition. Mortality was concentrated among rural children, particularly those from disadvantaged households, while fertility rebounded strongly among rural families after the famine. Thus, the famine altered cohort composition through both selective mortality and differential fertility. These mechanisms are complementary rather than competing explanations: both changed the socioeconomic composition of birth cohorts by affecting who survived and who was subsequently born. The resulting changes in cohort composition are precisely the object of interest in our analysis. Our estimates should therefore capture the long-run distributional consequences of famine-induced changes in the composition of birth cohorts.

Overall, the evidence suggests that the long-run consequences of the Great Famine operated less through the individuals who experienced the famine than through the composition of the cohorts born afterward. Famine severity substantially altered the socioeconomic composition of post-famine birth cohorts by increasing their rural population share, and these compositional changes translated into higher income inequality decades later. More broadly, the findings highlight population composition as a channel through which demographic shocks can shape the distribution of economic outcomes across generations.

5. Population Composition and Intergenerational Mobility

5.1 Conceptual Framework

The effect of population composition on inequality depends on intergenerational mobility. If children's economic outcomes were independent of family background, changes in population composition would have little effect on the distribution of income in the next generation. In reality, however, children from disadvantaged backgrounds face systematically lower probabilities of upward mobility. Consequently, a larger share of births among disadvantaged groups may increase inequality by concentrating a greater fraction of the population in environments with fewer opportunities for human capital accumulation and economic advancement.

This mechanism is particularly relevant in China because rural and urban households historically differed substantially in income, educational resources, and access to economic opportunities. Following the famine, fertility rebounded much more strongly in rural areas, increasing the rural share of subsequent birth cohorts. Existing evidence suggests that the quantity–quality tradeoff is more pronounced among resource-constrained rural households, whereas it is considerably weaker in urban China (Li et al., 2008; Rosenzweig and Zhang, 2009). As a result, a larger rural population share may intensify competition for scarce educational opportunities, reduce upward mobility among rural children, and ultimately contribute to higher income inequality in adulthood.

A key implication of this mechanism is that cohorts with larger rural population shares should face greater competition for scarce educational opportunities, resulting in lower educational attainment and reduced upward mobility among rural children. We examine this prediction directly below.

5.2 Evidence from the National College Entrance Exam

In contemporary China, college education is an critical opportunity and a primary channel of upward mobility for most youths, especially rural children, who generally lack alternative avenues for social advancement. Since 1977, rural and urban high school students have taken the same National College Entrance Exam (NCEE, or *gaokao*) and competed for a limited number of college slots. NCEE outcomes therefore provide a clean measure of the rural–urban gap in basic education quality (elementary and secondary) and serve as an informative indicator of relative social mobility between rural and urban children.

The 2000 census data contains rich information on all enrolled college students in that 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:

$$\mathrm{Ruratio}_{\mathrm{pt}} = \mathrm{c} + \alpha_{\mathrm{p}} + \gamma_{\mathrm{t}} + \beta \mathrm{Rshare}_{\mathrm{pt}} + \varepsilon_{\mathrm{pt}}, \quad (4)$$

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 4 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 4 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:

$$Rshare_{pt} = c_1 + \alpha_{1p} + \gamma_{1t} + b(FM_p \times T_t) + \delta_1(X_p \times T_t) + \varepsilon_{pt1}, \quad (2')$$

$$Ruratio_{pt} = c_2 + \alpha_{2p} + \gamma_{2t} + \beta Rshare_{pt} + \delta_2(X_p \times T_t) + \varepsilon_{pt2}. \quad (3')$$

These equations are similar to Equations (2) and (3), 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 (2) and (3), 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 4 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 (4) 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 5 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.

Given that the one-child policy also affected rural–urban fertility differentials and cohort composition, we exploit regional variation in policy implementation intensity as an alternative source of identification. Detailed construction of this instrument is described in Appendix S9. The IV estimates reported in Columns (3) and (6) of Table 5 are consistent with the baseline fixed-effects results and remain statistically significant. Overall, the evidence suggests that larger rural population shares reduced the relative probability of rural youths entering both senior high school and college.

Taken together, these findings provide evidence for a mobility-based mechanism linking differential fertility to long-run inequality. The famine-induced increase in rural fertility raised the rural share of subsequent cohorts, intensifying competition for educational opportunities among rural children and reducing their relative educational attainment. Because education constituted the primary channel of upward mobility in China, these compositional changes translated into lower intergenerational mobility and higher income inequality in adulthood. More broadly, the results suggest that differential fertility can affect long-run inequality not only through mechanical changes in population composition, but also by altering the distribution of opportunities available to the next generation.

6. Conclusions

We study the impact of population composition on income inequality using the large demographic shock generated by China's Great Famine of 1959–1961. Exploiting spatial variation in famine severity within a cohort-by-prefecture difference-in-differences framework, we show that cohorts experiencing larger famine-induced increases in rural population share subsequently exhibited significantly higher levels of income inequality. We further show that the effects operate partly through educational opportunities and intergenerational mobility. Cohorts with larger rural population shares experienced lower access to senior high school and college education among rural children, reducing opportunities for upward mobility.

Our findings suggest that demographic shocks can have long-lasting distributional consequences by altering who is born into the next generation. While a large theoretical literature has argued that differential fertility across socioeconomic groups may influence inequality, direct empirical evidence has been limited. We provide evidence that changes in cohort composition have persistent effects on the distribution of income decades later. More broadly, the results indicate that population composition is an important determinant of long-run inequality alongside institutions, education, technological change, and public policy.

Importantly, our findings should not be interpreted as implying that higher fertility among disadvantaged groups is inherently undesirable. The effects we document arise from the interaction between demographic change and unequal access to opportunity. When educational and mobility-enhancing institutions fail to adjust to demographic shifts, changes in population composition can generate persistent distributional consequences. The results therefore highlight the importance of institutions that expand opportunities as populations evolve.

More generally, the paper suggests that understanding long-run inequality requires attention not only to how resources are allocated among existing individuals but also to how demographic processes shape the composition of future generations. Historical shocks, migration, fertility transitions, and other demographic forces can alter the socioeconomic makeup of birth cohorts in ways that influence inequality decades later. Recognizing this demographic dimension may help explain the persistence of inequality across societies and provide a broader framework for understanding the interaction between population change and economic opportunity.

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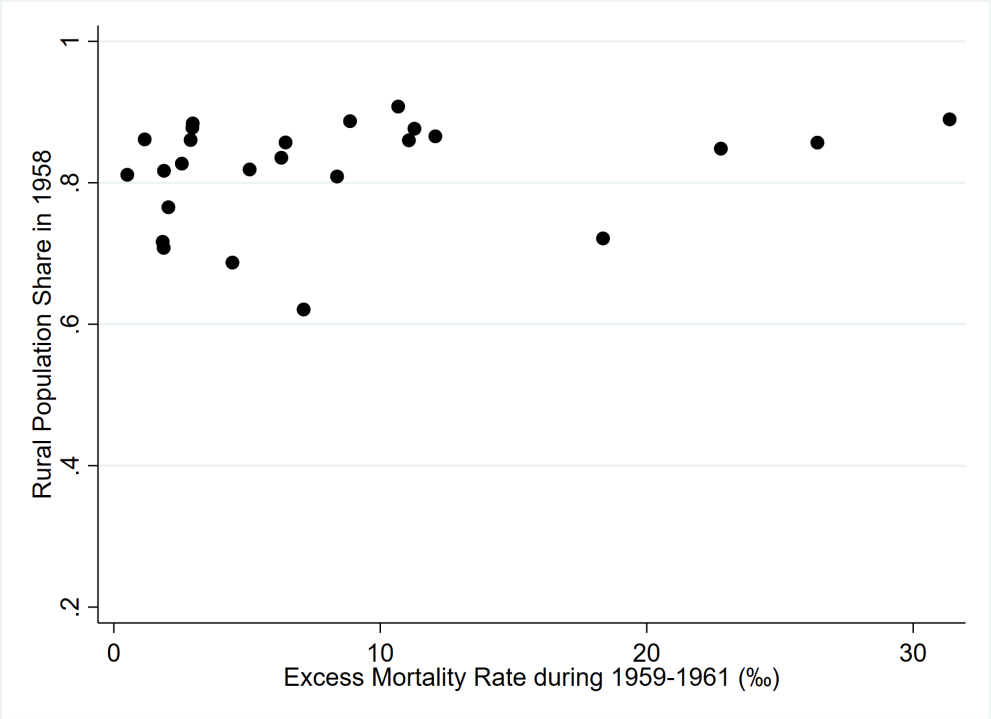
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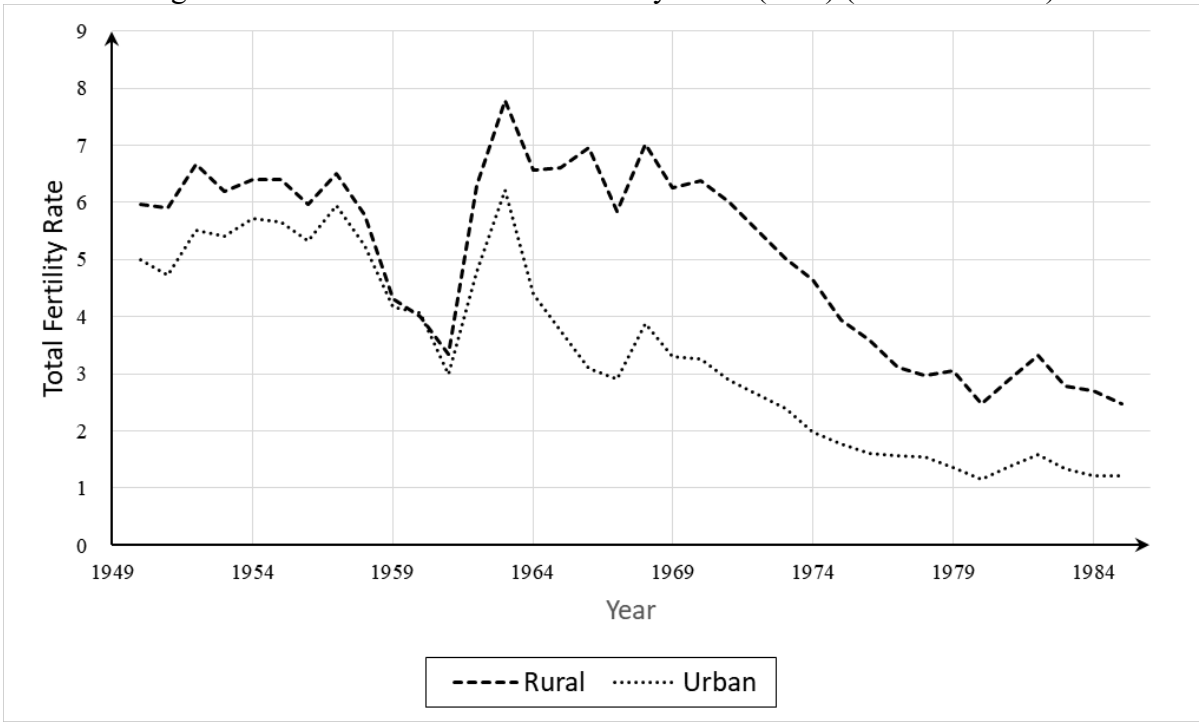
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Figure 1: Rural Population Share in 1958 and Average Rural Excess Mortality Rate in 1959–1961 (Provincial Level)



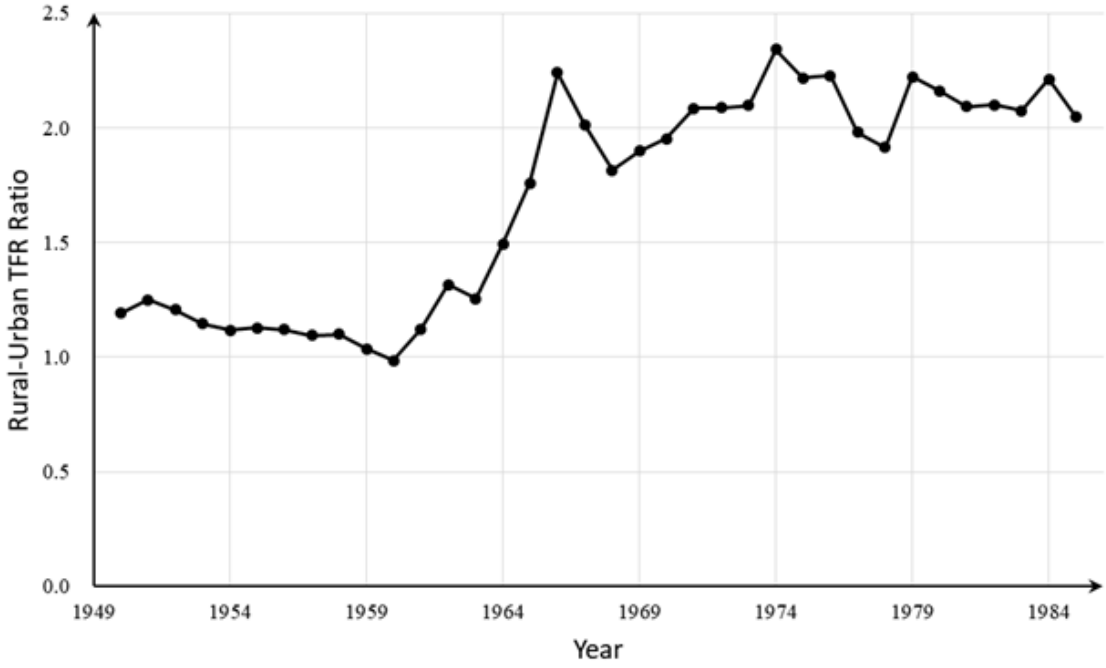
Note: This figure shows rural population share in 1958 and average rural excess mortality rate in 1959–1961. Data are from Meng et al. (2015).

Figure 2: Rural and Urban Total Fertility Rates (TFR) (National Level)



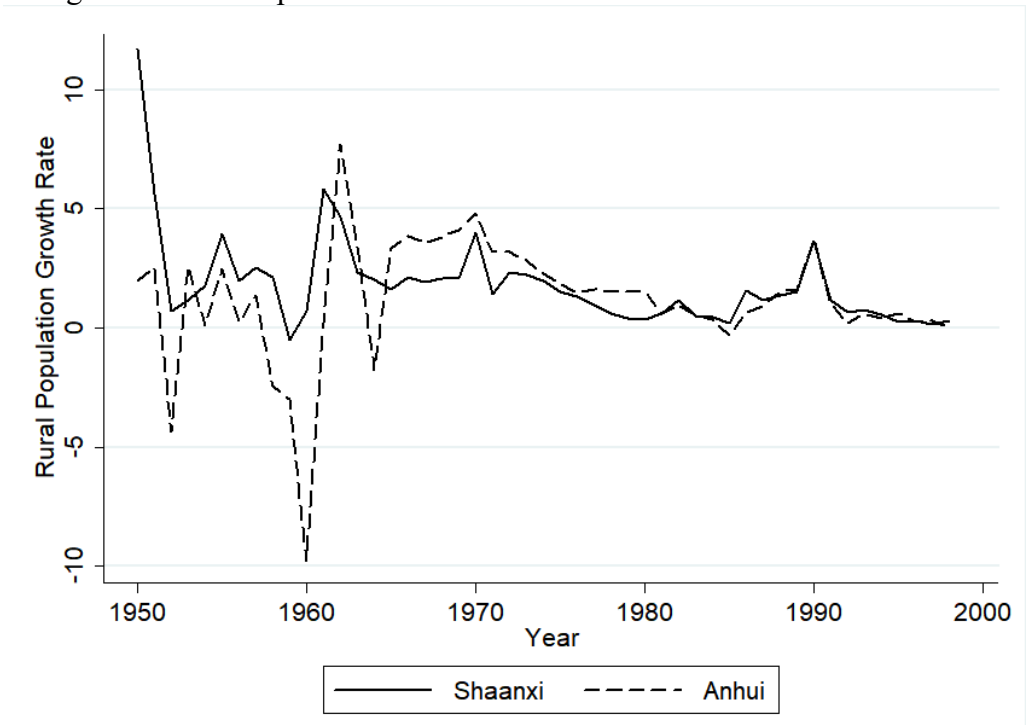
Note: This figure shows rural and urban total fertility rates from 1950 to 1985. Data are from Yao and Yin (1994).

Figure 3: Rural–Urban TFR Ratio (National Level)



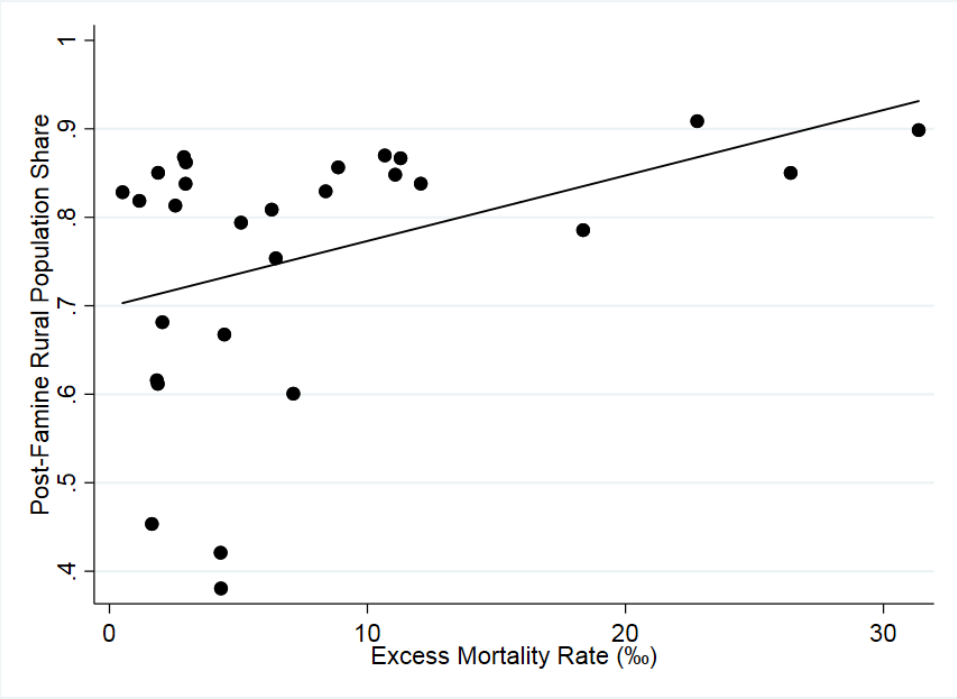
Note: This figure shows the rural–urban TFR ratio from 1950 to 1985. Data are from Yao and Yin (1994).

Figure 4: Rural Population Growth Rates of Shaanxi and Anhui Provinces



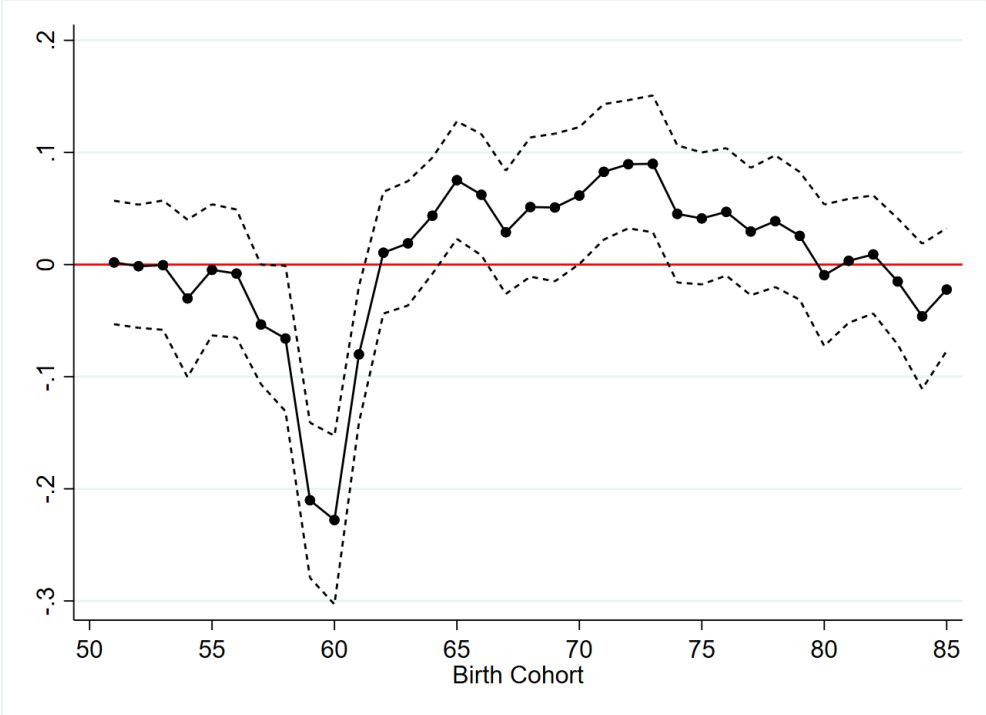
Note: This figure shows rural population growth rates of Shaanxi and Anhui provinces from 1950 to 2000. Data are from Meng et al. (2015).

Figure 5: Famine Severity and Post-Famine Rural Population Share for the 1962–1985 Birth Cohorts (Provincial Level)



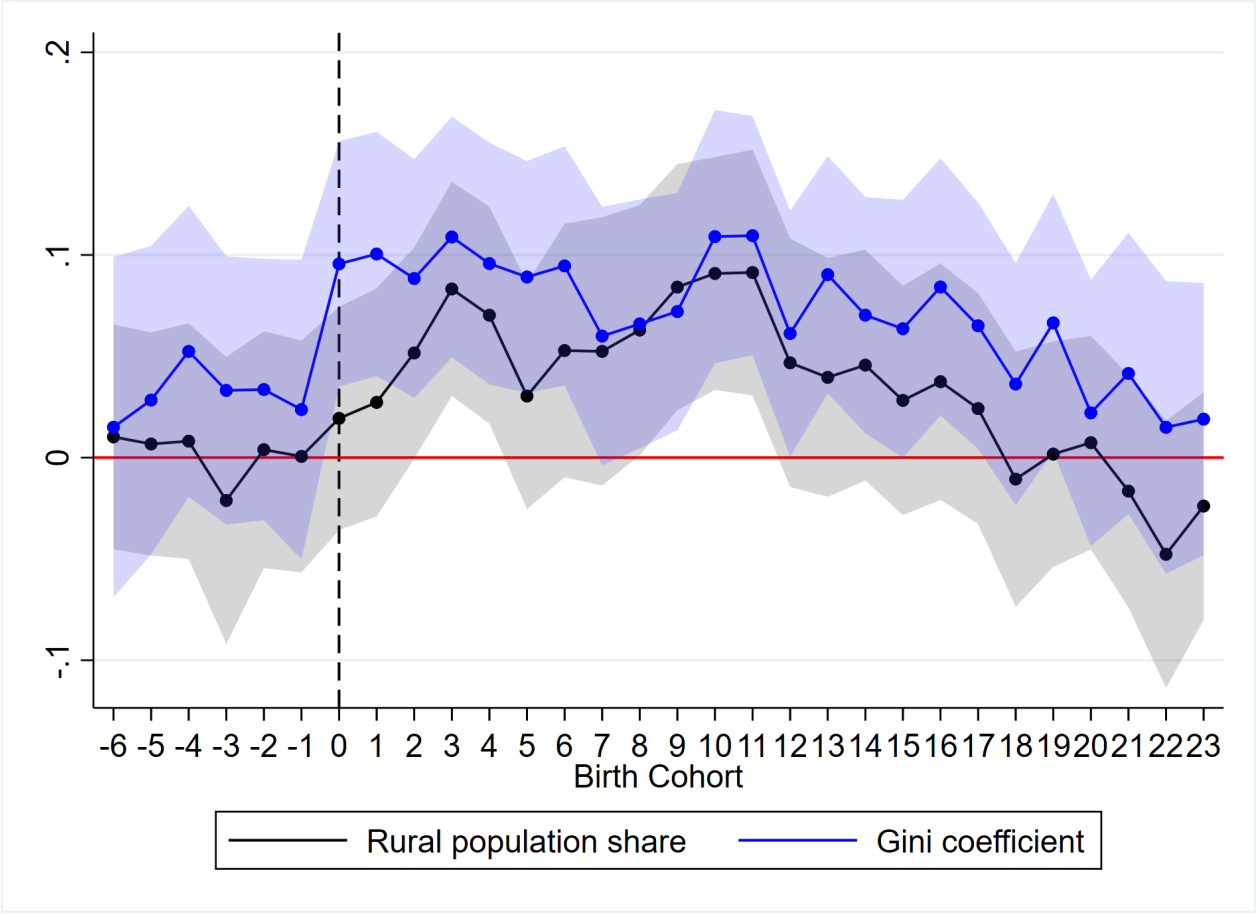
Note: This figure shows rural excess mortality rate during 1959–1961 and post-famine rural population share for the 1962–1985 birth cohorts. Data are from Meng et al. (2015).

Figure 6: Coefficients of the Interactions Famine Severity×Birth Cohort (1951–1985) in Equation (1)



Note: This figure reports the estimated coefficient b_t from Equation (1).

Figure 7: Dynamic Effects of Famine Severity on Cohort Population Composition and Income Inequality



Notes: This figure reports the dynamic effects of famine severity on cohort-level outcomes. The black and blue lines plot the estimated coefficients b_t from Equation (1), where the dependent variables are the rural population share and the Gini coefficient, respectively. The sample includes six pre-famine cohorts (1951–1956, corresponding to −6 to −1 on the horizontal axis) and post-famine cohorts (1962–1985, corresponding to 0 to 23), with the 1950 cohort serving as the omitted reference group. Control variables are the same as those in Table 2. Shaded areas indicate 95 percent confidence intervals.

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
	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: 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
	(1)	(2)	(4)
Rshare		1.490***	1.126***
		(0.358)	(0.310)
		First Stage	
Famine Severity×*Post*	0.049***	0.042***	0.043***
	(0.009)	(0.008)	(0.009)
Controls	Y	N	Y
Prefecture FE	Y	Y	Y
Year FE	Y	Y	Y
F statistic		28.841	25.175
Observations	7306	7306	7306

Notes: This table reports 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 1962–1980birth cohorts as the treatment group. It presents the estimated coefficients (b) (first stage) and (β) (second stage) from Equations (2) and (3). Control variables include a set of prefecture-level characteristics in 2005, 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). The table reports both reduced-form (RF) and IV estimates. Robust standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 3: 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
	(1)	(2)	(4)
Rshare		1.716***	1.287***
		(0.588)	(0.426)
		First Stage	
Famine Severity×*Post*	0.056***	0.036***	0.044***
	(0.014)	(0.010)	(0.011)
Controls	Y	N	Y
Prefecture FE	Y	Y	Y
Year FE	Y	Y	Y
F statistic		12.243	10.436
Observations	2288	2288	2288

Notes: This table reports 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. It presents the estimated coefficients (b) (first stage) and (β) (second stage) from Equations (2) and (3). Control variables are the same as in Table 1. The table reports both reduced-form (RF) and IV estimates. Robust standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 4: FE and DID Estimates of the Effect of Rural Population Share on the Rural–Urban Ratio of College Admission Probability

	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)
Famine Severity× $Post$		-0.019**			-0.013**	
		(0.007)			(0.006)	
			1st Stage			1st Stage
Famine Severity× $Post$			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: This table reports FE and DID estimates of the effect of rural population share on the rural–urban ratio of college admission probability. Panels A and B report results for benchmark and admission-adjusted measures, respectively. Columns (1) and (4) present FE estimates, reporting the coefficient (β) from Equation (4). Columns (2)–(3) and (5)–(6) report the corresponding RF and IV estimates from the DID specification, reporting coefficients from Equations ($2'$) and ($3'$), with the dependent variable replaced by the rural–urban ratio of college admission probability instead of the Gini coefficient. In the FE model, we control for the rural share of women of childbearing age for each of the 1979–1982 birth cohorts. In the DID model, we additionally control for the rural population share, agricultural productivity in 1958, and the same set of controls as in Table 1. Robust standard errors are in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5: 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: This table reports FE and DID estimates of the effect of rural population share on the rural–urban ratio of senior high school admission probability. 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. Panels A and B report results for benchmark and admission-adjusted measures, respectively. Columns (1) and (4) present FE estimates, reporting the coefficient (β) from Equation (4). Columns (2)–(3) and (5)–(6) report the corresponding RF and IV estimates from the DID specification, reporting coefficients from Equations (S8) and (S9) in the Appendix. 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.