




Influencing factors and efficiency of funds in humanitarian supply chains: the case of Chinese rural minimum living security funds

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Abstract

While humanitarian efforts are critical for assisting those affected by natural disasters, it is also essential for those affected by poverty, such as China's rural poor. In this regard, China introduced the rural minimum living security system to provide humanitarian relief to its rural poor. The aim of this study is to explore the influencing factors and efficiency of humanitarian supply chains funds using rural minimum living security funds (RMLSF) as an example. Based on data from 31 provinces (autonomous regions and municipalities) in China from 2007 to 2016, this study employs the logarithmic mean Divisia index approach to decompose the RMLSF and investigates the contributions of seven factors on the change therein. This study also uses the three-stage data envelopment analysis method to assess the poverty reduction efficiency of RMLSF. The results show that the economic development level, the extent to which minimum living security funds are tilted toward rural areas, and the fiscal expenditure scale are the three main factors for the increase in RMLSF. Moreover, the technical efficiency in most provinces and the average technical efficiency in the eastern and central regions are underestimated due to external ambient factors, whereas the average technical efficiency in the western region is overestimated. These results provide a basis for increasing the scale and efficiency of RMLSF.

Keywords Humanitarian supply chains · Rural minimum living security funds · Poverty reduction efficiency · LMDI decomposition · Three-stage DEA

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1 Introduction

With the rising frequency of disasters (Jabbour et al. 2019), an increasing number of people are being affected directly or indirectly, and the economy is suffering huge losses (Yadav and Barve 2015; Celik and Gumus 2015). Humanitarian relief is conducive to reducing the negative impacts of disasters. Humanitarian relief can be defined as governments, non-governmental organizations, and other institutions that provide human, financial, and material resources to people in affected areas. Disasters can be broadly divided into four types: calamities, destructive actions, plagues, and crises; poverty belongs to the category of plagues (Cozzolino 2012). Therefore, helping alleviate poverty is also an important objective of humanitarian relief.

In China, the poor are primarily concentrated in rural areas (Yao et al. 2004; Chen et al. 2019; Kakwani et al. 2019). Since the reform and opening-up, China has seen a rapid growth of economy. The living standards of people have risen, and rural poverty alleviation work has also yielded remarkable achievements. The poor population in rural areas has significantly decreased (Ravallion and Chen 2007), and their proportion has dropped from 96.2% in 1980 to 4.5% in 2016 (Ben 2018). Nevertheless, the rural poor population is still large. As of the end of 2019, there were 5.51 million rural poor people in China (State Statistical Bureau 2020). Achieving the target of eliminating absolute poverty by 2020 is a serious challenge (Liu et al. 2017). Therefore, rural poverty remains a crucial issue (Chen et al. 2016; Zhao et al. 2017), and it is particularly important to implement humanitarian relief to the rural poor in the country.

To provide humanitarian relief to this section, Chinese government introduced the rural minimum living security system in 2007. In light of the gap between the income per head of a family and the standard of minimum living security, the government subsidizes the rural households whose revenue per head is below this standard in cash; thus, the beneficiaries' income level can reach the benchmark of the minimum living security to ensure their basic survival needs. Instead of using all of their money for these needs, families receiving the payment could both improve their living standards and achieve long-term financial stability by investing part of their subsidized income in production activities (Gertler et al. 2012).

Since the comprehensive execution of the rural minimum living security system, the government's investment in it has risen year by year, the scale of rural minimum living security funds (RMLSF) has been expanding, the rural minimum living security standard has also been constantly improving, and the number of guaranteed objects shows a rising trend followed by decline. According to statistics from the Ministry of Civil Affairs (MOCA), at the end of 2007, 16.085 million households and 35.663 million people were covered by the rural minimum living security, the average minimum living security standard was 840 yuan per person per year, and a total of 10.91 billion yuan was granted throughout the year (MOCA 2008). As of the end of 2016, 26.353 million households and 45.865 million people were covered by the rural minimum living security, the annual expenditure of public finance at all levels on rural minimum living security was 101.45 billion yuan, and the national average standard in 2016 was 3744.0 yuan per person per year (MOCA 2017). At present, the rural minimum living security system is at the core of the Chinese poverty alleviation strategy (Golan et al. 2017) and is one of the world's biggest unconditional cash transfer projects (World Bank 2014; Golan et al. 2015, 2017; Ravallion and Chen 2015). The government is one of the main players in disaster relief (Duran et al. 2013). Therefore, it is undoubted that the Chinese government sectors play a vital role in poverty reduction.

During humanitarian relief operations, managers need to arrange transport for personnel and materials donated to the disaster areas and allocate them to the affected groups. Therefore, humanitarian supply chains play a critical part in these operations (Abidi et al. 2014) and are a kind of rescue network composed of material flow, service flow, capital flow, and information flow (Mentzer et al. 2001). Changes in funding are related to the improvement of humanitarian logistics performance and the recovery in affected areas (Jahre and Heigh 2008). Therefore, capital flow is indispensable, such as the flow of RMLSF from the government to the rural poor. As the provider of RMLSF, the government should not only pay attention to its amount, but also to the factors that affect the provision of RMLSF. This is important because it will influence the government's ability to provide humanitarian assistance to the rural poor. Exploring the influencing factors of RMLSF will help us understand its influencing mechanism better and explore ways to increase the input of RMLSF. Moreover, the contradiction between the scarcity of public financial resources and the growing demand for public financial expenditures puts the government under more pressure to do more with less money (Notten 2016). Therefore, the Chinese government should also be heedful of the poverty reduction efficiency (PRE) of the RMLSF. Evaluating the PRE of the RMLSF can reveal to what extent the government meets its expected poverty reduction goals, thus reducing wastefulness and improving target accuracy and policy effectiveness (Kakwani et al. 2019). Thus, exploring the influencing factors and efficiency of RMLSF is helpful for the Chinese government to implement humanitarian assistance for the rural poor better, so as to promote the harmonious and effective development of society.

In view of this, it is greatly practical importance to conduct a deep empirical analysis of the influencing factors of the RMLSF and its PRE. Thus, the research objective of this study is to explore the influencing factors and efficiency of humanitarian supply chain funds by taking RMLSF as an example. Specifically, this study uses the logarithmic mean Divisia index (LMDI) decomposition approach to investigate the factors impacting the RMLSF and investigate the contribution of each factor to the change therein. The three-stage data envelopment analysis (DEA) efficiency evaluation approach is employed to estimate the PRE of Chinese RMLSF to reveal its current allocation and offer a scientific basis for further optimizing the allocation and improving the PRE of RMLSF. The research questions of this study are: (1) what effects do the extent to which minimum living security funds are tilted toward rural areas, the structure of fiscal expenditure, the scale of fiscal expenditure, the economic development level, the degree of population aging, the regional distribution of the elderly, and the scale of the national elderly population have on the change in the RMLSF? (2) What is the PRE of RMLSF? (3) What are the effects of ambient factors on the efficiency of RMLSF?

2 Literature review

Since 2005, the humanitarian supply chains have attracted increasing attention from the academic community (Kovács and Spens 2010). Humanitarian supply chains are complex and extensive relief networks and scholars have placed great emphases on these chains.

As humanitarian supply chains involve many actors such as governments, non-profit organizations, and private enterprises, absence of coordination among the participants will seriously affect the effective implementation of rescue operations, and disaster-affected populations may suffer for longer (Jin et al. 2015). Thus, coordination among participants is vital for the success of humanitarian relief operations (Moore et al. 2003; Dubey et al. 2019a,

b). Research has addressed the coordination mechanisms among various participants in the humanitarian supply chains. For example, Balcik et al. (2010) describe the coordination mechanism that has been practiced in disaster rescue operations, as well as the relevant challenges. Kabra and Ramesh (2015) list 23 obstacles in the management of humanitarian supply chains and propose 15 solutions according to priority. Kabra et al. (2015) divide coordination related obstacles of humanitarian supply chains into five aspects: management, technology, culture, personnel, and organization.

Most humanitarian relief is targeted toward sudden and unpredictable disasters, which requires high agility in humanitarian supply chains. The more agile the humanitarian relief, the less economic and human losses the affected area will suffer. Therefore, some scholars have focused on the agility of humanitarian supply chains. For example, Dubey and Gunasekaran (2016) argue that agility is one of the three important features of humanitarian supply chains. Tatham et al. (2010) exploit a framework to define the agility of humanitarian supply chains and create a model, based on the humanitarian method, to assess agility. Through multivariate analysis, Dubey et al. (2014) find that agility had a significant effect on the performance of humanitarian supply chains before and after a disaster. Yadav and Barve (2015) identify 12 critical success factors that lead to a rapid humanitarian response and analyze the interdependence among these factors by using the interpretive structural modeling approach. The results show that the administration's policies and organizational structures are the most important driving factors.

Some scholars have compared humanitarian and commercial supply chains and have found similarities as well as significant diversities between them (Oloruntoba and Gray 2006). For instance, Olaogbebikan and Oloruntoba (2019) argue that they are similar in concept and theory. Meanwhile, Tomasini and Van Wassenhove (2009) and Bhattacharya et al. (2014) identify one difference as goal orientation; humanitarian supply chains are oriented toward a non-profit goal, while commercial supply chains are oriented toward a profit goal. Other scholars such as Altay and Labonte (2014) explore the challenges faced by the information flow in humanitarian supply chains and propose possible solutions.

To sum up, the existing research on humanitarian supply chains mainly focuses on coordination mechanisms among various actors, agility, information flow, and comparisons with commercial supply chains. Measuring and managing performance is essential to ensure an effective and efficient humanitarian supply chain, but few studies have focused on this aspect (Abidi et al. 2014). Research on the influencing factors and efficiency of funds in humanitarian supply chains is even scarcer.

Moreover, humanitarian relief includes not only emergency disaster relief, but also continuous relief (Venkatesh et al. 2014). Compared with sudden disasters such as earthquakes and tsunamis, poverty is persistent. Humanitarian relief to alleviate poverty requires continuous aid. China's rural minimum living security is a continuous aid project that the government provides humanitarian assistance to the rural poor. It plays a significant role in guaranteeing the fundamental living needs of the poor and can significantly alleviate poverty (Wu and Ramesh 2014; Gao et al. 2015). Most existing works on the minimum living security system mainly focus on its targeting efficiency (Wang 2007; Gustafsson and Deng 2011), the minimum living security standard (Yao 2012; Chen et al. 2019), the impact of minimum living security on household expenditure (Gao et al. 2010, 2014; Zhao et al. 2017), and the impact of fiscal decentralization on minimum living standard security funds (Qian and Roland 1998; Chen and Li 2018). However, significant gaps remain: first, few studies examine the influence of the extent to which minimum living security funds are tilted toward rural areas, the structure of fiscal expenditure, the scale of fiscal expenditure, the economic development level, the degree of population aging, the regional distribution of the elderly, and the scale

of the national elderly population on RMLSF. Second, the existing literature mostly studies the efficiency of minimum living security from the perspective of targeting efficiency, while relatively few studies examine the PRE from the perspective of minimum living security funds based on the input and output.

In contrast to other studies, ours focuses on the influencing factors and efficiency of funds of continuous aid programs in humanitarian supply chains by taking RMLSF as an example. This study makes four main contributions. First, we deem that continuous poverty alleviation projects like the rural minimum living security should be included in the investigation of humanitarian supply chain management. Most of the existing literature on this subject emphasize on sudden disasters, while few studies focus on the continuous relief projects. Second, this study examines the influencing factors and efficiency of funds in humanitarian supply chains, which have not been focused on in the existing literature, from the perspective of RMLSF. Third, in this study, we examine the effects of the extent to which minimum living security funds are tilted toward rural areas, the structure of fiscal expenditure, the scale of fiscal expenditure, the economic development level, the degree of population aging, the regional distribution of the elderly, and the scale of the national elderly population on RMLSF by employing the LMDI decomposition approach. Finally, this study calculates the PRE of RMLSF based on input–output by employing three-stage DEA approach, which is able to strip out the impacts of the ambient factors and random factors.

3 Methods and data

3.1 LMDI decomposition approach

The RMLSF is critical for guaranteeing the fundamental needs of the rural poor. This study uses the LMDI approach to decompose the RMLSF in China and analyzes the contribution of each factor to the change in the RMLSF to explore ways of expanding its scale. In recent years, the factor decomposition approach has been increasingly and extensively employed to analyze the changing characteristics of research objects and their influence mechanisms. The results decomposed by previous methods have residual terms, which are often unexplainable. The LMDI decomposition approach can make up for the shortcomings of previous decomposition methods and achieve non-residual decomposition of influencing factors (Ang 2015) without considering the endogenous problem. In addition, even if there are zero values in the data set, this method will not present calculative problems (Ang et al. 1998). Due to the above features, this method has been extensively employed in the domain of energy and environment (Yang et al. 2016; Chen et al. 2018) and has been the preferred method in the field of index decomposition analysis since 2000 (Ang 2015); yet, it is seldom used in the domain of humanitarian supply chains. Thus, this study employs the LMDI decomposition approach to decompose China's RMLSF into seven factors. The decomposition model is as follows:

$$RMLSE = \sum_i \frac{RMLSE_i}{MLSE_i} \times \frac{MLSE_i}{FE_i} \times \frac{FE_i}{GDP_i} \times \frac{GDP_i}{P_i} \times \frac{P_i}{AP_i} \times \frac{AP_i}{AP} \times AP \quad (1)$$

where i means province (autonomous regions, municipalities) i ; $RMLSE_i$ denotes the total amount of RMLSF of province i ; $MLSE_i$ denotes the total amount of minimum living security funds of province i ; FE_i denotes the total fiscal expenditure of province i ; GDP_i denotes the gross domestic product of province i ; P_i denotes the total population of province i ; AP_i denotes the population aged 65 and older in province i ; and AP denotes the population

aged 65 and older nationwide. Moreover, $\frac{RMLSE_i}{MLSE_i}$ indicates the proportion of RMLSF in the total amount of minimum living security funds in province i , reflecting the extent to which the local minimum living security funds are tilted toward rural areas. The higher the proportion, the more the local minimum living security funds are tilted toward rural areas. $\frac{MLSE_i}{FE_i}$ indicates the proportion of the minimum living security funds in the total fiscal expenditure in province i , reflecting the fiscal expenditure structure of the region. $\frac{FE_i}{GDP_i}$ indicates the proportion of fiscal expenditure in the GDP in province i , which reflects the scale of fiscal expenditure in the district. The larger the proportion, the larger the scale of fiscal expenditure in the region. $\frac{GDP_i}{P_i}$ indicates the per capita GDP of province i , which shows the economic development level of the district. The larger the value, the higher the level of economic development of the district. $\frac{P_i}{AP_i}$ indicates the ratio of the total population to the elderly population aged 65 and older in province i , which shows the extent of population aging in the district. The smaller the ratio, the more serious the extent of population aging in the district. $\frac{AP_i}{AP}$ indicates the ratio of the number of the elderly aged 65 and older in province i to that in the country, reflecting the regional distribution of the elderly. AP indicates the number of the elderly aged 65 and older nationwide, reflecting the size of the elderly population in China.

For simplicity, let $\frac{RMLSE_i}{MLSE_i} = URS_i$, $\frac{MLSE_i}{FE_i} = FES_i$, $\frac{FE_i}{GDP_i} = SFE_i$, $\frac{GDP_i}{P_i} = PGDP_i$, $\frac{P_i}{AP_i} = AS_i$, and $\frac{AP_i}{AP} = APD_i$. Then Eq. (1) can be reformulated as:

$$RMLSE = \sum_i URS_i \times FES_i \times SFE_i \times PGDP_i \times AS_i \times APD_i \times AP. \quad (2)$$

The LMDI approach has two decomposition forms: addition and multiplication. Ang (2015) indicates that, in general, it is more appropriate to use multiplication decomposition for intensity indicator and addition decomposition for quantity indicator. Moreover, the results of addition decomposition and multiplication decomposition can be converted into each other. This study decomposes the quantity indicator of RMLSF. Thus, this study uses the addition form of LMDI decomposition approach to decompose the RMLSF:

$$\begin{aligned} \Delta RMLSE &= RMLSE^T - RMLSE^0 \\ &= \Delta RMLSE_{URS} + \Delta RMLSE_{FES} + \Delta RMLSE_{SFE} \\ &\quad + \Delta RMLSE_{PGDP} + \Delta RMLSE_{AS} + \Delta RMLSE_{APD} + \Delta RMLSE_{AP} \end{aligned} \quad (3)$$

where $RMLSE^0$ and $RMLSE^T$ represent the scale of RMLSF in the base period and reporting period, respectively. $\Delta RMLSE$ demonstrates the increase in RMLSF from the base period to the reporting period. Moreover, $\Delta RMLSE_{URS}$, $\Delta RMLSE_{FES}$, $\Delta RMLSE_{SFE}$, $\Delta RMLSE_{PGDP}$, $\Delta RMLSE_{AS}$, $\Delta RMLSE_{APD}$, and $\Delta RMLSE_{AP}$ represent the changes in the RMLSF caused by the change in the extent to which minimum living security funds are biased toward rural areas, the structure of regional fiscal expenditure, the regional fiscal expenditure scale, the regional per capita GDP, the degree of regional population aging, the regional distribution of the elderly population, and the scale of the elderly population nationwide, respectively. The expressions of $\Delta RMLSE_{URS}$, $\Delta RMLSE_{FES}$, $\Delta RMLSE_{SFE}$, $\Delta RMLSE_{PGDP}$, $\Delta RMLSE_{AS}$, $\Delta RMLSE_{APD}$, and $\Delta RMLSE_{AP}$ are presented as Eqs. (4)–(10):

$$\Delta RMLSE_{URS} = \sum_i L(RMLSE_i^T, RMLSE_i^0) \ln \left(\frac{URS_i^T}{URS_i^0} \right), \quad (4)$$

$$\Delta RMLSE_{FES} = \sum_i L(RMLSE_i^T, RMLSE_i^0) \ln \left(\frac{FES_i^T}{FES_i^0} \right), \quad (5)$$

$$\Delta RMLSE_{SFE} = \sum_i L(RMLSE_i^T, RMLSE_i^0) \ln \left(\frac{SFE_i^T}{SFE_i^0} \right), \quad (6)$$

$$\Delta RMLSE_{PGDP} = \sum_i L(RMLSE_i^T, RMLSE_i^0) \ln \left(\frac{PGDP_i^T}{PGDP_i^0} \right), \quad (7)$$

$$\Delta RMLSE_{AS} = \sum_i L(RMLSE_i^T, RMLSE_i^0) \ln \left(\frac{AS_i^T}{AS_i^0} \right), \quad (8)$$

$$\Delta RMLSE_{APD} = \sum_i L(RMLSE_i^T, RMLSE_i^0) \ln \left(\frac{APD_i^T}{APD_i^0} \right), \quad (9)$$

$$\Delta RMLSE_{AP} = \sum_i L(RMLSE_i^T, RMLSE_i^0) \ln \left(\frac{AP^T}{AP^0} \right). \quad (10)$$

If $RMLSE_i^T \neq RMLSE_i^0$, then $L(RMLSE_i^T, RMLSE_i^0) = \frac{RMLSE_i^T - RMLSE_i^0}{\ln(RMLSE_i^T) - \ln(RMLSE_i^0)}$;
if $RMLSE_i^T = RMLSE_i^0$, then $L(RMLSE_i^T, RMLSE_i^0) = RMLSE_i^T = RMLSE_i^0$.

The objective of this study is to analyze the influencing factors and efficiency of humanitarian supply chains funds by taking RMLSF as an example. The LMDI approach is employed to explore the influencing factors of RMLSF. The three-stage DEA is utilized to estimate the PRE of RMLSF. The advantages and principles of this method are mentioned in Sect. 3.2.

3.2 Three-stage DEA model

The government ought to attach importance to the PRE of RMLSF when making use of the rural minimum living security to implement humanitarian relief to the rural poor. There are two reasons for this. One is that due to the scarcity of resources, the entire society is under pressure to do as many things as possible with the least resources, and the government is no exception. The other is that donors associated with humanitarian relief operations are becoming increasingly concerned about the use of donated funds and whether the rescue goals have been reached (Wei et al. 2019). The RMLSF are provided by the government, and the government's financial funds are mainly derived from tax revenue. Therefore, the rural minimum living security is essentially the government using taxpayers' money to help the rural poor. Taxpayers are concerned about the use and efficiency of the money they pay. Therefore, out of the responsibility to taxpayers, the government departments should seek to improve the PRE of the RMLSF.

The DEA approach is a non-parametric method (Pahlavan et al. 2012), and thus, it is unnecessary to set specific function forms (Kohl et al. 2019; Ouenniche and Carrales 2018) and the selection of input and output variables is flexible. Therefore, the DEA method has been extensively employed in the field of efficiency evaluation (Ding et al. 2017) and is one of the most commonly used models for evaluating the efficiency of economic subjects (Musa et al. 2020). For example, Liu et al. (2019) and Wang et al. (2020) use this approach to assess the innovation efficiency of manufacturing enterprises and the marine environmental efficiency of provinces and cities, respectively. However, the disadvantage of the traditional DEA model

lies in its neglect of the influence of ambient variables and random errors on efficiency values, and hence, the calculated efficiency values include the effect of the external environments and random errors. To remedy the shortcoming of the traditional DEA model and assess the efficiency of the decision-making unit (DMU) better, Fried et al. (2002) combine the DEA method with the stochastic frontier approach (SFA) and propose a three-stage DEA model. A significant merit of this model is its ability to exclude the effect of ambient factors and random errors on the efficiency of DMU; thus, the calculated efficiency value can genuinely reveal the internal management level of DMU. The construction of the three-stage DEA model is shown in “Appendix A”.

3.2.1 Input and output variables

This section estimates the PRE of the RMLSF in each province. Therefore, the RMLSF invested by the government is selected as the input indicator, and the rural minimum living security population and the income per head of the residents in the countryside are selected as the output indicators.

3.2.2 Ambient variables

According to Simar and Wilson (2007), the ambient variables should generally be selected from those factors that are not within the controllable range of the DMU but have an effect on the PRE of the RMLSF. The existing literature mostly chooses ambient indicators from three aspects: macroeconomic environment, social environment, and policy environment. In line with this idea, this study chooses ambient variables that affect the PRE of the RMLSF in different regions from the three aspects mentioned above.

Changes in income differences, migration opportunities for the poor, and ecological environment brought about by macroeconomic growth will all have a certain impact on poverty (World Bank 2001), which will influence the PRE of RMLSF. Therefore, this study selects the per capita GDP to represent the macroeconomic environmental variable of each region. The accumulation of human capital is closely related to the ability of residents in the countryside to master and use advanced technology and skills, which will affect the use of RMLSF and its efficiency of poverty alleviation. Therefore, this study chooses the average educational years of rural residents as the social environmental variable of each region. The implementation of the minimum living security is restricted by the local public finance (Golan et al. 2017). The government usually determines the quota of minimum living security funds according to the scale of available funds (Ben 2018). Under the restriction of the government’s available funds, relevant departments cannot determine the amount of the RMLSF in accordance with the actual needs of each rural poor person but can only roughly divide them into different levels according to their poverty degree and pay different amounts of RMLSF based on their poverty levels. Therefore, to some extent, the scale of the government’s available funds will have an impact on the PRE of the RMLSF. The scale of public finance revenue can measure the scale of the government’s available funds. Therefore, this study chooses the scale of the government’s public finance revenue as the policy environmental variable of each region.

3.3 Data sources and explanations

Although China initially implemented the rural minimum living security system to help the poor in the countryside as early as the early 2000s (Kakwani et al. 2019), it was not extended

to rural areas throughout the country until 2007, hence the comprehensive data related to rural minimum living security can only be traced back to 2007. In consideration of the data availability, the period examined in this study is 2007–2016.

This study regards the population living on rural minimum living security as the rural poor. The data of the rural poor in 31 provinces (autonomous regions, municipalities) are derived from China's Civil Affairs Statistics Yearbook (2008–2017), and the data of urban minimum living security funds and RMLSF in all provinces are from the Quarterly Report of Civil Affairs Statistics of the MOCA (Provincial Level) (2007–2016). These data are widely employed in studies about minimum living security. For instance, Golan et al. (2017) use these data to match CHIP data and explore the influence of rural minimum living security on poverty. The minimum living security funds are equal to the sum of urban minimum living security funds and RMLSF.

In this paper, the elderly refers to the people aged 65 and over. The number of the elderly in each province is calculated by multiplying the total population of each region with the proportion of the elderly in the total population. The data for this proportion are taken from the China Statistical Yearbook (2008–2017). The average educational years of the residents in the countryside in each province was obtained by adding the product of the population corresponding to each educational background and the corresponding educational years and then dividing it by the number of people aged six years and over. The educational years for the categories of not attending school, finishing elementary school, finishing junior middle school, and finishing senior high school are 0, 6, 9, and 12 years, respectively, and the educational years of junior college and higher education are the average educational years of junior college education, undergraduate education, and graduate education, which are 15, 16, and 19 years, respectively. The data are taken from the China Population and Employment Statistics Yearbook (2008–2017). The relevant data in the China Statistical Yearbook and China Population and Employment Statistics Yearbook are statistically analyzed by the National Statistical Bureau. The statistical data collected by the National Statistical Bureau are extensively employed by policy makers, international institutions, and scholars (Gustafsson et al. 2014).

The data of each province's general public budget expenditure and revenue, GDP, gross output value of agriculture, forestry, animal husbandry and fishery, rural population, and total population are all from the China Economic Information Network-Statistical Database.¹ With abundant data resources and complete historical data, this database is essential for beneficiaries such as research institutions, economic and management institutions, and universities. The GDP per capita in each province is estimated by the ratio of the GDP to the total population. The income per head level of the residents in the countryside in each province is gauged by the ratio of the total output value of agriculture, forestry, animal husbandry, and fishery to the number of residents in the countryside of each province. The scale of provincial public budget revenue is measured by the proportion of the general public budget revenue in the GDP.

4 Results and discussion

4.1 LMDI decomposition results

With respect to the absolute change in the RMLSF during 2007–2016 (see Table 1), China's RMLSF increased by 88,021.23 million yuan, including 20,767.54 million yuan in the eastern region, 25,988.75 million yuan in the midlands, and 41,264.94 million yuan in the western

¹ For details, please see <http://10.8.30.179:91/page/Default.aspx>.

Table 1 LMDI decomposition results of RMLSF change (2007–2016) (Unit: 10,000 yuan)

	China	East	Central	West
$\Delta RMLSE$	8,802,123.3	2,076,754.4	2,598,875.4	4,126,493.5
$\Delta RMLSE_{URS}$	2,881,671.35	538,272.27	999,007.22	1,344,391.86
$\Delta RMLSE_{FES}$	266,899.14	35,921.02	− 65,447.10	296,425.22
$\Delta RMLSE_{SFE}$	1,515,161.19	449,382.98	445,531.25	620,246.96
$\Delta RMLSE_{PGDP}$	3,952,497.31	965,321.61	1,181,039.37	1,806,136.34
$\Delta RMLSE_{AS}$	− 578,880.56	− 141,460.66	− 205,251.50	− 232,168.40
$\Delta RMLSE_{APD}$	− 22,191.22	− 3399.92	3759.67	− 8003.17
$\Delta RMLSE_{AP}$	786,966.08	232,717.09	240,236.49	299,464.69

Data Sources: The results are calculated by the authors by using the data of RMLSF, minimum living security funds, general public budget expenditure, GDP, total population, the elderly population, the national elderly population data in 31 provinces (autonomous regions, municipalities) according to the LMDI decomposition approach in the research of Ang (2015). The detailed sources of each data can be found in Sect. 3.3

region. Therefore, the absolute term shows that the government in China attaches increasing importance to the basic security role of RMLSF for poor residents in the countryside, and the new input of RMLSF is more biased toward the underdeveloped regions in the midlands and western areas. According to Liu and Xu (2016) and Liu et al. (2017), the poor in China are primarily centered on the remote mountains, frontiers, and minority nationality regions in the midlands and western areas. Therefore, the direction of RMLSF coincides with the spatial distribution features of the rural poor in China. This is similar to the Central Emergency Response Fund of the United Nations. It tends to provide humanitarian relief funds to poor countries suffering from more natural disasters (Robinson et al. 2017), and similarly, the Chinese government, when providing RMLSF to rural residents, tends to favor the underdeveloped areas in the central and western China where the poverty problem is more serious. In addition, although humanitarian relief stresses the principle of fairness (Anaya-Arenas et al. 2018), we should also take the spatial distribution of victims into consideration and arrange the relief funds reasonably and pertinently, rather than blindly emphasizing fairness.

From 2007 to 2016, the changes in RMLSF caused by the changes in the extent to which minimum living security funds are tilted toward rural areas, the structure of fiscal expenditure, the scale of fiscal expenditure, the economic development level, the degree of population aging, the regional distribution of the elderly, and the scale of the national elderly population are shown in Table 1.

From a comparison of the contribution of each influencing factor to the change in the RMLSF (see Fig. 1), whether nationwide or in the eastern, central and western areas of China, the increase in the economic development level is the chief cause for the increase in the RMLSF. Its contribution is 44.90% in the whole country, 46.48% in the eastern area, 45.55% in the central area, and 43.77% in the western area. It is thus clear that in more developed areas, economic development level makes greater contributions to the increase in RMLSF. The conclusion that economic growth will promote the increase in RMLSF is consistent with the Wagner's Law. According to Wagner's Law, as the per capita income increases, the absolute scale and the relative scale of the government public expenditure will increase, and the RMLSF are shared by the central and provincial governments. Therefore, the high-speed economic growth will promote the growth of RMLSF.

The second major factor contributing to the increase in the RMLSF is the extent to which the minimum living security funds are biased toward rural areas. The poverty level of the

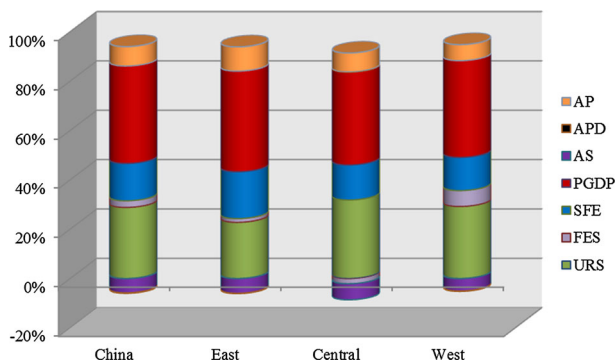


Fig. 1 Contribution of influencing factors from 2007 to 2016 (%). *Note* For simplicity, AP, APD, AS, PGDP, SFE, FES and URS here indicate the proportion of the change in the RMLSF due to the changes of the scale of the elderly population, the regional distribution of the elderly population, the degree of population aging, the per capita GDP, the scale of fiscal expenditure, the structure of fiscal expenditure and the extent to which the minimum living security funds are biased toward rural areas in the increase in RMLSF, which is the contribution of these factors

remaining poverty population in rural China is relatively deep. To realize the target of poverty alleviation for all the rural poor under current standards by 2020, the Chinese government will undoubtedly put more effort into the anti-poverty measures in rural areas, by increasing its investment, for example. The greater the extent to which the minimum living security funds are biased toward rural regions (that is, the higher the proportion of the RMLSF in the total amount of minimum living security funds), the larger the absolute scale of the RMLSF. The contribution of this factor to the increase in the RMLSF is 32.74% nationwide, and 25.92%, 38.44%, and 32.58% in the eastern, central and western areas of China, respectively. It can be concluded that the impacts of the extent to which the minimum living security funds are biased toward rural areas on the RMLSF in the underdeveloped areas of the central and western areas of China are larger than that in the developed area of eastern China. This indicates that it is reasonable to increase the investment of RMLSF in the rural areas of central and western regions.

Another crucial factor bringing about an increase in the RMLSF is the scale of fiscal expenditure, in line with the findings of Golan et al. (2017). They found that the change in RMLSF was related to the local fiscal capacity; the greater the fiscal capacity, the larger the RMLSF. The government's public financial capacity can be reflected to a certain extent by the fiscal expenditure. From another perspective, the increase in the government fiscal expenditure is positively related to the residents' income disparity (Blejer and Guerrero 1990). Increases in government fiscal expenditure will lead to a rise in the residents' income disparity. Moreover, the distributional effect of the income of government metastatic expenditures is relatively good. Therefore, to reduce the residents' income disparity, the Chinese government may consider enlarging the scale of transfer expenditure, including the expenditure on the rural minimum living security. This factor contributes 17.21% to the increase in the RMLSF in the country, and 21.64%, 17.14%, and 15.03% in the eastern, central and western areas of China, respectively. It is thus evident that from the perspective of a regional impact, the scale of the fiscal expenditure has the greatest impact in the eastern developed region.

The distribution of the rural elderly population is the least contributor to the change in the RMLSF, and the absolute value of its contribution is less than 0.3%. The reason may be that under the household registration system, there are limited opportunities for migrants from rural areas to enjoy medical services and pension support programs in cities, which increases their mobility cost for the rural elderly. This forces young people to leave their

elderly parents at home in the countryside while they migrate to cities for work (Tse 2013). As a result, the elderly in rural areas have been living in their hometown, and the possibility of migrating to other provinces and cities is very low. Thus, the regional distribution of the rural elderly population has not changed much during 2007–2016. Furthermore, the changes in the regional distribution of the elderly population across the whole country, in the eastern and the western areas of China lead to a slight decrease in RMLSF, while those in the central region result in a slight increase in the RMLSF.

Whether viewed from the national scope or from the scope of the three regions, the impact of fiscal expenditure structure, the degree of population aging, and the scale of the elderly population have relatively small impacts on the change in the RMLSF and their contributions are less than 12%. These three factors are conducive to the increase in RMLSF. The reasons are as follows: First, this study treats the proportion of the minimum living security funds in fiscal expenditure as the proxy variable of the fiscal expenditure structure. A larger proportion means more attention is paid by the Chinese government to the problem of poverty. In the report of the 19th Communist Party of China National Congress, President Xi Jinping declared that China should firmly triumph over the fight against poverty and make sure that the rural poor people can be lifted out of poverty under the current standards by 2020. The government in China is increasingly paying attention to the problem of rural poverty. Thus, the increase in the share of minimum living security funds in fiscal expenditure (that is, the improvement of the fiscal expenditure structure) will promote an increase in the absolute amount of RMLSF. Second, on the one hand, since the end of the 1990s, with rapid economic development, many members of the young labor force have moved from the countryside to the cities for work and life, resulting in the breakdown of the traditional model, where the rural elderly rely on family economic support (Liu 2014). On the other hand, compared with the countryside, the exit of the elderly in urban areas from the labor force market has a much smaller impact on their family income (Zhong 2011). Thus, the rural elderly faces a more serious poverty problem than the urban elderly (Du and Wang 2010). The growth rate of the elderly poor in the countryside is higher than that of the elderly in the countryside (Chen et al. 2016), leading to a higher proportion of rural poor among the elderly population in China (Cai et al. 2013). Hence, the increase in the national elderly population and the degree of population aging will increase the demand for RMLSF.

4.2 Results of three-stage DEA

4.2.1 Efficiency value in the first stage

Without considering the effect of the external ambient variables and random errors, the number of provinces at the frontier of technical efficiency (TE) fluctuated between 2 and 3 from 2007 to 2016, during which three provinces (Hainan, Tibet, and Guangxi) were at the frontier of TE in 2016. Their TE, pure technical efficiency (PTE), and scale efficiency (SE) had all reached 1. About half the provinces (15 provinces), especially the eastern ones (2/3), have relatively low TE, which is less than 0.6 (see Table 2). Only seven provinces (Beijing, Heilongjiang, Shanghai, Henan, Sichuan, Yunnan, and Gansu) have a lower SE than PTE, which demonstrates that technical factors play a leading role in the TE in these seven provinces. Before 2011, Tianjin was always at the frontier of TE; after 2011, however, Tibet replaced Tianjin. We can conclude that there are time and regional heterogeneity in the PRE of RMLSF, as well as in the efficiency of funds in the humanitarian supply chains (Table 2).

Table 2 Efficiency value in the first stage and the third stage (2016)

DMU	The first stage				The third stage			
	TE1	PTE1	SE1		TE3	PTE3	SE3	
Beijing	0.395	0.662	0.597	IRS	0.451	1	0.451	IRS
Tianjin	0.403	0.519	0.777	IRS	0.714	1	0.714	IRS
Hebei	0.725	0.729	0.995	DRS	0.786	0.804	0.977	IRS
Shanxi	0.585	0.586	0.998	IRS	0.57	0.656	0.869	IRS
Inner Mongolia	0.524	0.549	0.954	DRS	0.697	0.7	0.996	IRS
Liaoning	0.64	0.673	0.952	DRS	0.888	0.892	0.995	IRS
Jilin	0.763	0.801	0.952	DRS	0.972	1	0.972	IRS
Heilongjiang	0.695	1	0.695	DRS	0.864	1	0.864	DRS
Shanghai	0.544	1	0.544	IRS	0.337	0.885	0.381	IRS
Jiangsu	0.433	0.453	0.954	DRS	0.622	0.626	0.994	IRS
Zhejiang	0.371	0.383	0.968	DRS	0.493	0.544	0.908	IRS
Anhui	0.525	0.528	0.993	DRS	0.56	0.588	0.952	IRS
Fujian	0.58	0.6	0.967	DRS	0.962	0.985	0.976	IRS
Jiangxi	0.649	0.65	0.999	DRS	0.661	0.692	0.956	IRS
Shandong	0.572	0.578	0.989	DRS	0.672	0.672	0.999	–
Henan	0.817	0.918	0.89	DRS	0.878	0.974	0.901	DRS
Hubei	0.592	0.61	0.971	DRS	0.729	0.734	0.994	IRS
Hunan	0.868	0.91	0.953	DRS	0.928	0.968	0.958	DRS
Guangdong	0.555	0.562	0.988	DRS	0.622	0.645	0.965	IRS
Guangxi	1	1	1	–	1	1	1	–
Hainan	1	1	1	–	1	1	1	–
Chongqing	0.571	0.596	0.959	DRS	0.649	0.73	0.888	IRS
Sichuan	0.711	0.865	0.823	DRS	0.747	0.891	0.839	DRS
Guizhou	0.69	0.725	0.952	DRS	0.691	0.722	0.957	DRS
Yunnan	0.747	1	0.747	DRS	0.769	1	0.769	DRS
Tibet	1	1	1	–	0.432	0.805	0.536	IRS
Shaanxi	0.599	0.607	0.986	DRS	0.686	0.718	0.956	IRS
Gansu	0.827	0.921	0.898	DRS	0.836	0.92	0.908	DRS
Qinghai	0.958	0.977	0.98	DRS	0.806	1	0.806	IRS
Ningxia	0.565	0.582	0.971	DRS	0.618	0.741	0.834	IRS
Xinjiang	0.752	0.767	0.98	DRS	0.784	0.788	0.995	IRS
East	0.565	0.651	0.885		0.686	0.823	0.851	
Central	0.687	0.750	0.931		0.770	0.827	0.933	
West	0.745	0.799	0.938		0.726	0.835	0.874	
China	0.666	0.734	0.917		0.723	0.828	0.881	

TE1, PT1 and SE1 mean the technical efficiency, pure technical efficiency and scale efficiency in the first stage, respectively; TE3, PT3 and SE3 mean the technical efficiency, pure technical efficiency and scale efficiency in the third stage, separately; IRS, DRS and – separately represent increasing returns to scale, decreasing returns to scale, and unchanged returns to scale

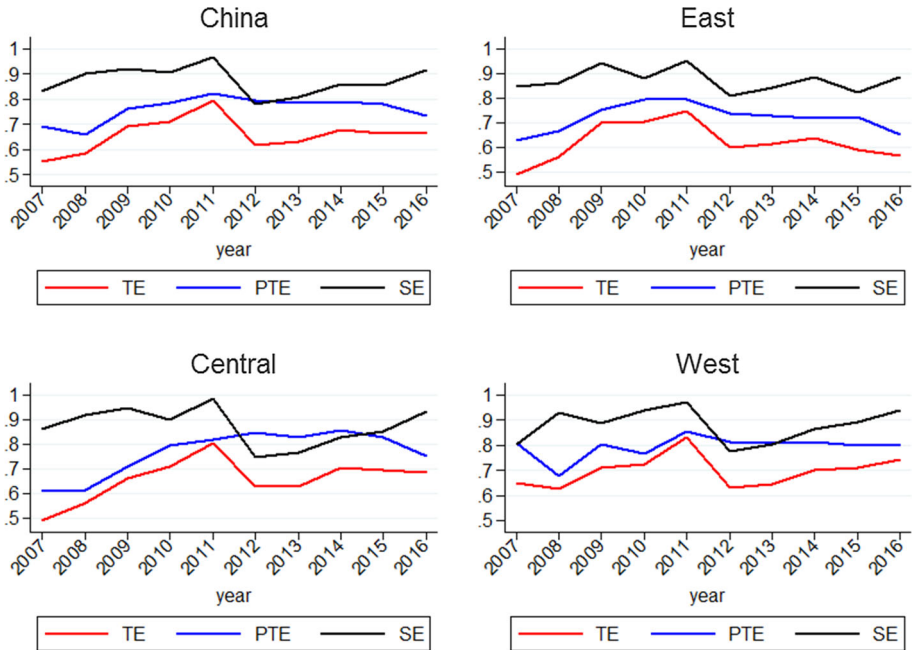


Fig. 2 The efficiency of RMLSF in China and three regions in the first stage. *Note* TE, PTE and SE respectively indicate technical efficiency, pure technical efficiency, and scale efficiency. The authors present this chart in the light of the efficiency values computed in the first stage

From a national perspective, the average TE of China improved from 0.550 to 0.666 during 2007–2016. This means that the allocation of RMLSF has been continuously optimized from 2007 to 2016. The average PTE tended to increase and then decrease slightly; the average SE tended to increase, decrease, and then increase again; and the average PTE was always lower than the average SE (except in 2012). This indicates that scale factors play a major role in the PRE of Chinese RMLSF, while technical factors play a secondary role.

The average TE of the three regions increased from 0.488, 0.490, and 0.648 in 2007 to 0.565, 0.687, and 0.745 in 2016, respectively. This demonstrated that the PRE of RMLSF increased, and the allocation of RMLSF was optimized to a certain extent in these three regions from 2007 to 2016. In addition, we can conclude that there is a regional heterogeneity in the change range of efficiency of RMLSF. Except for 2014, the average TE in the eastern and central areas was lower than that in the western region, which demonstrated that the allocation of RMLSF in the western area was more efficient than that in the eastern and central regions of China, and the PRE in the western region was higher. The average PTE in the eastern and central regions presented a fluctuating upward trend, whereas that in the western region presented a fluctuating downtrend. The average SE in the three regions showed a fluctuating upward trend, while the fluctuation range was different in different areas. Furthermore, the contribution of scale factors and technical factors to the efficiency of RMLSF varies from region to region. In the eastern area, the average PTE was always lower than the average SE, whereas in the central and the western areas, the average SE was lower than the average PTE in some years (see Fig. 2).

There are differences in economic, social and government policies in each region. The efficiency estimation results in the first stage did not eliminate the impacts of the external

environments and random errors. Therefore, the efficiency value cannot reflect the actual PRE of the RMLSF and the efficiencies in each region are not comparable. Therefore, an adjustment is needed.

4.2.2 The results of SFA regression in the second stage

In this stage, the slack variables of RMLSF computed in the first stage are taken as the explained variables, and the standardized per capita GDP, the average educational years of rural residents, and the scale of government public fiscal revenue are taken as the independent variables to investigate the effects of these three ambient variables on input slack variables. If the estimated coefficient is positive, it denotes that a rise in the ambient variable would lead to an increase in input slack variables, which will result in the increase in the wastage of RMLSF and have an adverse effect on the PRE. In case the regression result is negative, an increase in the ambient variable will result in the reduction of input slack variables, which will help lessen the wastage of RMLSF and have a beneficial impact on the PRE.

Except for the likelihood ratio (LR) test in 2016, which is significant at 5%, the LR tests in other years are significant at 1% (Table 3). It indicates that the external environments have a significant impact on the slack variable of RMLSF in various provinces. Therefore, adjusting the RMLSF, which is the input variable, is necessary in the second stage.

The effect of the three environmental variables (per capita GDP, average educational years of rural residents, and the scale of government public fiscal revenue) on the input slack variable are shown in Table 3.

1. Per capita GDP: The outcomes indicate that the coefficient of per capita GDP is negative and significant at the level of 1% during 2008–2010. It demonstrates that an increase in per capita GDP would reduce the input slack variable during this period, which is conducive to reducing the wastage of the RMLSF, thus having a beneficial impact on the PRE of RMLSF. This may be because of the impact of the financial crisis in 2008. In other years, the coefficient of per capita GDP is positive and significant at the level of 1%, indicating that during this period, an increase in per capita GDP would result in the increase in the input slack variable, leading to an increase in the wastage of RMLSF and thus having an adverse effect on the PRE of RMLSF. As rural poverty continuously declines, the remaining poor are increasingly concentrated in remote mountainous areas where the ecosystems are fragile and natural disasters are frequent. These areas are separate from economic development areas. Economic growth may widen the gap between poor areas and other areas, which will make the implementation of poverty relief tougher (Liu et al. 2017). Therefore, it is difficult for RMLSF to play a better role in poverty reduction. In addition, the improvement in the level of economic development will promote the expansion of government departments and reduce their motivation to control the cost of expenditure, which is not adverse to the improvement of the PRE of RMLSF.
2. The average educational years of rural residents: The results show that the average educational level of rural residents has a positive impact on the input slack variable in most years except in 2007 and 2012 and passes the significance level test of 1% (except in 2014). It indicates that the increase in the average educational years of rural residents will result in the increase in the input slack variable, leading to an increase in the wastage of RMLSF, which has a negative effect on PRE. This probably due to the fact that the beneficiaries with higher education will give priority to investment in human capital (Zhao et al. 2017) instead of basic subsistence expenditures like food and clothing (Gao et al.

2010) to raise their future income level, which is not helpful for increasing the current PRE of RMLSF.

3. The scale of government public fiscal revenue: From 2007 to 2016, the regression coefficient of the government public fiscal revenue scale and the input slack variable is always negative and significant at the level of 1%. It denotes that the improvement of the government's public fiscal revenue level will bring about a reduction in the input slack variable and reduce the wastage of RMLSF, which will have a beneficial impact on its PRE. It may be because the government's public fiscal revenue scale reflects the government's financial level. The greater the financial resources of regional governments, the more the funds that can be invested in rural public service (such as healthcare) and the construction of public infrastructure (such as roads). Better rural public services and public infrastructure lead to the improvement of the self-development ability of the poor, which drives the poor to invest their minimum living security income in production activities to improve their income level. The PRE of the RMLSF will also be improved.

4.2.3 Adjusted efficiency value in the third stage

In the third stage, the adjusted RMLSF are taken as the new input indicator, and the output indicators remain unchanged. We can calculate the efficiency value after eliminating the effects of ambient factors and random errors by using the BCC model again. Taking the efficiency in 2016 as an example, the PRE of the RMLSF of different regions in the "same environment" is revealed in Table 2.

Regarding the provinces, when the effects of external ambient factors and random errors are eliminated, Guangxi and Hainan are at the forefront of TE, PTE, and SE, and the efficiency values are 1. It indicates that the allocation of the RMLSF of these two provinces is relatively reasonable, and the RMLSF performs well in poverty reduction and achieves relatively high PRE. Only in six provinces (Beijing, Shanxi, Shanghai, Zhejiang, Anhui, and Tibet) is the PRE of the RMLSF relatively low and the TE less than 0.6. It can be seen that the PRE of the RMLSF in most provinces is relatively high if we take 0.6 as the threshold. Thirteen provinces have a higher PTE than SE. That is, the technical factors play the leading role in PRE of RMLSF in these 13 provinces, while the scale factors play a secondary role. Compared to the DEA efficiency estimation results in the first stage, the TE of 25 provinces increased (Heilongjiang, Jilin, Liaoning, Beijing, Tianjin, Hebei, Fujian, Guangdong, Shandong, Jiangsu, Zhejiang, Jiangxi, Anhui, Henan, Hunan, Hubei, Inner Mongolia, Sichuan, Chongqing, Yunnan, Guizhou, Ningxia, Gansu, Shaanxi, and Xinjiang). The TE of four provinces decreased (Shanxi, Shanghai, Tibet, and Qinghai) (see Fig. 3), among which Tibet's TE value dropped from 1 to 0.432. Furthermore, the TE of two provinces (Guangxi and Hainan) remained unchanged, and their TE values are 1 (see Fig. 3). This means that the PRE of the RMLSF in most provinces are underestimated because of ambient factors and random errors. As can be seen from Fig. 4, the PTE of most provinces (23 provinces) improved, and the PTE values of Jilin, Beijing, Tianjin, and Qinghai reached 1. The PTE of four provinces remained unchanged, and their PTE values are 1. Moreover, the PTE of four provinces declined, among which the PTE values of Shanghai and Tibet declined from 1 to 0.885 and 0.805 (see Table 2), respectively. This denotes that the PTE value of RMLSF in most provinces is underestimated before eliminating the influences of ambient factors and random errors. The SE of 15 provinces declined, while that of 14 provinces improved, and that of two provinces remained unchanged with the efficiency value of 1 (see Fig. 5). Thus, ambient factors and random errors conceal the actual situation of SE of most provinces and ultimately affect the evaluation of TE.

Table 3 The results of SFA regression in the second stage

	Constant term	Per capita GDP	Average educational years of rural residents	Government Public Fiscal Revenue Scale	σ^2	γ	Log likelihood	LR test of the one-side error
2007	5557.58*** (41.27)	5572.65*** (154.85)	1002.55*** (66.77)	-5276.72*** (10.61)	497,363,090 (1.00)	1.00 (0.00)	-334.81	10.35
2008	2527.76*** (402.09)	2335.90*** (584.02)	4031.65*** (50.66)	-2039.65*** (364.14)	1,388,923,800 (1.00)	1.00 (0.00)	-352.44	6.93
2009	2020.36*** (1.00)	780.41*** (1.00)	4613.27*** (1.00)	-5527.94*** (1.00)	1,588,847,200 (1.00)	0.98 (0.06)	-354.99	5.99
2010	4359.32*** (1.00)	1844.07*** (1.00)	2511.55*** (1.00)	-3546.90*** (1.00)	2,267,162,500 (1.00)	0.99 (0.01)	-357.84	11.32
2011	7014.70*** (1.00)	4512.25*** (1.00)	6538.57*** (1.00)	-10,167.21*** (1.00)	2,785,271,300 (1.00)	1.00 (0.05)	-359.59	14.20
2012	10,715.86*** (451.62)	14,390.58*** (1215.91)	917.83 (659.12)	-18,703.53*** (757.77)	4,309,145,800 (1.00)	0.99 (0.01)	-370.67	5.55
2013	10,569.84*** (607.15)	11,369.94*** (459.54)	11,054.60*** (716.75)	-18,608.64*** (702.98)	5,747,551,100 (1.00)	1.00 (0.00)	-374.64	6.54
2014	11,089.31*** (340.89)	16,860.22*** (515.85)	319.94 (651.54)	-18,109.70*** (703.38)	5,979,569,800 (1.00)	1.00 (0.00)	-375.18	6.70
2015	12,368.24*** (300.82)	11,358.80*** (169.45)	1924.61*** (568.91)	-10,368.75*** (1244.37)	8,040,628,400 (1.00)	1.00 (0.00)	-379.26	7.73
2016	613.49 (591.35)	18,388.82*** (896.45)	5670.91*** (85.80)	-24,949.41*** (2667.77)	10,884,565,000 (1.00)	0.98 (0.01)	-385.87	3.88

*** means being significant at the level of 1%; the values in () indicate corresponding estimated standard errors; the per capita GDP, the average educational years of rural residents and the government public fiscal revenue scale are standardized; σ^2 means the variance of mixed error items; γ means the proportion of variance of management inefficiency in total variance

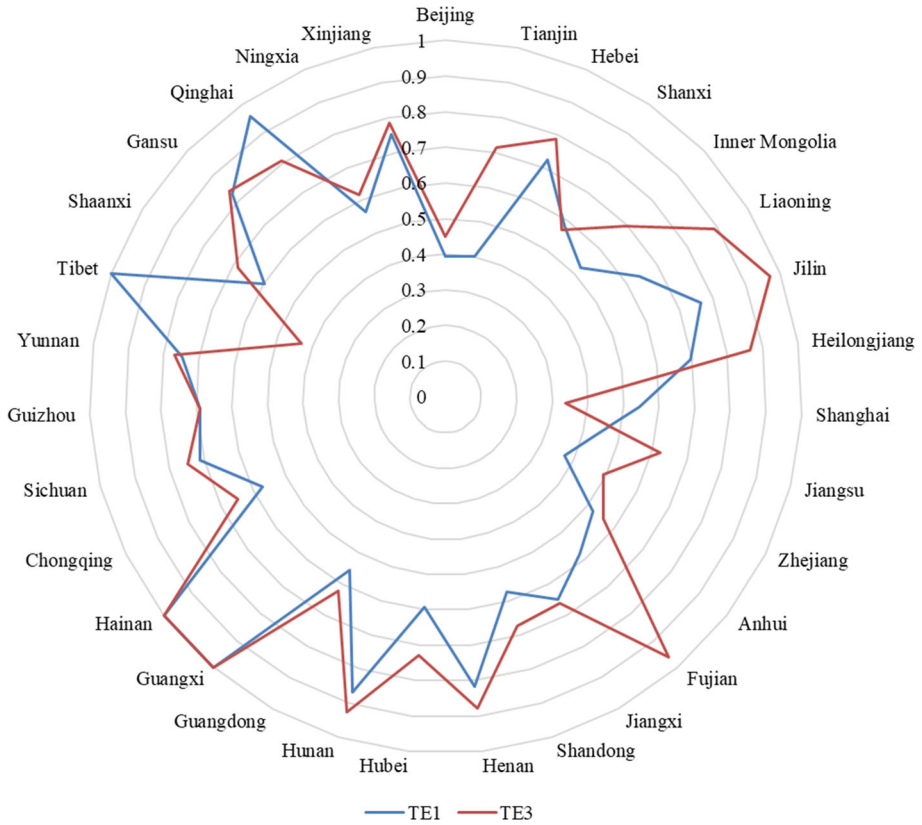


Fig. 3 The TE of RMLSF in All Provinces (2016). *Note* TE1 and TE3 indicate the technical efficiency in the first and third stage. The data are taken from Table 2

As for the situation of the three regions, after removing the effects of external ambient factors and random errors, the TE of the eastern, central, and western areas in China in 2016 is 0.686, 0.770, and 0.726, respectively. The average PTE is 0.823, 0.827, and 0.835, respectively, and the average SE is 0.851, 0.933, and 0.874, respectively. In the PRE of RMLSF, technical factors play a secondary role, while scale factors play the leading role. In comparison with the DEA efficiency estimation results in the first stage, the average TE and the average PTE of the eastern area improved whereas the average SE decreased, indicating that the improvement in the average TE is mainly because of the technical factors. The average TE, average PTE, and average SE of the central region increased. The average TE and average SE of the western area decreased, while the average PTE increased, demonstrating that the scale factors primarily caused the decrease in the average TE of the western area in China. Hence, it is clear that, before excluding the impact of external ambient factors and random errors, the average TE of poverty alleviation of RMLSF of the eastern and central areas in China is underestimated, whereas that of the western area in China is overestimated.

From a national perspective, after excluding the effects of external ambient factors and random factors, China's average TE increased from 0.666 to 0.723, the average PTE increased from 0.734 to 0.828, and the average SE decreased from 0.917 to 0.881. The scale factors always play a leading role, while the impact of technical factors improved. Therefore, before

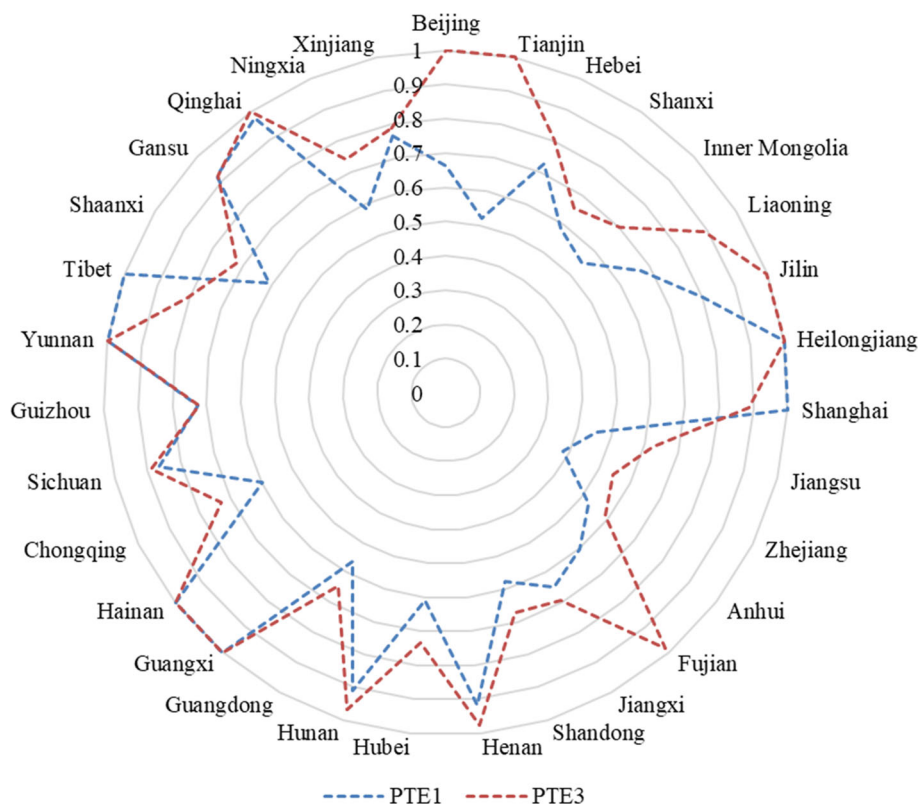


Fig. 4 The PTE of RMLSF in All Provinces (2016). Note PTE1 and PTE3 indicate the pure technical efficiency in the first and third stage. The data are taken from Table 2

excluding the effects of external ambient factors and random errors, China's average TE and average PTE are underestimated, and the average SE is overestimated. In addition, China's average TE is higher than 0.6 both before and after the adjustment, indicating that the PRE of Chinese RMLSF is relatively high and RMLSF has been well allocated. This result is consistent with the opinion of Gustafsson and Deng (2011), who also thought that the central and local governments used the minimum living security funds efficiently.

5 Conclusions and policy implications

Efficient and effective capital flow in humanitarian supply chains is critical for relief operations. This study takes the RMLSF as an example to explore the influencing factors and efficiency of humanitarian supply chains funds. Specifically, based on the data of 31 provinces (autonomous regions, municipalities) of China during 2007–2016, this study uses the LMDI approach to decompose the influencing factors of RMLSF into seven factors. It discusses the impacts of these factors on the RMLSF in China and its eastern, central, and western areas. Moreover, this study utilizes the three-stage DEA efficiency evaluation approach to explore the PRE of the RMLSF of each province.

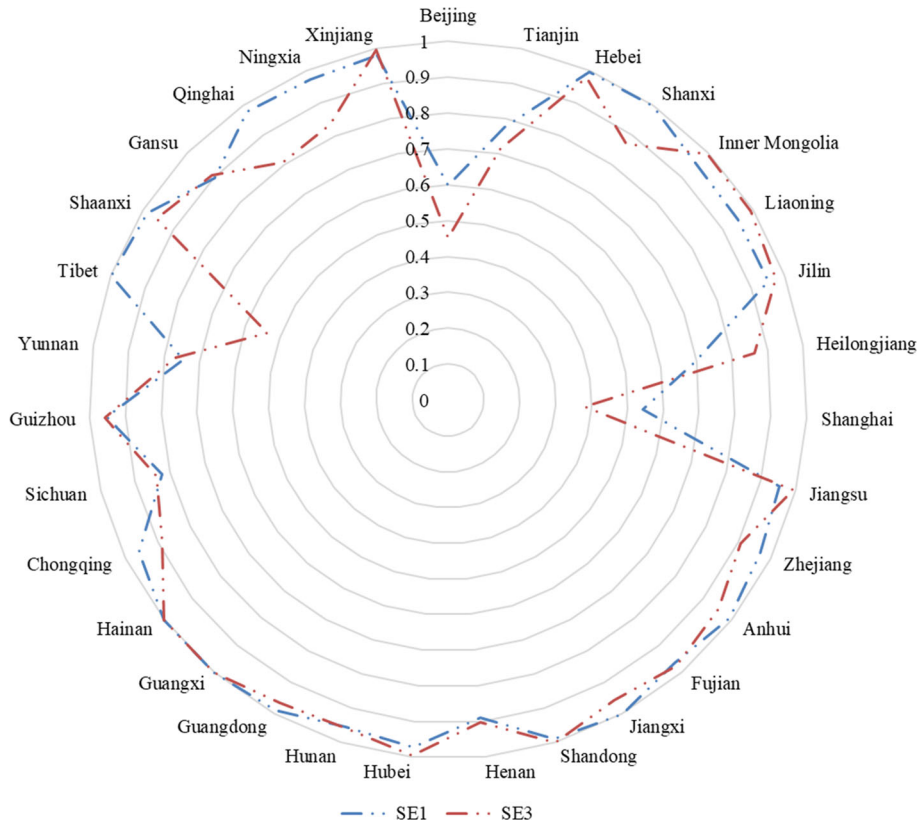


Fig. 5 The SE of RMLSF in All Provinces (2016). *Note* SE1 and SE3 indicate the scale efficiency in the first and third stage. The data are taken from Table 2

The results of the LMDI decomposition denote that the increase in the economic development level is the chief cause for the increase in the RMLSF, and its contribution is 44.90% in the whole country, 46.48% in the eastern area, 45.55% in the central area, and 43.77% in the western area in China. The second leading cause is the extent to which the minimum living security funds are biased toward rural areas. This factor has a greater influence on the underdeveloped regions in the central and western areas in China than in the developed areas in the eastern area in China. Another important factor contributing to the increase in the RMLSF is the scale of financial expenditure, which has the greatest impact on the developed regions in the eastern area in China. The factor contributing the least to the change in the RMLSF is the regional distribution of the rural elderly population, and its total contribution is less than 0.3%. The structure of financial expenditure, the degree of population aging and the scale of the elderly population have a relatively small influence on the change in the RMLSF, with contributions less than 12%.

The three-stage DEA analysis results signify that the PRE of China's RMLSF is relatively high. After removing the impact of external ambient factors and random errors, only Guangxi and Hainan are at the forefront of TE, PTE, and SE. The scale factors of most provinces play the leading role in PRE of the RMLSF. The provinces where technical factors play the leading role have increased. Due to the ambient factors and random errors, the PRE of RMLSF in

many provinces, the eastern and central regions, and the whole country is underestimated, while that in the western region is overestimated; the PTE of the vast majority of provinces, the three regions, and the whole country is underestimated and the average SE of the eastern and western regions is underestimated, while that of the central region and the whole country is overestimated.

In view of the analysis above, this study suggests some policy recommendations as below.

The rural minimum living security should be included in the studies on the humanitarian supply chain management. It is common knowledge that Chinese rural minimum living security is a continuous aid program conducted by the Chinese government to alleviate rural poverty. Venkatesh et al. (2014) emphasized that continuous aid program is an important field in the research of humanitarian supply chain management. Consequently, we ought to take note of the examination of rural minimum living security.

It is essential to give importance to the influencing factors and efficiency of funds in humanitarian supply chains. The smooth implementation of humanitarian relief operations cannot be separated from the support of funds donated. Understanding the influencing factors of funds in humanitarian supply chains is helpful in identifying the channels for increasing it. However, resources are limited. In order to improve the role of the funds in disaster relief, its efficiency is a very noteworthy issue.

Since it is difficult to achieve poverty reduction in rural areas without government policies and funds (Chen et al. 2016), the RMLSF, which are fiscal transfer payments from the government, are essential for alleviating poverty of the rural poor. Whether to raise the level of rural minimum living security or to cover more rural poor people, governmental departments must increase investment in RMLSF. We can find the channels to increase investment in RMLSF from the perspective of its influencing factors. First, stimulating economic development. As the level of economic development continues to improve, the resources that the government departments can obtain from the society will increase accordingly, which is beneficial for the Chinese government improving the social welfare levels as well as the level of rural minimum living security, so as to reduce poverty. Second, increasing the degree of the preference of minimum living security funds to the countryside, especially the underdeveloped regions in the central and western China, is necessary. China's poor are chiefly concentrated in the countryside, especially in the central and western rural areas. Increasing the degree of preference of the minimum living security funds for these areas will help alleviate China's poverty.

Although the PRE of the Chinese RMLSF is high, the scale of the remaining rural poor in China is still large, and the degree of poverty is higher. Undoubtedly, it is still essential to continuously optimize the assignment of the RMLSF and further increase its PRE. To realize the objective of poverty reduction in rural areas by 2020, it is important to put forward a more effective mechanism and approach to discern the rural poor and decide the amount of RMLSF needed. This would help minimize the operating costs of the rural minimum living security (Kakwani et al. 2019) and increase the PRE of RMLSF. At the same time, relevant supporting measures need to be strengthened to form a coordinated development mechanism with minimum living security. For example, financial investment in social public service like medical treatment and basic education in rural areas should be increased so as to inspire the poor in rural areas to increase their input of income into production activities and reduce their input in direct consumption activities, which will also serve to improve the PRE of the RMLSF.

This study has limitations as well. The data are from before 2016, and there could be changes in efficiency factors since then. In the near future, we would like to study the effect of the changes in efficiency factors on the PRE of RMLSF. In the medium and long term,

we will also pay attention to the continuous relief programs in humanitarian supply chain networks to enrich the humanitarian supply chains literatures.

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Compliance with ethical standards

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

Appendix A

A.1. The first stage

In this stage, we will use the BCC model, which can separate the two causes of DMU technology inefficiency: the poor efficiency of production technology, and not being in the optimum scale. The calculated efficiency values include three parts: technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE). The relationship among them is given by $TE = PTE \times SE$.

The DEA model is generally divided into output-oriented, input-oriented, and non-oriented. This study focuses on minimizing the inputs of RMLSF without reducing outputs. Thus, it chooses the input-oriented BCC model for efficiency analysis.

A.2. The second stage

DMU's efficiency value calculated at the first stage is affected by its internal management level as well as external environments and random errors (Fried et al. 2002). To remove the impacts of ambient factors and random errors, we will construct an SFA model for regression adjustment. In this model, the differences between the actual value and the target value of each input indicator (that is, the slack variable of each input indicator obtained at the first stage) are considered dependent variables, and the ambient variables (supposing the number is p) are considered independent variables. The model is constructed as below.

$$s_{ij} = f^i(z_j; \beta^i) + v_{ij} + u_{ij} \quad (\text{A.1})$$

where i and j represent the input i and the DMU j ($i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$), s_{ij} indicates the slack variable of input i of the DMU j , z_j represents the vector composed of p observable ambient variables of the DMU j , $z_j = (z_{j1}, z_{j2}, \dots, z_{jp})$, β^i denotes the parameter vector to be estimated, and $f(\cdot)$ is a functional form to express the impact of ambient variables on input slack variable. Generally, $f(\cdot) = z_j \beta^i$. $v_{ij} + u_{ij}$ denotes a mixed error, where v_{ij} demonstrates the stochastic disturbance term, $v_{ij} \sim N(0, \sigma_{vj}^2)$; u_{ij} denotes the management inefficiency term, $u_{ij} \sim N^+(u^j, \sigma_{uj}^2)$; and v_{ij} and u_{ij} are independent of

each other. $\gamma = \frac{\sigma_{u_{ij}}^2}{\sigma_{u_{ij}}^2 + \sigma_{v_{ij}}^2}$ indicates the proportion of variance of management inefficiency to the total variance. If $\gamma \approx 1$, management inefficiency is the primary cause. If $\gamma \approx 0$, u_{ij} can be removed from model (A.1). At this time, we can utilize ordinary least squares (OLS) directly to estimate model (A.1). Then, we use the ambient variable coefficients obtained to adjust the initial input indicators of each DMU; thus, all DMUs are in identical external environments and suffer the same random impact. The specific adjustments are as follows.

$$\hat{x}_{ij} = x_{ij} + \left[\max_j \{z_j \hat{\beta}^i\} - z_j \hat{\beta}^i \right] + \left[\max_j \{\hat{v}_{ij}\} - \hat{v}_{ij} \right] \quad (\text{A.2})$$

In the above equation, x_{ij} and \hat{x}_{ij} represent the actual value and adjusted value of input i of DMU j , respectively, while the remaining terms have the same meaning as in Eq. (A.1). Moreover, “ $\hat{\cdot}$ ” represents the estimated value, $\left[\max_j \{z_j \hat{\beta}^i\} - z_j \hat{\beta}^i \right]$ denotes the adjustment of ambient variables, and $\left[\max_j \{\hat{v}_{ij}\} - \hat{v}_{ij} \right]$ represents the adjustment of random error terms.

A.3. The third stage

The adjusted input \hat{x}_{ij} computed in the second stage replaces the primitive input x_{ij} as a new input indicator, and the output indicators remain unchanged. Then, we utilize the BCC model to compute DMUs’ efficiency values after excluding the impacts of ambient factors and random errors.

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