When Poverty Reduction Meets Democracy: An Investigation into the Use of Different Evaluation Methods for Assessing the Effectiveness of a Social Program

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When Poverty Reduction Meets Democracy: An Investigation into the Use of Different Evaluation Methods for Assessing the Effectiveness of a Social Program*

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Abstract
This paper evaluates the minimum living standard guarantee program (Dibao) in rural China using several methods including the income approach, the multidimensional poverty approach, and a proxy means test approach. We find that the targeting accuracy of the program appear greater the more comprehensive the evaluation method used - but all these methods find low levels of targeting accuracy. Because Dibao fund allocation is largely decided by the villagers, who take a more holistic view in selecting "poor" households than the various evaluation methods, we argue that the low targeting efficacy may be due to the lack of comprehensive evaluation method, as opposed to the low targeting of the program itself. This paper argues that the community-based targeting used by the Dibao program may be a better way to combat poverty in many developing countries, as it requires less administrative capacity and overcomes the difficulties of identifying poor households that qualify for assistance.

JEL classification: C52, H53, I38, O23
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1. Introduction

Accurate participant targeting is key to the success of a social program aimed at combating poverty and inequality (Ravallion 2009; Kakwani and Son 2016). Targeting involves administrative costs in identifying the households that qualify for the social program, and in distributing transfer payments. However, many poor countries have limited bureaucratic capacity and in the same time suffer from severe asymmetric information as informal sectors dominate the economy. With the constraint of administrative capacity and costs that identifying the poor involves, the best practice may be to leave some of the identification to villagers themselves, such as using local community-based targeting demonstrated in China's minimum living standard guarantee program (Dibao).

As the primary welfare program in rural China and one of the largest social safety net program in the world, the fundamental goal of Dibao is to help families in absolute poverty maintain a minimum level of livelihood by providing cash transfers to them (Han and Gao, 2019). Given the scale and the popularity of the rural Dibao program, rigorous evaluation can demonstrate the extent to which it meets its intended objective of reducing poverty, thus being able to reduce wasteful spending, increase target accuracy and improve policy effectiveness. It is therefore essential to be able to identify the genuinely poor who need government support. To identify the poor objectively, we need to know a metric of household welfare, which accurately measures the economic situation of different households.[2]

Compared with the existing literature, in addition to considering income poverty and multidimensional poverty measures, this paper also studies more choices such as the proxy means test and conducted a detailed examination of the targeting procedure. Because the Dibao approach is community-based targeting where community-based democratic targeting procedures overcomes information disadvantages and emphasizes the importance of grassroots in identifying real "poor" households, evaluation using the income and consumption approach, would suffer severe problems including high inclusion and exclusion errors. Although its targeting efficiency increased significantly when multidimensional measure and a proxy means test are used, they are still very low.

Dibao quota is decided by the upper level government, but its allocation to individual household relies on a highly decentralized community-based targeting approach in practice. Han and Gao (2019) provided a comprehensive review of the community-based targeting adopted by the Dibao program. We provide detailed case studies and found a much higher targeting efficiency that is not captured by either the income approach or the multidimensional measures. The low targeting measure by these approaches is likely due to their lack of comprehensive perspectives in identifying the poor. As we will show in section 2, the Dibao fund allocation adopts a community-based targeting and is largely decided in the villagers' meeting democratically. Villagers are able to take a holistic view in evaluating the poverty status of households in their own village as they hold more comprehensive information of the status of other villagers. Thus we believe that a social program that is evaluated as being ineffective using these approaches may in fact be accurate in targeting and very effective in achieving its goals. It may not be the Dibao program that is of low targeting effectiveness, but the issues with emulation methods.

As argued by Ravallion (2008) and Han and Gao (2019), if using monetary poverty only in

[2] Hanna and Olken (2018) compare the universal basic income system and the poverty targeting policies common in developing countries. They recommend the universal income approach because it does not suffer from an information disadvantage. However, as shown by Kakwani et al. (2021), the universal basic income approach suffers significant social welfare loss compared with other principles.

targeting evaluations, the poverty measurement errors will be misunderstood as targeting errors, while the two are actually different both conceptually and empirically. The democratic community based targeting approach of identifying households is more accurately targeted and of lower cost. We advocate that governments in developing countries should guide rural communities to establish more adaptive and rigorous frameworks in the community-based targeting of welfare programs,

This paper is part of a bigger study that the authors have undertaken to enhance the understanding of poverty and inequality reduction in theory and improve targeting efficiency of social programs in practice. Although this paper is China-focused, the findings should be of interest to development economists working in social protection in other developing countries. The data used is the fifth round of the Chinese Household Income Project (CHIPs) covering rural households in the year 2013 (CHIP 2013). These surveys are large and representative of China as a whole (Gustafsson, Li, and Sicular 2008). They are the best publicly available data source on Chinese household income and expenditures (Riskin, Zhao, and Li 2001).

This paper is organized as follows: Section 2 provides a discussion of China's Dibao program, the poverty line used, and the Dibao targeting in practice. Sections 3 to 6 provide our evaluation results using the different approaches. Section 7 concludes and discusses policy implications and recommendations.

2. Rural Dibao and poverty alleviation in China

2.1 An overview of Dibao

The minimum living standard guarantee program (Dibao) is a significant component of China's social assistance program. It provides unconditional cash support to help those whose income is lower than a certain level. According to the central government's stipulation, rural Dibao should be a strictly means-tested program, and any household with local rural registration (Hukou) is eligible to be a Dibao recipient as long as its income falls below the local Dibao threshold (Han and Gao, 2019; Kakwani et al. 2019,). The Dibao program was introduced in urban areas in the 1990s and was useful in reducing urban poverty. The Chinese government extended the Dibao program to rural areas in the early 2000s. In 2013, the rural Dibao program provided cash benefits to 29.3 million households covering 53.9 million individual beneficiaries (Ministry of Civil Affairs 2014). [3] Rural and urban areas have separate Dibao programs run by their respective local authorities and local officials have autonomy over how the program is run, how to screen applicants, and how to determine eligibility. Different regions have a distinct Dibao line, qualifying criteria, and ways of distribution. Golan et al.(2017) and Kakwani et al.(2019) provide detailed discussion of this social program. This section focuses on some of the key features that are different from many other practices of similar programs in other countries.

In principle, a household is eligible to apply for Dibao assistance if their income is lower than the threshold level in their local area; households do not have to meet any other conditions. The amount of cash transfer received is usually the difference between the income threshold level and the household's income. However, due to difficulties in identify the real income level of a

[3] The division of urban or rural Dibao depends on the Hukou status of the residence. A rural-urban migrant worker would be counted as rural if their Hukou status has not changed. Of course, a migrant worker would normally have relative high income so that they will not qualify. See Wang and Piesse (2010), Shen et al (2021) for a discussion rural urban divide due to taxation and subsidies, and Rangazas and Wang (2019), Rangazas et al (2022) for a discussion of rural urban migration and China's urban biased policy).

household, a lump sum is normally provided to the qualifying household, and there is a possibility of a high degree of inequity in the distribution of cash transfers across regions, which might create various welfare loss (Kakwani et al 2021; Villamil et al 2021).

Both central and local governments provide funding for the program with the central government providing about 60 percent of the total. The central government allocates funds for a province based on an estimation of the number of people in poverty and the extent of their poverty (Villamil et al.2021). The money flows from provincial to county to lower government levels to households.

Dibao program management is highly decentralized and is based on a de facto quota system. In practice, authorities estimate the number of poor in a region and then distribute funds accordingly. Then county-level officials decide the Dibao line and distribute funds through subsidiaries to villages, where villagers and local cadre decide who should get the money. It is possible that a more affluent village gets more quota than it needs, and another region may get much less, which can only barely cover the extremely poor.[4] National policy permits local governments to make use of a range of information to evaluate eligibility in practice. For instance, this might include not only household income, but also household structure, the presence of household members who are unable to work or are disabled, household assets, or housing conditions.

The Poverty Alleviation Office of the State Council in the "poverty alleviation and development of the archives for impoverished households"[5] (State Council 2014) provided a systematic guidance. Key points include: Every province set up their own local poverty alleviation standard, but they have to be no lower than the national rural poverty alleviation standard of 2,736 yuan per capita net income in 2013 (equivalent to 2,300 yuan in 2010). In addition, it pointed out that poverty identification should be based on the income, but should also comprehensively consider housing conditions, education, health status of the members of the household etc. It also states that the identification should be based on the whole household, and the procedure for this assistance is through farmer's application, democratic review by the villagers, public announcement, and a step-by-step audit method.

The Poverty Alleviation Office of the State Council does not design uniform implementation rules throughout the country, and the regions generally operate according to actual conditions. However, there are certain discrepancies among different regions. Below we summarize some of the general practices that we observed through our field studies.[6]

In practice, the Dibao program selects beneficiaries according to household income levels and uses various kinds of multidimensional poverty criteria to determine who should receive Dibao benefit. Many local governments have developed their own criteria, which are often different.

[4] In fact, large share of the targeting issues was from this regional quota inequality, rather than the targeting errors within a given region.

[5] Development of the archives for impoverished households (Jiandang Lika 建档立卡) is a method adopted by the Chinese government to combat poverty. Through data tracking on the conditions of the impoverished population, the causes of their problems can be analyzed, appropriate guidance on their development needs can be offered, targeted measures can be implemented in terms of funding, projects, and recipients.

[6] As part of a bigger project examining the effectiveness of social policy concerning poverty reduction and redistribution, we conducted many field studies including household visit, interviews, surveys, and case studies, in: Qingshui and Qin'an counties in Gansu province; Jingyuan and Longde counties in Ningxia province, Mengla county in Yunnan province, Xin county in Henan province, Zheng'an and Chishui counties in Guizhou province and Beichuan county in Sichuan province.

For example, many places look at five aspects in deciding whether a household should be included: 1) whether the family house is of good quality and good status;[7] 2) whether there is enough food; 3) whether there is a student in the household that needs financial support; 4) whether family members have good skills; 5) whether the household has any members who are disabled or suffer from severe illnesses.

2.2 A case study of Dibao identification

The ways of identifying the poor are not unified, but they share many similarities. Below we summarize the precise identification policy adopted by Xin County, Henan province[8] as an example of how local governments identify the poor households.[9]

2.2.1 Criteria for identifying the poor

Household per capita income is used as a fundamental standard for identifying the poor. A household is considered poor if their per capita annual income is below the national poverty line, which was 2,736 in 2013. In addition, they also take into consideration a so-called "two worry-frees and three guarantees" factor. Residents should be free of worrying about refined grains of staple food and seasonal clothes. Three guarantees are: 1) Compulsory education. If a household has children in education with a heavier burden of schooling; 2) Basic medical care. If family members suffer from major illness or chronic diseases, in need of regular hospitalization or long-term medical treatment with large medical expenditures, affecting normal production activities and normal life of family members; 3) Secure housing. If the family house is in poor condition, that is identified as C or D class dangerous housing. When a household has any of the above three conditions, even if their per capita net income is higher than the poverty line, they will be integrated into the poverty alleviation program.

2.2.2 The considerations for identifying the poor

The method for identifying the poor is designed to adhere to the principle of openness and fairness and follows that: 1) All households in the village should be visited; 2) The house, furniture and other basic living facilities should be inspected. Households with cars, large-scale agricultural machinery, high-end home appliances, shall not typically be recognized as poor; 3) Per capita net income should be calculated, and expenditure accounted for; 4) The quality of life should be compared with neighbors in the village. And whether the household has a member working in the public sector, or served as village cadres, or as legal persons or shareholders in the industrial and commercial sector registered enterprises, has a store, or housing in urban area should be identified; 5) A comparison of the household with the poverty standard should be undertaken. This should be a comprehensive approach and involve a discussion. There would also be household by household appraisal and a view obtained from most villagers on whether the household was poor; and 6) A poverty alleviation target for the households should be recommended and confirmed by the village committees and the party committee of the village, and this should be approved by the township government and party committee.

2.2.3 Poor identification process: the democratic approach

The primary selection. Based on the villager's own application, villagers will meet to decide,

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[7] It is up to the interpretation of the evaluators to decide how "good" is defined, but more or less they refer to whether the house is in a liveable condition, and where the family members have skills that enable them to make a living.

[8] Xin County is a typical impoverished county in Henan province, representative of the counties in the middle region of China. (Xiao et al 2022)

[9] From our field studies, we found that the rigorous procedure, such as the one used in Xin county, would help to minimize the political elite capture in community-based targeting implementation.

or a democratic council will be convened to draw up the primary list and make a public announcement in the village. At the village level, it is often the case that Dibao households were democratically decided by villagers based on their perceptions of the economic conditions of the households. For instance, in many places, villagers decide the allocation of Dibao through voting at the villagers' meetings.

Township audits. Townships audit the primary list with individual and household visits. This is to prevent local elite capturing, where the funds are allocated to the relatives of local elites. The final list must be signed by six cadres including the first party secretary of the village, the village head, and the township clerk who conducted the audit. The list is then made public for consultation.[10]

County-level review. The Poverty Alleviation Office of the county reviews and finalizes the list and confirms it publicly in the village.

As can be seen from this case study of the practice in Xin County, the approach they take can be understood as a community-based targeting. It starts from the villagers' meeting where villagers decide the allocation of Dibao through voting, and then go through several layers of checking to minimize elite capturing. During this process, the consideration goes beyond income, and includes other factors such as housing, health status of family members, education costs, etc. which is in line with Sen's "capability approach".

Because the purpose of this type of cash transfer program is to reduce real poverty, it is meaningful only when a more comprehensive approach is taken. Although the statistical evaluation results show low target accuracy, our case study shows a high level of satisfaction and sense of fairness among most of the villagers. We argue that this community-based targeting is a most comprehensive one that most follows the Chinese government's poverty reduction guidance, which argues for a more comprehensive approach. Thus we suggest this democratic approach as a policy improvement for similar program for other developing countries.

3. Evaluation based on income

3.1 Methodology

Within this mehodology household welfare is assumed to be determined by disposable income, which is the net income available to households for consumption. In many developing countries, it is difficult to accurately measure income due to the existence of a significant informal sector. Households' consumption during the survey period provides a better measure of their permanent standard of living than their current income for determining who is poor and who is not.

Measuring poverty among individuals requires the welfare of individuals. To derive an individuals' welfare, we assume that all individuals belonging to the same household experience the same standard of living. If we identify a household as poor, then all individuals belonging to this household are also identified as poor.

Since Dibao is a national program, this section evaluates Dibao using a national poverty line for the rural areas. The official poverty line is 2,736 yuan per person per year for 2013, which

[10] As Dibao is for extreme poor households that could not pull themselves out of poverty, there is little stigma attached to being listed publically.

is about 28 percent of the average per capita real income. The CHIPs survey provided both income and consumption data. We will use both as a basis for evaluating the Dibao program.

Exclusion error and leakages are commonly used indicators to evaluate targeting efficiency. Following Kakwani et al. (2019), the exclusion error is the percentage of poor whom we exclude from the program and is given by:

$$E = 1 - B_p$$

The exclusion error informs what percentage of eligible persons we exclude from the program. It is a measure of horizontal inequity when we do not treat individuals in the same economic circumstances equally.

We define leakage as the percentage of all beneficiaries who are not poor (or not eligible for the program).

$$L = \frac{B - HB_p}{B}$$

This equation measures the resources going to unintended beneficiaries of the program. Exclusion error and leakage are related such that

$$L = 1 - \frac{H}{B}(1 - E).$$

If the probability of selecting a beneficiary is equal to the headcount ratio of poverty ($B = H$), then leakage is equal to exclusion error ($L = E$). If $B < H$, $L<E$ and similarly, if $B > H$, then $L>E$. The difference between leakage and exclusion error is an indicative of the degree of mismatch in the program.

While both errors are undesirable, it is hard to simultaneously reduce them. If the number of beneficiaries increases as the program expands, then the exclusion error tends to be reduced but the leakages increase. Thus a reduction in one error may cause the other to increase. There is no simple formula to evaluate how well-targeted a program is. There might be a trade-off between the two errors; therefore, some normative judgment is needed in evaluating the program.

3.2 Results

To correspond with the results in the following sections, we deleted a few observations that lack the multidimensional poverty related indicators. Thus there are some small differences in numbers between the results in this section and the results in Kakwani et al. (2019).[11] Our estimation show that the number of Dibao recipients is 50.2 million, while the published statistics by the Ministry of Civil Affairs show that the number of people covered by Dibao in the fourth quarter of 2013 is 53.8 million (MoCA 2014). These two numbers are close.

In principle, Dibao coverage should be the real poor. However, we do not know the exact information of each family; we can only use some ancillary information to make judgments. The first type of common approach is based on per capita disposable income or per capita consumption expenditure as the base for measuring living standards. If the indicator is lower than the poverty standard, the individual is said to be in poverty.

Our rural data in Table 2 shows that there were 54.33 million people in poverty by the income measure and 54.38 million by the consumption measure. The corresponding income poverty

[11] Kakwani et al. (2019) examine the effectiveness of the rural Dibao program in China, using the income approach with data from the Chinese Household Income Project (CHIP2013). It finds low targeting accuracy, and large inclusion and exclusion errors, along with a negative social rate of return.

incidence and the consumption poverty incidence are around 8.6 percent, which is close to the rural poverty incidence of 8.5 percent published by the National Bureau of Statistics (NBS 2017).

Based on the income of the 54.33 million people living in poverty, only 7.98 million have access to Dibao, and up to 86.53 percent of poor people do not receive the transfer. This is a high exclusion error. Of the 50.23 million people who receive Dibao transfer, up to 85.43 percent are not really poor. This means a high level of leakage.

The results based on per capita consumption are similar to that based on income. Household consumption per capita was 7,620 yuan, below the household income per capita. However, due to the higher marginal consumption tendency of low-income groups, the incidence of poverty based on household consumption per capita is not significantly higher than the average household income per capita calculation. Based on household consumption, the exclusion error and leakage are also as high as 85.34 percent and 84.13 percent respectively.

<Insert Table 1>

4. Evaluation based on a multidimensional measure

4.1 Methodology

Only using the income dimension as the basis may not be enough. Sen's (1985, 2001) capability approach focuses on what individuals can do. Using the theoretical basis of the capability approach, we can judge the overall development ability of a family, and thus use it as a basis for estimating poverty. Based on Sen's theory, there have been many evaluation indexes for "human development" or "poverty" in the literature. Among them, the most widely used is the multidimensional poverty algorithm developed by Alkire and Foster (2011). This multidimensional approach has been popularized by the UNDP in their Human Development Reports.

The Center for Poverty and Human Development at Oxford University (OPHI) developed the Global Multidimensional Poverty Index (GMPI) based on the Alkire and Foster (2011) (AF method in short). The AF method is based on a counting approach. It identifies who is poor using two kinds of cut-offs: a deprivation cut-off for each indicator, and a single cross-dimensional poverty cut-off. Suppose there are n people in a country, and their well-being is evaluated by d indicators. We denote each person i's achievement in each indicator j by $x_{ij} \in \mathbb{R}$ for all $i = 1, \dots, n$ and $j = 1, \dots, d$. An $n \times d$ matrix X, contains the achievements of n persons in d indicators. The rows denote persons and columns denote indicators.

We denote the deprivation cut-off for indicator j by z_j in vector z. If any person i's achievement in any indicator j falls below the deprivation cutoff – that is, if $x_{ij} < z_j$ - then the person is deprived in that indicator. Otherwise they are non-deprived. Then, a deprivation status score g_{ij} is assigned to denote each person's deprivation status in each indicator based on z_j. In this case, person i is deprived in indicator j, $g_{ij} = 1$; if non-deprived, $g_{ij} = 0$.

Each indicator is assigned a weight based on the value of that deprivation relative to other indicator deprivations. Thus, a weighting vector w is used to weight each indicator j. We denote each indicator's weight to be w_j, such that $w_j > 0$ and $\sum_{j=1}^{d} w_j = 1$. Next, an overall deprivation score $c_i \in [0,1]$ of each person i is computed by summing the deprivation status of all d indicators, each multiplied by the corresponding weights w_j, such that $c_i = \sum_{j=1}^{d} w_j \, g_{ij}$. The deprivation scores of all n persons are summarized by vector c, where $c_i \in (0,1)$.

A person is identified as multidimensionally poor, if their deprivation score is greater than or equal to the value of the poverty cut-off denoted by k. Thus the ith person is poor if $c_i \geq k$, where $k \in (0,1]$; and non-poor if $c_i < k$.

In the AF method, based on the first cut-off and the weight of each indicator, a total poverty score vector c can be obtained. The vector c is further divided into states of poverty or non-poverty according to the second cut-off. Obviously, the choice of second cut-off, k, will affect the estimation results. For strict poverty identification criteria, a household is considered poor when multiple indicators of specific households are deprived. On the contrary, for a less strict poverty identification criteria, a household can be considered in poverty when one of the indicators is deprived. The case in which $k = 1$, is called the intersection approach in which a person must experience all deprivations to be identified as poor. When $0 < k \leq \min_j\{w_1, \dots, w_d\}$, it is referred to as the union approach where even one deprivation identifies each person as poor. For $\min_j\{w_1, \dots, w_d\} < k < 1$, it is referred to as the intermediate approach. Clearly, the appraisal of poverty is sensitive to cut-off k.

Under the AF framework, specific multidimensional poverty index can have different dimensions, indicators and their weights, deprivation cut-off for each indicator, and cross-dimensional poverty cut-off. The standard GMPI has detailed indicators and defines the critical cut-offs of deprivation indicators and cross-dimensional poverty cut-offs, which were introduced by Alkire and Robles (2017). It has three main dimensions: Health, Education, and Standard of Living.

We construct a multidimensional poverty index in China, based on the AF method and GMPI, but with consideration to China's circumstances. We maintain the GMPI structure but adjust it to get China's multidimensional poverty indicators in Table 3. Among them, the two indicators of the education dimension are basically the same as the GMPI; the two indicators of the health dimension are replaced by the health level score and the proportion of the self-funded medical expenses; the living condition dimension selects two indicators of drinking water and housing area and did not use the indicators of access to electricity, sanitation, cooking fuel and assets.

The reason for our adjustment is that GMPI is designed mainly based on low-income countries. GMPI is mainly designed for underdeveloped countries and China had already reached high-middle income status in 2013, so some of the indicators in GMPI are no longer suitable for the Chinese case. For example, GMPI has indicators such as child mortality, electricity coverage. However, in China, mortality rate for children under 5 is only 1.07 percent in 2015 (NBS 2016) and electricity coverage is more than 99 percent (NBS 2017). Some of the GMPI indicators and their deprivation thresholds do not apply to China's current situation. Our dataset also lacks some of the variable information such as nutrition intake.

The MPI weights reflect the normative assessment, defended previously in the HDI and HPI, that achievements in health, education, and living standards are roughly equal in intrinsic value (Alkire and Santos 2014). Equal weights across dimensions also ease the interpretation of the index for policy (Atkinson et al. 2002). Following these two ideas, the weights of the indicators in this paper are set to be the same. Alkire and Santos (2014) found that the effect of changing weights on MPI scores is weak. Shen et al.(2018) found that the MPI index is more sensitive to the assigned weight but adjusting the weight within a certain range did not affect the intertemporal comparison of MPI and the comparison between groups.

The choice of poverty cut-off k is the next issue in MPI evaluation. GMPI uses a poverty cut-off k of one-third or 33.33 percent. MPI in this section includes six indicators in three dimensions. So we report results for different poverty cut-offs with k being one-sixth, two-sixth, three-sixth, and four-sixth. Since the weights of the indicators are set to be the same, $k = 1/6$ means that a household is considered poor in at least one indicator from the multidimensional poverty measure. When k equals two-sixth, three-sixth, and four-sixth, it means a household is in multidimensional poverty, only when multiple (2, 3 or 4 out the 6 dimensions) indicators are simultaneously deprived.

<Insert Table 2 here>

4.2 Results

To compare the results in different situations, we reported targeting indicators in Table 3 when K takes different values. When $k = 1/6$, the MPI poverty incidence is 14.23 percent, when $k = 2/6$, the poverty incidence dropped to 1.58 percent if $k = 3/6$, the poverty incidence is only 0.05 percent. This shows that it is rare for Chinese rural households to be deprived of two or more indicators in Table 3 at the same time. Thus we focus on the case when $k = 1/6$ here.

When the MPI method is better than the income-only approach, the target efficiency should be higher. As we can see from Table 3, the exclusion error of 82.14 percent is below that of 86.53 percent in Table 2 using only income indicator. Under the MPI method, the leakage is 68.13 percent, much less than 85.43 percent of the single-income dimension. The proportion of the non-poor in Dibao is still high, but not as severe as those assessed by incomes or consumption poverty.

As discussed in Section 2, the government guidance requires other multidimensional factors like the standards of housing, education, and health to be taken into consideration, but income must be the primary base of assessment. This is equivalent to a combination of multidimensional poverty standards with the income standard. We add income into the multidimensional indicators assign the weight of income to one-fourth and call it “MPI+Income”. All indicators are kept the same and the weights of each dimension are adjusted from one-sixth to one-eighth. The income dimension means if household income per capita is lower than the official poverty line, all family members face income poverty.

With the income dimension information, the exclusion error has risen from 82.1 percent to 84.2 percent. The main reason for this result is that the combination of the two methods does not improve the exclusion error. Because the targeting efficiency of the income dimension is poor, and the exclusion error will be slightly affected when the income dimension is added. However, the leakage dropped from 68.1 percent to 57.5 percent, which means even with the income dimension included in the MPI, 57.5 percent of the non-poor are still present in Dibao.

<Insert Table 3 here>

5. Evaluation based on poor means test

In addition to the above methods, the means test or proxy means test (also known as poor means test) method is also used in many underdeveloped countries to identify poor families.

5.1 Methodology

Given the administrative difficulties associated with sophisticated means tests and the inaccuracy of simple means tests, the idea of using other household characteristics as proxies for income is appealing. In general, the proxy means test (PMT) literature uses regression analysis to predict welfare levels based on several combinations of variables that are easier to measure, then it assigns each individual a transfer equal to the difference between their predicted welfare level and the poverty line. PMT start at the bottom of the distribution of predicted welfare and uses-up a fixed budget, and then uses the Foster-Greer-Thorbecke (1984) family of poverty measures to compare the outcomes of various targeting schemes with untargeted and perfectly targeted transfers (see Grosh and Baker 1995).

In general, the predicted welfare levels of PMT are natural numbers and sometimes they are the fitted values of ordinary least square (OLS), quantile regression (QR), or other similar models. An alternative option is to predict the probability of a household entering a program. For instance, Chen et al. (2006) calculated the “propensity score” of households and evaluated the targeting of urban Dibao in China based on probit regression. Golan et al. (2017) applied Chen et al. (2006)’s idea on rural Dibao in China. Essentially, these practices calculate a “value” based on some easily observable proxy variables, and then use a “cut-off” to determine if a particular household should enter the program. This section uses the conventional PMT method to calculate the predicted welfare level of different households.

The PMT approach was used by Brown et al. (2018) to evaluate poverty targeting in nine African countries. They used OLS, QR and “poverty-weighted least-squares” (PLS) to estimate the relationship between the consumption of households and their characteristics. The proxy variables used in practice typically cover readily observed living conditions of the household, such as basic consumer durables or assets, demographic variables (size and composition) and attributes of the household head.

To be more operational in project execution, proxy indicators must be easy to observe and not be prone to false reporting. Common indicators include: some basic consumer durables or assets, demographic variables, and attributes of the household head. This section uses the same estimation method and selects the proxy variables of the same dimensions for China. The specific proxy variables for each dimension selected in this section are not exactly the same as in Brown et al. (2018). We use household per capita income, instead of consumption, as a measure of household welfare level. The main indicators selected in this section include some easy-to-observe assets in households, demographic variables, and the characteristics of the household head. Table 4 presents some descriptive statistics about these proxy variables.

The PMT method builds a relationship model between proxy information and household income, estimates the model coefficients based on known small-scale survey data of household income, and then infers poverty status to poor households with unknown household income.

A few things that can affect the estimation results are as follows: the first is the choice of models. This section mainly uses the results of OLS and QR, and the quantiles of QR are 10 percent, 30 percent, and 50 percent, respectively. The second is how to judge the poverty status after the model gets the fitted income. Since the outcomes of OLS or the QR regression model are conditional averages or conditional quantiles, the variances of fitted values will be less than that of observed values. The result is the tails of the fitted income distribution will shrink to the center of the income distribution, and the proportion of households counted by specific absolute poverty line will be less than that of observed income distribution. However, the conditional average or conditional quantiles determined by specific household characteristics still indicate the relative degree of poverty. Thus, the criteria used in PMT determines whether poverty is relative. In this paper, the lowest 10 percent, 20 percent, 30 percent, 40 percent, and 50 percent of the fitted income are considered poor. That is, in the study the targeting accuracy assume the Dibao households are in a fixed proportion of lowest income households of the total.

5.2 Extending PMT according to regional development differences

Considering that the poverty identification methods used in the actual poverty alleviation are different across regions and Dibao lines are different depending on the development levels of provinces. Given the different regional development levels in China, a PMT using a regional differentiated cut-off points may better identify the poor and evaluate the effectiveness of Dibao. We assume that the total number of Dibao allowances in each region of the CHIP data is a quota given by the government, and the actual Dibao targeting is occurring within each region. Another implication is that each region determines how many low-income families are planned to be supported in the given year according to local economic conditions, and then finds the corresponding poor families according to family status in the region. Because the income standards for receiving Dibao are different in different regions, we refer to this method as “Regional Differentiated Proxy Means Test” (RDPMT).

The PMT method ranks the country and the proportion of the population with the lowest score is defined as poor. The RDPMT treats the proportion of the population with the lowest score in each region as poor according to the quotas given by each region. There are three steps to take here:

First, according to the total rural population and a certain percentage θ, the overall size of the poor population identified at the national level is determined to be $p_{total} = N \cdot \theta$. For example, it is possible to set a plan of 30 percent of the total population to be identified as poor population.

Second, calculate the size of the poor population in each region $p_j = p_{total} \cdot \omega_j$ according to a certain proportional relationship. Here, according to the ratio of the distribution of the number of poor households in each region in the CHIP data, $\omega_j = \frac{DB_j}{DB}$.[12]

Third, the PMT score is calculated, and the PMT scores are ranked in each region, and the p_j individuals with the lowest scores are selected as the poor population.

5.3 Results

From Table 5, the results obtained by the PMT method are better than the results from single-income dimension and MPI, and the results of using the QR are better than those using OLS.

[12] Another idea is to use the proportion of the resident population in each region as the proportional relationship $\omega_j = \frac{pop_j}{\sum_j pop_j}$, which is equivalent to identifying the proportion of the poor population in each region. The problem for this practice is that it does not consider regional economic factors.

When using a QR model with a quantile of 30 percent and setting the lowest 30 percent of the population as the target of poor, the leakage fell to 47.5 percent, continuing to be lower than that in the previous sections. However, at this time it is assumed that the proportion of people who are poor has reached 30 percent, which is higher than the 21.4 percent of the MPI results. It makes the exclusion error high and still larger than 80 percent. In summary, PMT is better than the methods in previous sections, especially if the aim of Dibao is to target more poor people.

Table 5 also reports the results estimated based on the new RDPMT method. When low-income households with a minimum PMT score of 20 percent, 30 percent or 40 percent are identified as poor households, RDPMT will receive a lower leakage than that of PMT. For example, when using a QR model with a quantile of 30 percent and setting the lowest 30 percent of the population as the target of the poor, the leakage of PMT is 47.5 percent, while it is 44.5 percent in RDPMT. When considering regional differences, the evaluation of the Dibao targeting are better.

<Insert Table 4>
<Insert Table 5>

6. Comparison of different methods

To compare the results of the previous methods, we calculated the ratio of the poor population identified by each of the two methods to the poor population of only one certain type of method (Table 6). Obviously, if the ratio is higher, it means that the identification results of the two methods are more similar.

From the results, we can see that the income poverty is not a good evaluation criterion. The one-dimensional income poverty identification result has a low cross-over ratio with MPI result, which means that it is likely to be unreliable to identify non-income dimension information. The cross-over ratio of those identified as poor by income and simultaneously by PMT is relatively high, reaching 62.9 percent. The main reason for this is that the estimated explanatory variables of the PMT model also use income variables.

However, the proportion of those identified as poor by PMT, only 18.1 percent are income poor, even lower than the proportion that is simultaneously recognized by MPI (23.2 percent) when considering the differences in development levels between regions and allowing the use of the differentiated poverty standards in each region to be used, the cross-over ratio of RDPMT to income, MPI and MPI+income, are all lower than the PMT and their cross ratio (both horizontal and vertical); The cross ratio of RDPMT to Dibao is higher in the horizontal and vertical columns than in the PMT. This further means that the actual implementation of Dibao is significantly affected by regional development differences, and it is not appropriate to ignore regional differences when conducting national subsistence assessments.

According to all the above methods, we can also note that the exclusion error of all methods is above 80 percent, and the values are not much different; Leakage by income poverty, MPI, MPI+income, PMT and RDPMT become smaller respectively. The economic meaning of this lies in the following aspects: First, when we adopt an assessment method that is closer to the real Dibao household identification method in practice the proportion of non-poor households in the Dibao households gets lower and lower. The Dibao targeting may be better than the results of many literature evaluations. In the literature, due to the limited data and the simplified quantitative model, it is likely that the complex process in the actual implementation of the subsistence is not captured, and it is difficult to reflect the true targeting efficiency.

Second, regardless of the methods used, the exclusion error is high, which means some real poor was not able to enjoy the Dibao policy, partly due to regional disparity in deciding who is poor. Third, after using multiple sets of methods, leakage is still as high as 44 percent. If we continue to look for quantitative approaches that are closer to reality, this value is likely to continue to decline. However, it is difficult to expect a reduction to zero. This means that there are indeed many low-income households that do not meet the strict Dibao standards. While recognizing that many identification methods in the literature do not adequately consider the detailed implementation features, we also need to recognize that some targeting inaccuracies do inevitably exist.

<Insert Table 6>

7. Conclusions

China’s rural Dibao program is one of the largest minimum income cash transfer schemes in the world, but more studies are needed to know about its performance and targeting effectiveness. The few papers written on this all find that the program has a low targeting accuracy (Kakwani et al. 2019; Han and Gao 2019). By looking into the detailed Dibao practice from the program design by the central government and the program implementation in the local areas, this paper argues that the Dibao program may not be as ineffective as shown by statistical evaluations.

Information asymmetry is one of the fundamental problems in levying taxes and giving subsidies. Knowing the precise income levels of each household helps precision targeting but it needs strong state capacity and involves huge administrative costs, which many developing countries lack. Due to the lack of precise income information, China’s Dibao program follows a community-based targeting approach. The higher-level governments give quotas for Dibao assistance by estimating the number of poor households in a region, and villagers democratically decide which households will receive this quota.

When villagers decide who should get Dibao subsidies, they often take a holistic view of the circumstances of the household. This is in line with the guidance provided by the central government, which is that the evaluation should be based on income but should include other factors like health and education. Our field studies also helped us to design our approaches to this evaluation.

This paper provides a comprehensive empirical evaluation of the rural Dibao program. The evaluation was performed using several methods for assessing the effectiveness of China’s Dibao: (i) Real per capita disposable income and real per capita household consumption; (ii) multidimensional poverty measures; (iii) Multidimensional poverty measures plus income dimension; (iv) Proxy means test; (v) Regionally Differentiated Proxy Means Test. Our results show that the targeting effectiveness increases when more comprehensive methods are used.

However, no matter which method is estimated, it is difficult to cover most of the poor by Dibao. One solution is to increase the coverage, so that more poor people can benefit, like the universal basic income approach. Another reason for the low targeting effectiveness is due to the regional variation in development levels and in classifying who is “poor”, which subsequently apply different Dibao standards. One way forward is to gradually introduce unified Dibao criteria across regions.

Of course, the Dibao program is not the only way to reduce poverty. Further improvement of social security policies in rural areas, allowing more low-income families to obtain transfer income from other sources, would also help to reduce poverty. The Chinese Dibao program follows an approach that is accurate at the village level but may be not so effective at the macro level, because the actual identification process may vary, which may subsequently cause variations in the Dibao qualification across regions.

Whilst the community-based targeting effective for micro-level identification, the overall low targeting issues show by the evaluation methods may be due to the unbalanced distribution of the Dibao quota across regions. Given that regionally unbalanced development is one of the fundamental reasons for aggregate inequality in China, what needs to be done to improve the policy effectiveness is that the central authority should provide a more balanced Dibao quota, giving a greater weight to regional differences.

For poor countries, especially in countries where the state capacity is relatively weak, the community-based democratic practice that allows people to evaluate and decide the allocation of welfare fund may be the best way to overcome information asymmetries, to effectively help combating poverty, and achieve common prosperity (Kakwani et al. 2022).

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