Who Lost Most Wages and Household Income during the COVID-19 Pandemic in Poor Rural China?

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Abstract

China managed to eliminate all extreme poverty in rural areas in 2020. Poor households, however, may risk falling back into poverty due to the COVID-19. This paper examines the impacts of the pandemic on wages and household incomes among different groups in poor areas of rural China. Using a unique dataset from five poverty-stricken counties, we found that the pandemic has had large negative effects on wage income for migrant workers and workers in manufacturing, the private sector, and small enterprises. Compared with households relying on wage income, households relying on small businesses have suffered much more from the pandemic, whereas households depending on farming or transfer payments have been less affected. Although poor and ethnic minority households lost significant amounts of wage income due to the pandemic, they did not lose more household income than nonpoor and nonminority households. We conclude that support from the government has kept vulnerable households from suffering more than other households from the effects of COVID-19. Our findings suggest that the government can play a strong role in alleviating the negative impacts of the COVID-19.

Keywords: COVID-19, household income, poverty, rural China, wage

JEL code: E24, J31, P25

I. Introduction

The COVID-19 has reached almost all countries since its outbreak. According to the Sustainable Development Goals Report 2020 by the United Nations (UN, 2021), by late 2020, the world was not on track to achieve the Sustainable Development Goals (SDGs). The COVID-19 pandemic has made it even harder to reach those goals (Gupta et al., 2021; UN, 2021) by unleashing an unprecedented crisis that has eroded
much of the past progress made in alleviating poverty, as well as progress in improving health (Wang et al., 2021), food and nutrition security (Fan et al., 2020; 2021), and education (Engzell et al., 2021) over the past decade. As a result of the incomes lost during the pandemic (Egger et al., 2021; Gupta et al., 2021), millions of people globally could fall into extreme poverty (Decerf et al., 2021; Laborde et al., 2021).

Although China succeeded in containing the spread of the COVID-19 pandemic within the country, thanks to a combination of bold and relatively early public health and epidemic control measures, China faces extensive socio-economic challenges in its recovery. This is due to both the strict preventive measures implemented in the first quarter of 2020 (Tian, 2021), as well as wider shocks to the economy and their impacts on households (Rozelle et al., 2020) and enterprises (Dai et al., 2021). Despite the limited direct health impact of the COVID-19 pandemic in rural areas, challenges to the alleviation of poverty are rising. China lifted 770 million out of extreme poverty over the last four decades and eliminated extreme poverty by the end of 2020 based on current poverty standards (State Council Information Office of the People’s Republic of China, 2021), but more effort will be needed to prevent the low-income population from sliding back into poverty. Vulnerable groups who were at risk before COVID-19 are now at greater risk than ever. Those who were not considered vulnerable before the COVID-19 pandemic may become vulnerable (Lancet, 2020). The global recession resulting from the pandemic could further harm the poor by squeezing fiscal resources for poverty alleviation and reducing employment opportunities for the poor. In China, the government is especially concerned about poor households in poor rural areas. Determining how to mitigate the impact of the COVID-19 pandemic, not just on economic growth but on the wellbeing of vulnerable groups is therefore of great importance to the Chinese government. It is important to identify which groups experienced the most significant losses in wages and household income during the COVID-19 pandemic in order to help vulnerable groups to mitigate the negative impact of COVID-19.

Studies have shown that the COVID-19 pandemic has different impacts on various groups within the population (ILO, 2020; Bargain and Aminjonov, 2021). The poor, ethnic minorities, and other vulnerable groups were believed to be more negatively affected by the COVID-19 pandemic (Qian and Fan, 2020; Kumar et al., 2021; Nie et al., 2021). Given the importance of strong public policies to alleviate the negative effects of the COVID-19 pandemic (Gentilini et al., 2020; Song and Zhou, 2020), this argument may be challenged when a government plays a strong role in supporting the vulnerable and poor. Moreover, many studies on the impact of COVID-19 on employment or income rely on internet surveys (Du et al., 2020; Qian and Fan, 2020), phone surveys (Luo et al., 2020;
Dai et al., 2021; Wang et al., 2021), simulations (Zhang et al., 2020), or field data with small samples (Zhang and Hu, 2021), due to data unavailability and difficulties in obtaining data. Thus, studies using first-hand, face-to-face survey data with large samples are rare. Although several studies have examined the impact of the COVID-19 pandemic on employment in China (Che et al., 2020; Luo et al., 2020), the economic impacts of the COVID-19 pandemic on poor and vulnerable households living in poor rural areas are not well understood due to a lack of detailed and reliable household survey data.

This paper explores the differences in the impact of the COVID-19 pandemic on wages and household incomes among different groups in poor areas of rural China. It uses a unique dataset from five poverty-stricken counties where local governments implemented policies to help the poor. The survey was conducted in early June 2020 when the COVID-19 pandemic was just brought under control by the central and local governments. It found that the COVID-19 pandemic had large negative effects on wage income for migrant workers and those working in the manufacturing industry, the private sector, and small work units. Compared with households relying on wage income, households relying on small businesses suffer much more from the COVID-19 pandemic while households depending on farming or transfer payments are less affected. Although the poor and ethnic minority households lost a large amount of wage income due to the COVID-19 pandemic, they did not lose more household income than nonpoor and nonminority households. We argue that it is the support from the government that keeps vulnerable households from suffering more than other households from COVID-19. We suggest the government should provide more support for the vulnerable and poor groups during a crisis like the COVID-19.

This paper has two original aspects. First, it uses a unique dataset from five poverty-stricken counties where the governments implement many policies to help the poor. The first-hand data were collected through a household survey in June 2020, just after COVID-19 was contained in China, making fieldwork possible. The survey was conducted in five national and provincial counties designated as poverty stricken, including one in Hubei province, the epicenter of the pandemic. As far as we know, this is the first paper to use first-hand household survey data from a large sample of households in a poor rural area to examine the impact of COVID-19 on employment and income. Moreover, our sample includes rural residents, rural–urban migrants, and residents in small towns. We also managed to include many ethnic minority households in the survey. Besides the household survey, we conducted face-to-face interviews with local stakeholders at the county, township, and village/community levels in all the surveyed counties.

Second, this paper examines the changes not only in wage income but also in total household income and net income. By separating the impacts of the COVID-19
pandemic on personal wage income and household income, the results provide more insights into the impact of COVID-19 on poor rural areas. We use different measures and models of wage change and household income change. The results from different estimations are robust.

The remainder of the paper is organized as follows. Section II presents the data, the analytical framework, and the estimation methods. Section III examines the difference in wage losses among different groups during the COVID-19 pandemic. Section IV explores the difference in household income losses among different groups during the pandemic. Section V provides a conclusion and discusses limitations of the research and possible policy implications.

II. Data and estimation method

1. Data

This study used a unique dataset from a household survey conducted in June 2020, when the COVID-19 pandemic was contained in China and fieldwork was once again possible. As the survey was conducted after the pandemic was contained, it enabled us to obtain more precise information about what occurred during the pandemic. The survey was supported by China International Center for Economic and Technical Exchanges (CICETE), United Nations Development Programme (UNDP), United Nations Children’s Emergency Fund, United Nations Population Fund and United Nations Resident Coordinator Office. The survey was designed to assess the socio-economic impact of COVID-19 on poor rural areas. It was conducted through face-to-face interviews by trained data collectors. The household questionnaire included questions designed to obtain basic household demographic information, and details about wage employment, self-employment and business, agricultural activities, household income, and household expenditure.

Given a limited budget and limited human resources, we did not select the five survey counties by random sampling. Instead, we selected sample counties, villages/communities and households based on a purposive sampling design.

1We thank Dr. Bao Yang, Dr. Yufei He, Dr. Hehua Luo, Dr. Yao Tang and Dr. Rong Shi for helping with survey design and leading local survey teams. We are grateful to Mr. Jun Liu and colleagues from CICETE, data collectors from ten universities, local residents and officers in five surveyed counties for their assistance in the survey and interviews.

2Please see the report published by the UNDP for full information about the survey and questionnaires: https://www.cn.undp.org/content/china/zh/home/library/crisis_prevention_and_recovery/socioeconomic-impact-of-the-covid-19-pandemic-in-five-poverty-co.html.
First, there were four main criteria for selecting sample counties. (i) The selected counties should be national or provincial counties designated as poverty stricken. In other words, our sample only included poor areas. (ii) The selected counties had to be distributed in different geographical areas, so that our sample could capture different characteristics of different regions. (iii) At least some of the selected counties had to have ethnic minorities, to make it possible to assess the different impact on ethnic minorities. (iv) The selected counties had to be those in which the UNDP and China International Center for Economic and Technical Exchanges (CICETE) had poverty alleviation projects, ensuring that we could conduct the survey more easily, and so that sample counties could undertake follow-up projects funded by UNDP and CICETE. Among the selected counties, four were nationally designated poverty-stricken counties, namely: Chengbu County in Hunan Province, Zhouqu County in Gansu Province, Neixiang County in Henan Province, and Yilong County in Sichuan Province. The fifth survey site, Zhangwan District of Shiyan City in Hubei Province, is a provincially designated poverty-stricken county that was added to capture the situation in the province that was the epicenter of the pandemic.

Second, to analyze the impact of the pandemic on rural and urban areas better, three rural villages and three urban communities in each county were selected as survey sites. Together the survey covered 15 rural villages and 15 urban communities. Officially poor villages and nonpoor villages were both included, as were urban areas and peri-urban areas. Among the 15 villages included in the survey, seven were officially designated as poor. In urban areas, ten communities were located in central urban areas, while five were in peri-urban settings. In each village and urban community, at least 34 households were surveyed. The expected total number of households to be surveyed was 1,020, and the actual number of households surveyed was 1,183, consisting of 5,044 individuals.

Third, due to time and funding limitations along with practical challenges, the survey did not adopt probability sampling during the selection of sample households. In practice, the sample households selected in this assessment included different household types, with basic selection principles. (i) Rural households had to include those that mainly rely on farming or remittances from migrant workers as an income source, or are self-employed. In each village, half of the surveyed households (17 households) had to be registered poor households, and another half had to be nonpoor households. (ii) Urban households had to include those who mainly relied on wage incomes, and those individuals who were self-employed. In each urban community, surveyed households should cover at least ten migrants or families who rented their homes and at least ten urban households that were self-employed. (iii) Surveyed households ideally
had to include both children and the elderly, and had to include families from ethnic minorities and those whose members included individuals with disabilities.

2. Analytical framework and estimation method

The analytical framework of this study is presented in Figure 1. The COVID-19 pandemic affected different types of income, namely business income, wage income, transfer income, and farming income. This study focused on wage income. Thus, it first explored the difference in wage changes among different groups during the COVID-19 pandemic. As the pandemic may have affected different sources of income disproportionally, households with different main sources of income could also have been affected disproportionally. Thus, in our final specification, household income change was determined by household characteristics, regional characteristics, and the main source of household income. Based on the analytical framework in Figure 1, we can examine the differences in household income changes among different groups. As wage income was at the individual level and household income was at the household level, we used different estimation models for the changes in wage and household income.

Figure 1. The analytical framework of changes in wage and household income

The Wage_Change was measured in two ways. First, we measured the direction of Wage_Change. To estimate the impact of the COVID-19 pandemic on wage income, we asked “During January–May 2020, how did wage income change?” in the questionnaire. There were three options for an answer: increased, unchanged, and decreased. Based
on these three options, we created a dummy variable to indicate whether the wage decreased. Before asking this question, we also asked about working months and wages during 2019. Although this question is subjective, it relies on a comparison between wages in 2019 and January–May 2020. Second, we measured the magnitude of wage loss. In the questionnaire, we asked “how much did wage income decrease during January–May 2020?” for those reporting wage loss. With these two measures of Wage Change, we can explore the direction and the magnitude of wage change. Given the way we asked the questions, these two measures can be treated as the impact of the COVID-19 pandemic on wage income. The basic model of Wage Change is as follows:

\[ \text{Wage Change} = \alpha_0 + \alpha_1 \text{Household Characteristics} + \alpha_2 \text{Personal Characteristics} + \alpha_3 \text{Job Characteristics} + \alpha_4 \text{Regional Characteristics} + \mu, \quad (1) \]

In Equation (1), Household Characteristics indicates whether the person is from a poor household, an ethnic minority household, or a household in an urban area. Personal Characteristics include age, gender, and education level. Job Characteristics include job location, sector, ownership, and size of the work unit. Regional Characteristics are county dummies that control regional fixed effects, \( \alpha_0 \) is the constant, and \( \mu \) represents the random error term. As the direction of Wage Change is a dummy variable, we can use logit or probit models to explore the determinants of the direction of Wage Change. For robustness checks, we use both logit and probit models together with linear probability models (LPM, a special case of OLS) in practice. The magnitude of wage loss, it equals zero for those without wage loss. So, we use Tobit models to investigate the determinants of the magnitude of wage loss.

Household Income Change was measured in two ways. The first is a dummy indicating whether the total household income was reduced in 2020. To estimate the impact of COVID-19 on household income, we asked “in 2020, how did total household income change?” There are three options for the answer: increased, unchanged, and decreased. Based on these three options, we could create a dummy variable to indicate whether the total household income decreased. The second measure is a dummy of whether the household net income was reduced in 2020. In the questionnaire, we also asked “compared with 2019, how did household net income change in 2020?” There are three options: increased, unchanged, and decreased. Based on these three options, we could create a dummy variable to indicate whether the household net income decreased. Before we asked these two questions, we asked for details about the status of whether the household was involved in wage employment, business, or farming activities. We also asked for details about the impact of the COVID-19 pandemic on wage employment, business, and farming activities. Our measures therefore reflect
the direction of household income change accurately. The basic model of Household_Income_Change is as follows:

\[
\text{Household\_Income\_Change} = \beta_0 + \beta_1 \text{Household\_Characteristics} + \beta_2 \text{Main\_Source\_of\_Household\_Income} + \beta_3 \text{Regional\_Characteristics} + e
\]  

(2)

In Equation (2), Household\_Characteristics are variables indicating whether the household is a poor household, an ethnic minority household, or living in an urban area. The Main\_Source\_of\_Household\_Income is a categorical variable, including wage employment, self-employment (business), farming, and transfer payments. Regional\_Characteristics are county dummies that control regional fixed effects, \( \beta_0 \) is the constant, and \( e \) represents the random error term. As the two variables measuring the direction of Household\_Income\_Change are dummy variables, we use LPM, logit and probit models, to explore the determinants of the direction of total household income reduction and household net income reduction.

One concern about the estimation method is that no variable directly linked to the COVID-19 pandemic was included. The reason is twofold. First, the data only covered five poor counties. Four of them did not have any cases of COVID-19. These counties also implemented a strict lockdown policy during the COVID-19 pandemic. In this model, county dummies can capture part of the variation in policies related to the COVID-19 pandemic. Other good variables to measure the variation of policies related to the COVID-19 pandemic could not be found. Second, we wanted to explore the difference in the impacts of the COVID-19 pandemic among different groups rather than the determinants of the impacts of the COVID-19 pandemic.

Another concern related to our estimation method is the causality between the COVID-19 pandemic and Wage\_Change or Household\_Income\_Change. We admit that it is difficult to quantify the income loss caused by the COVID-19 pandemic. In the questionnaire, we try to produce an accurate estimate of income loss caused by COVID-19 in three ways. (i) For wage loss, we asked first for information about working time, wages, and other job-related characteristics as they were in 2019 and during the COVID-19 pandemic (January–May 2020). Based on the above questions, we then asked about wage changes during the COVID-19 pandemic. The wage change in the questionnaire is based on the assessment of the difference in wages between 2019 and the period of the COVID-19 pandemic. Most wage loss is linked directly to working time loss caused by the pandemic, so we believe the wage loss defined in the questionnaire is most likely caused by the pandemic, rather than other factors. (ii) Regarding business and farming activities, we asked for related information for both 2019 and 2020. We also asked about the main source of household income in both 2019 and 2020. Based on the information about
different types of income in both 2019 and 2020, we could obtain an accurate estimate of Household_Income_Change. In our sample, business income loss was most likely to be caused by the lockdown and the decrease in the number of customers. Both the lockdown and the reduction in customers are directly linked to COVID-19. Farming income is not affected much by the COVID-19 pandemic. We therefore believe that the household income loss defined in the paper is most likely to have been caused by COVID-19.

(iii) As we conducted the survey face-to-face in June 2020, when COVID-19 had just been contained, the information from questionnaires reflects a comprehensive picture of the impacts of COVID-19 on wage and household income. We also conducted face-to-face interviews with local stakeholders at the county, township, and village/community level in all of the surveyed counties. The information from these interviews confirms our results from questionnaires, indicating that our results are credible.

3. Sample characteristics
Table 1 shows that households in rural villages account for 49 percent of the total, with urban communities accounting for 51 percent. The urban and rural classification here was determined by the place of residence, not by hukou status. Rural hukou status was held by 18.6 percent of households who reside in urban communities. Thus, the sample covers not only local rural and local urban residents but also rural–urban migrants, which makes this analysis more comprehensive in terms of sample coverage.

Table 1. Sample size, household, and individuals’ characteristics

|                          | Households |        | Individuals |        |
|--------------------------|------------|--------|-------------|--------|
|                          | Observations | %     | Observations | %     |
| Total                    | 1,183      | 100   | 5,044       | 100   |
| Rural villages           | 580        | 49.0  | 2,516       | 49.9  |
| Urban communities        | 603        | 51.0  | 2,528       | 50.1  |
| Agricultural hukou       | 801        | 67.8  | 3,551       | 70.4  |
| Nonagricultural hukou    | 170        | 14.4  | 645         | 12.8  |
| Resident hukou           | 211        | 17.8  | 847         | 16.8  |
| Nonpoor households       | 862        | 72.9  | 3,728       | 73.9  |
| Poor households          | 321        | 27.1  | 1,316       | 26.1  |
| Han households           | 942        | 79.6  | 4,103       | 81.4  |
| Ethnic minority households| 241        | 20.4  | 939         | 18.6  |
| Yilong, Sichuan          | 244        | 20.6  | 930         | 18.4  |
| Zhouqu, Gansu            | 242        | 20.5  | 1,133       | 22.5  |
| Chengbu, Hunan           | 237        | 20.0  | 1,135       | 22.5  |
| Neixiang, Henan          | 236        | 20.0  | 1,030       | 20.4  |
| Zhangwan district, Hubei | 224        | 18.9  | 816         | 16.2  |

Source: Authors’ survey.
Table 1 also shows that there are 321 poor households in the survey, accounting for 27.1 percent of the total. A household was considered poor if it was registered as a poor household, received the minimum subsistence allowance (dibao), was covered by the “five guarantees” system (wubao), or was registered as a working poor household. The survey covered 241 ethnic minority households, representing for 20.4 percent of the total. A household was considered to be an ethnic minority household if any member was of a non-Han ethnicity.

Table 2 shows that the proportion of surveyed females was slightly lower than that of males, accounting for 48.3 percent of the total. The average sample age was 37.3 years old, with the average age in rural villages almost three years higher than that in urban communities. In terms of age groups, 60.4 percent are aged 16–59, 7.6 percent are infants and toddlers aged 0–5, 14.4 percent are aged 6–15, and 17.6 percent are aged 60 and older.

### Table 2. Distribution of individuals’ gender and age

|                   | Rural villages | Urban communities | Total |
|-------------------|----------------|-------------------|-------|
| Female (%)        | 47.7           | 48.9              | 48.3  |
| Male (%)          | 52.3           | 51.1              | 51.7  |
| Average age (years) | 38.8          | 35.9              | 37.3  |

| Age group (%)    | Rural villages | Urban communities | Total |
|------------------|----------------|-------------------|-------|
| 0–5              | 6.6            | 8.6               | 7.6   |
| 6–15             | 13.6           | 15.1              | 14.4  |
| 16–59            | 59.9           | 60.9              | 60.4  |
| 60 and older     | 19.9           | 15.4              | 17.6  |

Source: Authors’ survey.

## III. Wage losses among different groups during the COVID-19 pandemic

### 1. Wage change for different groups

For those 941 workers who worked from January–May 2020, 47.8 percent reported reduced wage income due to COVID-19, while 48.9 percent of respondents perceived no change, and 3.3 percent indicated an increase. For convenience, we merge those with increased wages and those with unchanged wages into a single group. Together, 52.2 percent of workers had the same or even higher wages during the COVID-19 pandemic.
Table 3 shows that 62.3 percent of wage earners from poor households reported wage loss during January–May 2020. The number of wage earners from nonpoor households is only 43 percent. The difference between wage earners from poor and nonpoor households is statistically significant at the 0.01 level. Among wage earners from ethnic minority households, 54.6 percent reported wage loss. Among wage earners from Han households, the number is 45.8 percent. The difference between wage earners from Han and ethnic minority households is also statistically significant at the 0.05 level. In short, wage earners from poor households and ethnic minority households were more likely to have lost wages during the COVID-19 pandemic.

### Table 3. Wage change for different groups during January–May 2020

| Household (%) | Unchanged or increased | Decreased | p value of χ² test |
|---------------|------------------------|-----------|-------------------|
| Nonpoor household | 57.0                   | 43.0      | 0.000             |
| Poor household   | 37.7                   | 62.3      |                   |
| Ethnicity (%)    |                        |           | 0.022             |
| Han              | 54.2                   | 45.8      |                   |
| Ethnic minority  | 45.4                   | 54.6      |                   |
| Total            | 491                    | 450       |                   |
| %                | 47.8                   | 52.2      |                   |

Source: Authors’ survey.

2. Wage losses during January–May 2020

To explore determinants of wage losses during January–May 2020, we control Personal_Characteristics, Job_Characteristics, and Regional_Characteristics in the models. Personal_Characteristics include age, gender, and education. Job_Characteristics include job locations, industries, ownership, and sizes of work units. Regional_Characteristics are county dummies and whether the household is located in an urban area. We use LPM, logit, and probit estimations and present marginal effects for each model in Table 4. The magnitude, direction, and significance level of the marginal effects are very close among the LPM, logit, and probit estimations.

First, there is no significant difference between workers in poor households and workers from nonpoor households after controlling for personal characteristics, job-related characteristics, and regional characteristics in the models. Workers from ethnic minority households, however, are still more likely to lose wages than workers from Han households.
Table 4. Models of wage reduction during January–May 2020 (marginal effects)

|                        | (1) LPM | (2) Logit | (3) Probit |
|------------------------|---------|-----------|------------|
| Poor household         | 0.045   | 0.039     | 0.039      |
| (0.053)                | (0.051) | (0.051)   |
| Ethnic minority households | 0.134** | 0.129**   | 0.128**    |
| (0.061)                | (0.061) | (0.059)   |
| Urban area             | –0.021  | –0.021    | –0.021     |
| (0.044)                | (0.042) | (0.043)   |
| Age                    | –0.003* | –0.003*   | –0.003*    |
| (0.002)                | (0.002) | (0.002)   |
| Male                   | 0.051*  | 0.045     | 0.044      |
| (0.030)                | (0.029) | (0.029)   |
| Education level: base = middle school |
| Primary school or below| 0.055   | 0.057     | 0.059      |
| (0.050)                | (0.048) | (0.049)   |
| High school            | 0.019   | 0.024     | 0.018      |
| (0.039)                | (0.038) | (0.037)   |
| College or above       | 0.003   | 0.001     | –0.003     |
| (0.054)                | (0.053) | (0.053)   |
| Job location: base = villages, |
| Towns, and counties    | 0.077   | 0.067     | 0.064      |
| (0.064)                | (0.060) | (0.062)   |
| Other counties within province | 0.192** | 0.185**   | 0.181**    |
| (0.078)                | (0.073) | (0.073)   |
| Other provinces        | 0.112   | 0.100     | 0.096      |
| (0.070)                | (0.067) | (0.068)   |
| Industry: base = manufacturing |
| Construction           | –0.109  | –0.113    | –0.107     |
| (0.076)                | (0.076) | (0.074)   |
| Wholesale and retail, accommodation and catering | –0.242*** | –0.241*** | –0.235*** |
| (0.068)                | (0.067) | (0.065)   |
| Water, electricity, gas, transportation, storage, post | –0.145* | –0.145* | –0.140* |
| (0.073)                | (0.075) | (0.072)   |
| Residential services, repairs and other services | –0.230*** | –0.229*** | –0.225*** |
| (0.074)                | (0.073) | (0.071)   |
| Science, education, health, culture, sport, government, and social organization | –0.310*** | –0.331*** | –0.319*** |
| (0.083)                | (0.086) | (0.086)   |
| Other                  | –0.195*** | –0.194*** | –0.184*** |
| (0.057)                | (0.056) | (0.055)   |
| Public sector          | –0.238*** | –0.238*** | –0.240*** |
| (0.056)                | (0.058) | (0.058)   |
| Size of work unit: base = 1–10 employees |
| 10–100 employees       | –0.072* | –0.068*   | –0.066*    |
| (0.037)                | (0.035) | (0.035)   |
| More than 100 employees | –0.162** | –0.162** | –0.158** |
| (0.071)                | (0.070) | (0.069)   |
| County: base = Zhangwan, Hubei |
| Yilong, Sichuan        | –0.133* | –0.129*   | –0.130*    |
| (0.077)                | (0.071) | (0.071)   |
| Neixiang, Henan        | –0.128* | –0.124*   | –0.125*    |
| (0.070)                | (0.069) | (0.069)   |
| Chengbu, Hunan         | –0.205*** | –0.196*** | –0.192*** |
| (0.062)                | (0.059) | (0.060)   |
| Zhouqu, Gansu          | –0.322*** | –0.312*** | –0.312*** |
| (0.052)                | (0.049) | (0.049)   |
| Observations           | 941     | 941       | 941        |
| $R^2$                  | 0.234   | 0.189     | 0.189      |

Source: Authors’ survey.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The outcome variable equals 1 if the wage decreased during January–May 2020; the outcome variable equals 0 otherwise. Cluster standard errors at the village or community level are in parentheses.
Second, compared to those working in villages, those working in other counties within the province were more likely to lose wages during the COVID-19 pandemic. There is no significant difference between those working in the village and those working in local towns and counties or other provinces. One possible reason is that most workers were working within their home provinces. During the COVID-19 pandemic, intercounty transportation was strictly controlled. Those working in other counties within the provinces were more likely to be out of work during the COVID-19 pandemic.

Third, in terms of impacts on particular industries, Table 4 shows no significant differences in the expected changes in wages between workers in manufacturing and workers in construction. Compared to workers in manufacturing, however, workers in all other industries except construction were less likely to lose wages during the COVID-19 pandemic. One reason the manufacturing industry was affected more than most other industries is inadequate demand – a problem that especially affects export firms (Dai et al., 2021).

Fourth, workers in the public sector – which includes not only local governments and the civil service, but also state-owned and collective enterprises – are significantly less likely to lose wages than those in the private sector. Public sector workers are less affected by the COVID-19 pandemic than workers in the private sector. One explanation is that public sector workers are more protected by contracts, social insurance, and working-time arrangements. The public sector is also more financially stable than the private sector.

Fifth, compared with workers in small or microwork units, workers in middle or large work units are less affected by the COVID-19 pandemic. The larger the work unit, the less the wage loss. One possible explanation is that big work units were more likely to be able to pay wages for workers during the pandemic; thus, their employees are better off compared with other groups in terms of wage income. Workers in big work units are also more likely to be protected by contracts, social insurance, and working-time arrangements.

Sixth, among the different regions, people in Zhouqu county have the lowest probability of wage reduction. This could be due to the relatively high local employment rate of approximately 51 percent, as wages of local employees are relatively less affected by the pandemic. People in Zhangwan county in Hubei province have the highest probability of wage reduction, because Zhangwan had the most cases of COVID-19 and was thus the most affected by the COVID-19 pandemic among the five counties surveyed. As Zhanwan is located in Hubei province, there were also more preventive measures within Zhanwan than in other counties.
3. Magnitude of wage reduction during January–May 2020

In the questionnaire, we asked “how much did wages decrease during January–May 2020?” for those reporting wage loss. The average wage income loss among those who reported a decrease was RMB9,105, while the median was RMB6,000. As a benchmark, Chinese residents’ average annual disposable income per capita in 2019 was RMB30,733, while the median was RMB26,523. It should be noted that the actual amount of \( \text{Wage Change} \) depends on pre-COVID levels of income. Thus, certain groups (e.g. women) faced smaller wage losses, possibly because their wages were lower in the first place, making their losses comparably smaller.

We used the Tobit model to explore factors affecting the magnitude of wage loss during January–May 2020. The outcome variable was the log of wage reduction. The values of those with unchanged or increased wages were set to 0. Table 5 shows the same pattern as the results in Table 4. In absolute terms, workers from poor households experienced the same wage reduction as those from nonpoor households. Wages decreased less for workers from Han households than for workers from ethnic minority households.

|                     | Coefficient | Standard Error |
|---------------------|-------------|----------------|
| Poor household      | 0.561       | 0.839          |
| Ethnic minority households | 2.403** | 1.103          |
| Urban area          | –0.222      | 0.746          |
| Age                 | –0.065*     | 0.034          |
| Male                | 0.913       | 0.564          |

Education: base = middle school
- Primary school or below: 0.967, 0.846
- High school: 0.327, 0.638
- College or above: –0.154, 1.023

Job location: base = villages
- Towns and counties: 1.148, 1.227
- Other counties within province: 3.374**, 1.364
- Other provinces: 2.024, 1.283

Industry: base = manufacturing
- Construction: –1.576, 1.246
- Wholesale and retail, accommodation and catering: –3.869***, 1.227
- Water, electricity, gas, transportation, storage, post: –2.270*, 1.168

(Continued on the next page)
(Table 5 continued)

| Industry: base = manufacturing | Coefficient | Standard Error |
|--------------------------------|-------------|----------------|
| Residential services, repairs and other services | -3.817*** | 1.249 |
| Science, education, health, culture, sport, governmental and social organization | -5.802*** | 1.607 |
| Other | -3.097*** | 0.945 |
| Public sector | -4.857*** | 1.081 |

| Size of work unit: base = 1–10 employees | |
|--------------------------------|-------------|----------------|
| 10–100 employees | 1.178* | 0.640 |
| More than 100 employees | -2.891** | 1.387 |

| County: base = Zhangwan, Hubei | |
|--------------------------------|-------------|----------------|
| Yilong, Sichuan | -2.653** | 1.238 |
| Neixiang, Henan | -2.763** | 1.188 |
| Chengbu, Hunan | -4.009*** | 1.002 |
| Zhouqu, Gansu | -6.566*** | 0.918 |

| Observations | 941 |
| Pseudo $R^2$ | 0.071 |
| Log pseudolikelihood | -181 |

Source: Authors’ survey.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The outcome variable is the amount of wage loss (in RMB) during January–May 2020. Cluster standard errors at the village or community level are in the second column.

Table 5 also shows that workers in manufacturing and construction had the same magnitude of wage reduction, whereas workers in all other industries had lesser wage reductions. Wage losses were also smaller for workers in the public sector than for those in the private sector. Workers in large work units faced less wage reduction than workers in small work units.

### IV. Household income losses among different groups during the COVID-19 pandemic

#### 1. Total household income losses in 2020

Of 1,110 households, 82 households reported an increase in household net income, accounting for 7.4 percent of the total households. For convenience, we merge the group of households with increased net income into the group of households with unchanged net income, as shown in Table 6.
Table 6. Change in household income for different groups in 2020

| Change in total household income | Household (%) | Unchanged or increased | Decreased | \( p \) value for the \( \chi^2 \) test |
|---------------------------------|--------------|------------------------|-----------|-----------------------------------|
| Nonpoor household               | 32.0         | 68.0                   |           | \( 0.095 \)                        |
| Poor household                  | 37.3         | 62.7                   |           |                                   |
| Ethnicity (%)                   |              |                        |           | \( 0.026 \)                        |
| Han                             | 35.0         | 65.0                   |           |                                   |
| Ethnic minority                 | 27.3         | 72.7                   |           |                                   |
| Total                           | 371          | 739                    |           |                                   |
| %                               | 33.4         | 66.6                   |           |                                   |

| Change in household net income  | Household (%) | Unchanged or increased | Decreased | \( p \) value for the \( \chi^2 \) test |
|---------------------------------|--------------|------------------------|-----------|-----------------------------------|
| Nonpoor household               | 33.1         | 66.9                   |           | \( 0.13 \)                        |
| Poor household                  | 37.9         | 62.1                   |           |                                   |
| Ethnicity (%)                   |              |                        |           | \( 0.39 \)                        |
| Han                             | 35.0         | 65.0                   |           |                                   |
| Ethnic minority                 | 32.0         | 68.0                   |           |                                   |
| Total                           | 382          | 728                    |           |                                   |
| %                               | 34.4         | 65.6                   |           |                                   |

Source: Authors’ survey.

Table 6 shows that nearly two-thirds of all households expected their total income in 2020 to decrease, whereas one-third thought that their incomes would remain unchanged or increase. Table 6 also shows that 62.7 percent of poor households reported a decreased net income, whereas the number for nonpoor households was 68 percent. The difference between poor and nonpoor households is statistically significant at the 0.1 level. As for ethnic minority households, 72.7 percent of them reported a decreased income, while for Han households the figure is 65 percent. The difference between ethnic minority and Han households is statistically significant at the 0.05 level.

Although wage workers from poor households and ethnic minority households faced greater wage loss than other households during the COVID-19 pandemic, their total household income was not affected as much as their wage income. Table 7 shows that there was no significant difference in total household income change in 2020 between poor and nonpoor households. This suggests that, compared with nonpoor households, poor households were not more affected by the COVID-19 pandemic in terms of total household income. The probability of a reduction in total household income for ethnic minority households, however, was lower than for Han households. This indicates that, compared with Han households, ethnic minority households were less affected by the COVID-19 pandemic in terms of total household income. From the interviews with
local government officials, we learned that it was support from the government that kept poor households from suffering more than other households during the pandemic. All five survey counties were poverty-stricken counties. For these counties, the central government had a strict policy of eliminating all extreme poverty by the end of 2020. The local government provided poor households with assistance in cash, employment, education, and medical care. These forms of assistance could help poor households to cope with the pandemic. We admit that these forms of government support are not linked directly to the pandemic. The motivation to support poor and vulnerable households most likely stems from political pressure to eliminate poverty rather than pressure to cope with the pandemic. Nevertheless, the support has helped the poor and vulnerable households in terms of income, employment, and medical care during the pandemic.

Table 7. Models of total household income reduction in 2020

|                          | (1)          | (2)          | (3)          |
|--------------------------|--------------|--------------|--------------|
|                          | LPM          | Logit        | Probit       |
| Poor household           | 0.026        | 0.025        | 0.025        |
|                          | (0.041)      | (0.039)      | (0.039)      |
| Ethnic minority          | –0.074*      | –0.085**     | –0.078*      |
|                          | (0.041)      | (0.043)      | (0.043)      |
| Urban area               | 0.029        | 0.032        | 0.032        |
|                          | (0.035)      | (0.035)      | (0.035)      |
| Main source of income:   |              |              |              |
| base = wage employment   |              |              |              |
| Self-employed            | 0.182***     | 0.186***     | 0.185***     |
|                          | (0.029)      | (0.029)      | (0.028)      |
| Farming                  | –0.224**     | –0.211**     | –0.213**     |
|                          | (0.096)      | (0.098)      | (0.098)      |
| Transfer payment         | –0.560***    | –0.559***    | –0.559***    |
|                          | (0.062)      | (0.059)      | (0.059)      |
| Location: base =         |              |              |              |
| base = Zhangwan, Hubei   |              |              |              |
| Yilong, Sichuan          | 0.027        | 0.029        | 0.029        |
|                          | (0.072)      | (0.074)      | (0.073)      |
| Neixiang, Henan          | 0.0001       | 0.0003       | 0.0001       |
|                          | (0.073)      | (0.072)      | (0.072)      |
| Chengbu, Hunan           | 0.167**      | 0.172**      | 0.167**      |
|                          | (0.075)      | (0.073)      | (0.073)      |
| Zhouqu, Gansu            | 0.029        | 0.034        | 0.032        |
|                          | (0.061)      | (0.062)      | (0.062)      |
| Observations             | 1,110        | 1,110        | 1,110        |
| $R^2$                    | 0.199        | 0.161        | 0.161f       |

Source: Authors’ survey.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. LPM represents the linear probability model. The outcome variable equals 1 if total household income is expected to decrease in 2020; the outcome variable equals 0 otherwise. Cluster standard errors at the village or community level are in parentheses.
The impact of the COVID-19 pandemic on household incomes is closely related to the main source of household income. The probability of households expecting decreased total income is highest among self-employed households, followed by households with incomes mainly from wage employment. The ratio is relatively low among households relying on agricultural and transfer incomes. For example, compared with households with incomes mainly from wage employment, the probability of expecting decreased total income is 0.18 higher for self-employed households; by contrast, the probability for farming-oriented households is 0.21 lower. In short, the COVID-19 pandemic has strong impacts on non-farm business and wage employment, while its impacts on farming are limited. A similar pattern is also found in Nigeria (Amare et al., 2021). The large effect of the COVID-19 pandemic on nonfarm businesses is due to the strict lockdown policy for business activities. Moreover, since the Spring Festival is the most important period of the year for business, the lockdown measures hit businesses severely. In contrast, there was relatively little agricultural activity during the lockdown. Accordingly, in our data, the effect of the COVID-19 pandemic on farming is limited.

2. Household net income losses in 2020

To compare changes in household net income, we also merge the groups with unchanged income and increased income into a single group. Table 6 shows no significant difference in loss of household net income between poor and nonpoor households or between Han and ethnic minority households.

The results from Table 8 are much like the results in Table 7. First, the impact of the COVID-19 pandemic on household net income was nearly the same between poor and nonpoor households. Compared with Han households, ethnic minority households were less affected by the pandemic in terms of household net income. As for sources of household income, self-employed households were the most affected, while households with incomes mainly from transfer payments are the least affected. Compared with households with incomes mainly from wage employment, farming-oriented households were less affected in terms of household net income.

Table 8. Models of household net income reduction in 2020

|                | (1) LPM | (2) Logit | (3) Probit |
|----------------|---------|-----------|------------|
| Poor household | 0.044   | 0.042     | 0.044      |
|                | (0.037) | (0.036)   | (0.035)    |
| Ethnic minority| −0.081  | −0.085*   | −0.081*    |
|                | (0.048) | (0.050)   | (0.047)    |
| Urban area     | 0.051   | 0.052     | 0.054      |
|                | (0.037) | (0.037)   | (0.036)    |
(Table 8 continued)

|                          | (1)   | (2)   | (3)   |
|--------------------------|-------|-------|-------|
|                          | LPM   | Logit | Probit|
| Main source of income: base = wage employment |       |       |       |
| Self-employed            | 0.170*** | 0.172*** | 0.173*** |
|                          | (0.036) | (0.037) | (0.036) |
| Farming                  | −0.236*** | −0.226*** | −0.226*** |
|                          | (0.080) | (0.082) | (0.082) |
| Transfer payment         | −0.579*** | −0.574*** | −0.574*** |
|                          | (0.059) | (0.053) | (0.054) |
| Location: base = Zhangwan, Hubei |       |       |       |
| Yilong, Sichuan          | 0.010 | 0.012 | 0.013 |
|                          | (0.067) | (0.070) | (0.069) |
| Neixiang, Henan          | −0.020 | −0.020 | −0.020 |
|                          | (0.069) | (0.069) | (0.068) |
| Chengbu, Hunan           | 0.094 | 0.096 | 0.094 |
|                          | (0.077) | (0.075) | (0.075) |
| Zhouqu, Gansu            | −0.016 | −0.011 | −0.011 |
|                          | (0.057) | (0.058) | (0.058) |
| Observations             | 1,110 | 1,110 | 1,110 |
| $R^2$                    | 0.191 | 0.152 | 0.152 |

Source: Authors’ survey.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. LPM represents the linear probability model. The outcome variable equals 1 if household net income is expected to decrease in 2020; the outcome variable equals 0 otherwise; cluster standard errors at the village or community level in parentheses.

V. Conclusion

Poor households are especially vulnerable during times of crisis, such as during the COVID-19 pandemic. By the end of 2020, China had lifted all of its poor rural citizens out of extreme poverty. Shocks like the COVID-19 pandemic, however, may put more households at risk of falling back into poverty. In this paper, we examined differences in the impacts of the COVID-19 pandemic on wage and household income among different groups in poor rural China.

Using a first-hand dataset collected in June 2020 from five poverty-stricken counties, we found that COVID-19 had a more significant negative impact on certain groups, characterized by a higher ratio of people reporting wage and household income losses. In terms of wage income, we showed that migrant workers and workers in the private sector, small work units, and manufacturing were affected more than other workers. These groups were already disadvantaged before the COVID-19 pandemic, and are more vulnerable to wage income loss now. As for household income, we found
that households relying on farming and transfer payments were less affected, whereas households relying on wage income and business were more affected.

Although the poor and ethnic minority households lost large amounts of wage income due to the COVID-19 pandemic, they did not lose more household income than other types of households. This is probably because poor and ethnic minority households are usually covered by government assistance and rely on transfer payments, making them less vulnerable to income losses during the pandemic. It was the support from the government that kept vulnerable households from suffering more than other households during the COVID-19 pandemic.

Our findings imply that the government can play a strong role in alleviating the negative impacts of the COVID-19 pandemic. We suggest that the government continue to support vulnerable and poor groups, including with cash transfers and assistance with employment, medical care, and children’s education.

We should be cautious in interpreting our results. We rely on the survey data from five poverty-stricken counties in poor rural areas. The survey data is not statistically representative and therefore cannot be generalized to the overall population. Nevertheless, as a portrait of a specific group of households and the wide-ranging economic effects the COVID-19 pandemic has had on these households and individuals in poor rural areas, analysis of this data provides useful information on the nature and magnitude of the economic impact of the COVID-19 pandemic.

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