



Multidimensional poverty vulnerability in rural China

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Abstract

Combating poverty is one of the most important issues worldwide. As the largest developing country, China has successfully begun poverty alleviation and made major achievements. However, research on multidimensional poverty and regional differences remains insufficient. Taking China Family Panel Studies data from 2016 to 2018, this study measures the vulnerability to multidimensional poverty indexes (VMPI) of families in rural China and its regional differences. The empirical results are as follows. (1) The headcount ratio of vulnerability to multidimensional poverty (VMP), the average vulnerability intensity, and the adjusted multidimensional vulnerability gap and quadratic gap have declined significantly. However, the rate of decline varies across regions. (2) The regional VMPI and the contribution rate of each region to the country's VMPI are both ranked by western, central, eastern, and northeastern from high to low. Results indicate that the number of VMP families is much more than the income-poor people. (3) Many VMP families in rural China come from non-poor or out-of-poor families, and the majority of income-poor families are trapped in VMP status with the risk of staying poor in the future.

Keywords Vulnerability to multidimensional poverty indexes · ROC curve · Regional differences · Poverty alleviation

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1 Introduction

Combating poverty is one of the most important issues for countries worldwide, especially developing countries. According to the Food and Agriculture Organization of the United Nations, 736 million people (10% of the world's population) continue to suffer extreme poverty in 2019 on less than USD 1.90 a day. China, which is the largest developing country in the world, has been committed to poverty reduction for more than 40 years and has made major achievements. All extreme poverty had been eliminated in China by the end of 2020, 10 years ahead of the goal of the UN 2030 Agenda for Sustainable Development. These efforts accelerated the global anti-poverty process. The targeted poverty alleviation, developmental poverty alleviation, and some Chinese-style approaches have important reference significance for the global anti-poverty cause.

However, this milestone is not the end of the poverty alleviation project in China, but the beginning of a new anti-poverty journey that focuses on secondary poverty and relative poverty (Zhang et al. 2018). The key point of the subsequent poverty alleviation in rural China is to prevent people from returning or falling into poverty (Chang et al. 2021; Huang et al. 2020; Yang et al. 2020). The requirement for this task is not only to recognize the current state of poverty of rural families but also to identify the risk of poverty that may pull them into poverty in the future. Therefore, recognizing the characteristics and measuring the probabilities of the target groups (i.e., who may stay in poverty or fall into poverty in the future) is the role of governors during decision-making about poverty alleviation in the new process. The group who is vulnerable to poverty has two distinct characteristics. The first is that the expected welfare is below the poverty line. The second is that they face a downside risk of falling into poverty due to the reduction of welfare and a deviation from standard levels. Recognizing and measuring the vulnerability to poverty of families from a multidimensional perspective has elicited strong research interest. The measure of vulnerability to multidimensional poverty can predictively recognize the risk and evaluate the probability of multidimensional poverty in households. On these bases, governors can provide precise anti-poverty assistance and design reasonable forward-looking policies to consolidate and enhance the effectiveness of poverty alleviation in China.

Four traditional methods are used to measure vulnerability to multidimensional poverty (VMP) (Gallardo 2019; Robles Aguilar and Sumner 2020). The first method was proposed by Calvo (2008), in which VMP is calculated based on the utility function of constant elasticity of substitution by summing up the threat level score of poverty in multiple welfare dimensions. However, this method can only be applied to panel data. Abraham and Kumar (2008) proposed the second method to measure VMP, in which VMP is obtained as the arithmetic mean of vulnerability scores in each dimension. However, this method can only apply to continuous or ordinal variables. Third, on the basis of the multinational poverty index (MPI), Feeny and McDonald (2016) used expected poverty to define vulnerability to unidimensional poverty and then extended it to multidimensions to measure VMP. However, this method ignored the heterogeneity of risk of welfare indicators in different dimensions. Fourth, researchers at Oxford University also developed a method to measure VMP (OPHI 2018). However, it ignores those people who are already poor but still at risk of continuing poverty in the future.

To avert the shortcomings of these methods, Gallardo (2019) proposed a new method called VMPI (vulnerability to multidimensional poverty indexes). It extends the unidimensional measurement of vulnerability to poverty in Gallardo (2013) into the multidimensional framework proposed by Alkire and Foster (2011). The new VMPI approach was constructed on the mean-risk behavior method, and the data-driven receiver operating characteristic (ROC) curve is adopted to derive the threshold of vulnerability to poverty for each dimension to avoid the subjectivity of threshold selection. The advantages of VMPI are as follows. (1) The method is applicable to cross-sectional data. (2) The variables can include not only the continuous and ordinal variables but also the binary variable. (3) The risk diversity among different indicators can be captured because VMP is calculated through a multiple perspective step by step rather than a simple summation. (4) Those people who are multidimensionally poor and at risk of continuing poverty are included in the measurement of VMPI. VMPI is more reasonable than the traditional methods, which only consider non-poor people in the VMP framework.

In addition to the method selection, another problem that needs to be solved before calculating the multidimensional poverty index is to determine the weight of each indicator. Existing research has mainly used the equal weight method to determine the weight (Hou 2017; Zhang and Yao 2020); however, this approach ignores the difference in the influence of each indicator on individual welfare to a certain extent. The choice of different indicator weights may also lead to different measurement results. Cherchye et al. (2008) proposed a robust method for assessing human development country rankings/classifications implemented through linear programming techniques. Permanyer (2011) presented a rigorous method to assess the extent to which the weight-based rankings are robust to the choice of alternative weights. The author suggested that the method can be used to assess the reliability of multi-attribute rankings. Foster et al. (2013) evaluated the robustness of rankings obtained from composite indices that combine information from two or more components via a weighted sum. They demonstrated links among the prevalence of robust comparisons, Kendall's tau rank correlation coefficient, and statistical association across components. Pinar et al. (2013) considered a weighting scheme that yields a best-case scenario for measured human development such as the official equally-weighted Human Development Index (HDI). They found that the best-case scenario hybrid index leads to a marked improvement in measured development over time when compared with the official equally-weighted HDI. Alkire and Fang (2019) used first order stochastic dominance method and regression analysis to test the stability of multidimensional poverty measures. They found that the multidimensional poverty measures are somewhat sensitive to the large change in weight. Pinar et al. (2020) derived a feasible range of multidimensional poverty that considers all admissible weights within the chosen lower and upper bounds of weights. And they found that different weights allocated to poverty dimensions can produce very different multidimensional poverty outcomes for a given population even in cases with small weight perturbations. Therefore, how to select and determine the optimal weights and improve the validity of the measurement method for multidimensional poverty vulnerability is also worth to study further. Implementing policies that consider the reduction of income poverty and multidimensional deprivation is difficult for developing countries due to limited resources. The relationship

between income poverty and multidimensional deprivation in developing countries must be empirically examined (Xie 2020). China has the largest poverty reduction population in the world, and it is the first country to complete the UN 2030 Sustainable Development Poverty Reduction Goal. China's poverty reduction programs and experience in poverty reduction are of great value to other developing countries. In recent years, some scholars have focused on the relationship and heterogeneity between income poverty and multidimensional poverty in China, but they have not reached a unified conclusion. Yang and Mukhopadhaya (2019) used China Health and Nutrition Survey data to study income and multidimensional poverty in China from 2000 to 2011. They found that the approach proposed by the Asian Development Bank shows an upward trend in income poverty after adjustment for vulnerability. However, according to the World Bank poverty line (\$1.25 or \$1.90), income poverty is decreasing. Wang et al. (2016) examined the relationship between income poverty and multidimensional poverty using 2011 China Health and Nutrition Survey data. They found that the coincidence of income poverty and multidimensional poverty is 31%, indicating that 69% of multidimensionally poor households are not considered poor in terms of income poverty. By using the rural data of China, Zhang et al. (2019) found that in 2014, the overlap between the income poverty and multidimensional poverty of rural households was only 18%, the concept of income poverty omitted 76% of the multidimensional poor households, and the concept of multidimensional poverty omitted 64% of the income poor households. From 2012 to 2014, only 16% of the households with income poverty alleviation achieved multidimensional poverty alleviation at the same time and only 18% from 2014 to 2016. Therefore, in the context of China's announcement that absolute poverty based on income poverty has been comprehensively managed, empirically testing whether and to what extent Chinese rural income-poor individuals are vulnerable to multidimensional poverty is worthwhile.

More studies have paid close attention to China's income poverty and multidimensional poverty (Li et al. 2019a), however, research on Chinese people's vulnerability to poverty remains lacking. Most studies have focused on the vulnerability to poverty from a unidimensional perspective rather than a multidimensional one (Cao et al. 2016; Ward 2016; Xu et al. 2017; Yu et al. 2020). The unidimensional measurement of vulnerability to poverty based on the consideration of income or consumption is insufficient to reveal the complexity and risk of poverty. Thus, measurements of multidimensionality of vulnerability to poverty need more attention. Yang et al. (2019) measured the VMP in rural China and declared that the essential difference between VMP and multidimensional poverty is the risk (i.e., reflected by vulnerability). Li et al. (2019b) presented an expanded three-dimensional framework as the "social exclusion-vulnerability-sustainable livelihood" to analyze the VMP of rural families and its spatial distribution characteristics based on China Health and Nutrition Survey data and a geographic information system. However, the thresholds of the vulnerability to poverty for each welfare indicator are set by experience, leading to negligence in the heterogeneity of deprivation risk among multidimensional indicators. Some core issues still lack sufficient research. What is the current situation of household VMP in rural China? Are the VMP groups consistent with the absolute poverty groups under the current standard of income? Will the increase in income definitely result in a decrease

in VMP? What is the main source of the transformation of the rural anti-poverty project during the post-poverty era? We attempt to respond to these questions.

Referring to Gallardo (2019) and Alkire and Foster (2011), we define the concept of VMP as the probability of rural families falling into or staying in multidimensional poverty in the future. This paper has three main contributions. (1) Based on the method of VMPI proposed by Gallardo (2019) and Chinese Family Panel Studies (CFPS) data from 2016 to 2018, this study provides a comprehensive framework to measure the VMP in rural Chinese families. Some critical indexes, such as the headcount ratio of VMP, average vulnerability intensity of VMP, adjusted multidimensional vulnerability gap, and quadratic gap are explored to reveal the characteristics of VMP in rural China. (2) The paper decomposes the indexes by regions to investigate the origins and contributions of VMP. The dynamic trends and regional heterogeneities are investigated to increase the insight from the analysis. (3) The comparison between VMP and income poverty is presented to distinguish the similarities and differences in the identification of the target groups of poverty alleviation in different periods.

The remainder of this paper is structured as follows. Section 2 proposes the methodology of VMP measurement. Section 3 constructs the indicators of the VMPI framework and explains the data sources. Section 4 presents the empirical analysis and discusses the results. Section 5 provides conclusions and policy applications.

2 Methodology

Referring to Gallardo (2019), the measurement of VMPI is carried out as follows. First, the target dimensions and indicators are determined to measure the VMP of households, and the weights of each index are determined. Second, the prediction threshold of each indicator per dimension based is calculated on the ROC curve, and whether the family is vulnerable to poverty is identified according to the threshold of each welfare dimension (unidimensional identification). Third, the value of VMPI and the related indicators of rural families are measured, then the vulnerability of families in the multidimensional space (multidimensional identification) is identified based on the multidimensional poverty threshold. Fourth, the VMPI of families is decomposed to reveal the contribution rate of each region.

2.1 Multidimensional identification

Assuming that $i = 1, 2, \dots, N$ represents the household, where N indicates the total number of families, and assuming that $m = 1, 2, \dots, M$ represents the welfare dimensions of a household in the VMPI framework, the multidimensional welfare of household i can be expressed as

$$y_i = (y_{i1}, y_{i2}, \dots, y_{iM}) \quad (1)$$

where $y_{im} \geq 0$ reflects the status of poverty of household i in the m welfare dimension. y_{im} is a binary variable with the value of 0 or 1. $y_{im} = 0$ means that household i is

identified as poor in the m dimension, while $y_{im} = 1$ means that household i is identified as non-poor in the m dimension.

According to Gallardo (2019), the vulnerability to unidimensional poverty corresponding to the welfare indicator defined by the binary variable is identified by the following formula:

$$p_{im} - \gamma_m \sqrt{p_{im}^2 (1 - p_{im})} \leq z_m^v \quad (2)$$

where p_{im} represents the probability that household i is non-vulnerable to poverty in the dimension m . γ_m is an advanced given risk aversion coefficient and $\gamma_m \in (0, 1]$. z_m^v is the vulnerability threshold on dimension m , corresponding to the poverty standard of the continuous variable (Gallardo 2019). Equation (2) indicates that household i is vulnerable to poverty in dimension m when $p_{im} - \gamma_m \sqrt{p_{im}^2 (1 - p_{im})} \leq z_m^v$. The value of z_m^v is usually determined by experience in most previous studies. For example, households are classified as vulnerable based on whether their probability of being poor in the future is greater than or equal to 0.5 or above the observed poverty rate (Chaudhuri et al. 2002; Hohberg et al. 2018; Pritchett et al. 2000). This classification method neglects the variability a household faces, and it does not always perform well in terms of prediction (Celidoni 2013). Following Hohberg et al. (2018), this study uses the receiver operating characteristic (ROC) curve to calculate the vulnerability thresholds of each dimension. ROC is a useful tool to find the threshold in which a binary predictor performs best, that is, to be as close as possible to the perfect prediction point (Gallardo 2019). The main advantage compared with the original thresholds is that the ROC allows one to consider accuracy metrics in terms of the true positive rate (TPR) or the false positive rate (FPR). In this study, TPR is the ratio of the correctly predicted number of non-poor households in each welfare indicator to the total number of non-poor households in the same indicator. FPR is the ratio of the falsely predicted number of non-poor households to the total number of poor households. The TPR and FPR can be balanced according to some prespecified criteria by varying the threshold point. The TPR and FPR will increase when the vulnerability threshold decreases. This characteristic of the ROC curve can be used to construct a vulnerability threshold and is less arbitrary than a vulnerability cutoff set at 0.5 probability of becoming poor (Hohberg et al. 2018). The ROC curve is drawn with the TPR as the ordinate and FPR as the abscissa, which is shown in Fig. 1.

The arrows in Fig. 1 indicate the best prediction point on the ROC curve that determines the best choice of threshold when predicting whether a household is vulnerable to poverty in each welfare dimension. The optimal prediction threshold for a binary predictor is then at that point over the ROC curve which is closest to the perfect prediction point (Gallardo 2019; Youden 1950).

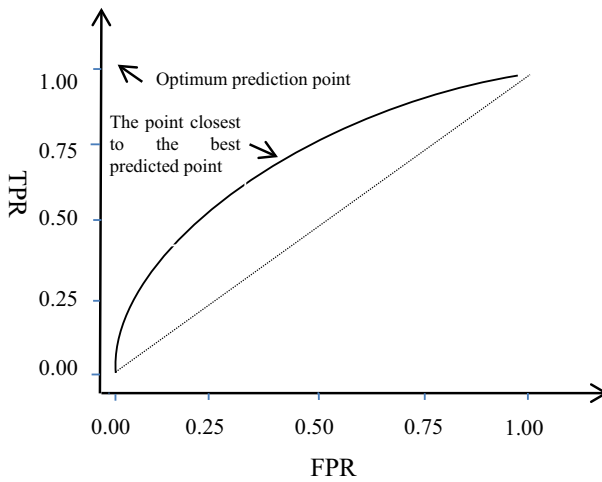


Fig. 1 ROC curve

We assume that $z^v = (z_1^v, z_2^v, \dots, z_M^v)$ is the vulnerability threshold vector corresponding to a household of its welfare indicators (from 1 to M) and that g_{im}^{v0} is an indicator function of household i on dimension m , where $g_{im}^{v0} = 1$ indicates the existence of vulnerability. $w = (w_1, w_2, \dots, w_M)$ represents weight vector, and $\sum_{m=1}^M w_m = 1$. Then, the vulnerability score s_i^v of household i is defined as follows.

$$s_i^v = \sum_{m=1}^M w_m g_{im}^{v0} \tag{3}$$

We assume that k is the multidimensional poverty threshold. When $s_i^v \geq k$, household i is identified as vulnerable to multidimensional poverty.

After identifying the state of VMP for each household, the next step is to measure the multidimensional vulnerability conditions of the population. One reasonable method is to use the multidimensional vulnerability headcount ratio (V^H), that is, the proportion of people who are vulnerable to multidimensional poverty in the population.

$$V^H = \frac{1}{N} \sum_{i=1}^N I_{s_i^v \geq k} \tag{4}$$

Here $I_{s_i^v \geq k} = 1$ if $s_i^v \geq k$, otherwise $I_{s_i^v \geq k} = 0$. Referring to Alkire et al. (2015) and Gallardo (2019), the normalized vulnerability gap of order α for household i in the welfare dimension m is as follows.

$$g_{im}^a = g_{im}^0 \left[\frac{z_m^v - (\mu_{im} - \gamma_m r_{im})}{z_m^v} \right]^\alpha, \alpha \geq 0 \tag{5}$$

On these bases, we further have the general vulnerability to multidimensional poverty measure of α order, as follows:

$$V^\alpha(Y, \gamma, z^v, k) = \frac{1}{N} \sum_{i=1}^N \sum_{m=1}^M w_m g_{im}^\alpha I_{s_i^v \geq k}, \quad \alpha \geq 0 \tag{6}$$

when $\alpha = 0$, V^0 represents the adjusted multidimensional vulnerability headcount ratio, which is adjusted according to the percentage of deprivation faced by vulnerable groups. Referring to Alkire et al. (2015), M_0 (the adjusted multidimensional poverty headcount ratio) represents the product of the multidimensional poverty headcount ratio of H (the percentage of multidimensionally poor people in a population) and the average intensity of deprivation A (i.e., the average deprivation score among the multidimensionally poor). Similarly, V^0 is the product of multidimensional vulnerability headcount ratio V^H (the proportion of people who are vulnerable to multidimensional poverty in the population) and the average vulnerability intensity V^A (the average vulnerability score among the vulnerable people). For $\alpha = 1$, the adjusted multidimensional vulnerability gap V^1 is obtained, which is used to measure the welfare-losing degree of people who are vulnerable to multidimensional poverty. For $\alpha = 2$, V^2 represents the adjusted multidimensional vulnerability quadratic gap, which is used to measure the inequality degree among welfare dimensions of the VMP population.

In addition, the vulnerability to poverty ratio (VPR) can be used to measure the share of VMP people in the poor population, which is expressed as the ratio of multidimensional vulnerability headcount ratio (V^H) to the multidimensional poverty headcount ratio of poverty (H) as follows:

$$VPR = \frac{V^H}{H} \tag{7}$$

The over-rate of vulnerability headcount ratio (ORV) can be used to measure the difference between V^H and H as follows:

$$ORV = V^H - H \tag{8}$$

2.2 Regional decomposition

To further investigate the regional differences in vulnerability to multidimensional poverty in rural China, we can decompose the indicators by region or dimension. c represents the regions, where $c = 1, 2, 3, 4$ corresponding to eastern, central, western, and northeastern regions respectively. The contributions of region c to the vulnerability headcount ratio and the average vulnerability intensity are expressed as ϕ_c^H and ϕ_c^A as follows:

$$\phi_c^H = \frac{\omega_c V_c^H}{\sum_{c=1}^4 \omega_c V_c^H} \text{ or } \phi_c^A = \frac{\omega_c V_c^A}{\sum_{c=1}^4 \omega_c V_c^A} \tag{9}$$

where ω_c represents the population share of each region, V_c^H represents the multidimensional vulnerability headcount ratio of region c , and V_c^A means the average vulnerability intensity of region c .

3 Indicators and data

3.1 Dimensions and indicators

In terms of choosing the dimensions and indicators to measure the vulnerability to poverty from a multidimensional perspective, researchers pointed out that some non-monetary dimensions should be considered in addition to traditional monetary dimensions such as the “wealth–income–consumption” triple indicators (Chaudhuri et al. 2002; Hoddinott and Quisumbing 2010). For example, non-monetary indexes include but not are limited to body condition (Dercon 2009; Dercon and Krishnan 2000), education and leisure (Ozughalu 2016; Sawada and Lokshin 2001), life status (Novignon et al. 2012), personal preferences, and subjective feelings, and access to basic services (Alwang et al. 2001; Coudouel and Hentschel 2000). On the basis of metrics such as the United Nations Millennium Development Goals, the MPI of the United Nations Development Program (UNDP), and the Outline of China’s Rural Poverty Alleviation and Development (2011–2020), this study constructs a measurement framework of VMPI comprising subjective and objective indicators. The four dimensions, namely, education, living conditions, healthcare, and psychology, and the ten indicators are shown in Table 1. The poverty deprivation values and the content of the judgment are based on the questions of the CFPS questionnaire. Adopting the internationally used double equal weight method, we obtain the weight of each indicator. That is, equal weight is set for each dimension, and is then equal for each index in the dimension. Table 1 reports the details of the measurement framework of VMPI.

3.2 China family panel studies data

The VMPI methods were calculated based on the cross-sectional data of the CFPS in 2016 and 2018. The CFPS project is a large-scale social tracking survey project led by the Institute of Social Science Survey of Peking University. The survey covers more than 25 provinces (municipalities and autonomous regions) in China. The survey aims to reflect the social, economic, demographic, and education changes in China by tracking the data on three levels: individual, family, and community. The CFPS project is carried out every two years, and two rounds of pre-survey and five rounds of full survey have been completed since 2007. In this paper, we adopt three types of questionnaires, namely, family, adult, and children to construct the data set of indicators by using the latest two rounds of CFPS data in 2016 and 2018. After matching the three types of samples, and excluding the urban household samples, the rural samples whose heads of household are less than 16 years old, and the rural samples whose major variables are missing, we obtained 5,970 valid samples of rural households for 2016 and 2018. The samples are regionally distributed as 1506, 1588,

Table 1 Dimensions, indicators, and weights

Dimension	Indicator	Poverty deprivation value	Weight
Education	Adult education	The years of education for family adults aged 16 and above are less than 3 years	1/8
	Out-of-school children	The family has children aged 6–15 out of school	1/8
Living condition	Clean drinking water	Clean water such as tap water, mineral water, bottled water, and pure water cannot be used for household cooking	1/12
	Cooking fuel	Household cooking fuels use non-clean energy such as firewood and coal	1/12
	Family assets	No durable consumer goods with a price of more than 2,000 CNY and a natural service life of more than 2 years are owned	1/12
Health care	Adult nutrition	An adult over 16 with the Body Mass Index less than 18.5	1/12
	Adult health	The family has an unhealthy adult (for example, suffering chronic disease)	1/12
	Medical security	The family has an adult without any kind of health insurance	1/12
Subjective psychology	Life satisfaction	The scores of life satisfaction (from 1–5) of family adults are all less than 3	1/8
	Future confidence	The scores of confidences in their future (from 1–5) of family adults are all less than 3	1/8

2117, and 759 from eastern, central, western, and northeastern regions, respectively, accounting for 25.23%, 26.60%, 35.46%, and 12.71% of the full sample. The samples have good representativeness of rural China due to its diversity and balance of regional distribution.

Table 2 reports the descriptive statistics of the data used for the VMPT estimation. On the basis of the ten indicators of the VMPI framework, we additionally chose ten control variables for the VMPI estimation to reflect the characteristics of the families and householders.

Table 2 Descriptive statistics of the data used for the VMPT estimation

Indicator	Definition	sample size	2016		2018	
			Mean	Standard deviation	Mean	Standard deviation
<i>Indicators of VMPI Framework</i>						
Adult education	1 = the education years of every adult is no less than 3; 0 = otherwise	5970	0.9041	0.2943	0.9462	0.2256
Out-of-school children	1 = no children aged 6–15 out of school; 0 = otherwise	5970	0.9245	0.2643	0.9889	0.1046
Clean drinking water	1 = clean water is used for household cooking; 0 = otherwise	5970	0.9161	0.2772	0.9126	0.2825
Cooking fuel	1 = clean fuel is used for household cooking; 0 = otherwise	5970	0.5763	0.4941	0.7120	0.4528
Family assets	1 = at least one durable goods are more than 2000 yuan; 0 = otherwise	5970	0.8022	0.3983	0.9202	0.2709
Adult nutrition	1 = the BMI of every adult is more than 18.5 kg/m. ² ; 0 = otherwise	5970	0.8501	0.3570	0.8891	0.3140
Adult health	1 = all adults are healthy; 0 = otherwise	5970	0.6363	0.4811	0.5938	0.4912

Table 2 (continued)

Indicator	Definition	sample size	2016		2018	
			Mean	Standard deviation	Mean	Standard deviation
Medical security	1 = the assurance for every adult is no less than 1; 0 = otherwise	5970	0.8378	0.3686	0.8276	0.3777
Life satisfaction	1 = the score of life satisfaction of every adult is no less than 3; 0 = otherwise	5970	0.9685	0.1747	0.9773	0.1486
Future confidence	1 = the score of future confidence of every adult is no less than 3; 0 = otherwise	5970	0.9762	0.1523	0.9792	0.1426
<i>Control variables</i>						
Family size	The number of family members	5970	4.1221	2.0010	3.8169	2.0107
Social capital	The logarithm of family's gift expenditure	5970	7.2821	1.9762	7.0856	2.2893
Land ownership	1 = the family get land from the collective; 0 = otherwise	5970	0.8965	0.1088	0.8716	0.3344
Years of adult education	Average years of education of family's adults	5970	6.3313	3.1065	6.7328	2.9356
Supported rate	Percentage of the elderly over 60 years old in the family	5970	0.2283	0.3216	0.2245	0.3336

Table 2 (continued)

Indicator	Definition	sample size	2016		2018	
			Mean	Standard deviation	Mean	Standard deviation
Family loan	1 = the family has loan; 0 = otherwise	5970	0.2383	0.4367	0.2180	0.4130
Age	The age of householder	5970	50.8376	13.6678	51.6567	14.4369
Gender	1 = a male householder; 0 = a female householder	5970	0.5567	0.4968	0.5571	0.4967
Marital status	1 = the householder is married; 0 = otherwise	5970	0.8630	0.3439	0.8437	0.3632
Job type	1 = householder engaged in agriculture work; 0 = otherwise	5970	0.6194	0.4855	0.5865	0.4925

4 Results and discussion

4.1 Unidimensional vulnerability threshold estimation based on ROC curve

We use the probit model to estimate the vulnerability thresholds for each welfare indicator. Then, we can derive the optimum prediction point of the ROC curve (i.e., z_m^v) based on the estimation results. For the robustness check, we also estimate the optimum prediction point of the ROC curve with the logit model by using the same variables and data. Table 3 reports the vulnerability threshold of each indicator estimated by the probit and logit models based on the ROC curve.¹ The vulnerability threshold of the adult education indicator measured by the probit model is 0.7273, which implies that household i is vulnerable to poverty in adult education indicator when $p_{im} - \gamma_m \sqrt{p_{im}^2(1 - p_{im})} \leq z_m^v$ (where m corresponds to the adult education indicator). According to Table 3, out-of-school children have the highest vulnerability threshold value among the 10 indicators, adult health has the lowest threshold value of the probit model, and clean drinking water has the lowest value of the logit model. From the perspective of dimensions, the vulnerability threshold value of the education dimension is relatively high among the four dimensions, whereas that of living conditions is relatively low. This finding indicates that the risks faced by different welfare

¹ The risk aversion coefficient γ is set as 0.6 in the probit and logit model. The reason is proposed in Sect. 4.2.

Table 3 Estimation results of poverty vulnerability threshold

Dimension	Indicator	Unidimensional vulnerability threshold	
		Probit	Logit
Education	Adult education (<i>educ</i>)	0.7273	0.7183
	Out-of-school children (<i>scho</i>)	0.8122	0.7932
Living condition	Clean drinking water (<i>drik</i>)	0.5817	0.4997
	Cooking fuel (<i>fuel</i>)	0.5283	0.5324
	Family asset (<i>aset</i>)	0.6661	0.6963
Health care	Adult nutrition (<i>nutr</i>)	0.6331	0.6232
	Adult health (<i>heal</i>)	0.5131	0.5197
	Medical security (<i>medc</i>)	0.7019	0.7062
Subjective psychology	Life satisfaction (<i>sati</i>)	0.7368	0.7177
	Future confidence (<i>conf</i>)	0.5585	0.5420

dimensions and indicators are diversified. In other words, the unidimensional vulnerability threshold cannot fully reflect the risk characteristics of welfare deprivation of rural families because the risks of being deprived in each welfare dimension/indicator are heterogeneous. By comparison, we can find that the difference between the vulnerability thresholds selected by the ROC curve under the probit and logit models is not significant.

4.2 Main results of VMPI estimation in rural China

To perform the VMPI method on the rural family with CFPS data, we determine the multidimensional vulnerability threshold (k) and the risk aversion coefficient (γ). To choose a suitable value of k , we calculate the multidimensional poverty-related indicators with the value of k as follows: 1/10, 2/10, 3/10, 4/10, 5/10, 6/10, 7/10, 8/10, and 9/10. The values of H and M_0 are 0 in 2016, with the value of k being 7/10 to 10/10 and the value of H and M_0 are 0 in 2018, with the value of k being 6/10 to 10/10. Obviously, the values of H and M_0 do not conform to reality, so this study only lists the calculation results when k is from 1/10 to 6/10. The results are shown in Table 4. Table 4 shows that when γ varying from 0 to 1, the value of the multidimensional poverty headcount ratio (H), the average intensity of deprivation (A), and their product, which is expressed as adjusted headcount ratio (M_0) will not change. This finding is consistent with the reality and confirms that the essential difference between multidimensional poverty and vulnerability to multidimensional poverty depends on the consideration of risk. $k = 1/10$ indicate that unidimensional poverty is regarded as multidimensional poverty and does not meet the definition of multidimensional poverty. The determination of k can refer to the Global MPI which is proposed by the UNDP and Oxford University. They recommend the cross-deprivation threshold to be 1/3. That is, the family member facing a consequence that equal to or more than 1/3

Table 4 Multidimensional poverty estimation with different parameters

γ	2016				2018			
	k	H	A	M_0	k	H	A	M_0
$0 \leq \gamma \leq 1$	1/10	0.4835	0.1608	0.0778	1/10	0.3611	0.1253	0.0452
	2/10	0.2166	0.1608	0.0348	2/10	0.1276	0.1253	0.0160
	3/10	0.0732	0.1608	0.0118	3/10	0.0348	0.1253	0.0044
	4/10	0.0191	0.1608	0.0031	4/10	0.0069	0.1253	0.0009
	5/10	0.0036	0.1608	0.0006	5/10	0.0012	0.1253	0.0001
	6/10	0.0005	0.1608	0.0001	6/10	0.0000	0.1253	0.0000

welfare indicators are deprived is identified as multidimensionally poor. By contrast, the people with the result of deprivation indicators between 1/5 and 1/3 are classified in the group who is vulnerable to multidimensional poverty (OPHI 2018). The logic of this definition of vulnerability is that those deprivation scores close to the defined multidimensional poverty threshold are at risk of becoming become multidimensionally poor. In terms of these suggestions, the threshold to identify the vulnerable to multidimensional poverty should be close to but slightly less than 1/3. Considering the indicators of the VMPI framework of our research, we set $k = 0.3$ (3/10) as the multidimensional vulnerability threshold, that is, at least 3 out of 10 welfare indicators for a person are deprived (i.e., identified as vulnerable to unidimensional poverty). Thus, that person can be identified as vulnerable to multidimensional poverty.

In addition, a consensus in the literature indicates that the proportion of people who are vulnerable poor is larger than those who are poor in developing countries (Feeny and McDonald 2016; Gallardo 2018; Günther and Harttgen 2009; Hohberg et al. 2018). According to the official reports of China, the poverty incidence rates in 2016 and 2018 were 4.5% and 1.7%, respectively. A comparison of the data in Table 4, we find that the multidimensional poverty headcount ratios in 2016 and 2018 are 7.32% and 3.48%, respectively, when $k = 0.3$, which are higher than the official data. The corresponding results of $k = 0.4$ are 1.91% and 0.69%, respectively, and lower than official data. Thus, $k = 0.3$ is confirmed to be a better choice of multidimensional vulnerability threshold for the VMPI estimation because it is better in line with the reality of poverty conditions in rural China.

In terms of the determination of the risk aversion coefficient γ , no internationally uniform standard has been made. However, some studies in countries such as Chile (Gallardo 2019), Pakistan (Azeem et al. 2018), and Tunisia (Nasri and Belhadj 2018) recommend that a value of 0.6 to 0.8 for γ may be suitable for developing countries. Thus, we examine the main results of VMPI with $\gamma = 0.6, 0.7$, and 0.8, respectively, when $k = 0.3$. Table 5 lists the results.

Table 5 shows that the multidimensional vulnerability headcount ratio V^H , the average multidimensional vulnerability intensity V^A , the adjusted multidimensional vulnerability headcount ratio V^0 , the adjusted multidimensional vulnerability gap V^1 , and the adjusted multidimensional vulnerability quadratic gap V^2 increase with the

increasing of γ when k is fixed as $k = 0.3$. In addition, the value of VPR (vulnerability to poverty ratio) and ORV (over-rate of vulnerability headcount ratio) have the same trends. The results indicate that the growth of risk aversion coefficient γ will lead to an increase in the numbers of families who are identified as vulnerable to multidimensional poverty in rural China. Given that the multidimensionally poor family will not change with the risk aversion coefficient, the increase in γ will result in a larger gap between the families who are vulnerable to multidimensional poverty and those who are multidimensionally poor. From the perspective of time, we can find that values of V^H, V^A, V^0, V^1 and V^2 in 2018 are much smaller than those in 2016 when γ is fixed. Corresponding to the reality, the results indicate that the degree, gap, and intensity of vulnerability to multidimensional poverty in rural China have dropped significantly from 2016 to 2018, confirming the major achievements of the anti-poverty project in China.

Then, which value of γ fits best with the reality of poverty in rural China? A comparison shows that $\gamma = 0.6$ results in the smallest values of each indicator. Given that China has the highest level of economic development among all developing countries, we assume that $\gamma = 0.6$ is the most suitable choice for the VMPI estimation of rural China. When we adopt the risk aversion coefficient as $\gamma = 0.6$, we can find that the multidimensional vulnerability headcount ratio V^H dropped from 47.32% in 2016 to 15.67% in 2018, which is reduced by 66.89% on the basis of 2016. The average multidimensional vulnerability intensity V^A changed from 45.92% in 2016 to 39.26% in 2018, and the extent of reduction is 14.50%. The significant decrease in the adjusted multidimensional vulnerability headcount ratio (V^0), the adjusted multidimensional vulnerability gap (V^1), and the adjusted multidimensional vulnerability quadratic gap (V^2) are also obvious because they drastically reduced from 21.73%, 6.50%, and 3.39% in 2016 to 6.16%, 4.19%, and 0.06% respectively, and the extent of reduction corresponds to 71.65%, 35.54%, and 98.26%. In addition, the vulnerability to poverty ratio (VPR), which reflects the share of people who are vulnerable to multidimensional poverty in the multidimensionally poor population, are 6.45 and 4.5 in 2016 and 2018, respectively.

4.3 Decomposition analysis

4.3.1 Decomposition by regions

In this section, we decompose the V^H and V^A by regions (under the condition of $k = 0.3$ and $\gamma = 0.6$) to obtain the regional headcount ratio of multidimensional vulnerability (V_c^H), the regional average vulnerability intensity (V_c^A), the regional contribution rate to vulnerability headcount ratio (φ_c^H), and the regional contribution rate to average vulnerability intensity (φ_c^A). Table 6 reports the decomposition results according to Eq. (9). The ranking of the regional headcount ratio of multidimensional vulnerability (V_c^H) in 2016 from high to low is western, central, eastern, and northeastern. In 2018, the order changed to central, western, eastern, and northeastern because the multidimensional vulnerability headcount ratio in the western region has been

Table 5 Main results of VMPI estimation with different risk aversion coefficient

<i>k</i>	Year	γ	V^H	V^A	V^0	V^1	V^2	VPR	ORV
3/10	2016	0.6	0.4732 (0.0065)	0.4592 (0.0021)	0.2173 (0.0014)	0.0650 (0.0005)	0.0339 (0.0003)	6.4645	0.4000
		0.7	0.5977 (0.0063)	0.4756 (0.0020)	0.2842 (0.0015)	0.0859 (0.0006)	0.0445 (0.0003)	8.1647	0.5245
		0.8	0.7749 (0.0054)	0.4873 (0.0019)	0.3776 (0.0015)	0.1149 (0.0006)	0.0596 (0.0004)	10.5858	0.7017
	2018	0.6	0.1567 (0.0047)	0.3926 (0.0018)	0.0616 (0.0007)	0.0419 (0.0005)	0.0159 (0.0002)	4.5000	0.1219
		0.7	0.2528 (0.0056)	0.3986 (0.0017)	0.1007 (0.0009)	0.0625 (0.0006)	0.0254 (0.0003)	7.2548	0.2179
		0.8	0.3879 (0.0063)	0.4097 (0.0017)	0.1589 (0.0010)	0.0869 (0.0007)	0.0378 (0.0004)	11.1346	0.3531

Standard errors in parentheses

reduced significantly. The results indicate that the risk faced by rural families in different regions is heterogeneous and that those families in western and central regions have a higher possibility to fall into multidimensional poverty in the future. From the perspective of variation, the trends of multidimensional vulnerability headcount ratio in rural China from 2016 to 2018 decrease by 31.56%. Among the regions, the highest reduction appears in the western region with a rate of up to 41.62%, and the eastern region is the lowest with a reduction rate of 20.42%. In terms of regional contribution rate to vulnerability headcount ratio (φ_c^H), the rates from high to low are ranked by western, central, eastern, and northeastern in 2016 and 2018. However, the contribution rate of the western region from 2016 to 2018 decreased by 7.97%, whereas the contribution rates of the central, eastern, and northeastern regions increased by 1.21%, 4.68%, and 2.09%, respectively. The reason why the contribution rate of the eastern region is higher than that of the northeastern region is that the samples from the former are much more than those from the latter.

We also focus on the regional average vulnerability intensity (V_c^A). As shown in Table 6, we order the regions from high to low as western, central, eastern, and northeastern according to the value of V_c^A in 2016; the order changes to western, central, northeastern, and eastern in 2018. From the perspective of variation, the trends of the average vulnerability intensity of the whole country decreased by 14.5% from 2016 to 2018. As regards the variation degree of the regional average vulnerability intensity, the comparisons result in a ranking from high to low in western, central, northeastern, and eastern, corresponding to 17.72%, 13.03%, 13.56%, and 11.43%, respectively. As regards the regional contribution rate to average vulnerability intensity (φ_c^A), although it decreased slightly in the western region and increased slightly in the central, eastern, and northeastern regions in 2018, it is generally stable with a ranking from high to low of western, central, eastern, and northeastern in 2016 and 2018.

Table 6 The results decomposed by regions ($k = 3/10, \gamma = 0.6$)

Decomposition path	Indicator	Symbol	Overall country	Eastern	Central	Western	North-western
	Sample share	ω_c	100%	25.23%	26.60%	35.46%	12.71%
Decomposed by vulnerability headcount ratio	Regional vulnerability headcount ratio	V_c^H	47.32%	43.82%	43.95%	56.97%	34.39%
		V_c^H	15.67%	15.27%	17.32%	15.35%	13.97%
Regional contribution rate to vulnerability headcount ratio		φ_c^H	–	23.36%	24.71%	42.69%	9.24%
		φ_c^H	–	24.57%	29.39%	34.72%	11.33%
Decomposed by the average vulnerability intensity	Regional average vulnerability intensity	V_c^A	0.4592	0.4391	0.4556	0.4791	0.4511
		V_c^A	0.3926	0.3889	0.3938	0.3942	0.3923
Regional contribution rate to average vulnerability intensity		φ_c^A	–	24.13%	26.39%	37.00%	12.49%
		φ_c^A	–	23.9%	26.47%	37.16%	12.48%

4.3.2 Decomposition by provinces

In addition to the unbalanced regional economic development, significant differences also exist in the economic development of China's provinces. Then, what is the multidimensional poverty vulnerability and its distribution in each province? Are there also significant differences? We further decompose rural multidimensional poverty vulnerability by province (see Table 7). In 2016, the headcount ratio of multidimensional vulnerability of each province varied from 0.1765 to 0.6133. The top three provinces in terms of headcount ratio of multidimensional vulnerability were Guizhou, Sichuan and Gansu; the bottom three provinces were Beijing, Liaoning, and Jiangsu. In 2018, the headcount ratio of multidimensional vulnerability of all provinces dropped significantly, and the overall range varied from 0 to 0.2609. The top three provinces in headcount ratio of multidimensional vulnerability were Chongqing, Shandong, and Shaanxi; the bottom three provinces were Beijing, Tianjin, and Zhejiang. In 2016, the average vulnerability intensity of each province varied from 0.3750 to 0.4968. The average vulnerability intensity of Sichuan, Gansu, and Guizhou was significantly higher than that of other provinces, and the average vulnerability intensity of Beijing, Tianjin, and Shanghai was significantly lower than that of other provinces. In 2018, except for the average vulnerability intensity in Beijing, which dropped to 0, the average vulnerability intensity in the rest of the provinces varied from 0.3417 to 0.4250. The average vulnerability intensity of Heilongjiang, Hunan, and Guangxi was higher than that of other provinces; the average vulnerability intensity of Beijing, Zhejiang, and Fujian was significantly lower than that of other provinces. From the perspective of contribution rate, the overall contribution rate of Henan and Gansu provinces to the total vulnerability of multidimensional poverty was the highest during the sample period. Taking average vulnerability intensity as an example, Gansu's contribution to the total average vulnerability intensity rose sharply from 7.93% in 2016 to 16.68% in 2018, and Henan correspondingly increased from 5.36 to 12.27%. The contribution rate of Beijing, Tianjin, and Hubei was relatively small; especially, the contribution rate of the total average vulnerability intensity in Beijing from 2016 to 2018 dropped from 0.11 to 0%.

4.3.3 Decomposition by dimensions

According to Zhang and Zhou (2014), this study decomposes the vulnerability of multidimensional poverty by dimensions. The results are reported in Table 8. In 2016, the indicator with the largest contribution to vulnerability of multidimensional poverty was cooking fuel, followed by adult health and future confidence, which contributed 18.02%, 18.01%, and 15.78% respectively, with a total of 51.81%. In 2018, the indicator that contributed the most to vulnerability of multidimensional poverty was confidence in the future, followed by cooking fuel and adult health, whose contribution rates were 25.17%, 21.23%, and 20.02%, respectively. The total is as high as 66.42%, which is 14.61 percentage points higher than that in 2016. Cooking fuel, adult health, and future confidence were always at a high level, and all showed an upward trend. This finding indicates that cooking fuel, adult health, and future confidence were the major risk factors for farmers to fall back into poverty in the future.

Table 7 The results decomposed by provinces ($k = 3/10, \gamma = 0.6$)

Provinces	Sample share	V^H		Contribution rate to vulnerability headcount ratio		V^A		Contribution rate to average vulnerability intensity	
		2016	2018	2016	2018	2016	2018	2016	2018
Anhui	1.44%	0.4302	0.1163	1.31%	1.07%	0.4189	0.3750	0.60%	1.38%
Beijing	0.28%	0.1765	0.0000	0.10%	0.00%	0.375	0.0000	0.11%	0.00%
Fujian	1.58%	0.4894	0.1383	1.63%	1.39%	0.4719	0.3718	0.75%	1.50%
Gansu	16.23%	0.5955	0.1053	20.42%	10.91%	0.4883	0.4015	7.93%	16.68%
Guangdong	7.27%	0.4249	0.1982	6.53%	9.20%	0.4638	0.4031	3.37%	7.46%
Guangxi	2.43%	0.5903	0.2139	3.03%	3.32%	0.4617	0.4033	1.12%	2.50%
Guizhou	3.77%	0.6133	0.2000	4.89%	4.81%	0.4737	0.3982	1.79%	3.82%
Hebei	6.93%	0.372	0.1763	5.45%	7.80%	0.4591	0.3876	3.18%	6.84%
Henan	12.36%	0.4851	0.1721	12.67%	13.58%	0.4335	0.3898	5.36%	12.27%
Heilongjiang	1.54%	0.5217	0.1087	1.70%	1.07%	0.454	0.4250	0.70%	1.67%
Hubei	1.06%	0.3968	0.127	0.89%	0.86%	0.425	0.3750	0.45%	1.01%
Hunan	1.99%	0.3782	0.1344	1.59%	1.71%	0.4269	0.4089	0.85%	2.07%
Jilin	2.06%	0.3903	0.0976	1.70%	1.28%	0.4505	0.4028	0.93%	2.11%
Jiangsu	1.22%	0.3288	0.0822	0.85%	0.64%	0.4358	0.3750	0.53%	1.17%
Jiangxi	2.76%	0.5394	0.1212	3.15%	2.14%	0.4551	0.3813	1.26%	2.68%
Liaoning	9.11%	0.3033	0.1544	5.84%	8.98%	0.4505	0.3870	4.10%	8.98%
Shandong	5.70%	0.4206	0.2412	5.07%	8.78%	0.4525	0.3908	2.58%	5.67%
Shanxi	5.66%	0.4566	0.1445	5.46%	5.22%	0.4587	0.3886	2.60%	5.60%

Table 7 (continued)

Provinces	Sample share	V^H		Contribution rate to vulnerability headcount ratio		V^A		Contribution rate to average vulnerability intensity	
		2016	2018	2016	2018	2016	2018	2016	2018
Shaanxi	2.20%	0.4846	0.2231	2.25%	3.13%	0.4544	0.3937	1.00%	2.21%
Shanghai	1.27%	0.4473	0.1184	1.20%	0.96%	0.4044	0.4028	0.51%	1.30%
Sichuan	5.83%	0.6034	0.2184	7.43%	8.13%	0.4968	0.4019	2.90%	5.97%
Tianjin	0.52%	0.4516	0.0323	0.50%	0.11%	0.3929	0.3750	0.20%	0.50%
Zhejiang	1.83%	0.3394	0.0459	1.31%	0.54%	0.4684	0.3417	0.86%	1.59%
Chongqing	1.16%	0.5217	0.2609	1.28%	1.93%	0.4549	0.3843	0.53%	1.14%
Yunnan	3.80%	0.4670	0.1013	3.75%	2.46%	0.4536	0.3823	1.72%	3.70%
Total	—	0.4732	0.1567	—	—	0.4592	0.3926	—	—

Table 8 The results decomposed by dimensions ($k = 3/10$, $\gamma = 0.6$)

Dimension	Contributions of dimensions		Indicator	Contributions of indicators	
	2016 (%)	2018 (%)		2016 (%)	2018 (%)
Education	13.42	4.94	Adult education	6.66	3.82
			Out-of-school children	6.76	1.12
Living condition	25.23	29.80	Clean drinking water	0.00	5.03
			Cooking fuel	18.02	21.23
			Family assets	7.21	3.54
Health care	37.81	37.44	Adult nutrition	15.71	17.39
			Adult health	18.01	20.02
			Medical security	4.09	0.03
Subjective psychology	23.55	27.82	Life satisfaction	7.77	2.65
			Future confidence	15.78	25.17

Moreover, future poverty alleviation policy design should pay more attention to the promotion and use of clean energy, the prevention of returning to poverty due to illness and the cultivation and stimulation of the endogenous motivation of poor households to eliminate poverty. The Chinese government's strategy of alleviating poverty first and then supporting "aspiration" has important practical significance for sustainable poverty alleviation in rural areas. The contribution rates of the two indicators of the education dimension were below 7% and showed a downward trend, indicating that education poverty alleviation has made relatively rapid progress compared with other indicators. Indicators of out-of-school children fell more sharply than indicators of adult education. The reason is that the progress of adult education is a long-term process, and its years of education cannot achieve a big breakthrough in a short time like the indicator of out-of-school children. This result is similar to Zhang and Zhou (2014).

4.4 Comparison of VMP and income poverty

The main measurement used by the government to identify the poor in rural China is the income threshold. That is, a person or a family with an income below a specific threshold is identified as poor. We aim to compare VMP and income poverty to reveal the influence of considering vulnerability on the poverty alleviation project. Retaining the condition of $k = 0.3$ and $\gamma = 0.6$, the main results of comparison for VMP and income poverty from the national and regional perspectives are shown in Table 9.

The proportion of income poverty is much smaller than that of VMP during 2016 and 2018, indicating that the families who are at risk of falling into multidimensional poverty are much more than those who are income poor. A comparison of 2018 data with 2016 data shows that the proportion of income poverty had dropped sharply. For example, the extent of reduction in the eastern region was more than 64% when

Table 9 The comparison of vulnerability to multidimensional poverty and income poverty in rural China

Indicator		Overall country (%)	Eastern (%)	Central (%)	Western (%)	Northeastern (%)
Family shares		100	25.23	26.60	35.46	12.71
VMP	2016	47.32	43.82	43.95	56.97	34.39
	2018	15.67	15.27	17.32	15.35	13.97
Income poverty	2016	6.75	4.65	6.55	9.49	3.69
	2018	2.96	1.66	3.02	4.11	2.24
VMP and income poverty	2016	5.63	3.85	5.54	8.12	2.37
	2018	2.36	1.53	2.77	3.07	1.19
Income poverty but not VMP	2016	1.12	0.80	1.01	1.37	1.32
	2018	0.60	0.13	0.25	1.04	1.05
VMP but not income poverty	2016	41.69	39.97	38.41	48.84	32.02
	2018	13.30	13.75	14.55	12.23	12.78

comparing the data of 2.96% in 2018 with 6.75% in 2016. Using the same logic, a drop of more than 53% appeared in the central and western regions; even the smallest reduction in the northeastern region is as high as 39.30%.

However, most income-poor families are also vulnerable to multidimensional poverty. According to Table 7, we can derive that the share of VMP families in the income-poor families are 83.41% (5.63%/6.75%) in 2016 and 79.73% (2.36%/2.96%) in 2018. These findings reveal that the families who are already income-poor remain at risk of remaining multidimensionally poor in the future. The year 2018 is a critical year for China to achieve total victory in the anti-poverty battle because the poor families in this period face a deep and long-term poverty. For them, eliminating poverty is difficult, whereas entering into poverty again is easy. Our investigation finds that the VMP families overlap with more than 80% income-poor families, meaning that the poverty identification and poverty assistance in rural China are accurate over the years. From the regional perspective, the proportion of families who are vulnerable to multidimensional poverty and income poverty in 2016 in the eastern, central, western, and northeastern regions are 3.85%, 5.54%, 8.12%, and 2.37%, respectively, while the data drop to 1.53%, 2.77%, 3.07%, and 1.19% in 2018. Although the western region achieves the biggest improvement from 2016 to 2018, the proportion of families who are vulnerable to multidimensional poverty and income poverty remains the highest among the regions. This finding indicates that the income-poor families in western rural areas with a relatively low economic level are at the highest risk of remaining multidimensionally poor in the future.

The VMP families in rural China partly come from those families who are out of poor or non-poor, but their population decreased from 2016 to 2018. The proportion

of families who are vulnerable to multidimensional poverty but not income poverty dropped from 41.69% in 2016 to 13.30% in 2018. The extent of reduction of this proportion in the western region is as high as 74.69% and is more than 60% in other regions. This finding shows that the anti-poverty project in rural China to prevent people from becoming poor and returning to being poor have achieved remarkable success from 2016 to 2018. This finding also reminds us that the differences between the identification of income poverty and VMP exist. We should pay more attention to the differences and their influences during the post-poverty era after 2020, which is characterized by relative poverty. If the rural population is still identified and assisted according to the income poverty standard, then a large number of people who are non-income poor but trapped in a state of vulnerability to multidimensional poverty will be excluded from assistance.

5 Robustness checks

Different weights of indicators may affect the calculation results of vulnerability of multidimensional poverty. To test the robustness of the above research, we further examine the vulnerability of multidimensional poverty under different weight selections. Given that health and education are important variables that cause multidimensional poverty (Acemoglu and Johnson 2007; Cheng et al. 2016; Li et al. 2020; Meyer and Mok 2019), we increase the weight of the three indicators of the healthcare dimension from 1/12 to 1/9, and the weight of the other dimensions is distributed according to equal weight. The results are reported in Table 11. Next, we increase the weights of the two indicators of the education dimension from 1/8 to 1/5, and the weights of the remaining dimensions are distributed according to equal weights. The results are shown in Table 12. In comparison with the results in Table 5, the results in Table 11 show that after increasing the weights of the three indicators of the healthcare dimension from 1/12 to 1/9 (the changing weight are shown in Table 10), the values of V^H , V^A , V^0 , V^1 and V^2 are basically stable, and the changes in the coefficient values of each indicator are relatively small. Taking $\gamma = 0.6$ as an example, after the weights are increased to 1/11, 1/10, and 1/9, the percent change in the values of V^H , V^A , V^0 , V^1 and V^2 are all small in 2016 and 2018, indicating that the results in Table 5 are robust. In comparison with the results in Table 5, after increasing the weight of the education dimension indicator from 1/8 to 1/5, the value of V^0 , V^1 and V^2 changes very little (see Table 12). Although with the increase of γ , the fluctuation range of V^H and V^A begins to increase, but as far as we choose $\gamma = 0.6$, the change in V^H and V^A is still relatively stable, indicating that the conclusions of this study are robust.

6 Conclusions

This study constructs an estimation framework to measure vulnerability to poverty from a multidimensional perspective for Chinese rural families based on a new VMPI method. On the basis of CFPS data from 2016 and 2018, we perform a VMPI estimation of rural China to investigate the multidimensional vulnerability headcount

Table 10 Indicator weights used for robustness checking

Dimension	Indicator	Weight 1	Weight 2	Weight 3	Original weight	Weight 4	Weight 5	Weight 6
Education	Adult education	1/5	1/6	1/7	1/8	4/33	7/60	1/9
	Out-of-school children	1/5	1/6	1/7	1/8	4/33	7/60	1/9
Living condition	Clean drinking water	1/15	2/27	5/63	1/12	8/99	7/90	2/27
	Cooking fuel	1/15	2/27	5/63	1/12	8/99	7/90	2/27
Health care	Family assets	1/15	2/27	5/63	1/12	8/99	7/90	2/27
	Adult nutrition	1/15	2/27	5/63	1/12	1/11	1/10	1/9
	Adult health	1/15	2/27	5/63	1/12	1/11	1/10	1/9
Subjective psychology	Medical security	1/15	2/27	5/63	1/12	1/11	1/10	1/9
	Life satisfaction	1/10	1/9	5/42	1/8	4/33	7/60	1/9
	Future confidence	1/10	1/9	5/42	1/8	4/33	7/60	1/9

Table 11 Results after adjusting the weights of health care dimension indicators

<i>k</i>	weight	γ	V^H	V^A	V^0	V^1	V^2	VPR	ORV
3/10	1/11 in 2016	0.6	0.4731 (0.0065)	0.4593 (0.0021)	0.2174 (0.0014)	0.0644 (0.0005)	0.0332 (0.0003)	6.4645	0.4000
		0.7	0.5989 (0.0063)	0.4765 (0.0020)	0.2854 (0.0015)	0.0856 (0.0006)	0.0439 (0.0004)	8.1831	0.5258
		0.8	0.7759 (0.0054)	0.4902 (0.0019)	0.3803 (0.0015)	0.1152 (0.0007)	0.0592 (0.0004)	10.5995	0.7027
1/10 in 2016	0.6	0.6	0.4732 (0.0064)	0.4595 (0.0020)	0.2174 (0.0014)	0.0637 (0.0005)	0.0325 (0.0003)	6.4645	0.4000
		0.7	0.5991 (0.0063)	0.4781 (0.0019)	0.2864 (0.0015)	0.0853 (0.0005)	0.0432 (0.0004)	8.1853	0.5260
		0.8	0.7765 (0.0053)	0.4938 (0.0018)	0.3835 (0.0015)	0.1154 (0.0006)	0.0587 (0.0004)	10.6087	0.7034
1/9 in 2016	0.6	0.6	0.4717 (0.0064)	0.4602 (0.0019)	0.2171 (0.0014)	0.0629 (0.0005)	0.0325 (0.0003)	6.4439	0.3985
		0.7	0.5982 (0.0063)	0.4804 (0.0018)	0.2873 (0.0016)	0.0848 (0.0005)	0.0423 (0.0003)	8.1716	0.5250
		0.8	0.7765 (0.0053)	0.4985 (0.0017)	0.3871 (0.0015)	0.1158 (0.0006)	0.0580 (0.0004)	10.6087	0.7033
1/11 in 2018	0.6	0.6	0.1573 (0.0047)	0.3946 (0.0017)	0.0621 (0.0007)	0.0420 (0.0005)	0.0159 (0.0002)	4.5144	0.1224
		0.7	0.2544 (0.0056)	0.4036 (0.0017)	0.1027 (0.0009)	0.0628 (0.0006)	0.0255 (0.0003)	7.3029	0.2196
		0.8	0.3902 (0.0063)	0.4185 (0.0016)	0.1633 (0.0011)	0.0878 (0.0007)	0.0383 (0.0004)	11.2019	0.3554

Table 11 (continued)

<i>k</i>	weight	γ	V^H	V^A	V^0	V^1	V^2	VPR	ORV
	1/10 in 2018	0.6	0.1585 (0.0047)	0.3966 (0.0017)	0.0628 (0.0008)	0.0421 (0.0005)	0.0159 (0.0002)	4.5481	0.1236
		0.7	0.2570 (0.0057)	0.4095 (0.0017)	0.1052 (0.0010)	0.0633 (0.0006)	0.0257 (0.0003)	7.3750	0.2221
		0.8	0.3941 (0.0063)	0.4286 (0.0015)	0.1689 (0.0012)	0.0888 (0.0007)	0.0387 (0.0004)	11.3125	0.3593
	1/9 in 2018	0.6	0.1585 (0.0047)	0.4002 (0.0018)	0.0634 (0.0008)	0.0422 (0.0005)	0.0158 (0.0002)	4.5481	0.1236
		0.7	0.2570 (0.0057)	0.4183 (0.0017)	0.1075 (0.0010)	0.0638 (0.0006)	0.0259 (0.0003)	7.3750	0.2221
		0.8	0.3941 (0.0063)	0.4428 (0.0015)	0.1745 (0.0013)	0.0900 (0.0007)	0.0392 (0.0004)	11.3125	0.3593

Table 12 Results after adjusting the weights of education dimension indicators

<i>k</i>	weight	γ	V^H	V^A	V^0	V^1	V^2	VPR	ORV
3/10	1/5 in 2016	0.6	0.4342 (0.0064)	0.4717 (0.0022)	0.2048 (0.0015)	0.0641 (0.0006)	0.0365 (0.004)	5.9314	0.3610
		0.7	0.5054 (0.0065)	0.4930 (0.0022)	0.2491 (0.0017)	0.0782 (0.0007)	0.0440 (0.0004)	6.9039	0.4322
		0.8	0.6025 (0.0063)	0.5109 (0.0022)	0.3078 (0.0018)	0.0971 (0.0007)	0.0543 (0.0005)	8.2311	0.5293
1/6 in 2016	0.6	0.6	0.4342 (0.0064)	0.4709 (0.0022)	0.2045 (0.0015)	0.0630 (0.0006)	0.0347 (0.0004)	5.9314	0.3610
		0.7	0.5054 (0.0065)	0.4967 (0.0021)	0.2510 (0.0017)	0.0780 (0.0006)	0.0427 (0.0003)	6.9038	0.4321
		0.8	0.6025 (0.0063)	0.5200 (0.0021)	0.3133 (0.0018)	0.0981 (0.0007)	0.0537 (0.0005)	8.2311	0.5293
1/7 in 2016	0.6	0.6	0.4799 (0.0065)	0.4558 (0.0021)	0.2187 (0.0014)	0.0657 (0.0005)	0.0349 (0.0003)	6.5561	0.4067
		0.7	0.5590 (0.0063)	0.4710 (0.0021)	0.2821 (0.0015)	0.0857 (0.0006)	0.0450 (0.0004)	8.1830	0.5258
		0.8	0.7748 (0.0054)	0.4800 (0.0020)	0.3719 (0.0015)	0.1136 (0.0006)	0.0596 (0.0004)	10.5858	0.7017
1/5 in 2018	0.6	0.6	0.1854 (0.0050)	0.3971 (0.0016)	0.0736 (0.0008)	0.0543 (0.0006)	0.0203 (0.0003)	5.3221	0.1506
		0.7	0.2221 (0.0054)	0.4168 (0.0017)	0.0926 (0.0009)	0.0702 (0.0007)	0.0284 (0.0004)	6.3750	0.1873
		0.8	0.2618 (0.0057)	0.4466 (0.0018)	0.1169 (0.0012)	0.0889 (0.0008)	0.0389 (0.0005)	7.5144	0.2270

Table 12 (continued)

k	weight	γ	V^H	V^A	V^0	V^1	V^2	VPR	ORV
	1/6 in 2018	0.6	0.1854 (0.0050)	0.3864 (0.0017)	0.0717 (0.0007)	0.0419 (0.0005)	0.0059 (0.0002)	5.3221	0.1506
		0.7	0.2221 (0.0054)	0.4106 (0.0018)	0.0912 (0.0009)	0.0689 (0.0006)	0.0277 (0.0003)	6.3750	0.1873
		0.8	0.2618 (0.0056)	0.4462 (0.0018)	0.1168 (0.0012)	0.0880 (0.0007)	0.0384 (0.0004)	7.5144	0.2270
	1/7 in 2018	0.6	0.2025 (0.0052)	0.3737 (0.0018)	0.0756 (0.0007)	0.0519 (0.0005)	0.0191 (0.0002)	5.8125	0.1668
		0.7	0.2779 (0.0058)	0.3884 (0.0018)	0.1079 (0.0009)	0.0684 (0.0006)	0.0274 (0.0003)	7.9760	0.2430
		0.8	0.3931 (0.0063)	0.4029 (0.0018)	0.1584 (0.0011)	0.0884 (0.0007)	0.0384 (0.0004)	11.2836	0.3583

ratio, average vulnerability intensity, adjusted multidimensional vulnerability gap, and quadratic gap to reveal the characteristics of rural families who are vulnerable to multidimensional poverty. In addition, we decompose the multidimensional vulnerability headcount ratio and the average vulnerability intensity by region to analyze the regional heterogeneity of vulnerability to poverty in rural China. A comparison of VMP and income poverty is proposed to illustrate the significant influence of considering vulnerability on poverty alleviation. The main conclusions are as follows.

First, the multidimensional vulnerability headcount ratio in rural China is much higher than the percentage of income poverty and multidimensional poverty. The multidimensional vulnerability headcount ratios in 2016 and 2018 are 47.32% and 15.67%, respectively. The proportions of income poverty are 6.57% and 2.96% in the same period, and the proportions of multidimensional poverty are 7.32% and 3.48%. The multidimensional vulnerability headcount ratio, the average multidimensional vulnerability intensity, the adjusted multidimensional vulnerability gap and quadratic gap dropped sharply from 2016 to 2018.

Second, the regional heterogeneities of poverty reduction are obvious. The ranking of multidimensional vulnerability headcount ratio from high to low in 2016 is western, central, eastern, and northeastern, whereas in 2018, it changes to central, western, eastern, and northeastern. The regional contribution rate to vulnerability headcount ratio is ordered from high to low as western, central, eastern, and northeastern in 2016 and 2018.

Third, the rural families who are income poor and vulnerable to being multidimensionally poor have decreased remarkably during the inspection period. The proportion of these families in rural China dropped from 5.63% in 2016 to 2.36% in 2018. And the ratios of eastern, central, western, and northeastern regions decreased from 3.85%, 5.54%, 8.12% and 2.37% in 2016 to 1.53%, 2.77%, 3.07% and 1.19% in 2018.

Fourth, the consideration of vulnerability to poverty is critical to the post-poverty era. Most income-poor families are also trapped in VMP status with the risk of remaining poor in future. Those families with dual identities are as high as 83.41% and 79.73% in 2016 and 2018. Furthermore, a certain part of the families who are vulnerable to multidimensional poverty come from non-poor or out-of-poor families.

Fifth, the sources of vulnerability of multidimensional poverty in China's rural areas are mainly reflected in three aspects: future confidence, adult health, and cooking fuel. The contribution rate of the three indicators to the overall vulnerability of multidimensional poverty exceeds 50%, and shows an upward trend. The contribution rate of the indicators of education dimension to vulnerability of multidimensional poverty is relatively low, all below 7%, and showing a downward trend.

On the basis of these findings, the policy applications are as follows. On one side, the identification of poverty in rural China should be changed from the single dimension of income to the multiple dimensions of non-monetary indicators such as education, life condition, health care, and psychology. The single standard of income poverty will exclude a large number of households who are vulnerable to multidimensional poverty, representing a hindrance to preventing people from becoming poor in the future. A reasonable approach to involve the vulnerable poor in anti-poverty assistance is to set a vulnerability standard beyond the income standard so that the people who are not income-poor but vulnerable to being multidimensionally poor can be identified

in the post-poverty era, which is characterized by relative poverty. This approach can help those people to fight against the risk of falling into poverty in the future. Thus, establishing a dynamic management mechanism for targeted poverty assistance in rural areas and incorporating the households who are vulnerable to multidimensional poverty into the relative poverty alleviation system are the major concerns of future anti-poverty policies for the Chinese government.

On the other side, poverty alleviation and assistance policies should be formulated based on the specific situations of different regions and provinces according to regional heterogeneity. The western region is still the focus of poverty alleviation work in the future, and vulnerability to dimensions such as education of adults and children, clean drinking water, nutrition, and confidence in life should be considered in designing anti-poverty policy there. Governors should take effective actions to narrow the gap between rural populations in western regions and others in terms of aspects such as social, economic, and development opportunities. Furthermore, risk management in poverty alleviation projects should be strengthened to improve the risk-resistant ability of rural families and reduce vulnerability to multidimensional poverty.

In addition, the enhancement of income in rural families is not always accompanied by the improvement of non-monetary welfare. In other words, the poverty alleviation policies purely aimed at raising incomes may not necessarily bring about effective improvements of welfare deprivation in other dimensions. Deprivations in factors such as using of clean energy and adult education in the structure of VMP are partially caused by the insufficient supply of public services from the government. The deprivation of subjective psychology is related to the lack of subjective initiative of the poor people and the social environment to a certain degree. Therefore, improving the social service system and consolidating the infrastructure construction in rural China is necessary to enhance the poverty assistance effect. For example, the following are useful in accelerating the anti-poverty process: increasing the promotion and use of clean energy in rural areas, the prevention of returning to poverty due to illness; and the supply of public services such as medical and healthcare, especially increasing the medical reimbursement ratio for those families who are not income poor but vulnerable to multidimensionally poor. At the same time, we should fully motivate some informal mechanisms such as “assistance for knowledge” and “excitation for courage” to play a significant role in reducing the vulnerability to multidimensional poverty in rural families. In addition, some soft measures, such as creating a fairer and more just environment and increasing the social participation of poor and vulnerable poor people, are very useful in promoting the profit sharing of reform and development and in enhancing the happiness and satisfaction of the VMP households in rural China.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

- Abraham RA, Kumar KSK (2008) Multidimensional poverty and vulnerability. *Econ Pol Wkly* 43:77–87
- Acemoglu D, Johnson S (2007) Disease and development: the effect of life expectancy on economic growth. *J Polit Econ* 115:925–985
- Alkire S, Fang Y (2019) Dynamics of multidimensional poverty and uni-dimensional income poverty: an evidence of stability analysis from China. *Soc Indic Res* 142:25–64. <https://doi.org/10.1007/s11205-018-1895-2>
- Alkire S, Foster J (2011) Counting and multidimensional poverty measurement. *J Public Econ* 95:476–487. <https://doi.org/10.1016/j.jpubeco.2010.11.006>
- Alkire S, Foster J, Seth S, Santos ME, Roche JM, Ballón AP (2015) *Multidimensional poverty measurement and analysis*. Oxford University Press, Oxford
- Alwang J, Siegel PB, Jorgensen SL (2001) Vulnerability as viewed from different disciplines
- Azeem MM, Mugeru AW, Schilizzi S (2018) Vulnerability to multi-dimensional poverty: an empirical comparison of alternative measurement approaches. *J Dev Stud* 54:1612–1636. <https://doi.org/10.1080/00220388.2017.1344646>
- Calvo C (2008) Vulnerability to multidimensional poverty: Peru, 1998–2002. *World Dev* 36:1011–1020. <https://doi.org/10.1016/j.worlddev.2007.10.001>
- Cao M, Xu D, Xie F, Liu E, Liu S (2016) The influence factors analysis of households' poverty vulnerability in southwest ethnic areas of China based on the hierarchical linear model: a case study of Liangshan Yi autonomous prefecture. *Appl Geogr* 66:144–152. <https://doi.org/10.1016/j.apgeog.2015.11.016>
- Celidoni M (2013) Vulnerability to poverty: an empirical comparison of alternative measures. *Appl Econ* 45:1493–1506. <https://doi.org/10.1080/00036846.2011.624271>
- Chang IS, Liu H, Wu J, Zhou C, Zheng L (2021) Process analysis of poverty eradication in China: a case study on photovoltaic projects for poverty alleviation. *Environ Impact Assess Rev* 90:106630. <https://doi.org/10.1016/j.eiar.2021.106630>
- Chaudhuri S, Jalan J, Suryahadi A (2002) *Assessing household vulnerability to poverty from cross-sectional data: a methodology and estimates from Indonesia discussion papers*
- Cheng M, Gai Q, Jin Y, Shi Q (2016) Human capital accumulation and farmer's income growth. *Econ Res J* 51:168–181
- Cherchye L, Ooghe E, Van Puyenbroeck T (2008) Robust human development rankings. *J Econ Inequal* 6:287–321. <https://doi.org/10.1007/s10888-007-9058-8>
- Coudouel A, Hentschel J (2000) *Poverty data and measurement preliminary draft for a sourcebook on poverty reduction strategies*
- Dercon S (2009) Rural poverty: old challenges in new contexts. *World Bank Res Obs* 24:1–28
- Dercon S, Krishnan P (2000) Vulnerability, seasonality and poverty in Ethiopia. *J Dev Stud* 36:25–53. <https://doi.org/10.1080/00220380008422653>
- Feeny S, McDonald L (2016) Vulnerability to multidimensional poverty: findings from households in Melanesia. *J Dev Stud* 52:447–464. <https://doi.org/10.1080/00220388.2015.1075974>
- Foster JE, McGillivray M, Seth S (2013) Composite indices: rank robustness, statistical association, and redundancy. *Economet Rev* 32:35–56. <https://doi.org/10.1080/07474938.2012.690647>
- Gallardo M (2013) Using the downside mean-semideviation for measuring vulnerability to poverty. *Econ Lett* 120:416–418. <https://doi.org/10.1016/j.econlet.2013.05.023>
- Gallardo M (2018) Identifying vulnerability to poverty: a critical survey. *J Econ Surv* 32:1074–1105
- Gallardo M (2019) Measuring vulnerability to multidimensional poverty. *Soc Indic Res* 148:67–103. <https://doi.org/10.1007/s11205-019-02192-y>
- Günther I, Harttgen K (2009) Estimating households vulnerability to idiosyncratic and covariate shocks: a novel method applied in Madagascar. *World Dev* 37:1222–1234. <https://doi.org/10.1016/j.worlddev.2008.11.006>
- Hoddinott J, Qisuumbing A (2010) *Methods for microeconomic risk and vulnerability assessments Social protection discussion papers and notes*
- Hohberg M, Landau K, Kneib T, Klasen S, Zucchini W (2018) Vulnerability to poverty revisited: flexible modeling and better predictive performance. *J Econ Inequal* 16:439–454. <https://doi.org/10.1007/s10888-017-9374-6>
- Hou Y (2017) Measurement decomposition and influencing factors analysis of long-term multidimensional poverty in Chinese rural areas. *Stat Res* 34:86–97

- Huang C-C, Jin H, Zhang J, Zheng Q, Chen Y, Cheung S, Liu C (2020) The effects of an innovative e-commerce poverty alleviation platform on Chinese rural laborer skills development and family well-being. *Child Youth Serv Rev* 116:105189. <https://doi.org/10.1016/j.chilyouth.2020.105189>
- Li G, Cai Z, Liu J, Liu X, Su S, Huang X, Li B (2019a) Multidimensional poverty in Rural China: indicators, spatiotemporal patterns and applications. *Soc Indic Res* 144:1099–1134. <https://doi.org/10.1007/s11205-019-02072-5>
- Li F, Zhang Y, Zheng X (2020) Evaluation of the effect of precision poverty alleviation policies based on the micro data of the poor population. *Econ Res J* 55:171–187
- Li X, Qi W, Tan C, Wang Y, Wang B (2019b) The measurement and spatial distribution of rural families' vulnerability to multidimensional poverty—an empirical analysis based on CHNS data High-tech communications 29: 1136–1147 (in Chinese)
- Meyer BD, Mok WKC (2019) Disability, earnings, income and consumption. *J Public Econ* 171:51–69. <https://doi.org/10.1016/j.jpubeco.2018.06.011>
- Nasri K, Belhadj B (2018) Measuring vulnerability to multidimensional poverty in Tunisia: dual cut-off method and Fuzzy Sets approach Working Papers
- Novignon J, Nonvignon J, Mussa R, Chiwaula LS (2012) Health and vulnerability to poverty in Ghana: evidence from the Ghana living standards survey round 5. *Health Econ Rev* 2:11. <https://doi.org/10.1186/2191-1991-2-11>
- OPHI (2018) Global Multidimensional poverty index 2018: the most detailed picture to date of the world's poorest people. Oxford Poverty and Human Development Initiative (OPHI), University of Oxford
- Ozughalu UM (2016) Relationship between household food poverty and vulnerability to food poverty: evidence from Nigeria. *Soc Indic Res* 125:567–587. <https://doi.org/10.1007/s11205-014-0845-x>
- Permyanier I (2011) Assessing the robustness of composite indices rankings. *Rev Income Wealth* 57:306–326
- Pinar M, Stengos T, Topaloglou N (2013) Measuring human development: a stochastic dominance approach. *J Econ Growth* 18:69–108. <https://doi.org/10.1007/s10887-012-9083-8>
- Pinar M, Stengos T, Topaloglou N (2020) On the construction of a feasible range of multidimensional poverty under benchmark weight uncertainty. *Eur J Oper Res* 281:415–427. <https://doi.org/10.1016/j.ejor.2019.08.047>
- Pritchett L, Suryahadi A, Sumarto S (2000) Quantifying vulnerability to poverty: a proposed measure, applied to Indonesia working paper
- Robles Aguilar G, Sumner A (2020) Who are the world's poor? A new profile of global multidimensional poverty. *World Dev*. <https://doi.org/10.1016/j.worlddev.2019.104716>
- Sawada Y, Lokshin M (2001) Household schooling decisions in Rural Pakistan policy research working paper series:34
- Wang X, Feng H, Xia Q, Alkire S (2016) On the relationship between Income poverty and multidimensional poverty in China OPHI Working Paper 101
- Ward PS (2016) Transient poverty, poverty dynamics, and vulnerability to poverty: an empirical analysis using a balanced panel from Rural China. *World Dev* 78:541–553. <https://doi.org/10.1016/j.worlddev.2015.10.022>
- Xie E (2020) Multidimensional deprivation and income poverty in China. *Chin J Popul Sci*: 87–99+128
- Xu D, Peng L, Liu S, Su C, Wang X, Chen T (2017) Influences of migrant work income on the poverty vulnerability disaster threatened area: a case study of the three Gorges reservoir area, China. *Int J Disaster Risk Reduct* 22:62–70. <https://doi.org/10.1016/j.ijdr.2017.03.001>
- Yang J, Mukhopadhyaya P (2019) Is the ADB's conjecture on upward trend in poverty for China right? An analysis of income and multidimensional poverty in China. *Soc Indic Res* 143:451–477. <https://doi.org/10.1007/s11205-018-1985-1>
- Yang L, Li M, Lu H (2019) Vulnerability to multidimensional poverty and risk management of farmers in deep poverty areas. *J South China Normal Univ (Soc Sci Edn)* 6:12–18
- Yang Y, de Sherbinin A, Liu Y (2020) China's poverty alleviation resettlement: progress, problems and solutions. *Habitat Int* 98:1021. <https://doi.org/10.1016/j.habitatint.2020.102135>
- Youden WJ (1950) Index for rating diagnostic tests. *Cancer* 3:32–35
- Yu R, Liang L, Su X, Cheng J (2020) A driver based framework for vulnerability assessment of the poverty stricken areas of Funiu mountain. *China Ecol Indic* 113:106209. <https://doi.org/10.1016/j.ecolind.2020.106209>
- Zhang X, Yao S (2020) Multidimensional poverty in rural China from 2010 to 2018: distribution and characteristics issues in agricultural economy. *Econ Lett* 204:109912

- Zhang Q, Zhou Q (2014) On the dynamic multidimensional measurement and decomposition of China's poverty: 1989–2014. *J Quant Tech Econ* 6:88–101
- Zhang H, Xu Z, Sun C, Elahi E (2018) Targeted poverty alleviation using photovoltaic power: review of Chinese policies. *Energy Policy* 120:550–558. <https://doi.org/10.1016/j.enpol.2018.06.004>
- Zhang Q, Li B, Zhou Q (2019) Poverty characteristics and dynamic transformation in Chinese rural areas: a comparative analysis of income poverty and multidimensional poverty issues in agricultural economy, pp. 31–42

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