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Who and which regions are at high risk of returning to poverty during the COVID-19 pandemic?

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Pandemics such as COVID-19 and their induced lockdowns/travel restrictions have a significant impact on people's lives, especially for lower-income groups who lack savings and rely heavily on mobility to fulfill their daily needs. Taking the COVID-19 pandemic as an example, this study analysed the risk of returning to poverty for low-income households in Hubei Province in China as a result of the COVID-19 lockdown. Employing a dataset including information on 78,931 government-identified poor households, three scenarios were analysed in an attempt to identify who is at high risk of returning to poverty, where they are located, and how the various risk factors influence their potential return to poverty. The results showed that the percentage of households at high risk of returning to poverty (falling below the poverty line) increased from 5.6% to 22% due to a 3-month lockdown. This vulnerable group tended to have a single source of income, shorter working hours, and more family members. Towns at high risk (more than 2% of households returning to poverty) doubled (from 27.3% to 46.9%) and were mainly located near railway stations; an average decrease of 10–50 km in the distance to the nearest railway station increased the risk from 1.8% to 9%. These findings, which were supported by the representativeness of the sample and a variety of robustness tests, provide new information for policymakers tasked with protecting vulnerable groups at high risk of returning to poverty and alleviating the significant socio-economic consequences of future pandemics.

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Introduction

Crisis and shocks, such as climate-related disasters, violent conflicts and pandemics can result in severe socio-economic losses, ecological impacts, and human suffering (Helbing, 2013). The impacts usually differ across population groups, with low-income groups often suffering the most (McPhillips et al., 2018). These crises are regularly accompanied by shrinking economies and damage to people’s livelihoods, which in turn have a strong impact on poverty. The poor suffer not only directly in terms of jeopardized personal safety, but also indirectly through a shortage of work and financial uncertainty (ESCAP, 2021). Therefore, understanding who and which regions are at high risk of falling into poverty and how crises shape the impact of poverty is critical to developing efficient responses.

The COVID-19 pandemic has disrupted the functioning of our natural, economic, and social systems, and has directly or indirectly impacted people depending on those systems. Poor people are particularly susceptible, and it was forecast that 71 million people would fall back into extreme poverty in 2020 following the outbreak of the pandemic (World Bank, 2020). Based on a review of the literature on the effects of COVID-19 (Acuto et al., 2020; Asare and Barfi, 2021; Bouman et al., 2021; Decerf et al., 2021; Douglas et al., 2020; Fajardo-Gonzalez et al., 2021; Hwang et al., 2020; Laborde et al., 2020a, 2020b; Leach et al., 2021; Padhan and Prabheesh, 2021; Rume and Islam, 2020; Rutz et al., 2020), the potential mechanism underlying a return to poverty as a result of the COVID-19 pandemic was identified (Fig. 1). Measures adopted to contain the pandemic, including social distancing, travel restrictions, and local transportation lockdowns, have affected the economy, society, and the environment. Assuming this, we focused on vulnerable groups who have recently emerged from poverty. There are two paths by which those who have been lifted out of poverty could fall back into poverty. The first is the direct impact on health as a result of contracting COVID-19. Health impacts might lead to loss of employment and increased expenditure on healthcare, driving them back into poverty. The second path is the indirect

impact on people’s income. Vulnerable people usually work as casual labourers with no assurance of regular employment, they have a single source of income and few savings, and thus are more likely to be pushed back into poverty as a result of lost wage income. The COVID-19 pandemic has destroyed tens of millions of jobs and livelihoods, resulting in migrant workers, daily wage labourers and some informal sector workers losing their source of income (ESCAP, 2021; UNDP, 2020; ILO, 2020). Identifying vulnerable groups at risk of falling back into poverty is critical to supporting the design of policies attempting to mitigate their losses.

Hubei Province, in which the city of Wuhan is located, was significantly affected in the early stages of the pandemic, and is also one of the main areas for poverty reduction in China. Understanding the impacts of COVID-19 on poor households in Hubei Province could provide policy implications on how to deal with the intertwined situation between poverty alleviation and future crises response. Therefore, in this study, we focused on the population that was lifted out of poverty at the end of 2019 in Hubei Province in an effort to identify those at high risk of returning to poverty as a result of the loss of employment caused by the COVID-19 pandemic. A total of 78,931 government-identified poor households in 100 towns in 10 counties were included in the sample used in this study. The 10 counties were located in the eastern, central, and western regions of Hubei Province to reflect the differences in geographical conditions and levels of socio-economic development in the various regions (Fig. 2). The per capita gross domestic product in central Hubei is much higher than that in the eastern and western regions, while the incidence of poverty in the western region is particularly high. The number of confirmed cases in central Hubei was much higher than that in the eastern and western regions in the initial stage of COVID-19. As can be seen from Fig. 2, over all the sample households, the average proportion of wage income to total income was 72%, indicating that wage income is critical for the poor households.

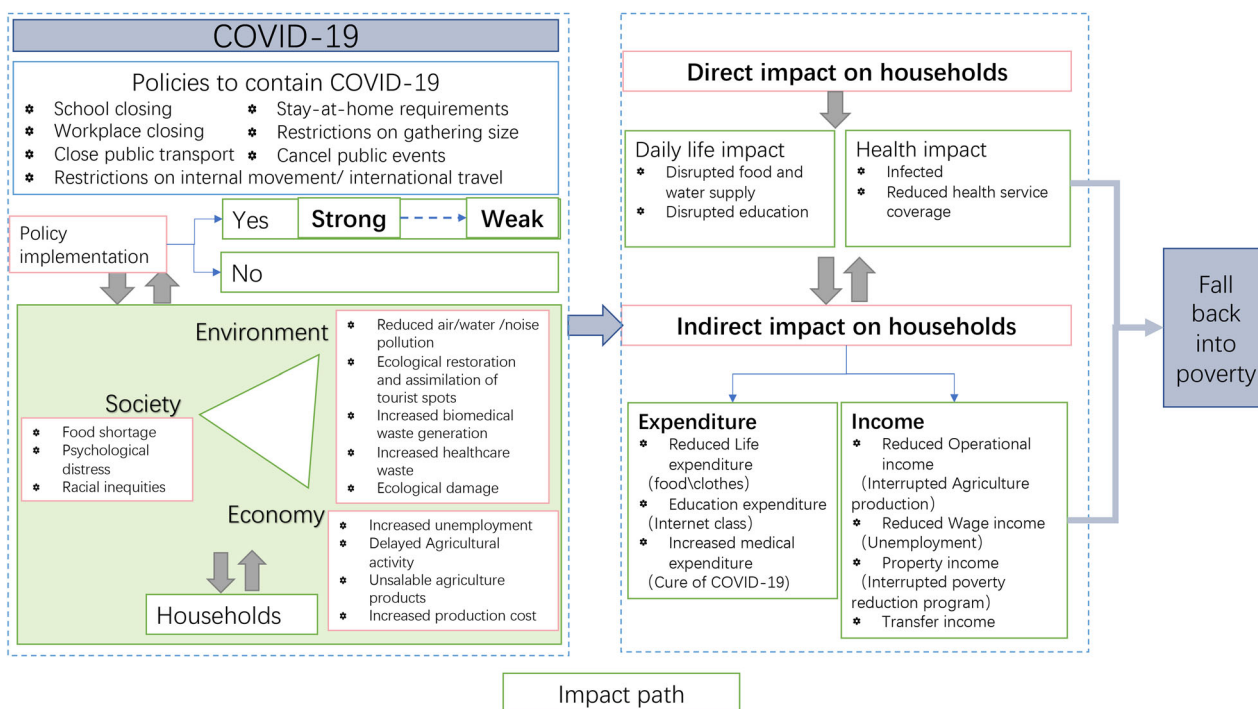


Fig. 1 The impact path of COVID-19 on poverty. There are two paths by which those who have been lifted out of poverty could fall back into poverty, which are direct impacts and indirect impacts.

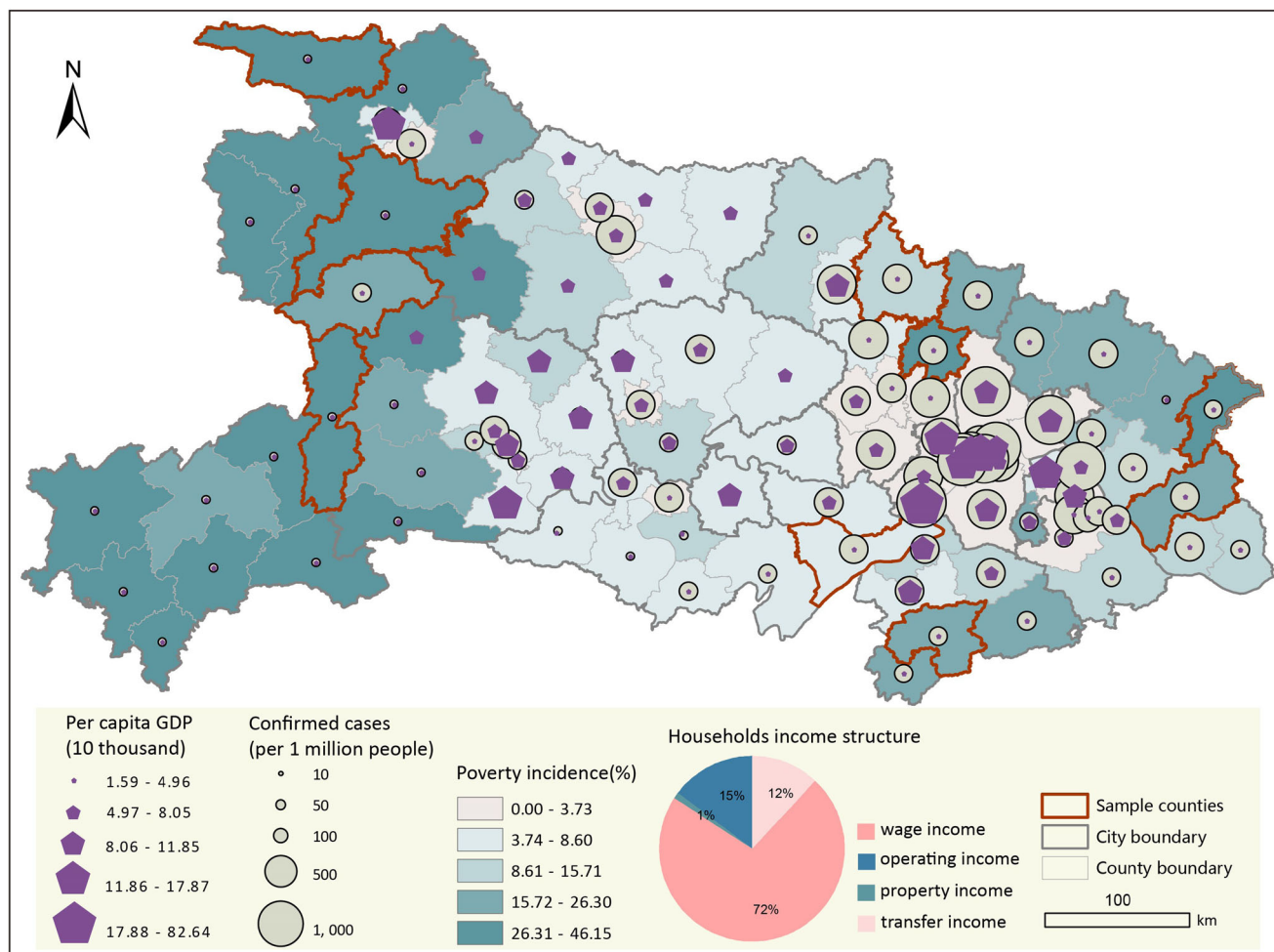


Fig. 2 Overview of the study area. The incidence of poverty, per capita gross domestic product, the number of confirmed COVID-19 cases in each county in Hubei Province; and the household income structure in sample counties.

To assess the impacts of different periods of the lockdown, we set three scenarios: lockdowns of 1, 2, and 3 months since the lockdown in Wuhan lasted for 76 days, from 23 January to 8 April 2020. We assumed that migrant workers in Hubei Province would not return to work for 3 months, and that the Wuhan lockdown primarily impacted those migrant workers who had to travel for work and relied on their wage income to support their families. Migrant workers account for a large proportion of poor households, and the lockdown would have had a significant impact on them. Under our three scenarios, migrant workers could not return to their workplace for either 1, 2, or 3 months, and thus lost their wage income for the period of the lockdown. The case study aimed to determine who was at high risk of returning to poverty, where they were located, and how the various risk factors shaped the return to poverty under the three scenarios. To evaluate the associations between the likelihood of a household returning to poverty and the household’s characteristics, a logistic regression model was employed. To identify the geographic distribution of the risk of returning to poverty and how it was affected by regional characteristics, we first assessed the relative importance of risk factors using the Lindeman, Merenda and Gold (LMG) method (Grömping, 2015b), and then constructed a semi-parametric generalized additive model (GAM) to predict the risk of returning to poverty (Hastie and Tibshirani, 1987). Regional characteristics were extracted from multiple data sources, including remote sensing images, the Internet, and statistical records (Ge et al., 2021; Liu et al., 2020). Detailed information on data collection, pre-

processing, and analysis can be found in the “Methods” section and the Supplementary Information.

Methods

Measuring the risk of returning to poverty. We conducted two field surveys in January and September of 2020 covering 10 counties in various regions of Hubei Province, as shown in Fig. 2, and obtained data on the total income and income structure of 91,125 impoverished households as at the end of 2019 in 100 towns in the 10 counties. After eliminating incomplete observations (those that were outliers or were missing data), we obtained a final sample of 78,931 households for our analysis. To investigate the factors affecting the risk of returning to poverty at the household level, we also collected data on the characteristics of each household, which are shown in Fig. 3. All the household-level data were obtained from the Office of Poverty Alleviation and Development in each county.

Here, we present a brief introduction to poverty identification and progress in poverty alleviation in China to help better understanding of the term “returning to poverty”. Under China’s national poverty identification standard, poor households were primarily identified based on their income, with consideration given to their housing, education level, and health conditions (SCIO, 2021). A household that was confirmed as poor was registered, and a file was created in the national poverty alleviation information system, which was the source of the data

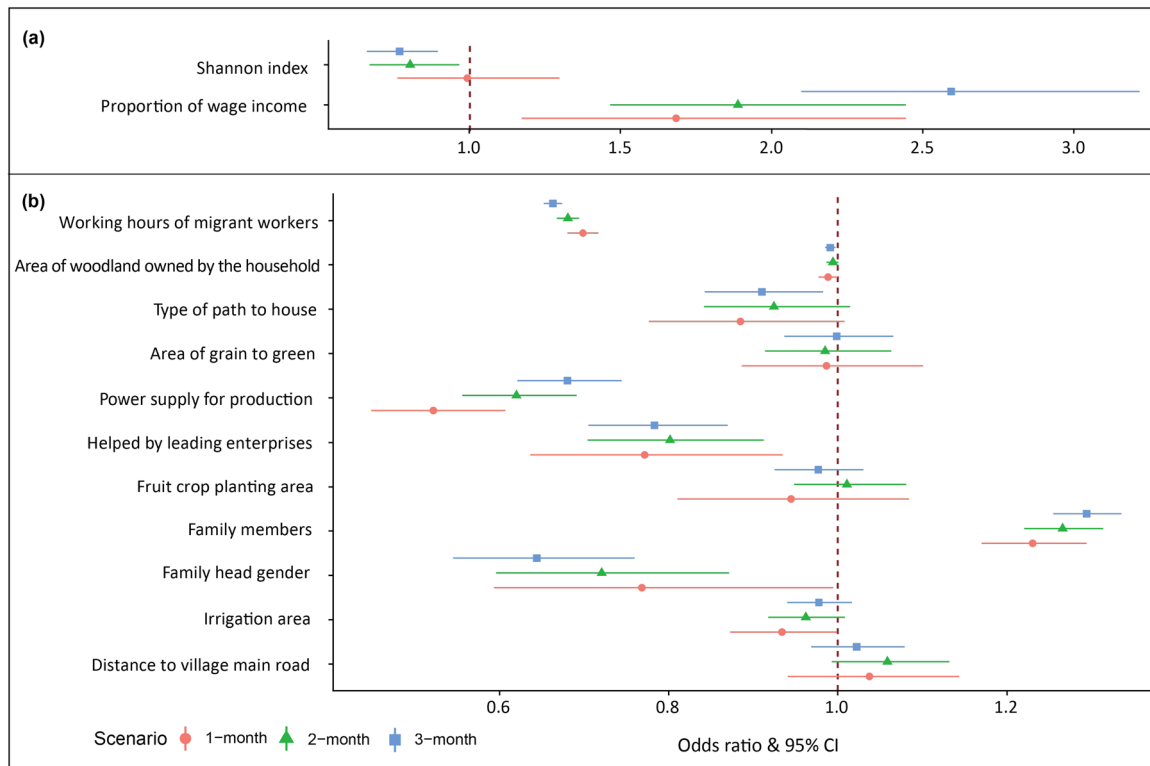


Fig. 3 Household characteristics correlated with the risk of returning to poverty. Values are odds ratios with 95% confidence intervals. **a** Correlation between income characteristics and the likelihood of returning to poverty (calculated using data from all the counties included in the sample ($n = 78,931$)). **b** Correlations between the other 11 household characteristics and the likelihood of returning to poverty (calculated using data from Yingshan County ($n = 17,972$)). All estimates are presented in Supplementary Table S1.

on total income, income structure, and household characteristics used in this study. The impoverished population was then adjusted every year based on national poverty standards. Early in 2021, China’s government announced that after years of effort, it had achieved the goal of eradicating extreme poverty. Thus, in this study, we focused on poor households that had been lifted out of poverty at the end of 2019 in Hubei Province with the aim of identifying the risk of them returning to poverty as a result of the loss of employment and income caused by the COVID-19 pandemic.

In this study, the total income of each household was considered to include four components: operating, wage, property, and transfer income. We also obtained the number of working months for migrant workers in 2019. The threshold for returning to poverty, as defined by the Office of Poverty Alleviation and Development in Hubei Province, was an annual household income of <5000 CNY.

We used three scenarios in which migrant workers who could not return to their workplace for $i = (i = 1, 2, 3)$ months lost their wage income for i months. Here, n denotes the number of working months of migrant workers and W denotes the wage income of each household. Assuming that the wage income is the same each month, the wage income of each household under the i -month scenario, denoted by w_i , was calculated as follows:

$$w_i = \frac{W}{n} * (n - i), i = 1, 2, 3. \tag{1}$$

Then, under the i -month scenario, when a household’s total income was less than 5000 CNY, we considered that the household had been pushed back into poverty. Here, the number of households pushed back into poverty for a town is denoted by P , the total number of poor households in a town is denoted by

M , and the risk of returning to poverty in a town is denoted by R , which is calculated as follows:

$$R = \frac{P}{M}. \tag{2}$$

Identifying the risk factors. Household-level characteristics were measured using 13 indicators: the Shannon–Weiner diversity index (see the Supplementary Information for details), the proportion of wage income, working hours of migrant workers, number of family members, gender of family head, fruit crop planting area owned by the household, type of path to the house, area of grain to green (cropland returning to forest) owned by the household, area of woodland owned by the household, irrigation area, shortest distance to the village’s main road, whether the household has access to power (binary value), and whether the household was helped by leading enterprises (binary value). The income structure data for each household were collected from all counties. However, detailed information on the other household characteristics was only available for Yingshan County. Therefore, we used two logistic regression models to identify the household characteristics that distinguished households at high risk of returning to poverty from those at lower risk. In our study, the response variable pertained to whether a household returned to poverty. In the first model, we analysed the impact of income characteristics on poor households in all counties and found that the proportion of wage income was consistently significantly associated with the risk of returning to poverty under all lockdown scenarios (Fig. 3a). In the second model, the other 11 indicators of household characteristics were analysed using data from Yingshan County. The results are

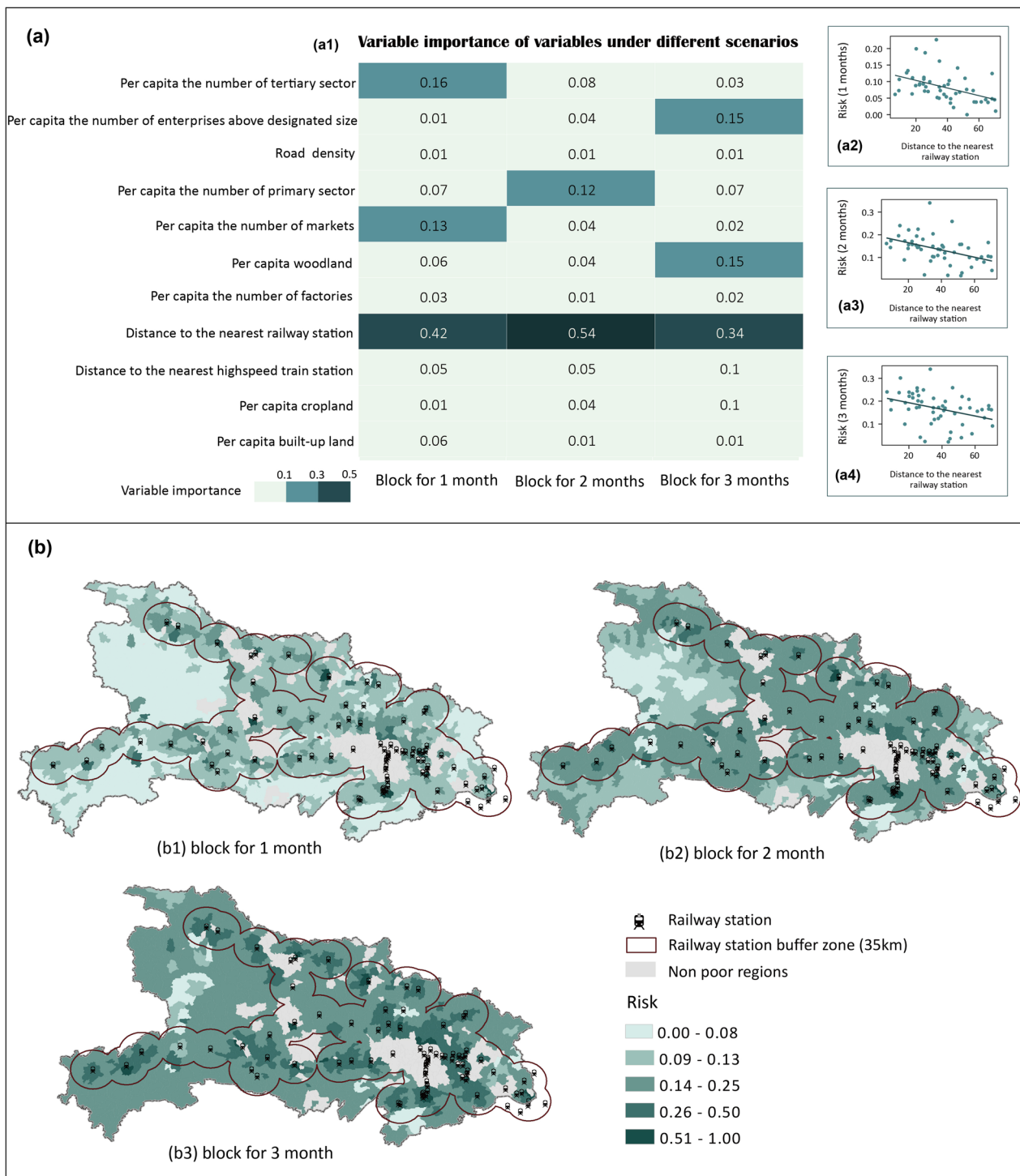


Fig. 4 The town-level importance ranking of various factors and their relationship with the risk of returning to poverty. a The importance ranking of various factors in relation to the risk of returning to poverty using the LMG approach in the multiple linear regression model and the bivariate relationship between risk and the distance to the nearest railway station under 1-, 2- and 3-month lockdown scenarios. **b** The estimated risk of returning to poverty for each town in Hubei Province under the three lockdown scenarios.

shown in Fig. 3b. Supplementary Table S1 lists the estimated odds ratios of returning to poverty and not returning to poverty.

The potential risk factors and selected factors at the town level are listed in Supplementary Tables S2 and S3, respectively. The variable selection and data sources can also be found in the Supplementary Information. We identified the relative importance of risk factors and their detailed relationship with the risk of returning to poverty through variable importance metrics

using the regression model, which is the LMG approach (Fig. 4a). The LMG approach is able to identify a variable’s direct contribution and its contribution in combination with all other predictors (Grömping, 2015b). The explanatory variables (risk factors) in the initial model were denoted as S as x_1, \dots, x_p , and the response variable (risk of returning to poverty) was denoted as Y . The R^2 of S was defined as the ratio of the residual sum of squares, denoted as RSS , to the total sum of squares,

denoted as SST, as follows:

$$R^2(S) = 1 - \frac{RSS}{SST}. \quad (3)$$

When the variable x_m was added to the model to form the new model M, the additional R^2 was defined as $\text{seq}R^2(M/S)$ as follows:

$$\text{seq}R^2(M/S) = R^2(M \cup S) - R^2(S). \quad (4)$$

The order of the explanatory variables is a permutation of the available variables, denoted by the tuple of indices $r = (r_1 \dots r_p)$. Let $S_k(r)$ denote the set of variables entered into the model before variable x_k in order r . Then, the portion of R^2 allocated to variable x_k in order r can be defined as follows:

$$\text{seq}(\{x_k\}/S_k(r)) = R^2(\{x_k\} \cup S_k(r)) - R^2(S_k(r)). \quad (5)$$

Then, for explanatory variable x_k , the LMG metric is calculated as follows:

$$\text{LMG}(x_k) = \frac{1}{p!} \sum_r \text{seq}R^2(\{x_k\}|r). \quad (6)$$

The LMG metrics were calculated using the R package `relaimpo_2.2-3` (Grömping, 2015a). Supplementary Tables S4–S6 show the importance ranking of the nine selected variables for the three scenarios based on the multiple linear regression model. The proportional marginal variance decomposition (PMVD) metrics were also calculated to verify the results of the LMG method in Supplementary Tables S4–S6. The results indicated that both the LMG method and PMVD identified the most important factor (distance to the nearest railway station). However, PMVD allocated more importance to this factor and less importance to other factors.

Mapping the risk of returning to poverty. We used the GAM to predict the risk of returning to poverty in Hubei Province at the town level based on the selected risk factors (Fig. 4b). The GAM is a semi-parametric extension of the generalized linear model, which assumes that the function is additive and the composite of the functions is a smoothing function (Hastie and Tibshirani, 1987). The GAM allows the regression coefficients of explanatory variables to be smooth curves, which can better capture the non-linear relationship between the response variable and the explanatory variable. The basic form of the GAM can be written as follows:

$$g(E(Y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \dots + f_m(x_m) \quad (7)$$

where $E(Y)$ represents the expectation of the response variable Y , $g(\cdot)$ represents the link function, β_0 represents the intercept and $f_1 \dots f_m$ represents the smooth function of the explanatory variables, which can be in the form of specified parameters, non-specified parameters, or semi-parameters.

The implementation of the GAM was divided into four steps. (A) *Variable selection*: We removed multicollinearity among the explanatory variables by computing the variance inflation factor of the explanatory variables. The selected variables are shown in Supplementary Table S3. (B) *Link function*: Since our response variable is a proportion within the interval (0,1), we selected the beta family function as our link function. (C) *Model fitting*: All possible models were compared and analysed, and the optimal model was selected. In this step, all variables selected after the collinearity diagnosis were imported into the full GAM, and then insignificant variables with a p -value > 0.01 were deleted. The estimated degrees of freedom and p -value for each variable in the initial full GAM and the final optimal variable under different lockdown scenarios are presented in Supplementary Tables S7 and S8, respectively. (D) *Model evaluation*: The residual

distribution was evaluated for the optimal model. The optimal principles of the model were as follows: (i) the influence of all explanatory variables in the model reached a significant level and (ii) the adjusted R^2 was greatest, while the Akaike information criterion was the smallest. The results of the model validation process are presented in Supplementary Table S9. The optimal GAM was then applied to the rest of the towns in Hubei Province to estimate the risk of returning to poverty at the town level. The selected variables and their influence on the risk of returning to poverty in the optimal GAM model under different lockdown scenarios are plotted in Fig. 4.

Results

Households that depend on a single source of income are at high risk of returning to poverty. The results based on the full household sample revealed that the percentage of households at risk of returning to poverty increased from 5.6% to 22% under the 3-month lockdown scenario. It was also found that the proportion of wage income was significantly consistently correlated with the risk of returning to poverty under all scenarios (Fig. 3a and Table S1). The changes in income structure and per capita income under the different scenarios are presented in the form of histograms in Supplementary Figs. S1 and S2. Working hours, number of family members, whether the household was supported by leading enterprises, and whether the household had access to power were factors that were consistently associated with the risk of returning to poverty under all scenarios (Fig. 3b and Table S1).

In general, high-risk households tended to have a single source of income, shorter working hours, and more family members, were not supported by leading enterprises and had no access to power. For every one-unit increase in income diversity and working hours, the likelihood of returning to poverty decreased by 15% and 32%, respectively (Supplementary Table S1). When households were supported by leading enterprises and supplied with power, the likelihood of returning to poverty decreased by 41% and 22%, respectively (Supplementary Table S1). This is primarily because households with diverse income sources are less affected by shocks, and more able to sustain their income and consumption (Porter, 2012). Poor households supported by leading enterprises and supplied with power are less likely to return to poverty. These two characteristics indicate that industrial development in villages could not only help poor households to overcome poverty, but also protect them from returning to poverty by cushioning them from external shocks. Therefore, efforts should be made to help households engaged in casual jobs with more family burdens, and those that are not supported by leading local enterprises.

Regions closer to train stations are at high risk of returning to poverty. Previous studies have found that people living in remote rural areas are more vulnerable and easily returned to poverty during an economic recession, such as that caused by the COVID-19 pandemic (Bennett et al., 2018; Dang et al., 2017; Hallegatte et al., 2020; Hone et al., 2019; Mueller et al., 2021; Schwarz et al., 2011). Conversely, this study found that in the early days of the COVID-19 outbreak, poor people who lived closer to train stations had a higher risk of returning to poverty as a result of traffic lockdowns and the travel ban in China. Our analysis revealed that the factors indicating transportation conditions were the most important factors related to the risk of returning to poverty in different regions under different scenarios (Fig. 4a1). The distance to the nearest railway station had a negative linear relationship with the risk of returning to poverty under all scenarios, as can be seen in Fig. 4a2–a4. On average, a

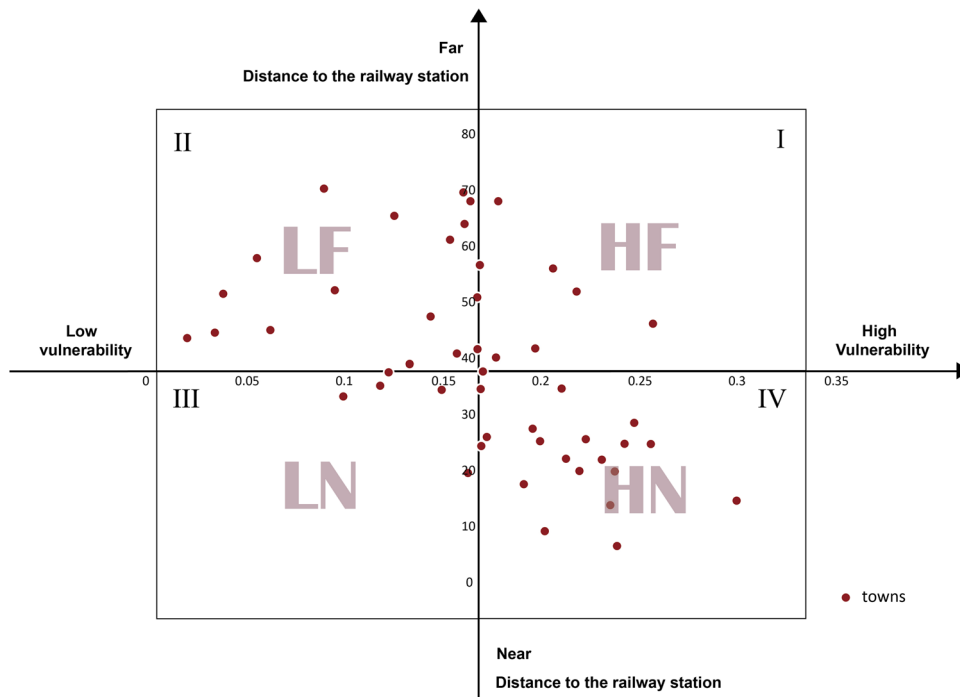


Fig. 5 A four-quadrant diagram of the correlation between the vulnerability of different regions (in terms of the risk of returning to poverty) and the distance to the nearest railway station. LF represents a lower risk of returning to poverty while being far from a railway station; HF represents a higher risk of returning to poverty despite being far from a railway station; LN represents a lower risk of returning to poverty despite being near a railway station; and HN represents a higher risk of returning to poverty while being near a railway station. The Pearson correlation test for vulnerability and the distance to the nearest railway station are presented in Supplementary Table S10.

decrease of 10 km in the distance to the nearest railway station increased the number of households being returned to poverty by approximately 2%. The impact of the variable distance to the nearest railway station remained almost unchanged over time, confirming its importance.

Figure 4b shows the estimated risk of returning to poverty under the three scenarios for each town in Hubei Province. We found that high-risk regions were always distributed in railway station buffer zones, while low-risk regions were distant from railway stations, indicating that the spatial pattern was relatively stable under different scenarios and that the results were stable under the chosen GAM. Furthermore, the spatial cluster map of the risk of returning to poverty also confirmed a stable spatial pattern (Supplementary Fig. S3).

We also found that some areas had a good balance in terms of development, and thus a lower risk of returning to poverty as a result of the COVID-19 pandemic. As can be seen from Fig. 5, the four-quadrant vulnerability diagram representing the relationship between the risk of returning to poverty and the distance to the nearest railway station, regions in the third quadrant were closer to a railway station but less vulnerable. These regions benefited from the prosperity brought about by the presence of the station, and might have had fewer migrant workers, making them less vulnerable to the impact of the COVID-19 pandemic.

Discussion

This case study in Hubei Province provided new information in terms of who was at high risk of returning to poverty, where they were located, and why they were at high risk in the initial stages of the COVID-19 pandemic. The responses to COVID-19 gradually improved in the later stages, most notably with the development of vaccines (Wouters et al., 2021). However, at the beginning of the pandemic, the entire society was overwhelmed (Wang et al.,

2020), with low-income groups suffering the most. Lessons from the early stages of the COVID-19 pandemic on the links between the pandemic and poverty could provide early warnings in relation to future shocks. This case study identified the households and regions at high risk of returning to poverty as a result of loss of income. This enables the targeting of high-risk populations and regions, and the development of effective policy responses in the initial stages of a shock. The analysis of risk factors provides guidance for policymakers aiming to initiate rapid responses in an effort to mitigate the effects of lost income.

The COVID-19 pandemic spread swiftly, and continues to disrupt the world today. Many countries have had to implement stringent lockdown measures, including travel restrictions and local transportation lockdowns, in an effort to control the pandemic (Liu et al., 2021). To minimize the risk of returning to poverty, China quickly adopted a host of policies when the COVID-19 pandemic emerged, and succeeded in eliminating absolute poverty by the end of 2020. For instance, local governments chartered point-to-point buses, trains, and planes to transport migrant workers back to their workplaces, provided personal protective gear, and facilitated the flow of labour and materials to enable enterprises to resume operations (McDonald, 2020b; Zhang, 2020). However, the people and regions that were lifted out of poverty remain vulnerable, and many other developing countries are still trapped in poverty as a result of the COVID-19 pandemic. Thus, identifying the households that are most vulnerable and where they are located is a key task in numerous countries.

While the construction of additional railway stations has accelerated the pace of urban development, the outbreak of the COVID-19 pandemic reversed this process and brought about deurbanization (Givoni, 2006; Puaschunder, 2021). Proximity to railway stations makes it more convenient for poor people to seek migrant work, and thus become more dependent on the wage

income from that work. Consequently, when they were locked down, they lost part or all of the income they were relying on to support their families, and thus were more vulnerable to the impact of COVID-19. Therefore, policies aimed at preventing a return to poverty should target rural households living in remote areas and those living near railway stations.

Once the lockdown was lifted, poor households were able to return to work, however, it is difficult to determine whether their lives returned to normal. Some poor households might be infected with the virus and lost their entire employment and income, while others might have only lost their income temporarily, but still fallen back into poverty because, for example, they were unable to make the required repayments on their loans. The development of vaccines was an important factor affecting the risk of returning to poverty in later stages. Given that this was one of the most crucial innovations in the fight against the virus (Vuong et al., 2022), as vaccination levels increased, many countries gradually abandoned their various non-pharmaceutical interventions (NPIs), including lockdowns (Sonabend et al., 2021). However, studies from China (Yang et al., 2021), the United States (Borcherding et al., 2021) and the European Union (Bauer et al., 2021) suggested that NPIs would still be required even when the population was fully vaccinated. The synergistic effect of NPIs and vaccination was 46.9% in 27 countries, whereas the effects of NPIs and vaccination alone were 20.7% and 28.8%, respectively (Ge et al., 2021). Therefore, despite rising vaccination levels, the relaxation of NPIs might have prevented enterprises and transportation systems from resuming operations, thereby increasing the risk of people falling into poverty.

There are also some limitations to our analysis. First, the study period was limited to the 3-month lockdown, even though many countries are still in the grips of the COVID-19 pandemic, and the impact could continue for a long time, even after the resumption of normal activity. Second, this study only focused on poor households that have been lifted out of poverty, but there would also be a large number of households that were not previously considered to be poor based on the poverty line that have fallen into poverty as a result of the COVID-19 pandemic. Third, since the COVID-19 pandemic and the measures imposed in an effort to control its spread have had a significant impact on the environment, economy, and society, and have affected the livelihoods of poor households. However, this study mainly focused on loss of household income induced by the COVID-19 pandemic control measures.

The COVID-19 pandemic continues to affect people's livelihoods, and households returning to poverty caused by COVID-19 will still appear. In future research, first, attentions on the later stages of the pandemic also deserved. Following the implementation of various measures aimed at mitigating the effects of COVID-19, the patterns of who and which regions are at high risk of falling into poverty is going to change. Therefore, identifying high-risk populations in the later stages of the pandemic is crucial when making policy decisions. In addition, the study sample should be extended to cover a wider range of people. Attention is usually focused on households that are considered poor, while marginalized populations are likely to be ignored. Finally, the impact of COVID-19 on other dimensions of poverty requires further exploration. In addition to causing loss of employment and income, COVID-19 impacts the poor in other ways, for example, through reduced availability of housing, education, and healthcare. Furthermore, the compound risk of the pandemic combined with other shocks, such as natural disasters and violent conflicts, also needs to be addressed.

Furthermore, global crises caused by COVID-19 could slow or even reverse many Sustainable Development Goals (SDG) implementation processes (Gulseven et al., 2020; Shulla et al., 2021). It is

important to understand the consequences of the COVID-19 pandemic related to other SDGs, such as the SDG3 (Health & Well-Being), SDG4 (Quality Education), SDG8 (Decent Work & Economic Growth), SDG12 (Consumption & Production), and SDG13 (Climate Action) (Guerriero et al., 2020). As a representative of SDG (SDG1: No poverty), our work provides a quantitative basis for exploring the risk of returning to poverty across different groups and regions, as well as policy-relevant evidence to lower the risk, which could provide guidance to increase the efficiency of the post-pandemic recovery process.

Data availability

The data and materials needed to support the paper's conclusions are included in supplementary information files.

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The authors declare no competing interests.

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