Great Famine, Differential Fertility, and Income Inequality: Evidence from China

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Abstract

With China's Great Famine (1959–1961) as an exogenous shock to the country's post-Famine fertility structure and rural–urban population composition, we empirically identify the causal effect of differential fertility across income classes on the income inequality of the next generation. We find that a higher rural population share induces a higher Gini coefficient for these cohorts several decades later. Further mechanism analysis shows that a higher rural population share induces a lower probability of rural youths gaining admission to college and senior high school, that is, a higher rural fertility reduces social mobility.

Keywords: Differential fertility, income inequality, Great Famine, population composition, social mobility

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1. Introduction

As commonly observed in the modern world, fertility level considerably differs across income classes, and poor families generally bear more children than rich families, particularly in developing countries. Such differential fertility across income classes may have important consequences. For instance, a higher fertility of the poor may aggravate the problem of poverty (because a larger share of population of the next generation could be trapped in poverty), and differential fertility could also affect the human capital investment in the next generation and further affect the long-term economic development of a society. Unsurprisingly, demographers and economists show great interest in this issue, and several influential studies theoretically demonstrate that fertility differentials across income classes may have important effects on the income distribution and further on the economic growth of a society (see Lam, 1986; Chu, 1987; Dietzenbacher, 1989; and Chu and Koo, 1990; Croix and Doepke, 2003).

However, the issue is very complicated, and drawing a clean conclusion merely through a theoretical analysis is difficult. Furthermore, even if differential fertility has an important effect on the income inequality of society, the mechanism through which the former affects the latter remains unclear. In addition, some studies find a positive correlation between income inequality and intergenerational income persistence (e.g., Corak, 2004; Björklund and Jäntti, 2011), but the cause is still a puzzle. Investigating the interactions between differential fertility and income inequality of the next generation could provide a potential solution to the puzzle. Undoubtedly, previous theoretical studies provide important insights into the issue. Nevertheless, whether and how differential fertility across income classes affects the income inequality of the next generation is more of an empirical rather than a purely theoretical issue. Despite the evident importance of the issue and given the immense difficulty in empirically examining the causal effect of differential fertility on income inequality, such empirical study has been lacking. To fill this gap in the literature, we attempt to provide a rigorous empirical analysis on the effect of differential fertility across income classes on the income inequality of the next generation.

Intuitively, if the fertility level of the low-income class is considerably higher than that of the high-income class and if social mobility is limited, then, the population of the next generation would contain a larger proportion of people who are trapped in poverty. Accordingly, the income inequality of the entire society may also increase. Lam (1986) theoretically analyzes the effects of fertility differentials across income classes on Lorenz curves and standard inequality measures and shows that such differential fertility affects the population composition of the next generation and may further affect the steady-state income inequality. However, the issue is very complicated and Lam (1986) shows that no general definite conclusion can be drawn from his theoretical analysis. Specifically, the effect of a change in the fertility of the poor on the income inequality cannot be predicted without knowing the actual magnitude of the change. For example, if an increase in the fertility of the poor increases the proportion of the poor, the Gini coefficient is likely to increase initially but must eventually decrease as the new entrants of the poor finally dominate the distribution and most people become poor. Chu and Koo (1990) prove that under several reasonable assumptions, a higher reproductive rate of the poor will lead to a less favorable income distribution in the steady state and in all transition periods.

The literature provides a solid foundation for empirical research. However, the issue itself is highly complicated and thus forms an immense obstacle for empirical investigations. In particular, both differential fertility and income inequality are endogenous and affected simultaneously by many other factors such as institutions and economic development, which makes the identification difficult. Fortunately, China's rural–urban divide, along with the exogeneous shock of the Great Famine (1959–1961) on its fertility structure, provides a unique natural experiment to empirically study this issue.

Indeed, a significant rural–urban gap exists in China. Urban areas are substantially more developed than rural areas, while urban residents also enjoy a considerably higher level of social welfare than rural residents over a long period. Urban areas have extensively better health, medical facilities, and educational systems than the rural ones. Urban families also have more resources to invest in children. Given the huge gap in rural and urban income and resources in China, differential fertility across rural and urban families may significantly affect the income inequality of the country's next generation.

The Great Famine primarily affected rural areas and can thus be considered an exogenous shock to China's fertility and population structure. Over 30 million people died during the Famine, most of whom lived in rural areas (Meng et al., 2015). Although the majority of the prime-age adults survived (Thaxton, 2008), the elderly and young children were heavily affected and estimates indicate that over half of the total deaths were of young children (Ashton et al., 1984; Spence, 1991). As expected, rural fertility rebounded substantially after the Famine and reached a historic summit in 1963. Meanwhile, China's rural–urban fertility ratio also increased substantially and remained at a high level for a long time. We show that the effect of the Famine on the rural–urban fertility ratio lasted for about 20 years and then gradually vanished. Unsurprisingly, recovering from the immense population loss during the Famine takes time for rural families. Moreover, the trauma effect of the Great Famine may also stimulate rural families to bear more children as a precaution against a potential crisis in the future.

With the Great Famine as a plausible exogenous shock to China's post-Famine fertility structure and rural–urban population composition, we empirically study the long-term effect of such a dramatic shock on fertility structure on the income inequality in China. We use the Famine severity at the provincial and prefectural levels to instrument the rural population share of the post-Famine birth cohorts and find that a higher rural population share of the 1962–1985 birth cohorts induces a substantially higher Gini coefficient for these birth cohorts in 2005. That is, as a larger proportion of the new population concentrate in rural areas, the income inequality also increases substantially.

One important concern is whether the Great Famine is a valid IV for the post-Famine fertility structure or population composition, or whether the Famine affects the income inequality of the post-Famine birth cohorts only through affecting population composition of theses cohorts. Specifically, the Famine can have a long-lasting effect on the institutions, human capital investment, productivity, and ultimately the economic development of affected regions, all of which may directly affect income inequality in the long run.

We provide direct evidence that the Famine affects the income inequality of the post-Famine birth cohorts only through the channel of affecting differential fertility of these cohorts. We find that the effect of the Famine on post-Famine (1962–1985) rural population share diminishes over time, and the same is true for the effect of the Famine on income inequality. Specifically, the Famine has a strong and significant effect on the rural population share of the earlier (1962–1980) post-Famine birth cohorts, and such effect diminishes over time and vanishes for the post-1980 (1981–1985) birth cohorts. Surprisingly, the effect of the Famine on the income inequality of the post-Famine birth cohorts shows exactly the same pattern. Specifically, the Famine seems to have a considerable effect on the income inequality of the earlier post-Famine birth cohorts, and such an effect also diminishes to 0 for the post-1980 birth cohorts. These facts provide strong evidence that the significant estimates of the Famine on the income inequality of the post-Famine birth cohorts are likely due to the substantial effect of the Famine on the population composition of these cohorts.

Indeed, if the Famine affects the income inequality of the post-Famine birth cohorts through other channels, such as by directly affecting the regional institution or economic development, such effects are likely to be similar for different birth cohorts rather than diminish from earlier to later birth cohorts. Furthermore, the Famine seems to have no effect on the income inequality of the post-1980 birth cohorts, which is also inconsistent with the hypothesis that the Famine could directly affect income inequality in the long run.

To further confirm the validity of the Great Famine as an IV for the post-Famine fertility structure, we use China's birth planning policy as another IV for the rural–urban fertility structure and perform overidentification tests. As shown in the literature, China's birth planning policy was more strictly implemented in urban areas than in rural areas (Zhang, 2017), and such a two-tier policy could induce a much higher rural fertility than the urban one. Therefore, China's population control policy can be considered as another exogenous shock on the country's fertility structure. China initiated the "Later, Longer, Fewer" (LLF) birth planning policy in the early 1970s, and such a policy significantly reduced the country's fertility (Babiarz, 2018). We use the severity of the Great Famine and the LLF policy intensity as two instruments for the rural population share of the 1970–1978 birth cohorts. We then rely on overidentification tests to examine their validity.

In addition, we analyze the mechanism through which differential fertility or population composition affects income inequality of the next generation. Intergenerational income mobility is an important determinant of the dynamics of income inequality across generations. Intergenerational elasticity, i.e., the elasticity of children's income with respect to parents' income, is commonly used to measure intergenerational income persistence or mobility (Becker and Tomes, 1986; Solon, 1992; 2004; Mazumder, 2005; Corak, 2013; Chetty et al., 2014). Some empirical studies show that in many countries income inequality and intergenerational income persistence are positively correlated (Corak, 2004; Björklund and Jäntti, 2011). Krueger (2012) first uses "the Great Gatsby Curve" to describe such a positive correlation between income inequality and intergenerational income persistence. Fan et al. (2020) find that in China the intergenerational income persistence has been rising since 1979, after which the country initiated the reform and opening-up policy. The difference in human capital investment across income classes may be an important cause of such a decrease in intergenerational income mobility. Although China has invested more resources in the education sector since 1979, low income classes benefit much less than the high ones, which leads to a higher rather than lower social mobility (Li et al., 2013; Fan et al., 2020).

Chu and Koo (1990) prove that under three assumptions, a higher fertility of the poor will lead to a higher proportion of the poor and induce a less favorable income distribution with a lower social welfare level. We discuss these assumptions in detail and conclude that the first two assumptions are very likely to hold in China. Moreover, we empirically test their third and most critical assumption, which states that a higher reproduction rate of the poor worsens their upward mobility.

This third assumption seems quite reasonable. 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. Previous studies have shown that the tradeoff between the number of children and average child quality is more evident for rural families, whereas such a tradeoff relationship diminishes or even vanishes in urban China, where the resource constraint is less severe (Li et al., 2008; Rosenzweig and Zhang, 2009). Therefore, if rural families have more children, these children may become less competitive than their urban counterparts.

Furthermore, rural children would experience greater difficulty in climbing the social ladder, and social mobility would also decrease.

To measure the social mobility among rural and urban youth, we use the outcome of the National College Entrance Examination (NCEE) and the Senior High School Entrance Examination (SHSEE), which rural and urban high school graduates take to compete for the limited quota of college and senior high school admissions. We find 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.

Income inequality in China is reported to have already reached a level much higher than that in many developed countries recently and a substantial part of such high inequality is due to regional disparities and the rural–urban gap (Xie and Zhou, 2014; Zhang, 2021). However, the profound reason for such rapidly increasing inequality in China remains unclear. We show that the Great Famine may have a long-term effect on China's income inequality. Furthermore, as discussed earlier, China's two-tier population control policy may induce a much higher rural–urban fertility ratio, which may further have a non-negligible effect on the income inequality of the next generation. Therefore, China's two-tier population control policy may be another cause of its current high income inequality.

Existing literature finds a positive correlation between income inequality and intergenerational income persistence, the cause of which remains unclear. A higher income inequality may induce lower intergenerational income mobility, or lower social mobility can widen the income inequality, or these two factors interact as both cause and effect. This study proposes another possibility: a more fundamental factor, namely, differential fertility across income classes, positively affects both income inequality and intergenerational income persistence, and thus leads to a seemingly positive correlation between these two factors. This novel evidence provides a new perspective to understand the interaction between income inequality and social mobility.

2. Theoretical Discussion

Conceptually, whether and to what extent differential fertility across income classes affects income inequality of society largely depends on intergenerational income mobility. Specifically, if the intergenerational income elasticity is one, that is, children have the same income levels with their parents, then differential fertility would have a direct and strong effect on the income distribution of the next generation, which is a pure population compositional effect. At the other extreme, if the intergenerational income elasticity is zero, which means that children's income is uncorrelated with their parents' income, then differential fertility does not matter at all because children from different family backgrounds exactly have the same probability of falling into any income class. In reality, the intergenerational income elasticity is generally between zero and one, and children of rich and poor parents have different probabilities of falling into any income class, which makes the issue very complicated.

Lam (1986) analyzes the dynamics of differential fertility across income classes and income inequality of society. In a model of differential fertility and intergenerational mobility based on a Markov process governing transitions across income classes, there are *1, 2, ……, n* income classes (the income level increases with the number) with different fertility rates, and intergenerational mobility is described by a matrix M, where element M_{ij} is the probability that a child of class j becomes a member of class i. The first step to examine the effect of a higher fertility of the poor on the income distribution of the society is to investigate how a higher fertility of the poor affects the proportion of the poor. Lam first analyzes the effect of a change in F_1, the fertility of the poorest class, on the proportion in that class in the next period. He concludes that if $M_{1i} \leq M_{11} \forall i,$ implying that parents of other classes are less likely to produce poor offspring than the poor themselves, then an increase in the fertility of the poor will always lead to an increase in the proportion of the poor in subsequent period. However, the effect of a change in F_1 on a potential income inequality index is much more complicated and cannot be predicted without knowing the actual magnitude of the change. For example, if we consider the effect of an increase in the proportion of the poor on the Gini coefficient, the Gini coefficient is likely to increase initially but must eventually decrease as the new entrants of the poor finally dominate the distribution and most people become poor. Lam further shows that two inequality measures, namely, variance of log income and coefficient of variation, move in opposite directions in both the steady sate and transition in response to the elimination of fertility differentials. Such results raise serious concerns about the validity of income inequality measures and inequality comparisons when fertility rates differ across income classes.

The subsequent studies (Chu, 1987; Dietzenbacher, 1989) show that the issue is more complicated than expected and even Lam's simplest statement "if $M_{1i} \leq M_{11} \forall i,$ an increase of the fertility of the poor will lead to an increase in the proportion of the poor" does not necessarily hold and needs stronger conditions. For instance, if the children of the poorest class have a very high probability (say, 70%) of falling into the richest class, although they also have a slightly higher probability (say, 30%) of falling into the poorest class than the children of the richest class (say, 29%), then a higher fertility of the poor could lead to an increase in the proportion of the rich. Chu and Koo (1990) further systematically study the issue and conclude that under several more rigorous assumptions a higher fertility of the poorest class will lead to a higher proportion of the poor; moreover, the resulting income distribution will be conditionally first-degree stochastic dominated by the initial one (in a Markov branching process of income distribution dynamics). If an income distribution conditionally first-degree stochastic dominates (CFSD) the other one, it means it is better and more favorable than the other one in that it has a higher social welfare level. For example, if there are two initially identical income distributions and if we increase the income of the poorest class of the first one, then, it would dominate the other income distribution because its poorest class has a higher income level with other things being equal. Theoretically, the CFSD relation is an important concept and has stronger welfare implications than the income inequality measures. Specifically, a society with a lower income inequality and all people are poor does not necessarily dominate the other society with a higher income inequality. Although CFSD relation is a theoretically important concept, empirically testing such a relation is extremely difficult. Income equality is a practically more important concept and policy makers and the public care more about the income inequality measures such as the Gini coefficient. Although a lower income inequality level is not always the most desirable outcome, we still prefer a lower rather than a higher income inequality under most situations (except the situation under which income inequality is low and all people are poor). Thus, studying income inequality is practically important and also has strong policy implications.

Although we cannot reach a final conclusion about the effect of an increase in the fertility of the poor on different income inequality measures based on pure theoretical analyses, we can still make some reasonable inferences from these studies. According to Lam’s analysis, an increase in the proportion of the poor is likely to increase the income inequality measures such as the Gini coefficient initially, but the Gini coefficient will eventually decrease as the proportion of the poor becomes very high and most people become poor. Therefore, before the income distribution reaches the extreme point at which most people are poor, an initial increase in the proportion of the poor will probably increase rather than decrease the income inequality of society.

Our empirical investigations are based on the aforementioned theoretical literature. We intend to examine the effect of a plausible exogeneous increase of rural fertility in China on the income distribution of the county several decades later. According to Chu and Koo (1990), under three assumptions, an increase in rural fertility will induce a higher proportion of the poor and lead to a less favorable income distribution with a lower social welfare level. According to Lam (1986), an increase in the proportion of the poor is likely to increase the Gini coefficient (except the extreme situation under which the proportion of the poor becomes very high and most people are poor). Therefore, we discuss and empirically test the three assumptions in Chu and Koo (1990) and empirically identify the effect of an increase in rural fertility on the Gini coefficient of the country several decades later.

Some macroeconomics literature points out another possibility that income inequality may directly affect differential fertility. Kremer and Chen (2002) find that higher inequality levels tend to be associated with larger fertility differentials within a country. Croix and Doepke (2003) demonstrate that an increase in income inequality could increase the fertility differential between the rich and the poor, implying that additional weight is placed on families who provide little education; thus, an increase in inequality lowers average education and economic growth. Our empirical findings do not contradict such possibilities that income inequality could affect the current differential fertility across income classes. Furthermore, as we are studying the effect of the post-Famine differential fertility on the income inequality in 2005, the two-way causality may not be a problem because the income inequality in 2005 is unlikely to affect the differential fertility in the 1960s. Nevertheless, we cannot exclude the possibility that the current income inequality could be correlated with previous differential fertility in other ways. Therefore, we need to find plausible exogeneous shocks on differential fertility to resolve the potential endogenous problems in our identification.

3. Data

We use the 1% sample of the 1990, 2000 census and the 2005 mini census from the Chinese National Bureau of Statistics as our data sets, among which the 2005 census is the primary one. These three data sets cover 3,152,818 (1990), 3,742,658 (2000), and 996,588 (2005) households, with a record for each household. Each record includes information on demographic characteristics, occupation, education levels, income (in the 2005 mini census only), ethnicity, household type (rural or urban), and fertility of each individual living in the household. The 2005 census also records the income level of all the labor force, which can be used to calculate the Gini coefficient.

We mainly focus on the income equality of the 1962–1985 birth cohorts in 2005, who were born after the Great Famine.[4] We also compare the Gini coefficient of these birth cohorts with the 1950–1985 birth cohorts, who constitute the main labor force (20–55 years old) in 2005, to see to what extent these post-Famine birth cohorts are representative for the main labor force. We use the 2005 census data to calculate the Gini coefficient at the individual level for these birth cohorts in each province. In particular, we include all members of the labor force who are currently working in the province to obtain the Gini coefficient.

[4] Given that individuals born after 1985 are younger than 20 in 2005 and thus less likely to participate in the labor market, we do not include them in our analysis.

The 2005 mini census is the unique census data set that contains the information of respondents' income. Thus, it is the most representative data set available to for analyzing the income distribution of recent China. The Gini coefficients of the country at the individual level and family level obtained from the data are 0.496 and 0.483, respectively.[5] Xie and Zhou (2014) also use the 2005 mini census as one of the primary data sets to analyze China's income inequality. They demonstrate that the Gini coefficient calculated from the data is very close to the one published by Li et al. (2013) based on the 2007 survey of the Chinese Household Income Project (CHIP, 2007). They also calculate the Gini coefficients in China during the last four decades based on the database of the World Institute for Development Economics Research of the United Nations University, and their estimate of the Gini coefficient in 2005 is also very close to the one obtained from the mini census. Therefore, using the 2005 mini census is assuring to study China's income inequality situation in that year.

Similar to Meng et al. (2015), we use the 1990 census data to identify the rural and urban population size for the 1962–1985 birth cohorts and calculate the rural population share for these birth cohorts at the provincial and prefectural levels, which is the proportion of the population born in rural areas in each province and prefecture. We regard respondents' registered residence (where they have a hukou) in the census year as their birth places in the 1990 census. However, this information may not be completely accurate. People's hukou statuses may change over time and rural born children may acquire urban hukous later. Furthermore, rural residents may also migrate across provinces and obtain hukous in other cities over the decades. Nevertheless, such possibilities may not be a problem. Meng et al. (2015) discuss that rural populations are defined as households officially registered as agricultural (with rural hukous) and these statuses were assigned in the early 1950s. In addition, extremely limited mobility occurred from being a rural household to an urban household between then and 1990. Furthermore, they show that given Chinese policies against labor migration, minimal migration transpired across regions before 1990.[6]

Panel A of Table 1 shows the summary statistics for the main variables at the provincial level. The mean of the Gini coefficient for the 1950–1985 birth cohorts in 2005 is approximately 0.421, while the corresponding standard deviation is 0.044. Similarly, the mean and standard deviation of the Gini coefficient for the 1962–1985 birth cohorts are 0.413 and 0.046, respectively. Notably, the statistics for the Gini coefficient of the post-Famine birth cohorts (the 1962–1985 birth cohorts) and

[5] As we examine the income inequality of a certain region by birth cohort and members of a given family may belong to different birth cohorts, we thus primarily analyze the Gini coefficient at the individual level. Given that the Gini coefficients at the individual and family levels are very close, this choice should not make much a difference.
[6] We do not use the 1982 census data to calculate the rural population share of the post-Famine birth cohorts because accurate information on the hukou type of the respondents and information for the 1982–1985 birth cohorts are not available in the data. We do not use the 2000 and 2005 census data because migration from rural to urban areas and across regions became more common after 1990 and identifying the birth place of the 1962–1985 birth cohorts with these data also becomes more difficult.

main labor force are extremely similar, which indicates that the post-Famine birth cohorts are likely adequately representative for the main labor force when it comes to the issue of income inequality.

Panel A also shows that the variation of the Gini coefficient across provinces is not very large. However, such outcome does not mean that income inequality is insignificant across the country. In fact, regional inequality is an important source of income inequality at the national level. For example, if the Gini coefficients of both eastern and western regions are relatively low but the eastern region is substantially richer than the western region, then income inequality for the entire country will still be extremely high.

The means of the rural population share for the 1950–1985 and 1962–1985 birth cohorts at the provincial level are 0.741 and 0.758, respectively, while the corresponding standard deviations are 0.154 and 0.148, respectively. The rural population is considerably larger than the urban one for the majority of the provinces, while the rural population share also shows considerable variation across provinces.

We use the data of the Great Famine in Meng et al. (2015), which are originally from the National Bureau of Statistics (NBS) of China, to construct our instrument variable (excess mortality rate during the Famine) for the rural population share of the 1962–1985 birth cohorts. The means of the average rural mortality rate and average rural excess mortality rate during 1959–1961 are 1.71% and 0.79% (or 17.1‰ and 7.9‰), respectively and both have standard deviations of approximately 0.8% (or 8‰). Both variables show large variation across provinces while the latter, which measures the severity of the Famine in each province, shows more significant variation.

Panel B of Table 1 reports the corresponding summary statistics for the variables at the prefectural level. The mean of the Gini coefficient for the 1962–1985 birth cohorts in 2005 is approximately 0.40, while the corresponding standard deviation is 0.057. The mean of the rural population share for the 1962–1985 birth cohorts is 0.77, and the standard deviation is 0.18.

Similar to the strategy of Meng et al. (2015), we use the 1990 census data to calculate the average rural birth cohort size gap during 1959–1961, which indicates to what extent the size of these birth cohorts shrunk during the Famine, to measure the Famine severity at the prefectural level.[7] Panel B shows that the mean of the average rural birth cohort size gap for the 1959–1961 birth cohorts at the prefectural level is approximately 0.405 and the corresponding standard deviation is 0.168, which indicates that at the prefectural level the rural birth cohort size shrunk by 40% during the Famine, and the corresponding variation across prefectures is also considerable.

[7] We will discuss this variable in detail in section 5.4.

4. China's Great Famine (1959–1961)

China's Great Famine (1959–1961) was one of the worst famines in human history and caused heavy population loss. Yang (2013) concludes that 36 million people starved to death during the Famine, while 40 million others failed to be born. Numerous studies on the Great Famine reached a consensus that a significant decrease in food production in 1959 and the subsequent high government procurement from rural areas were the main causes of the Famine (Meng et al., 2015). The current study primarily focuses on the long-term effect of the Great Famine on China's population structure. We verify that the Famine can be considered as an exogenous shock on China's fertility structure and can thus serve as a valid instrument for the post-Famine rural–urban population composition.

As is well known, rural areas were much more affected by the Famine than urban areas, and most deaths were of rural residents. Although the majority of the prime-age adults survived (Thaxton, 2008), the elderly and young children were heavily affected and over half of the total deaths were of young children (Ashton et al., 1984; Spence, 1991). Consequently, rural fertility rebounded significantly after the Famine, and the fertility gap between rural and urban households increased sharply and maintained at a high level over a long period. We next plot several figures to demonstrate the exogeneity of the Famine and the short- and long-run effects of the Famine on the post-Famine fertility structure and population composition.

Given that the Famine was caused by crop failure and high government procurement and primarily struck rural areas, people may assume that those major agricultural provinces, which relied more on food production and had a larger share of the rural population, suffered more from the Famine. However, it is not the case at all. Figure 1 plots the rural population share in 1958 (before the Famine) and the average mortality rate (deaths per 1000) in 1959–1961 for all provinces and municipalities. The three municipalities directly under the central government (i.e., Beijing, Tianjin, and Shanghai) are in the lowest area of Figure 1. Evidently, they differed substantially from other provinces in many ways, had an extremely low rural population share, and were incomparable with these provinces. Figure 1 shows that except for the three municipalities, the rural population share and mortality rate across provinces appear to be uncorrelated. That is, mortality rates may either be extremely high or extremely low for provinces with similar rural population share.

We further calculate the excess mortality rate in rural areas during the Famine at the provincial level to accurately measure the extent to which each province was affected by the Famine. We use the mortality rate in 1957 (i.e., before the Famine happened) to predict the mortality rate in each province in 1959–1961 had there been no Famine. Thereafter, we subtract this predicted mortality rate from the actual mortality rate during the Famine to obtain the excess mortality rate. We further calculate the total excess deaths by multiplying the excess mortality rate by the total population. Given that the majority of the excess deaths were from the rural population, we divide the total excess deaths by the rural population to obtain the excess mortality rate in rural areas.

Figure 2 plots the rural population share in 1958 and the average excess mortality rate of the rural population during 1959–1961 at the provincial level. The plot looks similar to that in Figure 1 and the points are more scattered than those in Figure 1. Mortality rates across provinces show considerable variation. For provinces with a rural population share above 80%, some of their excess mortality rates are as high as 30‰, whereas the rates of others are close to 0. If we regress the rural population share in 1958 on excess mortality rate for all provinces, we obtain an insignificant coefficient of 0.005 (with the p value of approximately 0.15), which is nearly 0. Therefore, the severity of the Famine seems uncorrelated with the pre-Famine rural population share at the provincial level.[8] Accordingly, the Famine seems to be an exogenous shock on the population structure of each province.

As previously discussed, the survival rate of prime-age adults was high during the Famine, whereas the elderly and young children were heavily affected. In addition, over half of the total deaths were of young children. Intuitively, if most prime-age adults survived and many young children died in rural areas during the Famine, then, rural families would bear more children after the Famine to recover from the population loss. Thus, we expect that rural fertility rebounded significantly after the Famine.

Figure 3 shows the rural and urban total fertility rate (TFR) at the national level for 1950–1985 (the data are from Yao and Yin,1994). The rural TFR rebounded considerably after 1961 and reached the summit level soon, while urban fertility also increased substantially shortly after the Famine. The extant literature indicates that although urban areas did not suffer numerous deaths during the Famine, urban families also postponed their birth plans during the difficult time of the event (Yang, 2013). Thus, urban fertility also rebounded significantly and reached a summit after the Famine. Nevertheless, such a rebound in urban fertility is only a temporary adjustment and lasts only for 1 or 2 years. By contrast, rural families not only postponed their birth plans but also suffered a heavy population loss during the Famine. Thus, the Famine had a considerably more significant and long-lasting effect on post-Famine rural fertility. Unsurprisingly, the rural–urban fertility gap widened sharply after the Famine. Figure 4 conveys a similar information. Before the Famine, rural fertility was only slightly higher than the urban one, with the rural–urban TFR ratio being only slightly above 1. After the Famine,

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[8] Lin and Yang (2000) show that a higher rural population share induced a higher mortality rate at the provincial level during the Famine. This finding is not surprising because the rural population were much more affected by the Famine than the urban ones, and a higher percentage of rural population would mechanically lead to a higher average mortality rate of the entire province. Furthermore, such a finding does not contradict our statement that the severity of the Famine in rural areas is uncorrelated with the pre-Famine population structure. The Figures clearly show that the severity of the Famine as measured by excess rural morality rate is not systematically correlated with the population structure.

such ratio increased substantially and reached over 2 and remained at such a high level for a long period.

An alternative hypothesis for such a high post-Famine rural–urban fertility ratio could be that urban China started its demographic transition process ahead of rural China because the former had higher income. However, China's economic development has been stagnant for a long time before the implementation of the reform and opening-up policy in 1978, and no evidence shows that economic development is the main driver of China's demographic transition before 1978. Therefore, such a substantial increase in the rural–urban fertility ratio shortly after the Famine is unlikely to be caused by economic development.

Furthermore, the more stringent population control policies in urban areas may have also led to lower urban fertility. Nevertheless, China began to implement its population control policy in the early 1970s (Zhang, 2017), while the rural–urban fertility ratio increased substantially shortly after the Famine, which occurred 10 years before the implementation of the policy. Thus, China's two-tier population control policy is not the main cause of such a high post-Famine rural–urban fertility ratio.

Lastly, the post-Famine rural–urban fertility ratios are much higher in provinces that suffered more from the Famine. Even if other factors, such as economic development or the population control policy, could affect the rural–urban fertility ratio, they would definitely affect all the provinces. We have no reason to expect that these factors will largely affect the provinces that are more affected by the Famine. In other words, there is no evidence that these factors are systematically correlated with Famine severity at the provincial or prefectural levels.

We further investigate the effect of the Famine on the rural population growth rate by comparing such growth rates over time across provinces who were affected by the Famine at different levels. Figure 5 plots the rural population growth rates of Shaanxi and Anhui Provinces between 1950 and 2000. The excess mortality rate in Shaanxi during the Famine is extremely low, whereas that for Anhui is extremely high. Figure 5 shows that the rural population growth rates of both provinces rebound considerably after the Famine. For Anhui, which suffered a heavier population loss during the Famine, the rural population growth also rebounded more significantly after the Famine. The rural population growth rate of Anhui before the Famine was generally lower than that of Shaanxi. However, it exceeded that of Shaanxi shortly after the Famine and remained at a higher level for long time. Unsurprisingly, recovering from the immense population loss during the Famine takes time in those heavily affected provinces.

Given that the Great Famine mainly affected rural areas and urban areas were minimally affected, it could increase the post-Famine rural population share over a long period. We intend to use the rural excess mortality rate during the Famine to instrument for rural population share of the 1962–1985 birth cohorts to analyze the effect of the post-Famine population composition on the Gini coefficient for these post-Famine birth cohorts in 2005 at the provincial level.

Figure 6 plots the average excess mortality rate in rural areas during 1959–1961 and the rural population share for the 1962–1985 birth cohorts for all provinces and municipalities. Evidently, these two variables are positively correlated and provinces where rural areas suffered immense population loss during the Famine also have higher post-Famine rural population shares. Furthermore, the Great Famine is unlikely to directly affect the income inequality of the 1962–1985 birth cohorts who were born after the Famine. Therefore, the exclusion restriction condition is likely to be satisfied and the excess rural mortality rate during the Famine could be a valid instrument variable for the rural population share of these post-Famine birth cohorts. We will further discuss and verify the validity of this IV in detail later.

To further examine the effect of the Famine on the post-Famine fertility and population composition over time, we estimate the following equation to obtain some suggestive evidence:

$$Rshare_p^t = b^t M_p + \varphi^t R_p^t + \theta^t X_p + \varepsilon_p^t, \tag{1}$$

where $Rshare_p^t$ is the rural population share of birth cohort t (1962–1985) in province p, M_p is the rural excess mortality rate during the Famine in in province p, R_p^t is the rural share of childbearing-age women for year t in province p, X_p include some pre-Famine provincial level characteristics (rural population share and agricultural productivity in 1958), and ε_p^t is the disturbance term.

Figure 7 plots the estimates for b^t for each t between 1962 and 1988 (we extend the birth cohort to1988 to check the trend in a longer term), and a 95-percent confidence interval is plotted by broken lines. Given that we have controlled the rural share of childbearing-age women in each year, Figure 7 actually provides the correlation between the Famine severity and post-Famine rural–urban fertility structure for the period of 1962–1988. Figure 7 indicates that the Famine is likely to have a long-term effect on the post-Famine fertility structure and population composition. The correlations between the Famine severity and post-Famine rural population share are significantly positive for all the earlier birth cohorts and begin to decrease after 1976 and diminish to 0 for the 1981 birth cohort and after. Intuitively, the effect of the Famine should be most significant for the earlier cohorts born shortly after the Famine and then decreases over time.

Figure 7 shows that the estimates for the earlier birth cohorts are relatively small and increase to some extent over time and maintain at a higher level for a long period. It is not difficult to explain such a pattern. As previously shown, given that both rural and urban fertility increased sharply shortly after the Famine, the rural–urban fertility ratio is not very high. Thus, the rural population share for these earlier birth cohorts is not very high. Given that urban households were much less affected by the

Famine than their rural counterpart, urban fertility returned to normal level in several years while rural fertility remained high over a long time (because it takes time for rural families to recover the population loss during the Famine). Thus, the rural–urban fertility ratio and rural population share could increase over time after the Famine.

Although Figure 7 demonstrates some suggestive evidence that the Famine may have had a long-lasting effect on the post-Famine rural–urban fertility structure and population composition, we cannot exclude other possibilities that other post-Famine factors or events may also induce such a demonstrated pattern. One concern is that China's population control policy may be an important cause of the decrease in the effect of the Famine on rural population share after 1978 as shown in Figure 7. However, a further examination can help us largely exclude this possibility. As mentioned earlier, China begun a "Later, Longer, Fewer" (LLF) birth planning policy in the early 1970s and tightened it to one-child policy (OCP) in 1979, and such two-tier population control policies can also increase the rural–urban fertility ratio and rural population share. Figure 7 shows that after 1971, the estimates remain significantly above 0 and begin to decrease from 1977, which is prior to the implementation of the OCP. Therefore, these facts are inconsistent with the argument that the LLP or OCP is the main cause of the pattern shown in Figure 7. Furthermore, we show in the Appendix that the Famine severity and the implementation intensity of the OCP as measured by fines of violation of the policy are uncorrelated. If we control the implementation intensity of the OCP for the post-1979 birth cohorts in the regression based on which Figure 7 is plotted, we still obtain similar results. Therefore, we can conclude that the population control policies are not the driving force for the pattern shown in Figure 7.

In sum, Figure 7 is completely consistent with our interpretation that the Famine has a long-term effect on the post-Famine fertility structure and population composition. Although we admit that other post-Famine factors or events can also affect the population composition of the country during that period, we have no reason to expect that these factors are systematically correlated with the Famine in any way. Finally, if other factors are fundamental determinants of the post-Famine rural population share, it is unlikely to observe the pattern shown in Figure 7.

5. The Effect of Differential Fertility on Income Inequality

We now estimate the effect of the rural population share (by birth cohort) on the Gini coefficient for the same birth cohorts several decades later at the provincial and prefectural levels.

5.1 Differential Fertility and Population Composition: Theoretical Clarification

We intend to investigate the effect of differential fertility of rural and urban households after the Famine on the income inequality of the corresponding post-Famine birth cohorts. However, in practice, we use the rural population share of the post-Famine birth cohorts to substitute for the fertility differential between rural and urban households. Although differential fertility and population composition of the next generation are closely related, there is still subtle difference between them. We now prove that under certain scenarios, these two concepts could be equivalent.

Let α be the rural population share of a certain birth cohort; let N_1, N_2 be the number of women of childbearing age (15–49 years old) of the same year in rural and urban areas, respectively; let n_1, n_2 be rural and urban fertility in the same year, respectively. We can obtain the following:

$$\alpha = \frac{N_1 n_1}{N_1 n_1 + N_2 n_2} = \frac{1}{1+\frac{N_2 n_2}{N_1 n_1}} \ . \tag{2}$$

Therefore, rural population share α is actually a function of the rural-urban fertility ratio $\frac{n_1}{n_2}$. Furthermore, if the ratio of rural and urban numbers of childbearing-age women ($\frac{N_1}{N_2}$) is given, there is a one-to-one correspondence between α and $\frac{n_1}{n_2}$. Thus, it is actually equivalent to estimate the effects of rural population share and rural-urban fertility ratio on income inequality if we control the variable $\frac{N_1}{N_2}$ (or $\frac{N_1}{N_2+N_1}$, which is the rural share of childbearing-age women) in the regressions.

Intuitively, differential fertility across income classes affects income inequality through changing the proportion of the offspring of the poor and rich in the total population and further affecting the income distribution of the next generation. For example, if rural fertility is much higher than the urban ones, then the population of the next generation would contain a larger share of rural children, and thus income inequality of this generation may increase accordingly. Considering that population composition is easier to measure and interpret and it is also the critical determinant of income inequality, we mainly investigate the effect of rural population share on the income inequality of the next generation with the rural share of childbearing-age women as a control in the empirical practice.

5.2 Rural Population Share and Income Inequality: Provincial Level Evidence

In practice, we use the Famine severity to instrument for the rural population share of the post-Famine birth cohorts (the 1962–1985 birth cohorts) and estimate the effect of the rural population share of these cohorts on the income inequality of the same cohorts in 2005 at the provincial and prefectural levels. The first- and second-stage estimations are as follows:

$$Rshare_p = c_1 + \mathrm{b} M_p + \theta_1 X_p + \varepsilon_{p1}, \tag{3}$$

$$Gini_p = c_2 + \beta\ Rshare_p + \theta_2 X_p + \varepsilon_{p2}, \tag{4}$$

where $Rshare_p$ is the rural population share for the 1962–1985 birth cohorts in province (or prefecture) p, $Gini_p$ is the Gini coefficient for these same birth cohorts of province (or prefecture) p in 2005, c_1 (c_2) is a constant, M_p is the average rural excess mortality rate during 1959–1961 in province (or prefecture) p, X_p represents a set of provincial (or prefectural) level characteristics; ε_{p1} (ε_{p2}) is the disturbance term. β is the estimator of interest.

We include three sets of provincial (or prefectural) characteristics (see the Appendix for the details). First, given that the pre-Famine population structure and economic development level may be correlated with the future fertility and economic development degree, we control the rural population share and agricultural productivity in 1958. Second, we control the rural share of childbearing-age women for the post-Famine period of 1962–1985. Third, we also control a set of provincial (or prefectural) characteristics in 2005, which may directly affect the income inequality of that time. Specifically, we control the characteristics related to the regional economic development, such as income per capita,[9] GDP, agricultural and industrial output shares in GDP, and the share of migrant population in total population.[10] Given that population density and social welfare policy may also affect income inequality, we also control population density and unemployment insurance participation rate in 2005.

Table 2 shows the OLS and IV estimates of the effect of the rural population share for the 1962–1985 birth cohorts on the Gini coefficient in 2005 at the provincial level. Panel A reports the benchmark estimate results. Column (1) shows the OLS estimate, and the coefficient of the rural population share is approximately 0.3, which indicates that an increase of 10% in rural population share corresponds to an increase in Gini coefficient by 0.03 at the provincial level. Column (2) reports the reduced-form result and shows that the instrument (the average rural excess mortality rate during 1959–1961) is significantly correlated with the Gini coefficient for the 1962–1985 birth cohorts in 2005. Specifically, an increase of 1% in rural excess mortality rate during the Famine corresponds to an increase of the Gini coefficient of the post-Famine birth cohorts in 2005 by 0.016 at the provincial level. Column (3) lists the IV estimate. Compared with the OLS estimate, the coefficient for the rural population share becomes substantially larger and is significant at the 1% level. Specifically, the coefficient of the rural population share is approximately 0.55, which implies that an increase of 0.1 in rural population share would increase the Gini coefficient by 0.055, or an increase of 13.5% in rural population share (0.1/0.74, where 0.74 is the mean of rural population share) would increase the Gini coefficient by 13.1% (0.055/0.42, where 0.42 is the mean of the Gini coefficient), and this estimate almost doubles that of the OLS one. The lower panel shows that the coefficient for the Famine severity

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[9] Alternatively, we can control GDP per capita, which is strongly correlated with income per capita. Given that income per capita is more relevant when studying income inequality, we control it instead.

[10] Migrant population share in total population is another dimension of population composition and thus can affect Gini coefficient directly, and it also reflects to what extent a region is attractive to migrants, which is also an important regional characteristic. We will discuss how to resolve the problems arising from migration in detail later.

in the first-stage regression is about 0.029, which indicates that an increase of 1% in the rural excess mortality rate would increase the post-Famine rural population share by 2.9%, which is a non-negligible impact. Furthermore, the Kleibergen-Paap (K-P) F statistic of the first-stage regression is above 13, thereby implying that the instrument is not weak, which should be obvious.

In the above benchmark regressions, we use the 1990 census data to calculate the rural population share of each province on the basis of respondents' hukou type at the time of the census, and we use the 2005 census data to calculate the Gini coefficient on the basis of their residence and workplace. We include all the labor force members who are currently working in each province to obtain the Gini coefficient of the province in 2005. However, people born in one province may migrate to other provinces after growing up. Although migration was rare before 1990, there had been a steady inflow of migrants from the western and central regions to the more developed eastern regions in 2005. Given that some migrant workers in each province in 2005 are originally from other provinces, the above strategy may be problematic. Fortunately, the 2005 census data also include information on respondents' migration status, which we can use to identify their home provinces.

In the survey of the 2005 census, question "R6" is related to the respondents' hukou registration location. If the respondents' hukous were registered in where they were currently residing, then, we identify them as local residents. By contrast, if the respondents' hukous were registered in other places rather than where they were currently living, we identify them as migrant population and further take the registration location of their hukou as their hometown.

Such an identification of the respondents' migrant statuses may not be completely accurate. For example, if a respondent was born in one province, later successfully admitted to college in another province, obtained a hukou after graduation, and lived there permanently, then, we include her in the sample of the province of her residence rather than her home province in 2005. Theoretically, we should include all the respondents who were born during 1962–1985 in the province in the sample of this province in 2005, and such an inaccurate choice of the sample may induce problems. However, given Chinese government's extremely tight control on the hukou system over a long period, it is very difficult for most people to change their hukou statuses, particularly switch hukou from a region to another. Given that the most typical migration in China was that people left their hometown and worked in other cities without obtaining the hukou there, we can precisely identify the migration statuses of these people with the above method in the census data.[11]

We now include those migrant population in their home provinces and perform similar estimations to those in Panel A of Table 2 to check whether the results remain robust. Panel B of Table

[11] See the Appendix for further discussions about migration.

2 provides the corresponding estimates with such migration adjustment. Compared with the benchmark estimation, Column (4) shows that the OLS estimate becomes smaller, while Column (6) indicates that the IV estimate remains similar and statistically significant different from 0.

If we include those migrant workers in their home provinces, then we should also consider the difference in living cost between their residences and their hometowns. For example, a migrant worker from Shaanxi worked in Shanghai and earned a 3000 Yuan monthly salary, while similar workers in his hometown can only earn 1500 Yuan per month. In this case, we cannot say that this worker's salary is twice as high as that of workers in his hometown because the cost of living in Shanghai is also substantially higher than that back home. Therefore, given the difference in the cost of living across provinces, those migrant workers' income may be incomparable to that in their home provinces.

We now further adjust the price difference across provinces to render the income earned in different regions comparable. We use the spatial price index for all provinces in 2004, which was calculated by Brandt and Holz (2006), to adjust the nominal income in all provinces. We then perform the similar estimations to these in Panel B of Table 2 and report the corresponding estimate results with such migration and price adjustment in Panel C of Table 2. Compared with the estimate results in Panel B, Columns 7–9 of Panel C show no substantial changes in the estimates, which indicates our estimates are robust.

Meng et al. (2015) show that the Famine severity is positively correlated with per capita food production across rural areas and such a positive correlation results from the inflexible and progressive government procurement policy. That is, the government procured more grains from historically more productive regions. If these regions experienced a larger absolute production drop, the consequent over-procurement would lead to less food retention and higher mortality rates in these regions. However, this scenario is not a problem in our analysis. In fact, we have already controlled the pre-Famine grain productivity in the regressions, and the estimates remain similar whether with and without the control. We next argue that such a positive correlation of Famine severity and grain productivity can make our estimates more robust.

The Famine severity may be correlated with the pre-Famine income inequality at the provincial level. Specifically, if the pre-Famine income inequality of the provinces heavily affected by the Famine were extremely high and such high inequality persisted for a long time, then the causality between the post-Famine population composition and income inequality in 2005 would be contaminated. However, no evidence suggests that those provinces where income inequality was high suffered more from the Famine. In fact, the opposite situation is likely to be true. As previously discussed, in provinces where famine was more severe, the pre-Famine agricultural productivity was also higher. Given that China was actually an agricultural country before 1978 and its income inequality was mainly caused by the huge rural–urban gap, provinces where agricultural productivity was higher were likely to have lower rather than higher income inequality. Therefore, despite the lower pre-Famine income inequality in provinces heavily affected by the Famine, such income inequality became higher several decades later, which presents stronger evidence of the treatment effect.

We now further divide the post-Famine birth cohorts into several sub-cohorts to examine the effect of the Famine on earlier and later cohorts to check how such effects change over time. Specifically, we divide the post-Famine birth cohorts into six sub-samples and rerun the regression in Panel A of Table 2 and present the IV estimation results in Table 3.[12]

Table 3 shows that the IV estimates of the effect of rural population share on the Gini coefficient decrease from the earlier to the later birth cohorts. Specifically, the estimate is as large as 0.64 for the 1962–1965 birth cohorts, and it gradually decreases to 0.3–0.5 for the 1970–1977 birth cohorts and becomes insignificantly different from 0 for the post-1978 birth cohorts. Similarly, the reduced-form estimate is 0.02 and significant at the 5% level for the 1962–1965 birth cohorts, and it decreases to 0.009 for the 1978–1981 birth cohorts and further decreases to 0.006 and becomes insignificantly different from 0 for the 1982–1985 birth cohorts. The lower panel of Table 3 shows that the correlation between the Famine severity and post-Famine rural population share also decreases over time and becomes insignificantly different from 0 for the later birth cohorts, which is consistent with the pattern demonstrated in Figure 7.[13]

Given that the later birth cohorts are much less affected by the Famine than the earlier ones, we can also identify the effect of the Famine on the post-Famine birth cohorts with a Difference-in-Differences (DID) framework, with the earlier birth cohorts as the treatment group and the later ones as the control group.

Similar to Duflo (2001), we estimate the following regressions:

$$Rshare_{pt} = c_1 + \alpha_{1p} + \gamma_{1t} + b(M_p \times T_t) + \varphi_1 \mathrm{R}_{pt} + \delta_1(X_p \times T_t) + \varepsilon_{pt1}, \quad (5)$$

$$Gini_{pt} = c_2 + \alpha_{2p} + \gamma_{2t} + \beta Rshare_{pt} + \varphi_2 \mathrm{R}_{pt} + \delta_2(X_p \times T_t) + \varepsilon_{pt2}, \quad (6)$$

where $Rshare_{pt}$ is the rural population share of birth cohort *t* in province (or prefecture) p, c_1 (c_2) is a constant, α_{1p} (α_{2p}) is a province (or prefecture) fixed effect, γ_{1t} (γ_{2t}) is a birth cohort fixed effect, M_p is the excess mortality rate during the Famine in province (or prefecture) p, T_t is a dummy that indicates whether the birth cohort *t* belongs to the earlier birth cohorts, R_{pt} is the rural share of

[12] The benchmark estimates by birth cohort and the corresponding estimates with migration and price adjustment are similar, and we only report the former here.

[13] One concern is that different birth cohort may be different to some extent. Thus, the estimates in Table 3 may be confounded with birth cohort effects. However, the same birth cohorts across province or prefecture may still be largely comparable. Thus, Table 3 still provides informative estimates of the effect of the Famine on the Gini coefficient. In next section we will obtain the DID estimates with a panel data set in which the birth cohort fixed effect can be controlled to resolve this problem to a greater extent.

childbearing-age women for year t in province (or prefecture) p, X_p is a vector of provincial (or prefectural) level controls similar to those in regressions (3) and (4), and $Gini_{pt}$ is the Gini coefficient for birth cohort t in province (or prefecture) p in 2005. β is the estimator of interest.

To estimate regressions (5) and (6), we need to determine the cutoff year between the pre- and post-treatment groups. Following Duflo (2001), we estimate the following equation similar to Equation (5):

$$Rshare_{pt} = c + \alpha_p + \gamma_t + \sum_{t=1962}^{1984} b_t(M_p \times d_{pt}) + \varphi \mathrm{R}_{pt} + \sum_{t=1962}^{1984} \delta_t(X_p \times d_{pt}) + \varepsilon_{pt}, \quad (7)$$

where d_{pt} is a dummy that indicates whether the rural population share of province (or prefecture) p is for the birth cohort t (a birth cohort dummy). As discussed earlier, we mainly focus on the post-Famine (1962–1985) birth cohorts. In these estimates, we measure the time dimension of exposure to the Famine with 23 (1962–1984) birth cohort dummies and take the 1985 birth cohort as the control group, and this dummy is omitted from the regression. Thus, each coefficient b_t can be interpreted as an estimate of the effect of the Famine on a given birth cohort.

We estimate Equation (7) at the provincial level and plot the b_t in Figure 8. Each dot on the solid line is the coefficient of the interaction between the birth cohort dummy and excess mortality rate during the Famine (a 95-percent confidence interval is plotted by broken lines).

Predictably, Figure 8 looks very similar to Figure 7. It indicates that the Famine seems to have a significant effect on the population composition of the earlier birth cohorts, and such an effect finally diminishes, and the estimates become insignificantly different from 0 for the post-1980 birth cohorts. Therefore, we select the earlier birth cohorts (1962–1980) as the treatment group and the later birth cohorts (1981–1985) as the control group and further estimate Equations (5) and (6).[14]

Table 4 presents the corresponding estimation results. Similar to Table 2, Panels A, B, and C show the benchmark regression results, results with migration adjustment, and results with migration and price adjustment, respectively. Panel A demonstrates that the benchmark estimation results are similar to those in Table 2. Column (2) presents the IV estimate and the coefficient is 0.61 and significant at the 1% level, which is larger than the corresponding estimate obtained from the cross-section regression (Column (3) in Table 2). Panels B and C present similar results. After estimating the model with migration and price adjustment, we obtain larger estimates which are always significant at the 1% level. Compared with those estimates in Table 2, estimates in Table 4 are generally larger and more significant. Given that the estimates in Table 4 are based on the DID regression with a panel

[14] The exact cutoff year between the pre- and post-treatment groups does not matter much, and the most important point is that the population composition of the earlier birth cohorts is much more affected by the Famine than the latter ones.

data set, in which provincial and birth cohort fixed effects are controlled, they should be more accurate and reliable. Overall, the estimates in Table 4 confirm the robustness of our empirical results.

5.3 The Validity of the Famine as the IV for the Post-Famine Fertility Structure

As previously discussed, one concern is raised regarding the validity of the Famine severity as the IV for the post-Famine fertility or population structure as follows: the Famine may affect the income inequality of affected regions through other channels rather than affecting the post-Famine fertility structure. Undoubtedly, the Famine could have comprehensive effects on affected regions, even in the long run. Specifically, the Famine may affect regional institutions, physical and human capital investment, productivity, among others, all of which could have non-negligible effects on economic development and income inequality.

We have controlled some important variables related to the economic development level to alleviate the potential issue arising from the direct effect of the Famine on income inequality. Furthermore, the estimation results above present strong evidence that the Famine is very likely to affect the income inequality of the post-Famine birth cohorts by affecting the population composition of these cohorts. Evidently, Figure 7 and Table 3 demonstrate that the effect of the Famine on post-Famine fertility and population structure seems to diminish over time. Moreover, Table 3 further indicates that the effect of the Famine on the income inequality of post-Famine birth cohorts exhibits a similar pattern. In other words, for the earlier post-Famine birth cohorts of which the Famine has a significant effect on the rural population share, the Famine also considerably affects their income inequality; for the later birth cohorts, the Famine has no effect on the rural population share, and the Famine does not affect their income inequality. These facts provide direct evidence that the exclusion restriction seems to be satisfied, and the Famine probably serves as a valid IV for the post-Famine fertility or population structure.

Indeed, if the Famine affects the income inequality of the post-Famine birth cohorts through other channels, such as by directly affecting the regional institution or economic development, such effects are likely to be similar for different birth cohorts and may not diminish from earlier to later birth cohorts. Furthermore, the Famine has no effect on the income inequality of the post-1980 birth cohorts, which is also inconsistent with the hypothesis that the Famine could directly affect income inequality in the long run.

To further verify the validity of the Great Famine as an IV for the post-Famine fertility structure, we present another IV to perform an overidentification test. As shown in the literature, China's population control policy is more strictly implemented in urban areas than the rural ones, and such a two-tier population policy also induces a much higher rural fertility than the urban one (Zhang, 2017; Wang and Zhang, 2018). Therefore, we can use the implementation intensity of the population control policy as another IV for China's rural–urban fertility structure or population composition. The population control policy could be a valid IV because it directly affects fertility and is unlikely to affect the income inequality of affected cohorts by affecting other factors rather than fertility, such as institutions and regional productivity several decades later.

Given that China's one-child policy (OCP) was implemented after 1979 and the Great Famine did not affect the population composition of the post-1980 birth cohorts, the OCP is not a feasible IV for the overidentification test. However, even before the implementation of the OCP, China has begun a voluntary yet strong family planning campaign with the slogan "Later, Longer, and Fewer" (LLF) in the early 1970s. This policy was very successful, and China's overall fertility rate was halved during 1970 and 1978 (Zhang, 2017). Given that the Great Famine also affects the rural–urban fertility structure of the 1970–1978 birth cohorts, we can use both the Famine severity and implementation intensity of the LLF policy to instrument for the population composition of these birth cohorts to perform the overidentification test.

We estimate the following equations:

$$Rshare_p = c_1 + \mathrm{b}M_p + dL_p + \theta_1 X_p + \varepsilon_{p1}, \tag{3'}$$

$$Gini_p = c_2 + \beta\, Rshare_p + \theta_2 X_p + \varepsilon_{p2}. \tag{4'}$$

These regressions are similar to Equations (3) and (4), the only difference is that we include L_p, which is the implementation intensity of the LLF policy in province *p*, in the first-stage regression.

In practice, we use the birth planning program timing to proxy for the implementation intensity of the LLF policy at the provincial level. As shown in Babiarz et al. (2018), the LLF policy timing shows significant variation across provinces. Table 5 demonstrates the LLF implementation time for different provinces. Some provinces initiated the policy as early as in 1970, and some others launched the campaign after 1975. Given that we focus on the 1970–1978 birth cohorts, we can use the LLF policy timing to construct the variable of the policy implementation intensity for these cohorts. Specifically, if the policy was initiated in one province in 1970, then, all the 1970–1978 birth cohorts in this province were affected. Thus, we assign the number 1 as the policy implementation intensity to this province. Similarly, if a province initiated the policy in 1971, then 8 (1971–1978) out of 9 (1970–1978) birth cohorts were affected. Thus, we assign the number 8/9 as the policy implementation intensity to this province, and so on.

We estimate Equations ($3'$) and ($4'$) and report the results in Panel A of Table 6. Column (1) shows the IV estimates without controls and the coefficient of rural population share is 0.2 and significant at the 10% level. Column (2) reports the IV estimates with controls and the corresponding coefficient doubles and significant at the 1% level. The bottom Panel presents the results of overidentification test and the P values are always larger than 0.10, which indicates that we cannot reject the null hypothesis that the IVs satisfy the exclusion restrictions.

In the above analysis, we assume that the birth planning policy affects the fertility immediately after its implementation. However, given the ten-month child-bearing period, the policy may have a time lag between its implementation and being effective to reduce fertility. For instance, many women may have already been pregnant when the policy was announced. Thus, the fertility will not decrease immediately in the future months. The policy is likely to reduce fertility effectively after 10 months or one year of its implementation. Therefore, we now assume that the policy affects the fertility after one year of its announcement and calculate the policy implementation intensity for the 1971–1978 birth cohorts and redo regressions ($3'$) and ($4'$).

Panel B of Table 6 reports the estimate results. Compared with Panel A of Table 6, the estimates in Panel B change little, which confirms the robustness of our identification.

5.4 Rural Population Share and Income Inequality: Prefectural Level Evidence

Although we have obtained robust estimates of the effect of the rural population share on the income inequality several decades later at the provincial level, the sample size is not large enough to be fully convincing. We now further obtain corresponding estimates at the prefectural level.

The data on the mortality rate during the Famine at the prefectural level are unavailable. Meng et al. (2015) use the 1990 census data to calculate the birth cohort size of survivors during the Famine among the agricultural population to proxy for Famine severity at the county level. They show that birth cohort size during 1959–1961 is negatively correlated with Famine severity because it captures the reduced fertility and increased mortality caused by the Famine. In addition, they further argue that this Famine severity index has several advantages over the mortality rate data.

Similar to the strategy of Meng et al. (2015), we first obtain the rural birth cohort size of each year over the period 1950–1970 for each prefecture from the 1990 census data and then fit a trend line of the prefecture rural birth cohort size during this period. We further calculate the gap between the actual and trend values of the rural birth cohort size during the Famine (1959–1961) and finally obtain the ratio of this gap and the corresponding trend value to proxy for the Famine severity at the prefectural level.[15] Figure 9 plots the prefectural average rural birth cohort size of each year over the period 1950–1970 (the solid line) and the trend line of the birth cohort size during this period (the

[15] We choose the period 1950–1970 to fit the trend line of fertility because the Famine happened exactly in the middle of this period. Furthermore, as mentioned earlier, China begun to implement the population control policy after 1970. Then, fertility of the county begun to decrease. Thus, the time trend of the fertility after 1970 was confounded with the effect of other factors such as the population control policy. In fact, the rural birth cohort size gap obtained from the period 1950–1970 is highly correlated with the Famine severity at the provincial level. This correlation decreases when we extend the period to the 1970s and 1980s, which confirms the validity of our exercise.

dotted line). Evidently, the birth cohort size decreased dramatically during the Famine, resulting in a considerable gap between its actual and trend values. Thus, this variable, the average rural birth cohort size gap during the three years of the Famine (1959–1961), measures to what extent rural birth cohort size shrinks during the Famine and thus largely reflects the Famine severity. We also calculate the corresponding rural birth cohort size gap for each province and compare this indicator with the rural excess mortality rate during the Famine, the alternative measure of Famine severity. We determine that the correlation of these two variables is as high as 0.85 at the provincial level, which confirms the validity of the rural birth cohort size gap as an effective indicator of Famine severity. Thereafter, we use this rural birth cohort size gap to instrument the post-Famine rural population share for the 1962–1985 birth cohorts and obtain the corresponding estimates of the rural population share on the Gini coefficient of these birth cohorts in 2005 at the prefectural level.

We now estimate Equations (3) and (4) at the prefectural level and report the estimation results in Table 7, which correspond to the estimates at the provincial level presented in Table 2. Panel A lists the benchmark estimate results. Column (1) shows that the OLS estimate and the coefficient of the rural population share is approximately 0.1, which indicates that an increase of 10% in rural population share corresponds to an increase of 0.01 in Gini coefficient at the prefectural level, and the magnitude of the correlation seems at most modest. Column (2) reports the reduced-form result and shows that the instrument (the average rural birth cohort gap during 1959–1961) is significantly correlated with the Gini coefficient for the 1962–1985 birth cohorts in 2005. Column (3) reports the IV estimate. Compared with the OLS estimate, the coefficient for the rural population share is larger and still significant at the 5% level. The lower panel shows that the coefficient of the rural birth cohort size gap in the first stage regression is approximately 0.3 and significant at the 1% level, and the K-P F statistic of the first stage regression is above 17, implying that the instrument is not weak.

Similar to Table 2, Panels B and C of Table 7 report the corresponding estimates with migration adjustment and both migration and price adjustment, respectively. Generally, the estimates do not change much. Column (6) shows that the estimate with migration adjustment becomes larger and more significant than the benchmark estimate in Column (3). Furthermore, Column (9) shows that after considering the difference in living cost across prefectures, the estimate remains similar and still significant at the 5% level. In summary, even if we consider labor force migration across prefectures, we still obtain robust estimates of the effect of the rural population share on the Gini coefficient. In sum, Table 7 presents evidence that a higher rural population share (or a higher rural fertility) would induce a higher Gini coefficient several decades later, although the magnitude of such an effect seems to be smaller than that of the provincial-level estimates.

Similar to the empirical strategies at the provincial level, we divide the post-Famine birth cohorts into six sub-samples and rerun the corresponding regressions at the prefectural level and present the IV estimation results in Table 8, which correspond to estimates at the provincial level presented in Table 3. The results presented in Table 8 show a similar pattern to those at the provincial level. Specifically, the coefficient of the IV estimate for the 1962–1965 birth cohorts is 0.21, and it gradually decreases to 0.11–0.14 for the 1970–1977 birth cohorts and becomes insignificantly different from 0 for the post-1978 birth cohorts. Meanwhile, the coefficient of the first-stage regressions also decreases in general from the earlier to the later birth cohorts.[16]

We now perform the corresponding DID analysis at the prefectural level. We first estimate Equation (7) at the prefectural level and plot Figure 10 on the basis of the estimates obtained. As expected, Figure 10 looks very similar to Figure 8. The estimates are significant for the earlier birth cohorts and begin to decrease after 1970 and become insignificant for the post-1980 birth cohorts, which is consistent with our expectation that the Famine has a long-lasting effect on the post-Famine fertility and population composition, but such an effect diminishes over time.

Similar to the exercise at the provincial level, we select the earlier birth cohorts (1962–1980) as the treatment group and the later birth cohorts (1981–1985) as the control group and estimate Equations (5) and (6) at the prefectural level.

Table 9 presents the estimation results. Column (2) shows that the coefficient of the IV estimate for the benchmark regression is 0.884 and significant at the 1% level. This estimate is much larger than the corresponding coefficient obtained from the cross-section regression (Column (3) in Table 5). Similar to the estimation results at the provincial level presented in Table 4, Panels B and C report the IV estimates with migration and further with price adjustment, respectively. These estimates become larger and are always significant at the 1% level. Although these coefficients are surprisingly much larger than the ones presented in Tables (7) and (8), which are obtained on the basis of the cross-section analysis, they are close to the corresponding DID estimates at the provincial level presented in Table 4.

Reassuringly, the DID strategy has clear advantages over the cross-section analysis and is likely to generate more reliable estimates of the causal effect of interest. Given that the DID estimates of the effect of the rural population share on the Gini coefficient at the provincial and prefectural levels provide similar results, our empirical results seem reliable and robust.

[16] The first-stage estimates are expected to decrease to 0 for the post-1978 birth cohorts. Table 6 demonstrates that these estimates become smaller but remain significantly different from 0. It should be noticed that the first-stage estimates do not necessarily have a causal interpretation. Next, we will show that the first-stage estimates do decrease to 0 in the DID regressions in which prefecture and birth cohort fixed effects are controlled, which are also likely to provide more accurate and reliable estimates of the causal effect.

6. Potential Mechanisms: Further Investigation

6.1 Theoretical Discussion

As mentioned earlier, 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, namely, rural and urban, which are high and low income groups, respectively. 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 poor family child is more likely to be poorer than the rich family child. 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, rural and urban children can fall into the poor or rich class after they grow up. However, rural children are more likely to fall into the poor class than urban children. Given that China's income inequality is mainly caused by the huge rural–urban income gap and the poorest population primarily concentrate in remote and backward rural areas, Assumption 2 probably holds. In fact, although some urban children may also fall into the poor class, their situations remain considerably better than those rural children from remote mountainous areas and whose parents constantly live in extreme poverty.

Assumption 3 states that if the fertility of the poor increases, then their children will have a higher conditional probability of becoming poorer. That is, a higher fertility of the poor worsens the upward mobility of their children. This assumption is the most critical one and actually identifies the fundamental mechanism through which differential fertility across income classes affects the income inequality of the next generation. We will discuss and empirically test whether this assumption holds in China.

Intuitively, if an increasing new population concentrate in backward rural areas, it may become more difficult for rural children to acquire the 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 constraint, 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, social mobility will also decrease correspondingly.

6.2 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 all take the National College Entrance Exam (NCEE, or *gaokao* in Chinese) and compete for the limited quota of college admission. 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 good indicator of social mobility among rural and urban children.

The 2000 census data contain rich information of all enrolled college students in the census year. In the questionnaire of the census, questions R9 and R10 ask the respondents when they moved to the current residence and where they migrated from, and question R11 further asks them the type of their original residence, which can be used to identify their hukou type before they were admitted to college. For these college students, they generally took the NCEE in their hometown[17] and then migrated to the city where their colleges are located. Thus, we can accurately identify all college students' hometown and hukou type on the basis of the information contained in questions R9–11. We exclude the college graduates in our analysis, because many college graduates migrated to other cities after graduation and it is difficult to identify their hometowns and original hukou types, particularly for those who had already graduated for many years.

These college students were generally 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) of 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

[17] In China, high school graduates can only take the NCEE in their hometown where their hukous are registered.

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 estimate the following equation with the fixed-effect (FE) model:

$$\mathrm{Ruratio}_{pt} = c + \alpha_p + \gamma_t + \beta \mathrm{Rshare}_{pt} + \varphi \mathrm{R}_{pt} + \varepsilon_{pt}, \quad (8)$$

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, R_{pt} is the rural share of childbearing-age women for year t in province p, and ε_{pt} is the disturbance term.

Column (1) of Table 10 reports the fixed-effects estimate of the effect of the rural population share on the rural–urban ratio of the probability of gaining admission to college (for youths aged 18–21 in the census year). The coefficient of the rural population share is approximately -0.51 and significant at the 5% level. The estimate indicates that an increase of 1% in the rural population share can reduce the aforementioned ratio by 0.0051 or by 3% in percentage (given that the mean of the rural–urban ratios of the probability of gaining admission to college is approximately 0.17), which is evidently non-negligible.

We include all the 18–21-year-old youths in our analysis based on the fact that most college students belonged to these age cohorts. However, this practice may not be perfectly accurate. Specifically, some 18–21-year-old youths may still be in high school and have not taken the NCEE, and some others may have already graduated from college. Thus, if we exclude these individuals from the college student sample, we will underestimate the probability of gaining admission to college for each birth cohort. We need to make some adjustments to resolve the bias caused by such possibilities.

First, for those 18–21-year-old respondents who already graduated from college, many of them migrated to other cities after graduation. Thus, we cannot accurately identify their hometowns and original hukou types. However, we can identify all these respondents in the 2000 census. We find that only less than 2% of 18–21-year-old youths who go to college have graduated in the census year. Accordingly, dropping them from our analysis may not be a problem. Second, we identify those 18–21-year-old respondents who are still in high school preparing for the prospective NCEE, calculate the expectation for their admission to college, further obtain the number of potential college students in the future, and include them in the college student sample. Specifically, we identify all the enrolled high school and college students from each province. Then, we can calculate the probability for high school students' admission to college by dividing the number of college students by the number of high school students. Finally, we multiply this probability by the number of 18–21-year-old high school students to obtain the number of potential college students for each birth cohort in the future in each province. Finally, we obtain a more reliable and accurate indicator of the rural–urban ratio of the probability of gaining admission to college for each birth cohort.

Column (4) presents the FE estimate results with such college admission adjustment. Compared with the benchmark estimate presented in Column (1), the coefficient does not change much and remains significant at the 1% level, which confirms the robustness of our results.

Earlier, we show that the effect of the Great Famine on the post-Famine population composition diminishes over time, and the estimates of such an effect become 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 ratio of the probability of gaining admission to college for the 1979–1982 birth cohorts, with the 1979–1980 birth cohorts being the treatment group (the population composition of which was still affected by the Great Famine to some extent), and the 1981–1982 birth cohorts being the control group (who were hardly affected by the Great Famine).

Specifically, we estimate the following equations:

$$Rshare_{pt} = c_1 + \alpha_{1p} + \gamma_{1t} + b(M_p \times T_t) + \varphi_1 \mathrm{R}_{pt} + \delta_1 (X_p \times T_t) + \varepsilon_{pt1}, \qquad (5')$$

$$Ruratio_{pt} = c_2 + \alpha_{2p} + \gamma_{2t} + \beta Rshare_{pt} + \varphi_2 \mathrm{R}_{pt} + \delta_2 \left(X_p \times T_t\right) + \varepsilon_{pt2}. \qquad (6')$$

These equations are similar to Equations (5) and (6). The only difference is that the dependent variable in the second-stage regression is $Ruratio_{pt}$ (the rural–urban ratio of the probability of gaining admission to college 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, which are similar to those in Equations (5) and (6), and T_t is a dummy that indicates whether the birth cohort *t* belongs to the earlier (1979–1980) birth cohorts.

Columns (2) and (3) of Table 10 report the benchmark DID estimation results. Column (2) presents the reduced-form result and shows that the instrument (the average rural excess mortality rate during 1959–1961) is negatively correlated with the rural–urban ratio of the probability of gaining admission to college for the 1979–1982 birth cohorts in 2000. In other words, in those provinces more severely affected by the Famine, it is also more difficult for rural children to gain admission to college for the earlier post-Famine birth cohorts. Column (3) reports the IV estimate, and the coefficient doubles the FE estimate in Column (1). Columns (5) and (6) report the DID estimation results with the aforementioned college admission adjustment, and the coefficients remain similar to those of the benchmark results, which confirms the robustness of our identification.

6.3 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 inevitable step to take the NCEE and seek admission to college. Similar to the NCEE, rural and urban junior high school graduates took the Senior High School Entrance Examination (SHSEE), and the competition was not as fierce as the NCEE but still rigorous in the 1990s. We can identify all the senior high school students and their information such as hometown and hukou status from the 2000 census data. These students were generally 15–18-year-old youths in the census year. That is, the majority of them belong to the 1982–1985 birth cohorts in the 2000 census. Similarly, we can obtain the rural and urban birth cohort size for each year of 1982–1985 and for all provinces from the 1990 census data. We can obtain the number of senior high school students for each birth cohort (rural and urban) of all provinces from the 2000 census data. Finally, we can calculate the probability of rural and urban youths being in senior high school for each birth cohort at the provincial level and further calculate the rural–urban ratio of this probability. We further combine this data set with the rural population share for these same cohorts (the 1982–1985 birth cohorts) and eventually obtain a panel for all provinces.

We estimate Equation (8) with the obtained data. Now, 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 11 shows that the FE estimate of the coefficient of rural population share is approximately -1.5 and significant at the 5% level. The estimate indicates that an increase of 1% in the rural population share can reduce the aforementioned ratio by 0.015 or by 5% in percentage (given that the mean of the rural–urban ratios of the probability of gaining admission to senior high school is approximately 0.3), which is considerable.

Given that some 15–18-year-old youths may still be in junior high school and have not taken the SHSEE and some others may have already graduated from senior high school, we need to make some adjustments to resolve the bias caused by such possibilities. We first identify those 15–18-year-old respondents who already graduated from senior high school. Then, we further identify their hometowns and original hukou types and include them in the sample of senior high school students. We also identify those 15–18-year-old respondents who were still in junior high school preparing for the prospective SHSEE and then calculate the expectation for their admission to senior high school (similar to the analysis for college students). We then obtain the number of potential senior high school students in the future among them and also include them in the senior high school student sample. Accordingly, we can obtain a more reliable and accurate indicator of the rural–urban ratio of the probability of gaining admission to senior high school for each birth cohort.

Column (4) of Table 11 reports the FE estimate results with such senior high school admission adjustment. The coefficient of rural population share is approximately -1.1 and significant at the 1% level. The estimate indicates that an increase of 1% in the rural population share can reduce the aforementioned ratio by 0.011 or by 3% in percentage (given that the mean of the adjusted rural–urban ratios of the probability of gaining admission to senior high school is approximately 0.35).

As discussed before, 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 the income inequality several decades later. In other words, 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 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 the fines. Consequently, even if rural and urban households face the same fines, they were still affected at different degrees.[18] 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：

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

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

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 $(6')$.

[18] In reality, rural and urban families faced the same fines as measured by years of household income in 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.

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 11 presents the IV estimate results. Compared with the FE estimate in Column (1) the coefficient of rural population share becomes much larger and still significant at the 5% level. Column (6) of Table 11 reports the IV estimate results with senior high school admission adjustment, and the coefficient is also much larger than that of the corresponding FE estimate.

Although the coefficients of the estimates with senior high school admission adjustment are smaller than those of the benchmark regressions, they are also more significant or more accurately estimated with much smaller standard errors. Therefore, these estimates may be more reliable.

The estimates in Tables 10 and 11 indicate that a higher rural population share reduces the rural–urban ratios of the probability of gaining admission to college and senior high school for youths at the provincial level. That is, as a larger proportion of new population are concentrated in rural areas, it would be more difficult for rural youths to gain admission to senior high school and college and get out of poverty. This finding partly explains the negative effect of the rural population share on income inequality several decades later because a higher rural population share also reduced the social mobility among rural and urban youths.

We have shown that all the three assumptions are very likely to hold. Thus, the mechanisms through which rural–urban fertility differential affects the income inequality of the next generation become clear.

To sum up, the comprehensive evidence demonstrated above indicates that the plausible exogeneous shock of the Great Famine (1959–1961) on the post-Famine fertility structure of the country results in a higher rural population share for the 1962–1985 birth cohorts and further causes 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 decreases, and such findings explain the mechanism through which differential fertility affects income inequality of the next generation, that is, a higher fertility of the poor reduces the upward mobility of their children.

7. Concluding Remarks

China has created an economic growth miracle since the implementation of the reform and open policy in 1978. Meanwhile, income inequality in China also increased substantially, and the Gini coefficient of the country maintains at a high level after 2000. Numerous studies have investigated the reasons for this high income inequality and attempted to identify solutions to reduce such inequality at the national level. However, no consensus has been reached on this issue.

In this study, we show that China's Great Famine (1959–1961) has a long-lasting effect on the rural–urban fertility ratio, and as a larger share of new population concentrated in backward rural areas, income inequality also increased significantly. We use the Famine severity to instrument for post-Famine rural–urban population composition and find that a higher rural population share induced a higher Gini coefficient several 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 further indicates that such an increase in the rural population share of the country increased the income inequality at the national level. Therefore, China's high income inequality may be partially caused by the Great Famine and its later two-tier population control policy, both of which have induced a larger share of new population concentrated in rural areas.

We also provide evidence that differential fertility across the rural–urban divide in China increases income inequality because it reduces social mobility of the next generation. Under China's scenario, the ever-present rural–urban divide and the hukou system result in opportunity inequality among rural and urban children, and a larger share of rural children aggravates such inequality and further reduces the probability of rural children climbing up the social ladder and get out of poverty. In other countries, despite the absence of such apparent rural–urban divide similar to China, an invisible divide persists between the poor and rich, which also generates opportunity inequality among children with different family backgrounds. Undoubtedly, the most effective way to mitigate the potential negative effect of differential fertility is to provide all citizens, regardless of their family backgrounds, with equal opportunities to acquire scarce resources, such as education and job opportunities. How to achieve such objectives remains a great challenge for both the government and scholars.

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

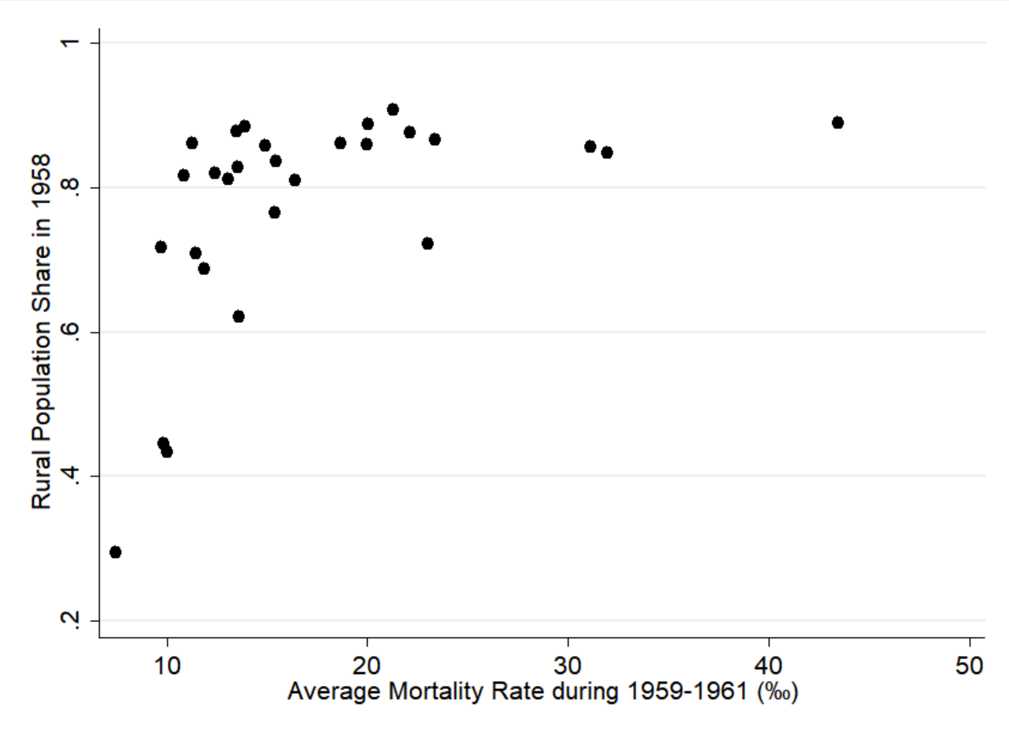

Figure 2: Rural Population Share in 1958 and Average Rural Excess Mortality Rate in 1959–1961 (Provincial Level)

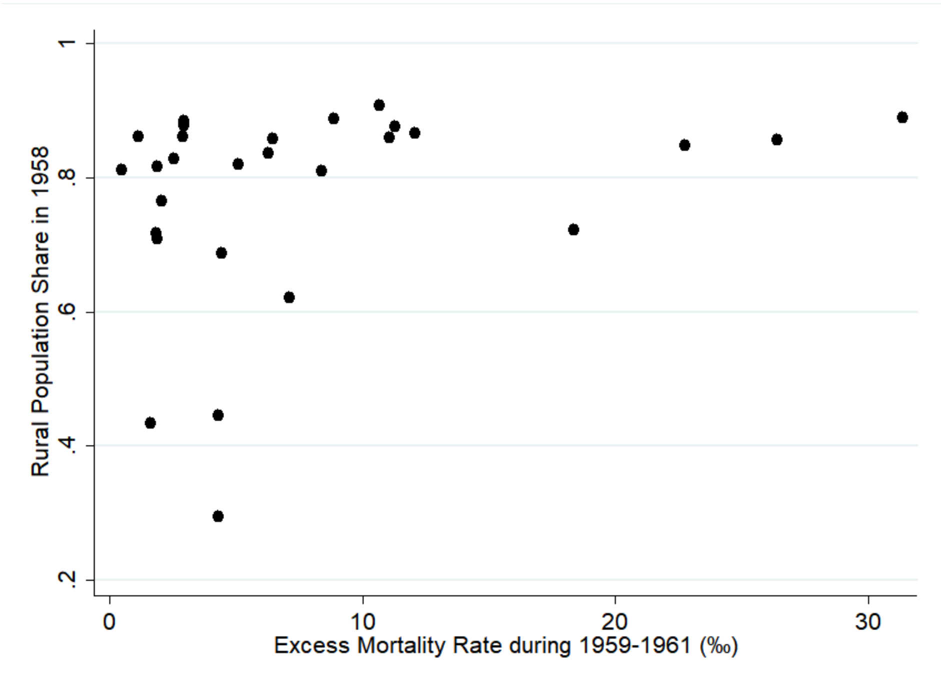

Figure 3: Rural and Urban Total Fertility Rates (National Level)

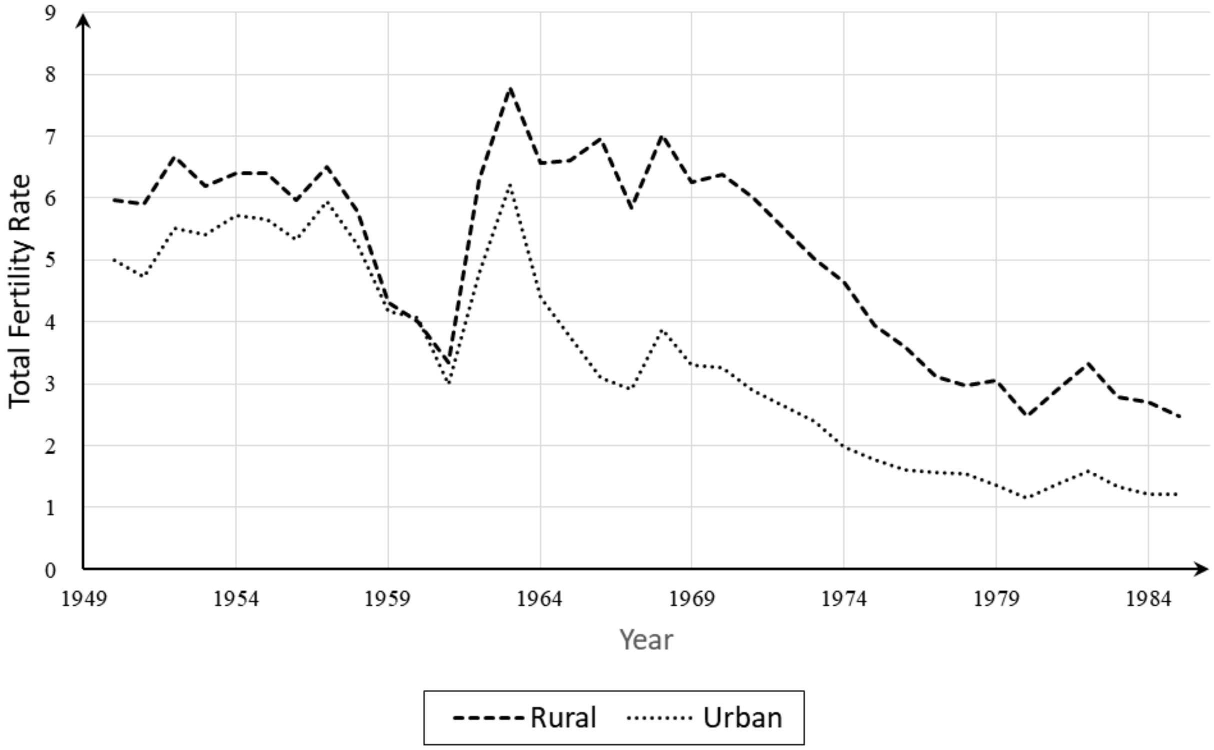

Figure 4: Rural–Urban TFR Ratio (National Level)

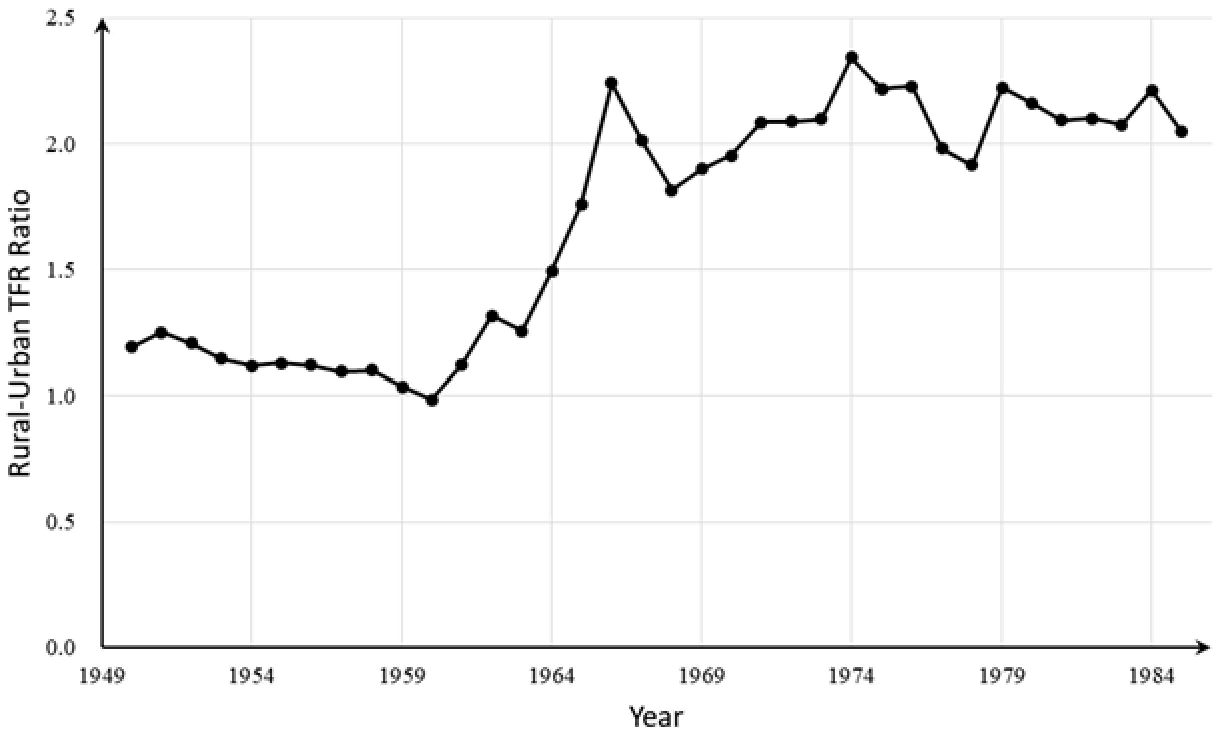

Figure 5: Rural Population Growth Rates of Shaanxi and Anhui Provinces

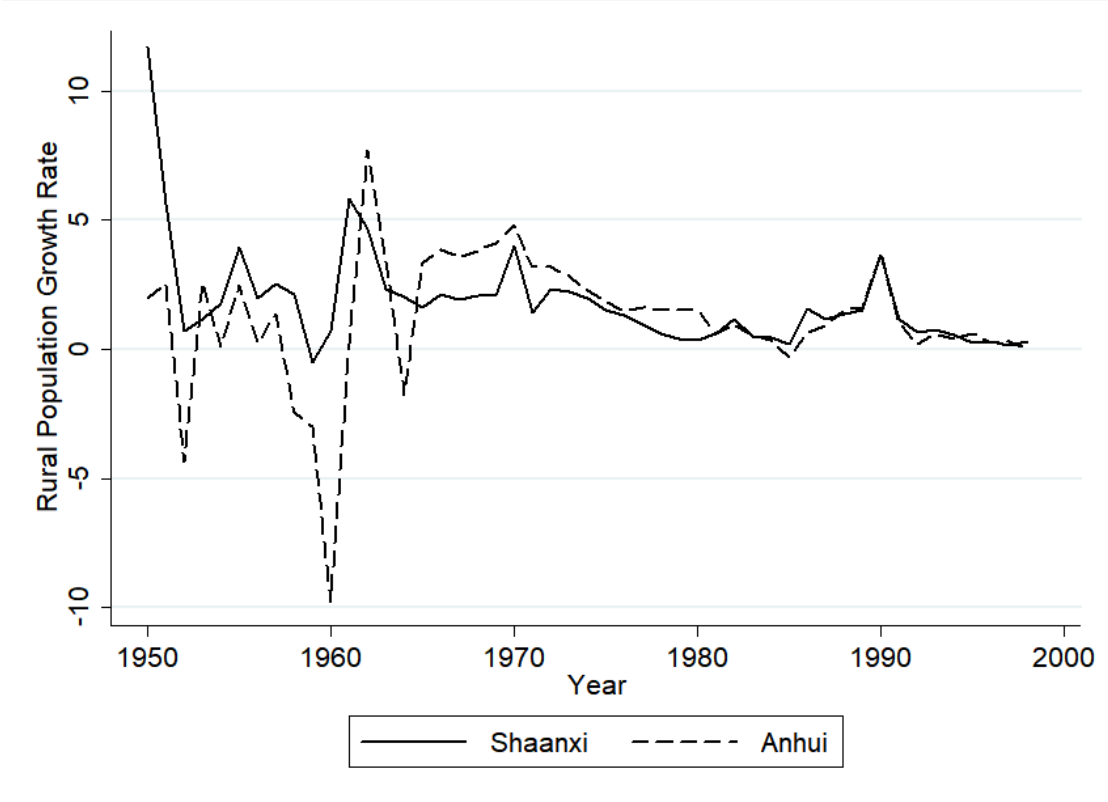

Figure 6: Rural Excess Mortality Rate during 1959–1961 and Post-Famine Rural Population Share for the 1962–1985 Birth Cohorts (Provincial Level)

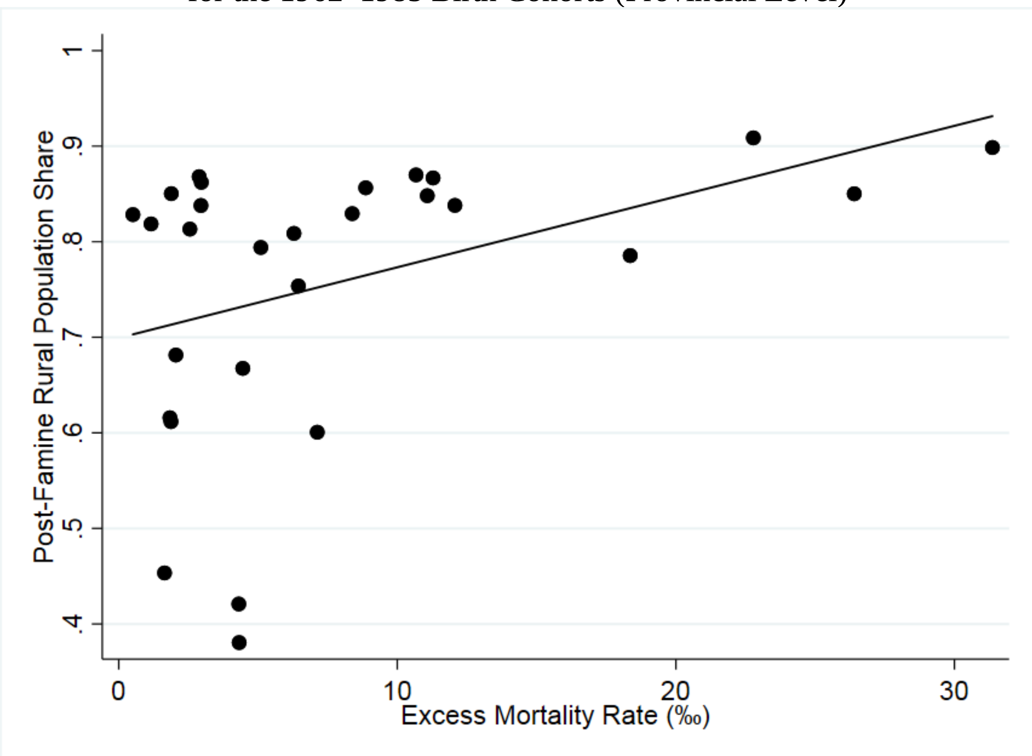

Figure 7: Correlation between Famine Severity and Post-Famine Rural Population Share, by Birth Cohort (Provincial Level)

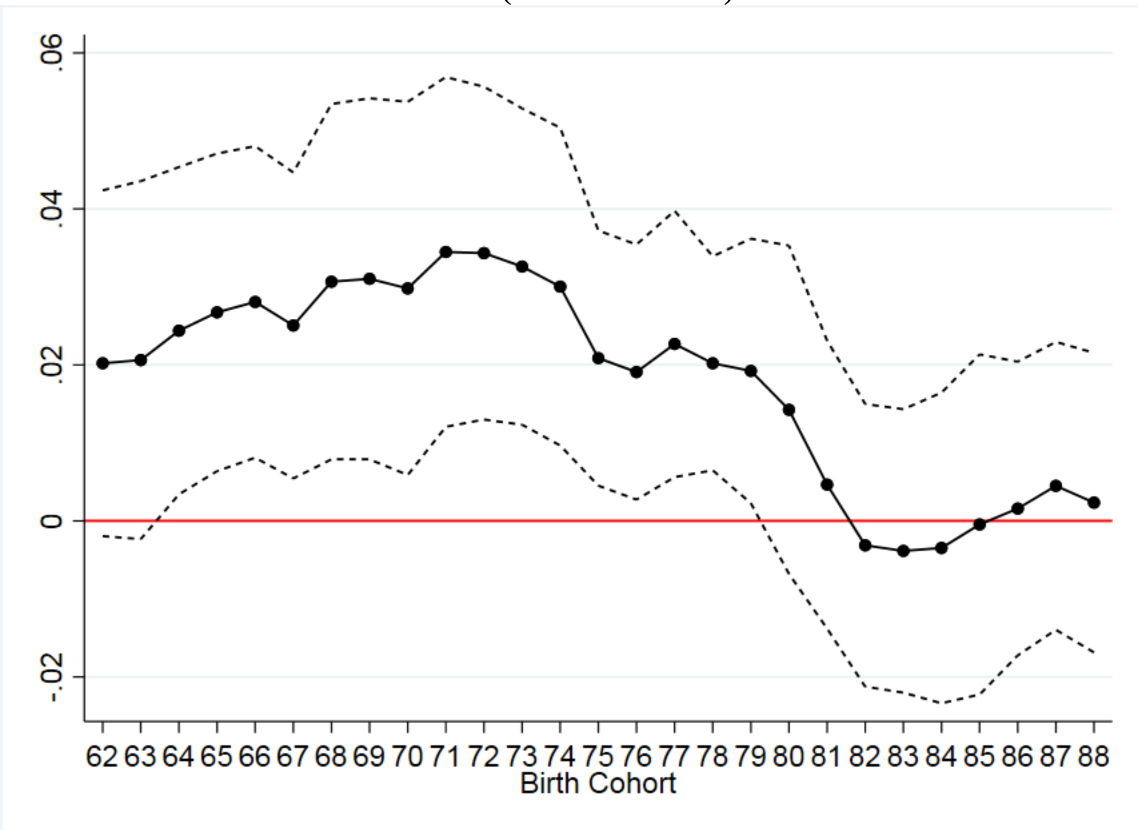

Figure 8: Coefficients of the Interactions Excess Mortality Rate×Birth Cohort (1962–1984) in Equation (7) (Provincial Level)

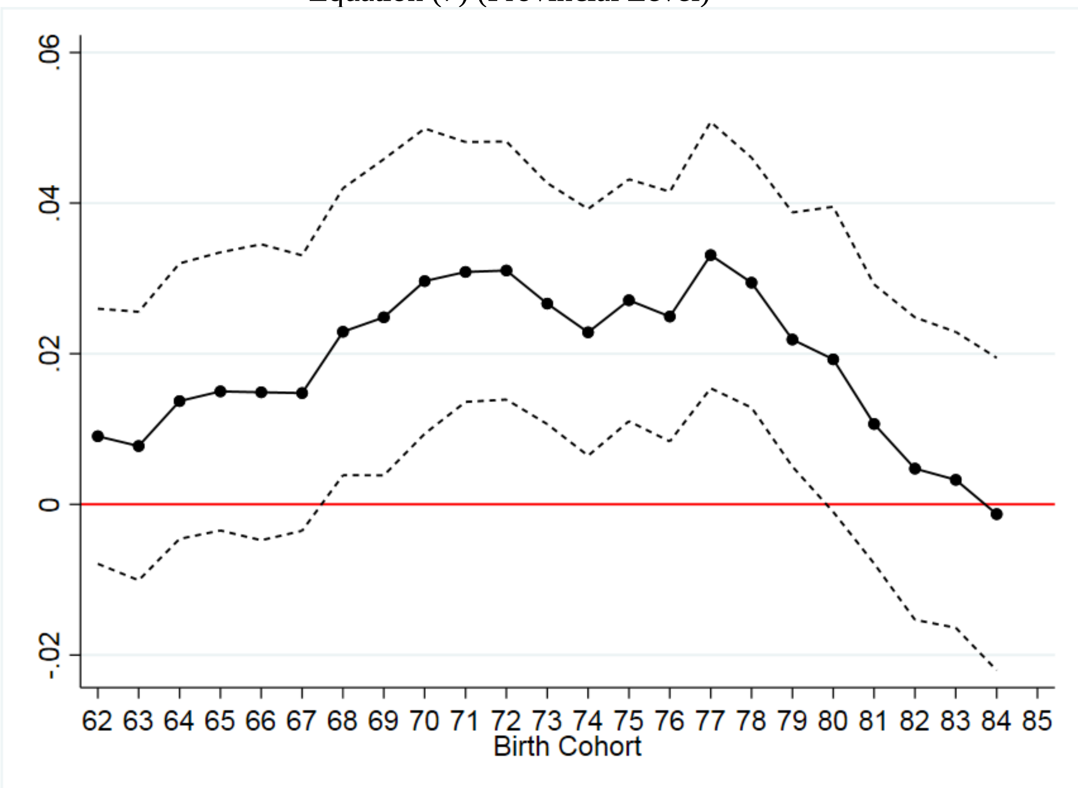

Figure 9: Rural Birth Cohort Size Gap during the Great Famine (1959–1961) (Prefectural Level)

Figure 10: Coefficients of the Interactions Excess Mortality Rate×Birth Cohort (1962–1984) in Equation (7) (Prefectural Level)

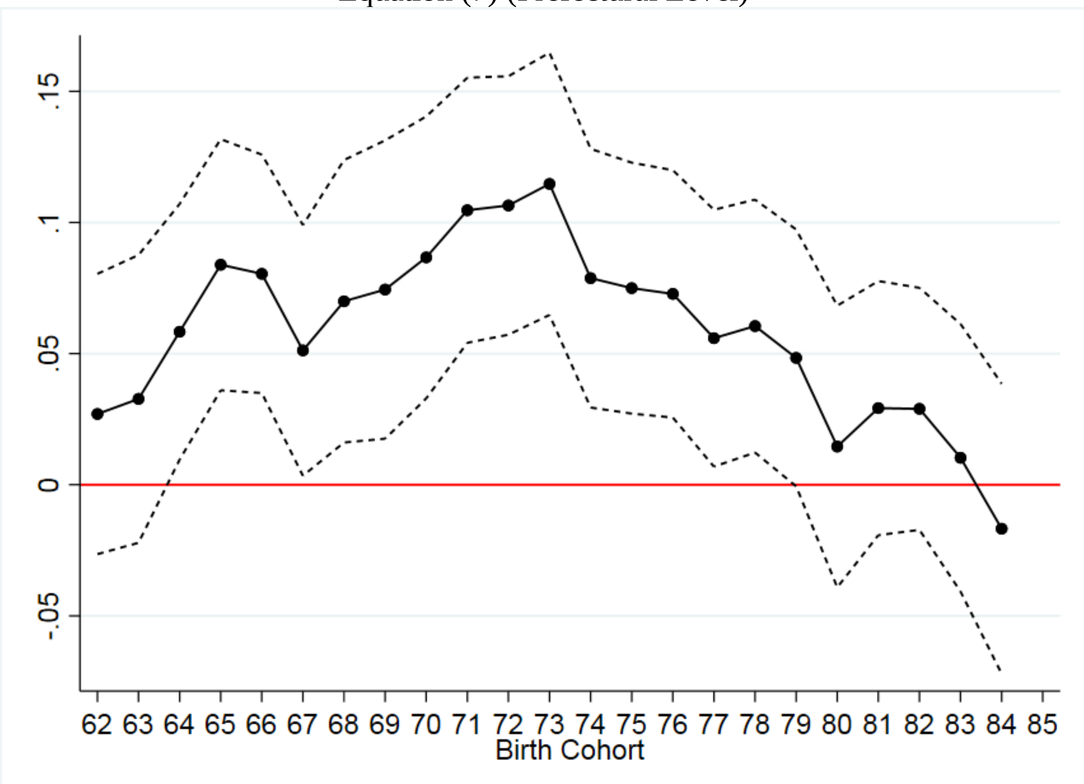

Table 1: Summary Statistics

Variables	Definition	Obs.	Mean	S.D.
	A. Provincial Level			
1950–1985 Birth Cohorts				
Gini	Gini coefficient	28	0.421	0.044
Rpshare	Rural population share	28	0.741	0.154
1962–1985 Birth Cohorts				
Gini	Gini coefficient	28	0.413	0.046
Rshare	Rural population share	28	0.758	0.148
IV				
Mortality rate	Average rural mortality rate during 1959–1961 (unit: %)	28	1.714	0.800
Excess mortality rate	Average rural excess mortality rate during 1959–1961 (unit: %)	28	0.790	0.800
	B. Prefectural Level			
1962–1985 Birth Cohorts				
Gini	Gini coefficient	291	0.396	0.057
Rshare	Rural population share	291	0.772	0.183
Birth cohort size gap	Average rural birth cohort size gap during 1959–1961	291	0.405	0.168

Table 2: OLS and IV Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1985 Birth Cohorts (Provincial Level)

	Dependent variable: Gini coefficient								
	A. Benchmark regression			B. Migration adjustment			C. Migration and price adjustment		
	OLS	RF	IV	OLS	RF	IV	OLS	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rshare	0.322**		0.547***	0.271		0.477**	0.274*		0.404**
	(0.144)		(0.186)	(0.170)		(0.209)	(0.156)		(0.176)
Excess Mortality Rates		0.016***			0.014**			0.012**	
		(0.005)			(0.005)			(0.005)	
			1st Stage			1st Stage			1st Stage
Excess Mortality Rates			0.029***			0.029***			0.029***
			(0.008)			(0.009)			(0.009)
Kleibergen-Paap F statistic			13.504			11.277			11.636
Observations	28	28	28	28	28	28	28	28	28
R-squared	0.887	0.887	0.865	0.878	0.881	0.856	0.895	0.887	0.887

Notes: Control variables in all regressions include rural population share and agricultural productivity in 1958, post-Famine (1962–1985) rural share of women of childbearing age, 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 2005. Panel A reports the benchmark estimation results, and Panels B and C list the estimation results with migration and price adjustment, respectively. We report the OLS, reduced form (RF), and IV estimation results for all the three situations.
Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3: IV Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1985 Birth Cohorts, by Birth Cohort (Provincial Level)

	1962–1965		1966–1969		1970–1973		1974–1977		1978–1981		1982–1985	
	RF	IV	RF	IV	RF	IV	RF	IV	RF	IV	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rshare		0.637**		0.579**		0.365***		0.548***		0.348		0.565
		(0.268)		(0.211)		(0.111)		(0.174)		(0.213)		(1.188)
Excess Mortality Rates	0.017**		0.020***		0.015***		0.018***		0.009*		0.006	
	(0.006)		(0.006)		(0.005)		(0.005)		(0.005)		(0.009)	
		1st Stage		1st Stage		1st Stage		1st Stage		1st Stage		1st Stage
Excess Mortality Rates		0.027***		0.034***		0.041***		0.033***		0.027***		0.010
		(0.008)		(0.008)		(0.009)		(0.008)		(0.008)		(0.010)
K-P F statistic		12.892		17.802		23.022		17.019		12.578		0.997
Observations	28	28	28	28	28	28	28	28	28	28	28	28
R-squared	0.816	0.743	0.852	0.720	0.877	0.875	0.907	0.873	0.875	0.884	0.864	0.812

Notes: We control all variables same to those in Table 2 in all regressions. We report the reduced form (RF), and IV estimation results for six sub-cohorts for regressions with migration and price adjustment. Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 4: DID Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1980 Birth Cohorts (Provincial Level)

	Dependent variable: Gini coefficient					
	A. Benchmark regression		B. Migration adjustment		C. M&P adjustment	
	RF	IV	RF	IV	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Rshare		0.613***		0.704***		0.713***
		(0.161)		(0.177)		(0.172)
Excess Mortality Rates× T_t	0.012***		0.013***		0.014***	
	(0.003)		(0.003)		(0.003)	
		1st Stage		1st Stage		1st Stage
Excess Mortality Rates× T_t		0.019***		0.019***		0.019***
		(0.003)		(0.004)		(0.003)
Province FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
K-P F statistic		55.33		55.13		54.65
Observations	672	672	672	672	672	672
Adj R-squared	0.905	0.905	0.874	0.874	0.892	0.892

Notes: We control all variables same to those in Table 2 in all regressions. Panel A reports the benchmark estimation results, and Panels B and C list the estimation results with migration and price adjustment, respectively. Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5: LLF Birth Planning Program Timing

Year	Num. of Provinces	Remarks
1970	3	Jiangsu, Guangdong, Hainan
1971	7	Liaoning, Jilin, Guangxi, Chongqing, Sichuan, Guizhou, Gansu
1972	8	Tianjin, Hebei, Heilongjiang, Jiangxi, Shandong, Hubei, Yunnan, Qinghai
1973	5	Shanxi, Shanghai, Fujian, Shaanxi, Ningxia,
1974	3	Anhui, Henan, Hunan
1975	1	Xinjiang
1979	1	Inner Mongolia

Table 6: IV Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1970s Birth Cohorts, Overidentification Test (Provincial Level)

	A. Current period: 1970-1978		B. One year lag: 1971-1978	
	(1)	(2)	(3)	(4)
Rshare	0.208*	0.407***	0.207*	0.420***
	(0.105)	(0.137)	(0.104)	(0.135)
	1st Stage	1st Stage	1st Stage	1st Stage
Excess Mortality Rates	0.072***	0.035***	0.071***	0.035***
	(0.020)	(0.011)	(0.020)	(0.010)
Birth Control Intensity	0.044	0.018	0.070	0.012
	(0.074)	(0.048)	(0.063)	(0.043)
Control Variables	N	Y	N	Y
K-P F statistic	8.543	13.018	8.843	12.204
Observations	26	26	26	26
Overidentification Test				
Hansen J statistic	0.310	0.520	0.575	0.214
P Value	0.578	0.471	0.448	0.644

Notes: We control all variables same to those in Table 2 in Columns (2) and (4).
Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7: OLS and IV Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1985 Birth Cohorts (Prefectural Level)

	Dependent variable: Gini coefficient								
	A. Benchmark regression			B. Migration adjustment			C. Migration and price adjustment		
	OLS	RF	IV	OLS	RF	IV	OLS	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rshare	0.105***		0.117**	0.090***		0.134***	0.088***		0.113**
	(0.016)		(0.053)	(0.014)		(0.048)	(0.014)		(0.046)
Birth Cohort Size Gap		0.037**			0.044***			0.038**	
		(0.019)			(0.016)			(0.016)	
			1st Stage			1st Stage			1st Stage
Birth Cohort Size Gap			0.319***			0.326***			0.332***
K-P F statistic			23.383			22.414			23.811
Observations	291	291	291	291	291	291	291	291	291
R-squared	0.469	0.388	0.468	0.409	0.338	0.388	0.480	0.414	0.473

Notes: Control variables include a set of prefectural level characteristics in 2005, including income per capita, GDP, agricultural and industrial output share in GDP, migrant population share in total population, population density, and fiscal expenditure per capita. Panel A reports the benchmark estimation results, and Panels B and C list the estimation results with migration and price adjustment, respectively. We report the OLS, reduced form (RF), and IV estimation results for all the three situations.
Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8: IV Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1985 Birth Cohorts, by Birth Cohort (Prefectural Level)

	1962–1965		1966–1969		1970–1973		1974–1977		1978–1981		1982–1985	
	RF	IV	RF	IV	RF	IV	RF	IV	RF	IV	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rshare		0.210***		0.150**		0.137***		0.115**		0.075		-0.031
		(0.070)		(0.062)		(0.052)		(0.058)		(0.070)		(0.084)
Birth Cohort Gap	0.060***		0.044**		0.045**		0.034*		0.018		-0.012	
	(0.021)		(0.021)		(0.020)		(0.020)		(0.021)		(0.021)	
		1st Stage		1st Stage		1st Stage		1st Stage		1st Stage		1st Stage
Birth Cohort Gap		0.293***		0.310***		0.348***		0.324***		0.288***		0.253***
		(0.070)		(0.068)		(0.067)		(0.067)		(0.067)		(0.066)
K-P F statistic		17.595		20.496		27.144		23.492		18.605		14.655
Observations	291	291	291	291	291	291	291	291	291	291	291	291
R-squared	0.272	0.207	0.285	0.335	0.350	0.407	0.383	0.387	0.442	0.424	0.402	0.370

Notes: We control all variables same to those in Table 5 in all regressions.
Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: DID Estimates of the Effect of the Rural Population Share on the Gini Coefficient for the 1962–1980 Birth Cohorts (Prefectural Level)

	Dependent variable: Gini coefficient					
	A. Benchmark regression		B. Migration adjustment		C. M&P adjustment	
	RF	IV	RF	IV	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Rshare		**0.884*** **		**1.119*** **		**1.152*** **
		(0.186)		(0.205)		(0.206)
Excess Mortality Rates× T_t	0.049***		0.060***		0.060***	
	(0.010)		(0.011)		(0.011)	
		1st Stage		1st Stage		1st Stage
Excess Mortality Rates× T_t		0.056***		0.054***		0.052***
		(0.009)		(0.009)		(0.009)
Prefecture FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
K-P F statistic		70.8		70.49		70.77
Observations	6,648	6,648	6,720	6,720	6,720	6,720
Adj R-squared	0.631	0.631	0.528	0.528	0.571	0.571

Notes: Control variables in all regressions are same to those in Table 5. Panel A reports the benchmark estimation results, and Panels B and C list the estimation results with migration and price adjustment, respectively.
Robust standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 10: FE and DID Estimates of the Effect of Rural Population Share on Rural–Urban Ratio of the Probability of Gaining Admission to College (Provincial Level, 1979–1982 Birth Cohorts)

	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 the probability of 18–21-year-old youths gaining admission to college, and the independent variable is the rural population share for the 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 11: FE and IV Estimates of the Effect of Rural Population Share on Rural–Urban Ratio of the Probability of Gaining Admission to Senior High School (Provincial Level, 1982–1985 Birth Cohorts)

	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
Fine			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 the probability of 15–18-year-old youths gaining admission to senior high school, 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 of the fines are from Ebenstein (2010).

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