Epidemics, Convergence, and Common Prosperity: Evidence from China

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Abstract
This article investigates the impact of previous epidemics on rural development and convergence, and identifies the impact’s mechanism based on convergence tests. Using a balanced panel of 31 provinces, the empirical results from 2002 to 2019 show that epidemics decelerated convergence in rural per capita income. The mechanism analysis shows that the accelerated divergence in wages and the decelerated convergence in business income were the major drivers, which also led to decelerated convergence in rural per capita consumption. Although epidemics have not threatened rural food consumption and the Engel coefficient of rural households, these two indicators of basic living needs have failed to achieve convergence across regions. The overall impact of an epidemic on convergence in rural–urban income disparity has also been insignificant, indicating that epidemics have affected rural and urban development simultaneously. Finally, COVID-19 is likely to decelerate convergence in rural income, rural consumption, and urban income.

Keywords: common prosperity, epidemics, regional disparity, rural convergence, rural–urban disparity
JEL codes: D24, I10, O47, Q10

I. Introduction

Common prosperity (gongtongfuyu) is an important target in China, as one of the government’s stated objectives is to achieve coordinated development across regions
and alleviate inequality by accelerating the growth rate in slow-growth regions and lagging regions (Fan, 2013). In other words, China needs to ensure equitable access to basic public services and to reduce regional and urban-rural disparities significantly. A convergence test is a typical approach for studying the issue of disparity, as it can indicate whether lagging regions are catching up with the leaders (Yuan et al., 2021). In the context of common prosperity, it is important to study regional disparities and urban-rural disparities together using convergence methods, and to find approaches to accelerating progress in the regions that are lagging behind and to enabling them to catch up.

The outbreak of epidemics, including COVID-19, has severely affected rural areas in China, as agriculture and many economic activities have been disrupted and postponed (Song and Zhou, 2020). Non-agricultural sectors and urban areas have also suffered severe shocks due to COVID-19, which has impacted the income of rural migrant workers and has led to a further decline in rural income. In comparison with the extensive literature on other shocks, such as climate change (Chen and Gong, 2021), there has been insufficient research on epidemic-related shocks. Moreover, existing studies have mainly focused on the effects of epidemics on agricultural and rural development rather than on the heterogeneity across regions (Gray, 2020; Laborde et al., 2020; Siche, 2020). Given the vulnerability of lagging regions, it is necessary to investigate the effect of epidemics on rural convergence further in the context of the objective of achieving common prosperity. To mitigate the impact of COVID-19, it is critical to further explore the impact mechanism of epidemics and identify the pathways through which epidemics have influenced rural convergence in addition to their direct effects on rural development. Income, consumption, and basic living level are also important indicators of rural development that must be considered in order to achieve common prosperity. After the analysis of regional disparity, it is equally important to study how epidemics affect rural–urban disparities, which must also be eliminated to achieve common prosperity.

COVID-19 is recognized as a secondary infectious disease but controlled as a primary infectious disease in China, so this article evaluates the impact of previous epidemics (i.e. primary and secondary infectious diseases) on convergence to project
the potential impact of COVID-19. Many studies (Zhang et al., 2020; Gong et al., 2021) have predicted the effect of COVID-19 based on previous epidemics. Indeed, the impact of COVID-19 and that of previous epidemics have some differences, but COVID-19 and previous epidemics are still comparable to some extent as the transmission patterns and control measures for infectious diseases in the same category are similar. Unlike natural disasters (e.g. earthquakes and typhoons), COVID-19 (and other infectious diseases) does not impact assets and infrastructure, and its economic impact is mainly due to the panic effect and control measures. People fear a disease because of the incidence and death rates, as well as the level of control measures. However, the impact of COVID-19 is likely to be more severe than that of previous epidemics in China. This implies that the projection based on the estimated impact of previous epidemics is the lower bound of the actual impact of COVID-19, although it still provides useful and important information.

This article evaluates the impact of epidemics on rural development and convergence, and further identifies the impact mechanism that can be used to find appropriate methods to mitigate the negative impact of epidemics. First, the article introduces two convergence tests (unconditional β-convergence and conditional β-convergence) to estimate whether rural convergence has occurred. Second, considering the impact of epidemics, it incorporates the incidence rate and death rate during epidemics into the conditional β-convergence test. On the one hand, incorporating the variables of epidemics as independent variables can help estimate their (average) impact on rural development. On the other hand, incorporating the interaction between epidemic variables and the lagged value of rural development can help estimate their impact on rural convergence. Third, rural per capita income is divided into wages, business income, property income, and transfer income, allowing us to explore the major pathways through which epidemics affect total income. Finally, according to the estimated results, this article projects the impact of COVID-19 on convergence and presents a series of policy implications.

Using a balanced panel dataset of 31 provinces in China from 2002 to 2019, the research reported in this article found that epidemics, and especially the incidence rates of primary and secondary infectious diseases, have had negative impacts on rural per capita incomes and have decelerated their convergence (this was mainly driven by the accelerated divergence in the net income from wages and the decelerated convergence in net business income), indicating that epidemics significantly hindered rural development and its convergence. This study also found that the insignificant impact of epidemics on convergence in rural–urban income disparity has been at the expense of simultaneously slowing down convergence between rural and urban per capita income. Similarly, the
epidemics not only directly reduced rural per capita consumption but also decelerated its convergence. However, epidemics have not affected the level of convergence in the Engel coefficient of rural food consumption and rural households, indicating that they have had limited effects on food security and the basic living level.

This article makes three contributions to the literature. First, to the best of our knowledge, this is the first study to analyze the impact of epidemics not only on rural development but also on rural convergence. Second, we identify the impact mechanism of previous epidemics on rural development, as well as the approaches to accelerating the convergence of such development. This could help find efficient methods to mitigate the adverse effects of COVID-19 and other public health emergencies. Third, this article integrates regional convergence and urban–rural convergence to ensure a more comprehensive study of the process of achieving common prosperity.

The remainder of this article is organized as follows. The next section reviews the literature. Section III describes the model used in this article. Section IV introduces the data and variables. Section V presents and discusses the empirical results. Section VI concludes the article and discusses its policy implications.

II. Literature review

1. Income convergence in rural China

China’s economy has sustained rapid growth through a series of economic reforms since 1978. However, whether this rapid growth has been achieved through an even growth pattern remains controversial. Many scholars have attempted to analyze trends in various aspects of regional disparity through a series of convergence tests. On the one hand, some studies have shown increasing regional disparities. For example, Fujita and Hu (2001) revealed that the income disparity between the coastal area and the interior increased between 1985 and 1994. Xie and Zhou (2014) pointed out that China’s income inequality reached high levels due to regional disparities. On the other hand, some scholars believe that convergence has been achieved as the lagging regions are catching up with the leading ones. For example, Cai and Du (2011) reported that the wages of unskilled and skilled workers have been converging since 2003. Xin and Qin (2011) concluded that the input accumulation in China’s western area and the technological progress in the central and western areas effectively narrowed the gap with the eastern area.

In terms of rural development, existing studies have mainly focused on the urban–rural income gap (Guo et al., 2020; Li et al., 2020) whereas the convergence in rural income has been largely neglected by scholars. To the best of our knowledge, Li and Cheong (2016) is the only existing study on the convergence in China’s rural income
that employed the stochastic kernel approach and found that convergence into a unimodal income distribution was possible in the long run. Although the urban–rural income gap is a major issue and has drawn much attention, it is equally important to investigate regional disparities in rural areas. For example, if some factors (e.g. epidemics) simultaneously affect rural and urban income in some lagging regions, this change can be detected by the analysis of rural income, rather than the urban–rural income gap.

2. Channels of epidemics affecting rural development

Some scholars have investigated the impact of epidemics and have reported that there have been three major channels through which epidemics, and their control measures, have affected rural development. First, epidemics may lower the labor supply in rural areas. When epidemics break out, workers may fall ill or die, while other family members devote their productive time to taking care of patients and mourning the dead (FAO, 2003). Individual self-protection measures and government control measures prevent people from working. For example, lockdown orders enforced during epidemics led to a reduction in paid work and income for rural families (Hamadani et al., 2020). Considering the large population of migrant workers in China, the impact of epidemics on urban and non-agricultural sectors may significantly affect households in rural areas. These factors may lead to a decline in rural income (Mutangadura and Sandkjaer, 2009).

Second, epidemics have limited input allocation and market transactions. On the one hand, the outbreak of epidemics compounds the difficulties for farmers in obtaining the requisite inputs and services in agricultural production. Strict quarantine measures (such as the transport interruption and closure of borders) instituted by governments have also negatively affected supply chain activities (Sumo, 2019). The World Bank (2015) pointed out that a lack of harvest teams resulted in a 50 percent decline in rice yield from the previous year. On the other hand, farmers have been at a disadvantage in market transactions during epidemics. Traders were reluctant to buy rice in contaminated areas during the Ebola outbreak, which lowered the price of rice and reduced the bargaining power of the producers (FAO, 2016). These limitations for farm households during the outbreak of epidemics have affected agricultural output significantly and consequently resulted in reduced business income for rural households.

Third, epidemics have caused social panic, which has affected consumption. The social panic surrounding epidemics has changed the consumption behavior of individuals, which has led to food shortages, price shocks, and market disruptions (Gong et al., 2020). On the one hand, panic buying and food hoarding affect food availability in the market (Yu et al., 2020) and lead to erratic fluctuations in food
prices (Zhang et al., 2020). On the other hand, consumers are unwilling to choose foods that are difficult to store, transport, and process due to logistical and storage limitations (Kodish et al., 2019), causing poor sales of these foods. Unstable prices and demand for agricultural products during epidemics may bring economic uncertainty to farmers and, therefore, affect rural income (FAO, 2016).

3. Different impacts of epidemics across groups and regions
A growing body of literature emphasizes that epidemics impact different groups and regions differently. The differences in socioeconomic, place-based, and race-based disparities may lead to varying effects from epidemics (Chowkwanyun and Reed, 2020).

On the one hand, epidemics may have a greater impact on vulnerable populations. The impacts of epidemics vary among people based on gender, race, income level, education, and employment (Pellowski et al., 2013). For example, evidence from China has suggested that COVID-19 is deadlier for infected men than for infected women (Gebhard et al., 2020). Millett et al. (2020) reported that counties with more black residents had more COVID-19 diagnoses, using data on COVID-19 cases and deaths in the US. Pellowski et al. (2013) pointed out that AIDS was more likely to occur among the poor. Denning et al. (2011) and Song et al. (2011) stated that HIV was more likely to affect individuals who studied below the high school level and who were unemployed.

Similarly, epidemics may have different effects in different geographic areas. The impacts of epidemics vary across regions due to many factors, such as poverty level, population structure, cultural diversity, different laws and policies, unequal access to healthcare resources, and population density (Mutangadura and Sandkjaer, 2009; Song et al., 2011; Reif et al., 2014). For example, a high level of poverty and a lack of necessary infrastructure may result in greater difficulties in fighting epidemics, which can explain why epidemics have greater impacts in low-income regions (SASI, 2011). Davies et al. (2020) suggested that in countries with larger demography of young people, the incidence rate of COVID-19 would be lower than that in countries with an older population. Using data from the National HIV Surveillance System and the American Community Survey, Song et al. (2011) suggested that there was a significant correlation between population density and the AIDS diagnosis rate. Using a nationally representative sample of US adults, Kumar et al. (2012) stated that the absence of certain workplace policies, such as paid sick leave, would increase the incidence rate of H1N1 influenza.

The different impacts of epidemics across groups and regions may lead to different effects on rural development, which, in turn, may hinder convergence in China. In other words, epidemics may prevent lagging regions from catching up with the most successful regions in development, as the lagging regions may suffer from more
severe challenges during the outbreak of an epidemic, considering the larger share of vulnerable populations and the presence of fewer healthcare resources – a situation that is not conducive to the elimination of regional and rural–urban disparity.

III. Model

1. $\beta$-Convergence tests for rural development

To test convergence in rural development, this article employed two convergence tests that are widely used in existing studies: unconditional $\beta$-convergence and conditional $\beta$-convergence (e.g. Yao et al., 2019; Gong, 2020a). We follow the approaches described by Sala-i-Martin (1996) and Young et al. (2008) to establish the unconditional $\beta$-convergence test using the formula

$$\Delta Y_{it} = \beta_1 + \beta_2 Y_{it-1} + \epsilon_t,$$  (1)

where $Y_{it}$ and $Y_{it-1}$ are the key variables of rural development of province $i$ in periods $t$ and $t - 1$, respectively. As a result, $\Delta Y_{it} = (Y_{it} - Y_{it-1}) / Y_{it} \approx \ln Y_{it} - \ln Y_{it-1}$ accounts for the growth rates of these key variables. The present paper uses four key variables of rural development, namely, rural per capita income, rural consumption, rural–urban income disparity, and the Engel coefficient of rural households. The coefficient $\beta_2$ in Equation (1) indicates the speed of convergence. Taking rural per capita income as an example, a statistically significant negative $\beta_2$ illustrates that provinces with lower rural income achieved faster growth, which implies that unconditional $\beta$-convergence has occurred.

Given that some scholars emphasize the fact that convergence will occur at different levels in each region due to various region-specific structural characteristics (Madsen, 2007; Gong, 2018), this article introduces the conditional $\beta$-convergence, which occurs when provinces achieve $\beta$-convergence that is conditional on controlled variables. The conditional $\beta$-convergence proposed in this article uses the formula:

$$\Delta Y_{it} = \beta_1 + \beta_2 Y_{it-1} + \delta z_{it} + \epsilon_t,$$  (2)

where $z_{it}$ vectors represent a group of growth drivers, including agriculture structure, technological innovation, infrastructure condition, educational level, irrigation area, damage area, agricultural finance intensity, openness, and marketization degree. If $\beta_2$ is statistically significantly negative, a conditional $\beta$-convergence can be confirmed to occur.

2. Effect of epidemics on rural convergence

To predict the effect of epidemics on convergence in rural development, we add the interactions between $Dis_{it}$ and $Y_{it-1}$ to Equation (2). $Dis_{it} = c (Dis1_{it}, Dis2_{it})$ vectors two
epidemic variables, in which $\text{Dis}_{1i}$ accounts for the incidence rate and $\text{Dis}_{2i}$ accounts for the death rate in province $i$ in period $t$, both in logarithms. The incidence rate measures the number of new cases of primary and secondary infectious diseases per 100,000 people, and the death rate measures the number of deaths per 100 infected cases, indicating the infectivity and toxicity of epidemics, respectively. The model is expressed as follows:

$$\Delta Y = \beta_1 + \beta_2 Y_{i,t-1} + \beta_3 \text{Dis}_{i,t} \times Y_{i,t-1} + \beta_4 \text{Dis}_{i,t} + \delta z_{it} + \varepsilon_t = \beta_1 + \beta_2 Y_{i,t-1} + \beta_3 \text{Dis}_{1i} \times Y_{i,t-1} + \beta_4 \text{Dis}_{2i} + \delta z_{it} + \varepsilon_t.$$  

(3)

Taking rural per capita income as an example, a statistically significant negative $\beta_2$ indicates that rural per capita income will converge if there are no epidemics and other factors are equal. Moreover, $\beta_3 = c (\beta_{31}, \beta_{32})$ and $\beta_4 = c (\beta_{41}, \beta_{42})$ vector the impact of epidemics. On the one hand, a statistically significant positive $\beta_3$ indicates that epidemics will decelerate convergence in rural per capita income (if $\beta_2$ is negative) or accelerate its divergence (if $\beta_2$ is positive). On the other hand, a statistically significant negative $\beta_4$ indicates that epidemics can directly hinder growth in rural per capita income; $\beta_4$, herefore, measures the average impact of epidemics, whereas $\beta_3$ indicates that leaders or laggards suffer more from epidemics. In the context of the aim of achieving common prosperity, $\beta_4$ determines the impact of epidemics on “prosperity,” whereas $\beta_3$ determines the impact of epidemics on “common,” which means that the difference is diminishing.

In addition to income, consumption and basic living levels are important indicators of rural development and must be considered in achieving common prosperity. We therefore estimated the impact of epidemics on convergence in rural per capita consumption and the Engel coefficient of rural households. Furthermore, besides convergence across regions, we were interested in convergence in rural–urban disparity, which is a dominant component of overall inequality (Li et al., 2013); we therefore estimated the impact of epidemics on convergence in rural–urban income disparity.

3. Mechanism analysis of the effects of epidemics

It is important to investigate further the mechanisms by which epidemics affect rural convergence. Rural per capita income can be divided into four parts, namely income from wages and salaries, net business income, net income from properties, and net income from transfers. Using each of these four parts as the dependent variable, respectively, in the conditional convergence test, we are able to further investigate the different impacts of epidemics on each part of the total income:

$$\Delta S^n = \beta^n_1 + \beta^n_2 S^n_{i,t-1} + \beta^n_3 \text{Dis}_{i,t} \times S^n_{i,t-1} + \beta^n_4 \text{Dis}_{i,t} + \beta^n_5 z_{it} + \varepsilon_{it}, \forall n = 1, 2, 3, 4,$$  

(4)
where $S_i^n$ is the $n$th part of rural per capita income in logarithm. $\Delta S_i^n$ accounts for the growth rate of the $n$th part of rural per capita income. The impact of epidemics on convergence in the $n$th part of rural per capita income can be estimated from Equation (4).

4. Endogeneity problem

In this article, endogeneity may be an issue because of the causality between economic development and epidemics. Epidemics can lead to panic effects and control measures, both of which will decelerate economic growth, decrease employment, and reduce income. However, economic growth may have an impact on the scope of epidemics. For example, more active economies could have a larger number of infected cases due to more frequent communication and travel, but these economies may have more funding and technologies to fight against epidemics. Inspired by Gong and Sickles (2020; 2021), this article treats lagged values of the endogenous variables (in this case, epidemics) as instruments and employs a two-stage least-square approach to deal with this issue. The lagged incidence and death rates from epidemics can be valid instrumental variables (IVs) for two reasons. First, infectious diseases can be sustained through human-to-human transmission, and thus the incidence and death rate from epidemics in two consecutive years are strongly related. Second, unlike natural disasters, such as earthquakes and typhoons, epidemics have no significant negative impact on infrastructure and assets. Once epidemics disappear, the economy and society can recover almost immediately. As a result, epidemics in the previous year can affect current economic development only through their impact on the current condition of epidemics, which makes the lagged condition of epidemics a valid IV. To address the potential simultaneity bias of other control variables, this article follows Gong (2020b) and replaces other control variables with their lagged values to check the robustness. To summarize, this article uses the lagged incidence rate ($Dis_1_{it-1}$) and the lagged death rate ($Dis_2_{it-1}$) as the instrumental variables while using the lagged control variables ($z_{it-1}$) to take the place of $z_{it}$. We find that our estimated results are robust when considering endogenous problems in Section V.

IV. Data and variables

We use a balanced panel of 31 provinces in the Chinese mainland from 2002 to 2019. This article collects three groups of variables. (i) Explained variables: This article uses five explained variables, namely rural per capita income, urban per capita income, rural consumption, rural–urban income disparity, and the Engel coefficient of rural households. Rural per capita income is measured by the log of the per capita disposable income of rural households. Rural per capita consumption is measured as the log of the per capita
consumption expenditure of households. Urban per capita income is measured by the log of the per capita disposable income of urban households. Rural–urban income disparity is calculated by taking the ratio of rural per capita income to urban per capita income. (ii) The proxy variables for epidemics: This article focuses on primary and secondary infectious diseases during epidemics and uses the death rate and incidence rate from primary and secondary infectious diseases as proxy variables, which reflect toxicity and infectivity (Zhang et al., 2020). Although COVID-19 is recognized as a secondary infectious disease, the prevention and control measures adopted for COVID-19 are based on primary infectious diseases. We therefore focus on primary and secondary infectious diseases, which ensure that epidemics’ pathological characteristics and control levels in this article are consistent with COVID-19. (iii) Control variables: This article controls agriculture structure, technological innovation, infrastructure condition, educational level, irrigation area, damage area, agricultural finance intensity, openness, and degree of marketization (measured by the marketization index) (Gong et al., 2021). See Table 1 for detailed definitions and descriptions.

### Table 1. The variables and related statistics (31 provinces’ panel data), 2002–2019

| Variable                  | Unit/notation | Mean   | Standard deviation | Min. | Max. |
|---------------------------|---------------|--------|--------------------|------|------|
| Rural income              | RMB1,000      | 8.04   | 5.53               | 1.46 | 33.20|
| Income from wages         | RMB1,000      | 3.47   | 3.53               | 0.14 | 21.38|
| Net business income       | RMB1,000      | 3.20   | 1.67               | 0.59 | 8.26 |
| Net income from properties| RMB1,000      | 0.25   | 0.29               | 0.00 | 2.13 |
| Net income from transfers | RMB1,000      | 1.12   | 1.22               | 0.03 | 9.52 |
| Rural consumption         | RMB1,000      | 6.27   | 4.34               | 1.00 | 22.45|
| Rural food                | RMB1,000      | 2.23   | 1.28               | 0.53 | 8.18 |
| Rural Engel coefficient   | –             | 0.39   | 0.08               | 0.24 | 0.69 |
| Rural/urban ratio         | –             | 0.36   | 0.07               | 0.19 | 0.54 |
| Urban income              | RMB1,000      | 21.15  | 12.08              | 5.90 | 73.80|
| Incidence rate            | persons per 10,000 | 25.90 | 9.94               | 9.10 | 73.8 |
| Death rate                | %             | 0.42   | 0.44               | 0.03 | 2.81 |
| Farming share             | %             | 54.0   | 9.4                | 31.0 | 81.0 |
| Forestry share            | %             | 4.8    | 3.7                | 0.7  | 42.4 |
| Animal husbandry share    | %             | 32.2   | 9.7                | 10.8 | 67.5 |
| Fishery share             | %             | 9.0    | 9.3                | 0.0  | 34.0 |
| Educational level         | Proportion of high school completion | 0.254  | 0.104             | 0.030 | 0.699 |

(Continued on the next page)
(Table 1 continued)

| Variable                        | Unit/notation                  | Mean  | Standard deviation | Min. | Max. |
|---------------------------------|--------------------------------|-------|--------------------|------|------|
| Irrigation area                 | Million hectares               | 2.0   | 1.5                | 0.1  | 6.2  |
| Damage area                     | Million hectares               | 1.1   | 1.0                | 0.0  | 7.4  |
| Agricultural finance intensity  | Agricultural financial stock / agricultural GDP | 0.90  | 1.37              | 0.08 | 12.49 |
| Infrastructure                  | Highway mileage / land area    | 0.758 | 0.502              | 0.030| 2.145|
| Technological innovation        | Invention patents / real GDP   | 2.907 | 4.620              | 0.140| 48.840|
| Openness                        | International trade / GDP      | 0.290 | 0.338              | 0.100| 1.681|
| Marketization degree            | Marketization index            | 6.29  | 2.13               | –0.30| 11.30|

Overall, data on the economic variables are from the *China Statistical Yearbook* (2003–2020), whereas data on the death rate and incidence rate of primary and secondary infectious diseases are from the *China Health Statistics Yearbook* (2003–2020). We also used the *China Compendium of Statistics* (1949–2008) and provincial-level statistical yearbooks to complement and adjust the main dataset. Table 1 presents the summary statistics of the variables during the sample period, and Figure 1 shows the trend of key variables over time.

Figure 1. Trends in the key variables over time

Source: *China Statistical Yearbook* (2003–2020) and *China Health Statistics Yearbook* (2003–2020).
V. Estimation results

1. Impact of epidemics on rural convergence

To test whether convergence has occurred, this article uses an unconditional $\beta$-convergence test and a conditional $\beta$-convergence test. Column (1) of Table 2 shows the estimations of the unconditional $\beta$-convergence tests for rural per capita income. The estimated negative coefficient of the lagged rural per capita income (logarithm) indicates that provinces with lower rural per capita income, on average, achieved faster income growth than provinces with higher rural per capita income, which implies that rural convergence has occurred in the last two decades.

Table 2. The overall impact of epidemics on rural convergence

| $\Delta Y_t^r$ | Rural per capita income | (1) | (2) | (3) |
|----------------|------------------------|-----|-----|-----|
| $Y_{t-1}$      | -0.011***              | -0.019* | -0.113*** |
|                | (0.003)                | (0.010) | (0.034) |
| $Dis_1 \times Y_{t-1}$ | 0.017***              | 0.001 |
|                | (0.005)                | (0.003) |
| $Dis_2 \times Y_{t-1}$ | -0.145***            | -0.007 |
|                | (0.046)                | (0.024) |
| $Dis_1$        | -0.210***              | 0.019*** | 0.989*** |
|                | (0.024)                | (0.067) | (0.286) |

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. Standard errors are in parentheses. $Dis_1$ and $Dis_2$ represent the incidence and death rates of epidemics, respectively. $Y_t^r$ are key rural development variables in logarithms.

Column (2) shows the estimations of the conditional $\beta$-convergence test. Compared with the coefficient of the lagged rural per capita income (in logarithm) in column (1), column (2) shows that rural per capita income can achieve a higher speed of convergence when control variables are constant. Column (3) presents the regression result when we consider the direct and indirect effects of epidemics. First, the coefficient of the lagged rural per capita income (in logarithm) is significantly negative, indicating the convergence in rural income without epidemics. Second, the coefficient of the interaction $Dis_1 \times Y_{t-1}$ is significantly positive, which implies that the increase in the incidence rate of epidemics decelerates the speed of cross-province convergence. The infectivity of epidemics (represented by incidence rate), therefore, has adverse effects on rural convergence across provinces in China. Moreover, the infectivity of epidemics also has a direct negative
impact on rural income, as the coefficient of incidence rate \((Dis1)\) is significantly negative. Column (3) shows that the toxicity of epidemics affects neither rural development nor its convergence, as the coefficients of the death rate during epidemics \((Dis2)\) and its interaction with rural income \((Dis2 \times Y_{t-1})\) are both insignificant.

Overall, based on the above estimation results, it has been more difficult for the provinces with low rural per capita income to catch up with provinces with high rural per capita income when epidemics occurred. Moreover, the impact of epidemics was mainly driven by infectivity (represented by the incidence rate) rather than toxicity (represented by the death rate). To summarize, epidemics hindered not only “prosperity” (income growth) but also “common prosperity” (income convergence), at least in rural areas.

2. The mechanism by which epidemics affect rural convergence

To mitigate the effect of epidemics on the convergence of rural per capita income, we need to investigate the mechanism of how epidemics affect such convergence. Rural per capita income is therefore divided into four parts, namely income from wages and salaries, net business income, net income from properties, and net income from transfers, and the impact of epidemics on various sources of income is analyzed further. Table 3 presents the estimated results. Column (1) shows the baseline model (same as the one listed in column (3) of Table 2), and columns (2)–(5) show the regression results for net income from wages and salaries, net business income, net income from properties, and net income from transfers, respectively.

Table 3. The impact mechanism of epidemics on rural convergence

| \( \Delta Y_t \) | Rural income | Income from wages and salaries | Business income | Income from properties | Income from transfers |
|-----------------|--------------|-------------------------------|-----------------|------------------------|----------------------|
| \( Y_{t-1} \)   | -0.113***    | 0.015                         | -0.306***       | -0.180***              | -0.281***            |
|                 | (0.034)      | (0.062)                       | (0.117)         | (0.053)                | (0.258)              |
| \( Dis1 \times Y_{t-1} \) | 0.017***     | 0.019*                        | 0.055***        | 0.062***               | 0.006                |
|                 | (0.005)      | (0.010)                       | (0.021)         | (0.008)                | (0.041)              |
| \( Dis2 \times Y_{t-1} \) | 0.001        | 0.012**                       | 0.009           | 0.039***               | 0.027                |
|                 | (0.003)      | (0.006)                       | (0.011)         | (0.005)                | (0.020)              |
| \( Dis1 \)      | -0.145***    | -0.170**                      | -0.450***       | -0.342***              | 0.000                |
|                 | (0.046)      | (0.076)                       | (0.164)         | (0.044)                | (0.262)              |
| \( Dis2 \)      | -0.007       | -0.094**                      | -0.079          | -0.193***              | -0.143               |
|                 | (0.024)      | (0.044)                       | (0.086)         | (0.022)                | (0.124)              |
| Control variables | Yes         | Yes                           | Yes             | Yes                    | Yes                  |
| Constant        | 0.989***     | -0.013                        | 2.872***        | 0.854***               | 0.440                |
|                 | (0.286)      | (0.471)                       | (1.012)         | (0.286)                | (1.663)              |

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. Standard errors are in parentheses. \( Dis1 \) and \( Dis2 \) represent the incidence and death rates of epidemics, respectively. \( Y_{t-1} \) are key rural development variables in logarithms.
Column (2) shows that the net income from wages experienced neither convergence nor divergence in the absence of infectious diseases, but both the incidence and death rates during epidemics caused the net income from wages and salaries to diverge. Moreover, higher incidence and death rates during epidemics can also directly decrease the growth rate of wages and salaries. In terms of business income (see column (3)), the infectivity of epidemics can slow down the growth rate and decelerate convergence, whereas the toxicity of epidemics has had neither a direct nor an indirect impact. Column (4) provides an analysis of property income, and the result implies that both the infectivity and toxicity of epidemics can hinder the growth rate as well as convergence. In terms of transfer income, the estimations in column (5) indicate that epidemics have had no significant effect on this income source.

To summarize, divergence in the net income from wages and decelerated convergence in net business income and net income from properties have been the major driving forces for decelerated convergence in rural per capita income. There were two main reasons for this phenomenon. First, low-income regions have common characteristics, such as poor capital, greater resource misallocation, and a fragile livelihood environment (DFID, 1999), all of which have resulted in the weak anti-risk capacity of companies and family business activities. When epidemics occur, these enterprises and business activities may fail to respond effectively or adapt to such shocks. Epidemics may have a more serious impact on net income from wages and net business income created by these companies and business activities. Second, to find a higher paying job, more rural laborers in low-income regions tend to choose to flow into high-income regions. However, quarantine and self-protection measures during epidemics restrict the cross-regional labor flow and significantly affect the net income from the wages and salaries of rural households in low-income regions. These results highlight the importance of immediate relief measures and fiscal policy support for companies and business activities in low-income regions during epidemics. Furthermore, relaxing quarantine measures and promoting timeous work resumption are critical for economic recovery after epidemics. Finally, transfer income, which is vital in guaranteeing the basic living needs of lagging regions and poor households, has not been affected by epidemics.

3. More discussions on rural convergence
In addition to the level of income, the consumption and basic living level are important indicators of rural development that must be considered when attempting to achieve

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2Although the marginal impact of epidemics on property income is significant, it is not the major driver because property income only accounts for 3 percent of the rural per capita income in the sample period.
common prosperity. In this section, we replace rural per capita income with rural consumption, rural food consumption, and the Engel coefficient of rural households. Table 4 presents the regression results. Column (1) shows the baseline model for comparison. The results in column (2) indicate that epidemics (in both their infectivity and toxicity) decelerate convergence in rural consumption, and the rate of convergence is almost the same as those in rural income. The decelerated convergence in rural per capita income may therefore lead to a decelerated convergence in rural consumption at the same rate, highlighting the importance of stabilizing the income level in low-consumption regions.

Table 4. The impact of epidemics on rural consumption convergence

| $\Delta Y_t$ | Rural income | Rural consumption | Rural food | Rural Engel coeffi cient |
|-------------|--------------|------------------|-----------|-------------------------|
| $Y_{t-1}$   | -0.113***    | -0.115*          | -0.137    | -0.007                  |
|             | (0.034)      | (0.067)          | (0.089)   | (0.082)                 |
| Dis1 $\times Y_{t-1}$ | 0.017***    | 0.017*          | 0.018    | -0.008                 |
|             | (0.005)      | (0.010)          | (0.014)   | (0.015)                 |
| Dis2 $\times Y_{t-1}$ | 0.001      | 0.009*          | 0.011    | 1.345                   |
|             | (0.003)      | (0.005)          | (0.007)   | (1.213)                 |
| Dis1        | -0.145***    | -0.125          | -0.122    | -0.008                 |
|             | (0.046)      | (0.086)          | (0.106)   | (0.015)                 |
| Dis2        | -0.007       | -0.078*         | -0.076    | 1.414                   |
|             | (0.024)      | (0.044)          | (0.054)   | (1.212)                 |
| Control variables | Yes | Yes | Yes | Yes |
| Constant    | 0.989***     | 0.787           | 0.863     | 0.015                   |
|             | (0.286)      | (0.559)          | (0.665)   | (0.084)                 |

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. Standard errors are in parentheses. Dis1 and Dis2 represent the incidence and death rates of epidemics, respectively. $Y_t$ are key rural development variables in logarithms.

In addition to addressing the effects on overall consumption, the effect on basic food consumption should be considered. Columns (3) and (4) show that epidemics have had no significant impact on the growth rate and convergence in rural food consumption or the Engel coefficient of rural households, indicating that rural residents’ basic living needs were guaranteed, regardless of epidemics. However, rural food consumption and the Engel coefficient of rural households fail to achieve convergence, which means that the lagging regions have failed to catch up with the leaders in their basic standards of living. In other words, the existing social security system can ensure that the basic living conditions of rural residents will not be affected by epidemics, but it has failed to help the lagging regions achieve faster growth and catch up with the leaders, regardless of epidemics. As a result, a better social security system and greater support are needed for regions with a lower basic life level.
4. The impact of epidemics on rural–urban convergence

In addition to the regional disparity, Table 5 analyzes the rural–urban income disparity, which is another important dimension of the overall inequality that requires resolution in the context of the aim of achieving common prosperity. Column (2) indicates that epidemics have not had any impact on rural–urban income disparity across regions. As we pointed out in the literature review, the disadvantage of studying rural–urban income disparity is that it fails to show the change in rural and urban income when both incomes change at the same speed. The results further confirm the importance of analyzing convergence in rural income across regions. Moreover, the insignificant impact of epidemics on the rural–urban income gap implies that urban residents may also suffer from the negative impact of epidemics, and the impact should be similar in rural areas. To confirm this argument, column (3) reports the impact of epidemics on urban per capita income. As we predicted, the channels and magnitude of the effect of epidemics on urban income are quite similar to the effects on rural income, which confirms our findings concerning the rural–urban income gap.

Table 5. The impact of epidemics on rural–urban disparity convergence

| $\Delta Y_t$ | Rural income (1) | Rural/urban ratio (2) | Urban income (3) |
|-------------|------------------|----------------------|-----------------|
| $Y_{t-1}$   | -0.113***        | -0.137               | -0.136***       |
|             | (0.034)          | (0.134)              | (0.036)         |
| Dis1 × $Y_{t-1}$ | 0.017***        | 0.004                | 0.023***       |
|             | (0.005)          | (0.022)              | (0.005)         |
| Dis2 × $Y_{t-1}$ | 0.001           | -0.013               | 0.004          |
|             | (0.003)          | (0.011)              | (0.003)         |
| Dis1        | -0.145***        | 0.000                | -0.228***      |
|             | (0.046)          | (0.008)              | (0.053)        |
| Dis2        | -0.007           | 0.005                | -0.036         |
|             | (0.024)          | (0.004)              | (0.028)        |
| Control variables | Yes            | Yes                  | Yes            |
| Constant    | 0.989***         | 0.023                | 1.386***       |
|             | (0.286)          | (0.046)              | (0.347)        |

Notes: *** represents significance at the 1 percent level. Standard errors are in parentheses. Dis1 and Dis2 represent the incidence and death rates of epidemics, respectively. $Y_u$ are key rural development variables in logarithms.

5. Projection of COVID-19 on convergence

As mentioned in Section I, although the impact of COVID-19 is likely to be more severe than that of previous epidemics (i.e. primary and secondary infectious diseases), we believe that they are still comparable in transmission patterns, control measures, and effect mechanisms, which means that we can predict the lower boundary of the actual
impact of COVID-19 based on the estimated impact of previous epidemics. It is worth noting that the actual impact of COVID-19 may be more serious than our projection, but our projection still provides useful references as a lower boundary. In this subsection, we use the coefficients estimated above to project the possible impact of COVID-19.

Based on Equation (3), we can derive the indicator of convergence as \[ \delta = \hat{\beta}_2 + \hat{\beta}_{31} \text{Dis}_1 + \hat{\beta}_{32} \text{Dis}_2, \] where the coefficients \( \hat{\beta}_2, \hat{\beta}_{31}, \) and \( \hat{\beta}_{32} \) are estimated in the previous sections. It is worth noting that a negative \( \delta \) refers to convergence and a positive \( \delta \) refers to divergence. A more negative \( \delta \) implies faster convergence. We can, therefore, use \(-\delta\) to account for the convergence rate. As the national incidence and death rates for infectious diseases in China in 2020 have been released by the National Health Commission of the People’s Republic of China, we can project and compare the rate of convergence with and without COVID-19. Table 6 reports the estimated rate of convergence with and without COVID-19, as well as the change due to COVID-19. Owing to COVID-19, the rate of convergence for rural income decreased from 0.0243 to 0.0238, which implies that the convergence speed decelerated by 2.3 percent. In terms of rural consumption, the rate of convergence slowed down by 2.9 percent from 0.0694 to 0.0674 because of COVID-19. Finally, COVID-19 also lowered the rate of urban income convergence from 0.0160 to 0.0153, indicating a decrease of 4.8 percent. To summarize, our projection implies that COVID-19 is likely to slow the convergence in rural income, rural consumption, and urban income.

Table 6. Rate of convergence with and without COVID-19

| Rate of convergence | Without COVID-19 (1) | With COVID-19 (2) | Change (%) (3) |
|---------------------|---------------------|------------------|----------------|
| Rural income        | 0.0243              | 0.0238           | –2.3           |
| Rural consumption   | 0.0694              | 0.0674           | –2.9           |
| Urban income        | 0.0160              | 0.0153           | –4.8           |

VI. Conclusions and policy implications

This article investigated the impact mechanism of epidemics on rural development and the approaches to accelerating its convergence. To the best of our knowledge, this is the first study to analyze not only the effects of epidemics on rural development but also the impact on its convergence in China.

Using a balanced panel of 31 provinces in China for 2002–2019, the estimation results show that: (i) conditional \( \beta \)-convergence has been achieved in rural per capita
income, but epidemics could decelerate this convergence; (ii) accelerated divergence in net wage income and decelerated convergence in net business income have been the major drivers for decelerated convergence in rural per capita income, which has led to decelerated convergence in rural consumption; (iii) although epidemics have not threatened rural food consumption and the Engel coefficient of rural households, these two indicators of basic living needs have failed to achieve convergence across regions; (iv) the overall impact of epidemics on convergence in rural–urban income disparity has been insignificant due to the similar impact of epidemics on urban convergence; and (v) COVID-19 is likely to decelerate the convergence in rural income, rural consumption, and urban income. Based on these findings, this article suggests the following policy implications for responding to COVID-19 or other public health emergencies and mitigating the negative impacts of epidemics.

First, once epidemics are under control, it is vital to eliminate quarantine measures and promote the resumption of work and production immediately in addition to providing support for enterprises and family business activities in low-income regions. This article finds that accelerated divergence in net wage income and decelerated convergence in net business income have been the main reasons for decelerated convergence in rural per capita income, which have led to decelerated convergence in rural consumption. For rural residents, epidemics will likely affect income from both the agricultural and non-agricultural sectors, presenting a new challenge of consolidating the achievement of poverty alleviation in the context of COVID-19. Necessary fiscal support and immediate relief measures (such as temporary subsidies) should be offered to ease the burden on enterprises and family business activities in low-income regions.

Second, building a better social security system and improving basic living standards in low-income regions is crucial. Although epidemics have had no impact on convergence in rural food consumption and the Engel coefficient of rural households, there has been a failure to achieve cross-region convergence during epidemics. In other words, the current social security system can effectively guarantee the basic living needs of low-consumption rural residents during epidemics, but it has failed to help lagging regions catch up with leading regions. As COVID-19 has lasted much longer than previous epidemics, such as SARS and H1N1, the continuing negative effect on rural income may gradually lead to a decline in food consumption in the absence of an improved social security system.

Third, compared with regional disparities, rural–urban disparities seem to be a more difficult issue to tackle in the context of common prosperity. This article finds that both rural and urban convergences have occurred in the last two decades (although epidemics can decelerate both), indicating that regional disparity (in both rural and urban areas)
is diminishing. However, the rural–urban disparity does not converge. It is therefore important to promote the rural revitalization strategy, especially in lagging regions, to achieve common prosperity.

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