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Community-based welfare targeting and political elite capture: Evidence from rural China

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ABSTRACT

Using nationally representative rural household survey data from the 2013 China Household Income Project (CHIP) and decomposable targeting differential measures, this article systematically evaluates rural Dibao's targeting performance based on both income and multidimensional poverty measures, and investigates the effects of political elite capture in its community-based targeting (CBT) implementation. We found that rural Dibao's targeting performance was quite poor based on income poverty standards. When based on multidimensional poverty, Dibao's targeting performance was better than based on income poverty. Dibao's intra-village targeting accounted for more of its targeting performance than inter-village targeting. We also found political elite capture effects to exist for both Dibao participation and transfer value received. Moreover, the political elite capture effect from close relatives was larger in magnitude than that from household members. Having a household member being a village leader in the village of residence had no significant elite capture effect, whereas having members with a political leader position outside the village of residence or being a non-leader political party member was associated with a greater chance of welfare participation. These findings suggest that targeting errors in developing countries' CBT welfare programs such as China's rural Dibao is still substantial and political elite capture may be one important reason for them.

1. Introduction

The issue of asymmetric information is central to the targeting of public welfare programs, particularly in rural regions of developing countries where informal economies dominate (Ravallion, 2017). As a potential solution to this problem, community-based targeting (CBT) has been frequently applied in welfare programs in developing countries (Mansuri & Rao, 2004; World Bank, 2003). One key argument in favor of CBT is that communities are able to identify the poor accurately by drawing on local information (Alderman, 2002). Moreover, compared with program administrators at the central or prefectural level, communities are more likely to be held accountable to local people and have greater incentives to use local knowledge to improve welfare targeting (Galasso & Ravallion, 2005).

While CBT allows for the use of local information, it nonetheless bears two considerations in practice. First, there always exists disagreement about what "poverty" means: the central governments typically define poor households based on income or consumption, whereas local communities often favor a multidimensional poverty identification approach. So, although the monetary poverty eligibility is usually stipulated by central regulations, the targeting decision in CBT is often based on both monetary and nonmonetary factors at the local level (Alatas, Banerjee, Hanna, Olken, & Tobias, 2012; Handa et al., 2012). If using monetary poverty only in targeting evaluations, the poverty measurement errors will be misunderstood as targeting errors, while the two are actually different both conceptually and empirically (Ravallion, 2008).

Second, the argument that local communities are more accountable to the poor was developed on the assumption that locally communities are homogeneous (Seabright, 1996). However, in rural regions of developing countries where substantial local heterogeneity and high costs of interjurisdictional mobility are ubiquitous, the accountability argument is no longer persuasive (Galasso & Ravallion, 2005). In these settings, the considerable discretionary power bestowed to local officials in CBT makes it easier

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for political elites to capture the limited welfare benefits (Bardhan & Mookherjee, 2000). Existing evidence suggests that the elite capture effect sometimes may overwhelm the information advantage in CBT (Mansuri & Rao, 2012).

This article provides new empirical evidence on the targeting performance of a CBT welfare program in rural China and contributes to the long-standing debate on the merit of CBT globally. Since its implementation nationwide in 2007, the rural Minimum Livelihood Guarantee, or Dibao program, has become one of the world's largest unconditional cash transfer programs. Dibao is a national policy, but it relies on a highly decentralized community-based targeting approach in practice (Kuhn, Brosig, & Zhang, 2016; Liu & Xu, 2016). In theory, given its advantages in accessing local information, CBT should help improve rural Dibao's targeting performance. However, a set of recent evaluation studies found rural Dibao to have sizable targeting errors (Golan, Sicular, & Umapathi, 2017; Han & Xu, 2013; Han & Gao, 2017; Kakwani, Li, Wang, & Zhu, 2017; Zhu & Li, 2017).

Against this background, this article uses data from the recently-released 2013 China Household Income Project (CHIP) to provide a comprehensive assessment of targeting in rural Dibao and explore the possible factors contributing to Dibao's targeting errors. Specifically, we address four sets of research questions. First, how was rural Dibao's targeting performance using a conventional income poverty measurement? Second, which factors other than household income influenced rural Dibao participation in its implementation? Third, how was rural Dibao's targeting performance based on a multidimensional poverty approach, and how did it compare with that based on income poverty measures? Forth, was there political elite capture effect in rural Dibao's targeting? If so, what kinds of political connection was more influential in increasing rural households' access to the Dibao program?

Our study makes three contributions to the existing literature. First, we use the targeting differential approach to evaluate Dibao's targeting performance. Compared to other targeting measures such as exclusion and inclusion errors, targeting differential has the advantage of being able to be decomposed into inter-community and intra-community components. The decomposition is useful for assessing the relative contribution of the two components for Dibao's overall targeting performance. While targeting differential has been used to analyze the targeting performance of CBT programs in Bangladesh, Peru, Tanzania, and Malawi (Galasso & Ravallion, 2005; Kilic, Whitney, & Winters, 2015; Pan & Christiaensen, 2012; Stifel & Alderman, 2005), our study is the first to apply targeting differential to assessing China's rural Dibao.

Second, most existing studies of Dibao and similar cash transfer programs rely on income measures in assessing targeting evaluations (Coady, Grosh, & Hoddinott, 2004; Gao, Yang, & Li, 2015; Han & Xu, 2014; Kakwani et al., 2017; Ravallion, 2009). In this study, we adopt not only income but also multidimensional measures to estimate welfare eligibility, as enabled by the rich CHIP data. By comparing the evaluation results of targeting based on income and multidimensional poverty, we investigate the extent to which rural Dibao's targeting errors arise from discrepancies between income and multidimensional poverty measures (Ravallion, 2008). Additionally, in order to obtain robust results, we use two ways of multidimensional poverty identification, namely propensity score approach and Alkire and Foster methodology, to evaluate rural Dibao's multidimensional targeting performance.

Third, we also examine the reason of Dibao's targeting errors by testing the effect of political elite capture. Although some qualitative studies observed the ubiquity of irregularities in rural Dibao's targeting process (Li & Li, 2015; Wei, 2014; World Bank, 2011), no study has quantitatively tested elite capture influence in rural Dibao using national survey data. Existing evidence on political elite capture in CBT programs in other countries is fairly mixed. Evidence from a ration card program in India, a public food transfer program in Ethiopia, and two agricultural subsidy programs in Tanzania and Malawi show a significant elite capture effect in their targeting process (Besley, Pande, & Rao, 2012; Caeyers & Dercon, 2012; Kilic et al., 2015; Pan & Christiaensen, 2012; Panda, 2015). In contrast, Alatas and colleagues (2012,2013) examined the allocation of targeted welfare benefits in Indonesia but did not find political elite capture effects. Most of these studies are only able to measure household political elite connection with one single dummy variable (e.g., whether the household has close associates in political positions). Enabled by the rich measures in our data, this study examines the heterogenous effects of different kinds of political elite connection in rural Dibao.

The rest of the article is organized as follows. Section 2 provides the background on rural Dibao's targeting. Section 3 reviews previous relevant literatures. Section 4 introduces the data. Section 5 analyzes rural Dibao's targeting performance based on income poverty. Section 6 presents the targeting results based on multidimensional poverty. Section 7 examines the effect of political elite capture in Dibao's targeting. The final section concludes and discusses policy implications.

2. Background on rural dibao's targeting

As the primary welfare program in rural China, the fundamental goal of Dibao is to help families in absolute poverty maintain a minimum level of livelihood by providing cash transfers to them. Since its implementation nationwide in 2007, rural Dibao has expanded dramatically. As shown in Table 1, the total number of rural Dibao recipients was 35.66 million in 2007. It increased continuously to peak at 53.88 million in 2013. Parallel to the growth in population coverage, the total government expenditure in rural Dibao grew from 10.91 billion yuan in 2007 to 86.69 billion yuan in 2013. Since then, the number of rural Dibao recipients turned to decline and dropped to 45.87 million by 2016. However, the total government expenditure in rural Dibao continued increasing and reached 101.45 billion yuan in 2016. Based on both the size of recipients and total government expenditures, China's rural Dibao has become one of the largest unconditional cash transfer programs in the developing world (World Bank, 2014). In addition, the expansions in rural Dibao are also evident by the increase in the Dibao threshold and transfer level (Table 1).

According to the central government's stipulation, rural Dibao should be a strictly means-tested program. 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. Total Dibao funds should be sufficient to cover all eligible households and ensure their income to be at or above the local Dibao threshold (*yin bao jin bao*).[1] However, rural Dibao's targeting is usually implemented in two stages in practice. The first stage is inter-village targeting. Based on the number of Dibao recipients on previous year and the severity of financial difficulties, central, province, and prefecture-level city government transfer Dibao funds to their subordinates all the way down to the county level government. The county governments allocate rural Dibao quota in terms of the number of recipients to townships and then townships allocate the quota to subordinate villages on the basis factors such as population size and structure, economic development conditions, and experiences with natural disasters and other shocks (Kuhn et al., 2016; Li &

[1] Although local governments are required to be mainly responsible for funding the rural Dibao program, central government also provides substantial financial support to localities with financial difficulties. According to official data from the Ministry of Civil Affairs (various years), the share of rural Dibao funds from central government had been more than 60% in total rural Dibao funds since 2009.

Table 1
Official statistics on China's rural Dibao program.

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Number of rural Dibao recipients (million persons)	35.66	43.06	47.60	52.14	53.06	53.45	53.88	52.07	49.04	45.87
% of total rural population	4.99	6.12	6.90	7.77	8.08	8.32	8.56	8.42	8.13	7.78
Total government expenditure in rural Dibao (billion yuan)	10.91	22.87	36.30	44.50	66.77	71.80	86.69	87.03	93.15	101.45
National average rural Dibao threshold (yuan/person, year)	840	988	1210	1404	1718	2068	2434	2777	3178	3744
National average rural Dibao transfer (yuan/person, year)	306	531	763	853	1258	1343	1609	1671	1900	2212

Source: National Bureau of Statistics (various years), Ministry of Civil Affairs (various years).

Walker, 2016; Sun, 2016). The second stage is intra-village targeting. After receiving the Dibao quota, the villages then are in charge of identifying Dibao recipients and allocating their Dibao quota (Kuhn et al., 2016). Given the practical challenges in accurate estimation of rural household income due to factors such as informal labor market and fluctuation in agricultural income, villages usually adopt a community-based targeting (CBT) strategy, rather than strict means testing, to identify Dibao recipients (Li & Li, 2015; Liu & Xu, 2016).

A typical rural Dibao CBT process includes four main steps: application, screening through in-home visits, participatory appraisal, and approval by township and county level Dibao administrators. Among these four steps, participatory appraisal plays the most crucial role in deciding the potential Dibao recipients (He, 2017). The participatory appraisal is carried out within the village committees, which include township Dibao administrators, village leaders, political party members, and other village representatives. A multidimensional poverty identification approach is always used to evaluate Dibao eligibility in participatory appraisals (Kakwani et al., 2017; Kuhn et al., 2016; Zhang, 2017). Besides income, other factors, such as assets, housing conditions, and whether households have members with serious diseases or disability are taken into consideration. Because the members of the village committees live in close proximity to potential Dibao recipients, their information advantage is helpful for improving Dibao's targeting performance.

Meanwhile, despite the information advantage, CBT creates the potential for elite capture in rural Dibao. When considerable discretionary power is given to the village committees in CBT practice, village leaders and other political elite tend to have disproportionately large influence on Dibao eligibility identification. They may limit the information flow on the Dibao program and manipulate the participatory appraisals to allocate Dibao transfers to their own households or other households that have close connection to them. There have been numerous reports of cases of gaining Dibao access because of relationships or connections in the Chinese media (Xinhuanet, 2017).

Since 2012, China's central government has paid more attention to the problem of erroneous identification and set regulations to improve rural Dibao's targeting performance. In December 2012, the Ministry of Civil Affairs issued the "Methods for Screening and Approving Dibao Benefits", which specified a set of concrete measures to be followed in rural Dibao's CBT. In October 2013, the Ministry of Civil Affairs issued the "Notification about Establishing and Strengthening the Long-term Mechanism for Social Assistance Supervision and Inspection", which prescribed a series of monitoring methods and established a filing system of Dibao recipients who are close relatives of Dibao administrators and/or village leaders. In 2014, a special rectification on mis-targeting in social assistance was carried out nationwide. Many were deemed mis-targeted and kicked off from the Dibao recipient roll, as reflected by the significant decrease in the number of rural Dibao recipients since 2014 (Table 1).

3. Literature review

(a) Targeting in developing countries

Welfare programs can rely on various targeting methods to identify their eligible poor groups[2]. The gold standard of targeting is verified means tests, under which complete information on household's income is collected and verified with income data from independent sources such as pay stubs and tax records. While the verified means tests are viable in developed countries, this targeting method is extremely rare in developing countries where a large share of household income come from informal sectors and the verifiable data on incomes is often unavailable (Coady et al., 2004). In absence of verified information on income, a few programs, such as Brazil's Bolsa Familia, use unverified means tests to identify eligible households. In the unverified means tests, eligible households are determined solely based on applicants' self-reported income information, so their targeting is less accurate than the verified means tests (Handa and Davis, 2006).

In addition, some imperfect targeting methods that do not require complete income data are commonly used in developing countries. For instance, programs based on geographic targeting channel benefits to regions where the extent of poverty seems the greatest (Schady, 2002). In demographic targeting, eligibility for benefits is determined by easily observed demographic characteristics such as age, gender, and disability status (Willmore, 2007). In some workfare and food subsidy programs, self-targeting is designed in such a way that take-up is expected to be much higher among the poor (Besley & Coate, 1992). Recently, a growing number of programs in developing countries choose to use proxy means tests (PMTs) to target the poor. Based on statistical models, PMTs employ a set of observable and verifiable household characteristics to predict the welfare scores, and the scores are in turn used for determining eligible households (Klasen & Lange, 2015; Brown, Ravallion, & van de Walle, 2016).

Community-based targeting (CBT) is another widely-used method for identifying benefit eligibility in developing countries. There are some advantages to CBT. First, CBT can take advantage of local information on households' welfare circumstances, so it can help achieve more accurate targeting with lower administration costs (Alderman, 2002). Second, under CBT, communities tend to choose a multidimensional interpretation of poverty, which might be more adaptable to local conditions and culture than a centrally-defined, purely income-based poverty measure (Schuring, 2014). Finally, participation in CBT may empower disadvantaged members in the community and potentially strengthen social capital (Conning & Kevane, 2002).

However, critics of CBT often point to issues of elite capture in its implementation (Caeyers & Dercon, 2012; Kilic et al., 2015; Mansuri & Rao, 2004; Panda, 2015). Several recent studies compared the targeting performance of CBT and PMTs in specific programs and found that CBT performed slightly worse in targeting the poor than PMTs (Alatas et al., 2012; Stoeffler, Mills, & del Ninno, 2016). However, CBT generated higher satisfaction in program communities than PMTs (Alatas et al., 2012). These findings reflect both the advantages and limitations of CBT.

[2] More detailed review of poverty targeting methods used in developing countries can be found in Coady et al. (2004) and Grosh, del Ninno, Tesliuc, and Ouerghi (2008).

(b) Multidimensional poverty and targeting

Poverty is a multidimensional phenomenon (Narayan, Chambers, Shah, & Petesch, 2000). Since the mid-1970s, several theoretical frameworks have been constructed to understand multidimensional poverty[3]. Among these, the most influential is Amartya Sen's capability approach (Sen, 1992). In the capability approach, Sen defines functionings as beings and doings that people value, and in turn defines capability as 'the various combinations of functionings that person can achieve'. Sen argues that poverty should be seen as multidimensional capability deprivations. Motivated by the capability approach, AF method (or dual cutoff counting method) was developed by Alkire and Foster and has become the most popular strategy of multidimensional poverty measurement (Alkire & Foster, 2011). Several recent studies have applied AF method to identify multidimensional poverty households and estimate the overall multidimensional poverty profile in rural China (Alkire & Shen, 2017; Yang & Mukhopadhaya, 2017; Yu, 2013).

In welfare targeting, both the poor and local practitioners increasingly acknowledge the multidimensional nature of poverty. Local communities tend to identify eligible households in multidimensional poverty rather than using pure income-based poverty definitions stipulated by the central government (Schuring, 2014). If still using income poverty identification in targeting evaluation, a part of estimated "targeting errors" may be due to different poverty definitions used by local communities and the central government (Alatas et al., 2012). Targeting evaluation based on a multidimensional poverty approach should be able to address this limitation at least partially.

Previous studies mostly used two methods to identify multidimensional poverty in welfare targeting analysis. The first is the propensity score targeting method developed by Ravallion (2008). Under this method, the relationship between observed program receipt and income as well as other non-income characteristics is estimated using a probit regression model. Based on the regression results, a probability of receiving benefits (i.e., propensity score) is predicted for each sample, and then the predicted score is used as a broader well-being metric to identify multidimensional poverty. The advantage of the method is that the list of poverty-relevant variables and their weights used to construct the multidimensional well-being metric are determined based on a regression model, so they are more objective and precise than those chosen only based on common sense or value judgement (Ravallion, 2008). However, a problem with this method is that, due to the dependence of propensity score on welfare receipt, the evaluated targeting performance based on the method is surely not worse than that based solely on income eligibility, which may not always be true in reality.

The second method is using a multidimensional poverty measurement independent of the household's observed benefit receipt, such as AF measurement, to identify eligibility and then evaluate the targeting performance of the welfare program (Azevedo & Robles, 2013; Han & Gao, 2017; Zhu & Li, 2017). The advantage of the method is that poverty identification is independent of observed program receipt, so it is more suitable for comparing the targeting efficiency based on multidimensional poverty with that based on conventional income poverty. However, the disadvantage of the method, especially using the AF multidimensional poverty framework, is that there is no consensus in how to choose the poverty dimensions, their weights, and deprivation cutoffs. Usually, these choices are based on common sense and value judgement, so researchers should be cautious in interpreting the results derived from the method (Alkire et al., 2015). The robust tests by setting different weights and cutoffs are often necessary for obtaining a reliable conclusion.

(c) Existing evidence on rural Dibao's targeting performance

A growing body of research has used large-scale household survey data to evaluate rural Dibao's targeting performance, with most using monetary measures to estimate eligibility and finding a sizable targeting error. A set of studies focused on the population-based targeting performance of rural Dibao. For example, using data collected in five provinces in central and western China in 2010 and an income poverty measure, Han and Xu (2014) found that 72% of eligible households were excluded, while 73% of households who received Dibao were actually ineligible. Using the CHIP 2007–2009 rural survey data and an income poverty measure, Golan et al. (2017) found much higher population targeting errors in rural Dibao in all three years. Using CHIP 2013 rural survey data and both income and consumption poverty measures, Kakwani et al. (2017) also found substantial exclusion and inclusion errors.

Another set of studies examined rural Dibao's value-based targeting performance. These studies used measures such as the share of cash transfers going to the poor to offer a more nuanced analysis of rural Dibao's targeting performance (Han & Xu, 2014; Kakwani et al., 2017; Liu & Xu, 2016). The empirical evidence shows that some higher-income groups also benefit from rural Dibao due to targeting errors. For example, Han and Xu (2014) found that, more than 40% of total rural Dibao transfer benefit went to the non-poor households. These studies also revealed that rural poor households often do not receive the full entitled transfer amount even if they are identified as Dibao recipients, leaving a benefit gap (Han & Xu, 2014; Han & Gao, 2017).

Given that the conventional targeting estimation based solely on monetary poverty could be erroneous or misleading, several recent studies evaluated rural Dibao's targeting performance based on a multidimensional poverty identification framework. Using different data sources, Han and Xu (2013) and Golan et al. (2017) applied a propensity score approach to analyze rural Dibao's targeting performance. Both studies found that applying a multidimensional poverty framework yielded smaller targeting errors than revealed by conventional analysis based on monetary poverty only. Han and Gao (2017) and Zhu and Li (2017) used the AF multidimensional poverty measurement and achieved similar findings. This set of results show that sizable targeting errors found in rural Dibao may be partly due to using improper poverty identification strategies in targeting evaluation.

Although a growing body of research has empirically tested political elite capture effect in developing countries' CBT programs (Besley et al., 2012; Caeyers & Dercon, 2012; Kilic et al., 2015; Pan & Christiaensen, 2012; Panda, 2015), no quantitative study examined this topic in China's rural Dibao. Existing qualitative studies help shed light on how political elite capture affects rural Dibao's targeting. In a remote village in south-central China, Li and Walker (2016) found that, in the early years of rural Dibao's implementation, some village leaders put Dibao funds directly into their own wallets because most members within the village did not know about the program. After village members became more aware of the program and higher-level governments stipulated concrete measures in the CBT process, village leaders no longer dared to seize Dibao funds directly, but changed their strategies to allocate Dibao benefits to their close relatives as well as other political elites such as communist party members within the village. This finding of within-village elite capture was echoed by several other qualitative studies (Geng, 2012; Kuhn et al., 2016; Li & Li, 2015). Wei (2014) found that political leaders outside the case

[3] These frameworks include the basic needs approach, the human right approach, the social inclusion approach, and the capability approach.

village also exerted their influence on Dibao's CBT. Five out of the 39 Dibao households in his case village received Dibao because they had political leaders outside the village in their kin networks. This study also found that, compared to elite capture related to political connections within the village, elite capture arising from political connections outside the case village was more difficult to be regulated because of the greater power and wider influence of the political elites outside the village, often at higher government levels.

4. Data

This study uses the newly available China Household Income Project (CHIP) 2013 rural dataset. CHIP is considered one of the best publicly available data sources on Chinese household income and expenditures (Gustafsson, Li, & Sato, 2014; Riskin, Zhao, & Li, 2001). The CHIP 2013 rural dataset includes detailed information on individual, household, and community characteristics. In addition, the availability of detailed information on Dibao participation and transfer value as well as political elite connection provides a unique opportunity to examine rural Dibao's targeting and political elite capture comprehensively in our study.

The sample of the CHIP rural dataset was drawn from a larger, nationwide rural household survey conducted by the National Bureau of Statistic (NBS) of China using a multistage stratified probability sampling design. Fourteen provinces or municipalities from eastern, central, and western China were covered in the CHIP 2013 rural dataset. We consider household as the unit of analysis in this study[4]. After dropping observations with missing data on key variables, our full analytical sample included 9973 rural households (consisting of 37,090 individuals) from 14 provinces, 199 counties, and 569 villages. We define households who reported receiving any Dibao transfer value greater than zero in the previous year as Dibao recipients. Among the 9973 households, 673 households (consisting of 2326 individuals) were Dibao recipients, representing a rural Dibao participation rate of 6.74% (in households) and 6.27% (in individuals). This is somewhat lower than the national rural Dibao participation rate of 8.56% (in individuals) based on official statistics published by the Ministry of Civil Affairs (Table 1). This difference may have arisen from under-sampling of poor households in the CHIP survey, a known feature of larger NBS survey samples from which the CHIP samples are drawn (Golan et al., 2017). We constructed sampling weights based on NBS's annual 1% population sample surveys and applied these weights in all our analysis to obtain nationally representative estimates.

Table 2 presents descriptive statistics for household head, household, and village characteristics in the full, Dibao, and non-Dibao samples. The results show significant differences in most characteristics between rural Dibao recipients and non-recipients. Heads of Dibao household were older and less educated, and were more likely to be female, ethnic minority, and not employed. Dibao households on average had smaller household size, a smaller share of members who were children but a greater share of members who were elders. They were more likely to have members with bad health or physical disability and less likely to have members with a migrant job. On a per capita basis, Dibao households had significantly lower pre-Dibao household income, financial assets, and house area. Dibao households were more likely to live in a house constructed with low-quality material and have catastrophic medical expenditures, and less likely to have a motorized vehicle, major appliances, or flushing toilet. The villages in which Dibao households lived were less likely to have buses, health care centers, or kindergartens, and more likely to be located in mountainous area and far away from township and county seats.

Table 3 shows the distribution of political elite connections in the sample. The dummy variable indicating political connections equals one if any household member was political elite or any household close relative was political elite. To understand the nuanced effects of different types of political elites, we further divided political elites within the household into three groups: village leader in village of residence, political leader outside village of residence, and political party member without leader position. The results show Dibao households tended to have political elite connections than non-Dibao households, although the difference was nonsignificant statistically. Specifically, Dibao households were more likely to have both a household member and a close relative who was a political elite. Among the three different types of political elite in the household, Dibao households were less likely to have a member who was a village leader in the village of residence but more likely to have a member who was a political party member without leader position.

5. Dibao's income poverty targeting

(a) Targeting differential and its decomposition

In this article, we use two kinds of targeting differential (i.e., population-based and value-based targeting differential) to measure rural Dibao's targeting performance and assess the relative importance of inter-village versus intra-village targeting. The inter-village targeting reflects higher-level governments' efforts at reaching poor villages, and the intra-village targeting describes the efforts of those villages to reach their own poor households (Galasso & Ravallion, 2005). Population-based targeting differential NT can be defined by the following equation[5]:

$$NT = NG^p - NG^n \tag{1}$$

where NG^p and NG^n measure the share of the Dibao recipients in eligible households (coverage) and the share of the Dibao recipients in ineligible households (leakage) respectively. If rural Dibao is perfectly targeted so that all eligible households participate in the program and no ineligible households benefited from the program, then NT reaches its maximum value 1. If the opposite is the case and rural Dibao perfectly targets the ineligible, then NT reaches its minimum value -1. In addition, a uniform allocation implies NT equals 0.

Following Galasso and Ravallion (2005), the population-based targeting differential can be decomposed into an inter-village component and an intra-village component:

$$NT = \underset{\text{(inter - village)}}{\frac{\sum_j N_j \left(NG_j - NG\right)\left(H_j - H\right)}{\sum_j \sum_i \left(H_{ji} - H\right)^2}} + \underset{\text{(intra - village)}}{\frac{\sum_j \sum_i \left(NG_{ji} - NG_j\right)\left(H_{ji} - H_j\right)}{\sum_j \sum_i \left(H_{ji} - H\right)^2}} \tag{2}$$

where i is a household index and j is a village index. H is the poverty head ratio among full sample. H_j is the poverty head ratio in village j. H_{ji} is a dummy variable indicating whether household i in village j is poor or not. NG is the coverage rate of rural Dibao among full sample. NG_j is the coverage rate of rural Dibao in village j. NG_{ji} is a dummy variable indicating whether household i in village j is

[4] We choose household rather than individual as the unit of analysis for the following reasons. First, although determining rural Dibao eligibility by individual has been found by some empirical studies (Kuhn et al., 2016; Zhang, 2017), the central government stipulates that rural Dibao eligibility should be determined by household, and this requirement has been reinforced in practice during recent years. Second, in rural China, household is the primary economic unit, so the received Dibao transfer is most likely shared among all members within the household even if only selected members received Dibao transfers in practice. Third, most previous studies on rural Dibao's targeting performance also used household as the unit of analysis (Golan et al., 2017; Han & Gao, 2017; Kakwani et al., 2017; Zhu & Li, 2017).

[5] Because the unit of analysis used in our targeting evaluation is household, population here refers to households rather than individuals.

Table 2
Descriptive statistics of sample characteristics.

	Full sample (N = 9973)		Dibao sample (N = 673)		Non-Dibao sample (N = 9300)	
	Mean	SD	Mean	SD	Mean	SD
Household head characteristics						
Age	52.904	11.649	57.857	12.770	52.545	11.482***
Female	0.089	0.285	0.130	0.337	0.086	0.281***
Education (Default: Primary school or less)	0.398	0.489	0.617	0.487	0.382	0.486***
Junior high school	0.484	0.500	0.334	0.472	0.495	0.500***
Senior high school or more	0.118	0.322	0.049	0.216	0.123	0.328***
Employment status (Default: Employed)	0.782	0.413	0.640	0.480	0.792	0.406***
Not employed	0.208	0.406	0.350	0.477	0.198	0.398***
Retired	0.010	0.102	0.010	0.102	0.010	0.102
Ethnic minority	0.072	0.259	0.124	0.329	0.069	0.253***
Household demographic characteristics						
Household size	3.692	1.438	3.340	1.578	3.717	1.424***
Share of members age <16	0.125	0.162	0.092	0.146	0.128	0.163***
Share of members age ≥60	0.222	0.335	0.398	0.398	0.209	0.327***
At least one member reporting bad health	0.203	0.402	0.513	0.500	0.181	0.385***
At least one member with disability	0.118	0.323	0.336	0.473	0.102	0.303***
At least one member with migrant job	0.435	0.496	0.345	0.476	0.441	0.497***
Household economic characteristics						
Pre-Dibao income per capita (thousand yuan)	10.751	9.723	6.431	4.486	11.063	9.923***
Financial assets per capita (thousand yuan)	12.323	26.016	6.059	9.292	12.776	26.767***
House area per capita (square meters)	45.401	31.127	43.999	35.327	45.502	30.801
House construction materials (Default: Concrete and brick)	0.588	0.492	0.386	0.487	0.603	0.489***
Brick and wood	0.326	0.469	0.423	0.494	0.319	0.466***
Bamboo, grass, and adobe	0.086	0.280	0.190	0.393	0.078	0.269***
Household has motorized vehicle	0.590	0.492	0.399	0.490	0.604	0.489***
Household has major appliances	0.615	0.487	0.329	0.470	0.636	0.481***
Household has flushing toilet	0.268	0.443	0.106	0.309	0.279	0.449***
Household had catastrophic medical expenditure	0.080	0.271	0.174	0.380	0.073	0.260***
Village characteristics						
Bus in the village	0.673	0.469	0.516	0.500	0.684	0.465***
Health care center in the village	0.861	0.346	0.803	0.398	0.865	0.342***
Kindergarten in the village	0.465	0.499	0.353	0.478	0.473	0.499***
Distance to township seat >10 km	0.122	0.327	0.180	0.384	0.117	0.322***
Distance to county seat >20 km	0.419	0.493	0.524	0.500	0.411	0.492***
Land condition of the village (Default: Plain)	0.453	0.498	0.228	0.420	0.469	0.499***
Hill	0.330	0.470	0.347	0.476	0.329	0.470
Mountain	0.217	0.412	0.425	0.495	0.202	0.402***

Note: This table and all subsequent tables are calculated based on CHIP 2013 rural survey data. Major appliances include air conditioner, water heater, computer, camera, video camera, stereo system, mid- and high-grade music instruments. Motorized vehicle includes vehicle for home use and motorcycle. The two variables indicate having at least one of these items, respectively. Catastrophic medical expenditure = 1 if out of pocket medical expenditure/(pre-Dibao income – food expenditure) ≥40%. Regression models (OLS for continuous variables and logistic regressions for binary variables) are used to test mean differences between the Dibao and non-Dibao samples. Significance level is indicated in the column for the non-Dibao sample.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3
Distribution of political elite connections in sample households.

	Full sample (N = 9973)		Dibao sample (N = 673)		Non-Dibao sample (N = 9300)	
	Mean	SD	Mean	SD	Mean	SD
Household has political elite connection	0.209	0.407	0.227	0.419	0.208	0.406
Any household member is political elite	0.183	0.387	0.190	0.393	0.183	0.387
Is village leader in village of residence	0.059	0.236	0.040	0.197	0.060	0.238***
Is political leader outside village of residence	0.023	0.151	0.029	0.168	0.023	0.150
Is political party member without leader position	0.112	0.316	0.132	0.339	0.111	0.314**
Any household close relative is political elite	0.037	0.188	0.045	0.206	0.036	0.187

Note: Political leader outside village of residence include department managers in state agencies, party organizations, and public institutions. Logistic regression models are used to test mean differences between the Dibao and non-Dibao samples. Significance level is indicated in the column for the non-Dibao sample.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

rural Dibao recipient or not. N_j stands for the total number of households in village j.

The population-based targeting differential follows an assumption of equal transfer values to all recipients. However, the variation of transfer values across recipients is common in welfare programs. For rural Dibao, households always received different transfer values depending on their characteristics. Under such circumstances, while the population-based targeting differential described above can capture the targeting decisions regarding who should participate in Dibao, the value-based targeting differential can help further account for the additional targeting decision regarding the value of transfer to each recipient.

Following Stifel and Alderman (2005), the value-based targeting differential can be defined as equation:

$$VT = VG^p - VG^n \tag{3}$$

where VG^p and VG^n measures the respective average transfer values among eligible and ineligible households. Following Kilic et al. (2015), equation (3) needs to be standardized by dividing both sides by VG^p. The results of standardized VT (i.e., SVT in Tables 4, 6, 8) can be compared across different poverty identification methods. If Dibao perfectly targets to the eligible, SVT reaches its maximum value 1. If Dibao perfectly targets to the ineligible, SVT equals negative infinity.

The value-based targeting differential can also be decomposed into an inter-village component and an intra-village component:

$$VT = \underset{\text{(inter - village)}}{\frac{\sum_j N_j \left(VG_j - VG\right)\left(H_j - H\right)}{\sum_j \sum_i \left(H_{ji} - H\right)^2}} + \underset{\text{(intra - village)}}{\frac{\sum_j \sum_i \left(VG_{ji} - VG_j\right)\left(H_{ji} - H_j\right)}{\sum_j \sum_i \left(H_{ji} - H\right)^2}} \tag{4}$$

where i and j are a household and village index respectively. H, H_j, H_{ji}, N_j have the same meanings with those in equation (2). VG is the average transfer value among the full sample. VG_j is the average transfer value for all households in village j. VG_{ji} is the Dibao transfer value received by household i in village j.

(b) Targeting performance based on income poverty

In this section, we analyze rural Dibao's targeting performance based purely on income poverty. We use household per capita pre-Dibao income to capture household welfare.[6] The income poverty identification can be carried out against different poverty thresholds. An initial choice for the poverty threshold is local Dibao thresholds determined by each county. The problem with this approach is that there are no standardized criteria for each county to determine the Dibao thresholds. In addition to basic consumption needs and price levels, local fiscal capability also substantially influences the local Dibao thresholds. Therefore, we first use three national poverty thresholds to identify households in income poverty, which enables cross-study and cross-national comparisons, and then use local Dibao thresholds. The first national poverty threshold is the rural official poverty line of 2300 Yuan per person per year in 2010 constant prices, which equals 2736 Yuan per person per year in 2013 prices after adjusting for CPI. The other two national poverty thresholds are 1.9 USD and 3.1 USD per person per day in 2011 PPP, which equals 2275 Yuan and 3711 Yuan per person per year in 2013 prices after adjusting for PPP and CPI.

The results of rural Dibao's targeting performance and its decomposition based on income poverty are presented in Table 4. Using the rural official poverty line as income poverty threshold, only 15.1% of the poor was found to have received rural Dibao, while the comparable figure for the non-poor was 6.1%. The population-based targeting differential was 0.09, indicating only slightly better performance than the uniform allocation approach. The share of population-based targeting differential attributable to the intra-village component (62.07%) was greater than that attributable to the inter-village component (37.93%). When we focus on the value-based targeting differential, the average Dibao transfer value among eligible recipients and non-eligible recipients were 257.73 and 82.27 Yuan respectively. The standardized value-based targeting differential (SVT) was 0.679. The share of value-based targeting differential attributable to the intra-village component (63.88%) was also greater than that attributable to the inter-village component (36.12%).

Using 1.9 USD and 3.1 USD per person per day as national income poverty thresholds, we conduct the same analyze and reach conclusions that are similar to those using the rural official poverty line. Specifically, both the targeting differentials and the share of targeting differential attributable to intra-village component using 1.9 USD as the income poverty threshold were slightly higher than those using the rural official poverty line. When using 3.1 USD per person per day as the income poverty threshold, the standardized value-based targeting differential was slightly higher than that using the rural official poverty line. However, the population-based, unstandardized value-based targeting differentials and the share of targeting differential attributable to intra-village component were slightly lower than those using the rural official poverty line.

Finally, when local Dibao thresholds are used in the same targeting analysis, we find that population-based targeting differential was slightly lower, and value-based targeting differential was slightly higher than those using three national poverty thresholds to identify income poverty. In addition, the shares of both population-based and value-based targeting differentials attributable to intra-village component using local Dibao thresholds were higher than those using three national poverty thresholds.

All in all, regardless whether national poverty thresholds or local Dibao thresholds were used, these targeting evaluation results based on income poverty measures suggest that a sizable share of the poor was excluded from rural Dibao and substantial Dibao funds were leaked into the non-poor group. The finding that the intra-village targeting dominated inter-village targeting both in population- and value-based targeting differential indicates that efforts of villages to reach their own poor households played a more important role than those of higher-level governments to reach poor villages in rural Dibao's overall targeting.

6. Dibao's multidimensional poverty targeting

(a) Poverty-related determinants of Dibao participation

In this section, we use a probit regression model to explore the determinants of observed rural Dibao participation. In the probit regression, the independent variables include a rich array of characteristics at the household head, household, and community levels. Specifically, these independent variables not only cover monetary poverty-related factors such as household income and financial assets, but also a great number of non-monetary poverty-related factors reflecting household demographic composition, human capital, durable goods ownership, and housing condition. We also control for province fixed effects to account for unobserved heterogeneity across provinces.

Results in Table 5 reveal that both monetary and non-monetary poverty-related characteristics were statistically significant predictors of Dibao participation. The regression results show that, as expected, higher household income and greater financial assets were association with lower probabilities of receiving rural Dibao. Among the non-monetary factors, regarding household head characteristics, Dibao participation was more likely for households

[6] In targeting evaluations, we need to use the counterfactual income, i.e., income in the absence of Dibao transfers, to measure household welfare. In theory, the counterfactual income can be influenced by behavior incentives arising from receiving cash transfers. However, by estimating the benefit withdrawal rates, evidence on Dibao program both in rural and urban China suggests that the behavior incentives were very limited (Golan et al., 2017; Han & Gao, 2017; Ravallion & Chen, 2015). Therefore, we estimate the counterfactual income as equal to the reported household total income minus the amount of Dibao transfers received by the household. Then we divide the counterfactual income by household size and use the per capita income to capture household welfare.

Table 4
Dibao's targeting performance and its decomposition based on income poverty (N = 9973).

Eligibility threshold	Local Dibao thresholds in 2013		1.9 USD/day (2275 yuan/year in 2013 Rmb)		2300 yuan/year (2736 yuan/year in 2013 Rmb)		3.1 USD/day (3711 yuan/year in 2013 Rmb)	
% eligible households	4.93		5.32		7.60		13.84	
Population-based targeting								
NG^p (Proportion of eligible households receiving Dibao)	0.144		0.154		0.151		0.142	
NG^n (Proportion of non-eligible households receiving Dibao)	0.063		0.063		0.061		0.055	
$NT = NG^p$ - NG^n	0.080		0.091		0.090		0.087	
Decomposition of *NT*	Value	%*NT*	Value	%*NT*	Value	%*NT*	Value	%*NT*
Inter-village component	0.012	15.49	0.033	36.14	0.034	37.93	0.037	42.53
Intra-village component	0.068	84.51	0.058	63.86	0.056	62.07	0.050	57.47
Value-based targeting								
VG^p (Average Dibao transfer value among eligible recipients)	294.61		277.389		257.732		236.164	
VG^n (Average Dibao transfer value among non-eligible recipients)	85.71		85.807		82.265		73.484	
$VT = VG^p$ - VG^n	208.90		191.581		175.037		162.681	
$SVT = VT/VG^p$	0.709		0.691		0.679		0.689	
Decomposition of *SVT*	Value	%*SVT*	Value	%*SVT*	Value	%*SVT*	Value	%*SVT*
Inter-village component	0.161	22.75	0.220	31.80	0.245	36.12	0.262	38.02
Intra-village component	0.548	77.25	0.471	68.20	0.434	63.88	0.427	61.98

Notes: Local Dibao thresholds in 2013 used in the table is in county level.
Sources: County-level Dibao thresholds are from Ministry of Civil Affairs data in 2013.

whose head was female, with low education level, not employed, or ethnic minority. As for household characteristics, Dibao participation was more likely for households who had a smaller household size, a higher share of old members, at least one member reporting bad health, at least one member with disability, had no member with a migrant job, had no motorized vehicle, no major appliances, no flushing toilet, or who faced catastrophic medical expenditure. With regard to community characteristics, Dibao participation was more likely for households who lived in the villages without health care center, without kindergarten, located in hills or mountain areas.

(b) Targeting performance based on propensity score approach

The propensity score approach was developed by Ravallion (2008) and first used to evaluate the targeting performance of China's urban Dibao program. Following Ravallion (2008), our analysis on rural Dibao's multidimensional poverty targeting is carried out in three steps. The first step is to estimate a probit regression model with Dibao participation as the dependent variable and a rich array of poverty-related factors as the independent variables. These results are reported in Table 5 and discussed above. The second step is to use regression results from the probit model to predict the probability of receiving Dibao (i.e., the propensity score) as a multidimensional poverty measure. In the third step, eligible households are identified based on the propensity scores and a poverty cutoff point. Specifically, households whose estimated propensity scores are above the cutoff point are classified as poor households eligible for Dibao. We then calculate rural Dibao's targeting differentials and their decompositions based on the multidimensional poverty measure.

Using the estimated coefficients from the probit models in Table 5, we calculate the probabilities of rural Dibao participation (i.e., propensity score). We then use three poverty cutoff points to identify multidimensional poverty. The first cutoff point is the observed Dibao participation rate in our sample. This cutoff point is used in Ravallion (2008) and Golan et al. (2017) to identify eligibility of urban and rural Dibao respectively. Since there were 673 Dibao recipients in our full sample, we take 673 as a cutoff number of Dibao-eligible households. The other two cutoff points are the poverty rates based on local Dibao thresholds and the rural official poverty line, respectively. Using these two cutoff points enables us to compare the income and multidimensional targeting performance under the same eligibility rates. Since there were 492 and 758 poor households based on local Dibao thresholds and rural official poverty line, we take 492 and 758 as the two respective cutoff numbers of Dibao-eligible households. After ranking all households from the highest to lowest propensity scores, we define the 492, 673, and 758 households who had the highest propensity scores as the eligible sample under three poverty cutoff points. These correspond to an eligibility rate of 4.93%, 6.74%, and 7.60% respectively. Then, using the results of multidimensional poverty based on the three poverty cutoff points, we estimate the targeting differentials and their decomposition respectively. The results are presented in Table 6.

Compared to the results based on income poverty presented in Table 4, the results of targeting differentials based on propensity score approach gives a much more positive picture of rural Dibao's targeting performance. For example, when using the poverty cutoff point determined by the rural official poverty line to identify multidimensional poverty, the population- and standardized value-based targeting differential were 0.309 and 0.891 respectively, compared to 0.090 and 0.679 based on income poverty under the rural official poverty line.

Moreover, we find that the positive change of targeting performance occurred mainly in decreasing exclusion errors. For population-based targeting, the percentage of eligible households receiving Dibao increased by 0.204 (from 0.151 to 0.355), but the percentage of ineligible households receiving Dibao decreased by only 0.016 (from 0.061 to 0.045). For value-based targeting, the average Dibao transfer value among eligible recipients increased by 295.64 Yuan (from 257.73 to 553.37 Yuan), but the average Dibao transfer value among ineligible recipients decreased by only 21.72 (from 82.27 to 60.55 Yuan).

Why do the exclusion errors decrease when shifting from income-based targeting to multidimensional targeting assessment? A major reason is that income measures used in conventional targeting evaluations mostly do not reflect necessary consumption needs such as out-of-pocket medical expenditures that reduce disposable income but are essential for survival. The

Table 5
Results of probit regression on rural Dibao participation (N = 9973).

	Coef.	SE
Household head characteristics		
Age	0.003	(0.002)
Female	0.236***	(0.056)
Education (Default: Primary school or less)		
Junior high school	−0.079**	(0.040)
Senior high school or more	−0.253***	(0.075)
Employment status (Default: Employed)		
Not employed	0.088**	(0.042)
Retired	−0.083	(0.183)
Ethnic minority	0.155**	(0.069)
Household characteristics		
Pre-Dibao income per capita (thousand yuan)	−0.026***	(0.005)
Squared Pre-Dibao income per capita	−0.001**	(0.000)
Financial assets per capita quartile 1 (Default)		
Financial assets per capita quartile 2	−0.057	(0.045)
Financial assets per capita quartile 3	−0.120**	(0.048)
Financial assets per capita quartile 4	−0.173***	(0.058)
Household size	−0.078***	(0.018)
Share of members age < 16	−0.075	(0.139)
Share of members age $\geq$ 60	0.231***	(0.072)
At least one member reporting bad health	0.405***	(0.040)
At least one member with disability	0.487***	(0.044)
At least one member with migrant job	−0.137***	(0.041)
Ln(house area per capita) (square meters)	−0.023	(0.037)
House construction materials (Default: Concrete and brick)		
Brick and wood	0.008	(0.043)
Bamboo, grass, and adobe	0.032	(0.060)
Household has motorized vehicle	−0.084**	(0.041)
Household has major appliances	−0.150***	(0.042)
Household has flushing toilet	−0.100*	(0.059)
Catastrophic medical expenditure	0.142***	(0.052)
Village characteristics		
Bus in the village	−0.062	(0.041)
Health care center in the village	−0.123**	(0.048)
Kindergarten in the village	−0.098**	(0.038)
Distance to township gov't >10 km	−0.044	(0.055)
Distance to county seat >20 km	−0.026	(0.038)
Land condition of the village (Default: Plain)		
Hills or low mountain	0.237***	(0.050)
Mountain	0.358***	(0.054)
Province fixed effects	Yes	
Log likelihood	−3186.8796	
Likelihood ratio test chi2	1855.06***	
Pseudo R^2	0.2254	

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

households whose incomes are just above the poverty threshold are often improperly identified to be ineligible for Dibao in conventional targeting evaluations but in effect considered eligible from a multidimensional perspective. The propensity score approach used above not only takes into consideration family catastrophic medical expenditures, leading to a more accurate assessment of family economic conditions, but also other characteristics such as employment status and household age composition that are likely to be considered in Dibao's practice, thus contributing to decreased exclusion errors based on multidimensional poverty targeting as compared to those based on income poverty targeting.

As to the decomposition of targeting differentials using the propensity score method, consistent with earlier findings based on income poverty, we find that intra-village targeting dominated inter-village targeting in both population and value-based targeting. We obtain similar results when using the other two poverty cutoff point to identify multidimensional poverty, reflecting that the targeting evaluation results based on propensity score method are robust to the choice of the poverty cutoff points.

(c) Targeting performance based on AF methodology

In this section, we apply AF methodology proposed by Akire & Foster (2011) to identify multidimensional poverty, and then use it as Dibao eligibility to estimate the targeting differentials and their decomposition results[7]. The advantage of AF method is that its multidimensional poverty identification is independent of observed Dibao receipt, so it is more suitable for comparing targeting performance based on multidimensional poverty with that based on conventional income poverty.

Table 7 lists the dimensions, indicators, deprivation cutoffs, and weights for each indicator used in AF multidimensional poverty measurement. We follow three criteria in selecting the dimensions and indicators. First, the data on these dimensions and indicators are available. Second, they have been used in previous studies on AF measurement in rural China (Alkire & Shen, 2017; Yang & Mukhopadhaya, 2017; Yu, 2013). Third, these dimensions and indicators have been found as poverty-related determinants of rural Dibao participation by previous literatures (Golan et al., 2017; Kuhn et al., 2016; Zhang, 2017; Zhu & Li, 2017). We set the deprivation cutoffs for each indicator based on previous studies on AF measurement in rural China. In order to obtain robust results, we use two sets of weights in the AF measurement. The first set is equal weights among all dimensions and indicators, in which each indicator is given a weight of 1/8. Considering income and assets are stipulated as the most important eligibility criteria in Dibao's official documents, in the second set of weights, the income and assets indicators are given a weight of 2/10, and other indicators are given a weight of 1/10.

To identify multidimensional poverty using AF methodology, it is crucial to determine the poverty cutoff (k). The selection of k value should depend on the specific program context and the purpose of the research at hand. In targeting evaluations, identifying too many or too few multidimensional poverty scenarios could cause misleading policy implication. Considering the income poverty rate based on rural official poverty line in our sample being 7.6%, we choose three k values under which the calculated multidimensional poverty rates is not far away from 7.6%. For equal weights (weight1) measurement, we set k = 3/8, 4/8, 5/8. For unequal weights (weight2) measurement, we set k = 4/10, 5/10, 6/10.

In Table 8, we provide the targeting differentials and their decomposition results based on AF multidimensional poverty measures with different weights and k values. When selecting k = 4/8 under weight1 and k = 5/10 under weight2, the percentages of eligible households are 8.40% and 8.44% respectively, which are very similar to the income poverty rate (7.60%) based on the rural official poverty line. No matter using which set of weights, with the increase in k, the percentage of eligible households decreased sharply, and both the population-based and value-based targeting differentials increased moderately. Although lower than those based on the propensity score approach (comparing results in Table 8 and Table 6), the targeting differentials based on AF methodology are higher than that based on income poverty measures (comparing results in Table 8 and Table 4), which is robust with different weights and k values. Moreover, similar to results based on propensity score approach, we also find that the positive change of targeting performance occurred mainly in decreasing exclusion errors. The decomposition results of both population-based and value-based targeting differentials based on AF methodology reveal that Dibao's intra-village targeting accounted for more of its targeting performance than inter-village targeting, consistent with findings based on income poverty measures.

[7] The technical details of the AF methodology can be seen in Akire & Foster (2011) and Alkire et al. (2015).

Table 6
Dibao's targeting performance and its decomposition based on propensity score approach (N = 9973).

Poverty cutoff points determined based on:	Poverty rate using local Dibao thresholds		Observed Dibao participation rate		Poverty rate using rural official poverty line	
% eligible households	4.93		6.74		7.60	
Population-based targeting						
NG^p (Proportion of eligible households receiving Dibao)	0.378		0.354		0.355	
NG^n (Proportion of non-eligible households receiving Dibao)	0.053		0.048		0.045	
$NT = NG^p - NG^n$	0.325		0.307		0.309	
Decomposition of *NT*	Value	*%NT*	Value	*%NT*	Value	*%NT*
Inter-village component	0.100	30.87	0.094	30.77	0.094	30.32
Intra-village component	0.225	69.13	0.212	69.23	0.215	69.68
Value-based targeting						
VG^p (Average Dibao transfer value among eligible recipients)	639.236		556.948		553.370	
VG^n (Average Dibao transfer value among non-eligible recipients)	69.933		64.046		60.548	
$VT = VG^p - VG^n$	569.303		492.902		492.822	
$SVT = VT/VG^p$	0.891		0.885		0.891	
Decomposition of *SVT*	Value	*%SVT*	Value	*%SVT*	Value	*%SVT*
Inter-village component	0.255	28.63	0.253	28.56	0.252	28.32
Intra-village component	0.636	71.37	0.632	71.44	0.639	71.68

Table 7
Dimensions, indicators, deprivation cutoffs, and weights used in AF multidimensional poverty measurement.

Dimension	Indicator	Deprivation cutoff (deprived if...)	Weight1	Weight2
Income and assets	Pre-Dibao income per capita	Pre-Dibao income per capita < rural official poverty line (2300 yuan/year in 2010)	1/8	2/10
	Major appliances and vehicle ownership	Household owns none of the following: air conditioner, water heater, computer, camera, video camera, stereo system, mid- and high-grade music instrument, motorcycle, or car	1/8	2/10
Housing and utility	House area per capita	House area per capita <19 square meters (half of the median in full sample)	1/8	1/10
	Toilet	No flush toilet	1/8	1/10
Health	Health status	Any household member reporting bad health	1/8	1/10
	Catastrophic medical expenditure	Out-of-pocket medical expenditure/(pre-Dibao income - food expenditure) $\geq$40%	1/8	1/10
Education	Adult completion of primary education	No household member aged 16 years or older and not attending school has completed primary education	1/8	1/10
	Child school attendance	Any child aged 7–15 not attending school	1/8	1/10

Table 8
Dibao's targeting performance and its decomposition based on AF methodology (N = 9973).

	Weight1: k = 3/8		Weight1: k = 4/8		Weight1: k = 5/8		Weight2: k = 4/10		Weight2: k = 5/10		Weight2: k = 6/10	
% eligible households	22.36		8.40		1.91		18.05		8.44		3.18	
Population-based targeting												
NG^p (Proportion of eligible households receiving Dibao)	0.173		0.248		0.267		0.180		0.229		0.262	
NG^n (Proportion of non-eligible households receiving Dibao)	0.037		0.051		0.064		0.043		0.053		0.061	
$NT = NG^p - NG^n$	0.136		0.197		0.203		0.137		0.177		0.201	
Decomposition of *NT*	Value	*%NT*	Value	*%NT*	Value	*%NT*	Value	*%NT*	Value	*%NT*	Value	*%NT*
Inter-village component	0.043	32.00	0.052	26.50	0.057	28.21	0.043	31.66	0.048	26.95	0.053	26.46
Intra-village component	0.092	68.00	0.145	73.50	0.146	71.79	0.094	68.34	0.129	73.05	0.148	73.54
Value-based targeting												
VG^p (Average Dibao transfer value among eligible recipients)	261.486		408.567		557.753		267.641		377.302		461.920	
VG^n (Average Dibao transfer value among non-eligible recipients)	48.333		67.334		86.997		58.195		70.081		83.986	
$VT = VG^p - VG^n$	213.153		341.233		470.756		209.446		307.221		377.934	
$SVT = VT/VG^p$	0.815		0.835		0.844		0.783		0.814		0.818	
Decomposition of *SVT*	Value	*%SVT*	Value	*%SVT*	Value	*%SVT*	Value	*%SVT*	Value	*%SVT*	Value	*%SVT*
Inter-village component	0.220	27.03	0.180	21.53	0.183	21.73	0.204	20.41	0.168	20.68	0.186	22.71
Intra-village component	0.595	72.97	0.655	78.47	0.661	78.27	0.579	73.92	0.646	79.32	0.632	77.29

Table 9
Regression results on the effects of having political elite connection on Dibao participation and Dibao transfer value received (N = 9973).

	Logistic		Tobit	
	OR	SE	ME	SE
Household has political elite connection	1.441***	0.121	19.737***	4.876
Household head characteristics				
Age	1.003	0.004	0.216	0.237
Female	1.518***	0.163	27.565***	6.130
Education (Default: Primary school or less)				
Junior high school	0.833**	0.067	−10.927**	4.538
Senior high school or more	0.544***	0.086	−33.263***	8.527
Employment status (Default: Employed)				
Not employed	1.196**	0.096	12.937***	4.640
Retired	0.946	0.324	−11.214	20.221
Ethnic minority	1.336**	0.176	18.140**	7.681
Household characteristics				
Pre-Dibao income per capita (thousand yuan)	0.947***	0.009	−3.079***	0.588
Squared Pre-Dibao income per capita	0.999***	0.000	−0.065***	0.023
Financial assets per capita quartile 1 (Default)				
Financial assets per capita quartile 2	0.913	0.078	−7.836	4.969
Financial assets per capita quartile 3	0.758***	0.072	−15.012***	5.427
Financial assets per capita quartile 4	0.680***	0.082	−22.632***	6.566
Household size	0.841***	0.031	−13.443***	2.092
Share of members age <16	0.890	0.247	−1.301	15.619
Share of members age ≥60	1.412**	0.199	17.605**	7.978
At least one member reporting bad health	2.197***	0.169	43.762***	4.548
At least one member with disability	2.389***	0.197	55.952***	4.996
At least one member with migrant job	0.754***	0.061	−17.491***	4.652
Ln(house area per capita) (square meters)	0.954	0.070	−0.362	4.150
House construction materials (Default: Concrete and brick)				
Brick and wood	1.018	0.087	−0.005	4.863
Bamboo, grass, and adobe	1.051	0.120	6.090	6.655
Household has motorized vehicle	0.834**	0.067	−10.356**	4.598
Household has major appliances	0.731***	0.061	−21.288***	4.767
Household has flushing toilet	0.772**	0.096	−9.865	6.587
Catastrophic medical expenditure	1.280**	0.124	19.275***	5.701
Village characteristics				
Bus in the village	0.898	0.072	−5.266	4.565
Health care center in the village	0.794**	0.073	−17.167***	5.362
Kindergarten in the village	0.807***	0.061	−6.905	4.283
Distance to township gov't >10 km	0.949	0.100	−0.921	6.091
Distance to county seat >20 km	0.965	0.072	−8.592**	4.296
Land condition of the village (Default: Plain)				
Hills or low mountain	1.673***	0.170	32.448***	5.628
Mountain	1.993***	0.216	41.283***	6.141
Province fixed effects	Yes		Yes	
Log likelihood	−3190.1124		−11299.581	
Likelihood ratio test chi2	1848.59***		1937.69***	
Pseudo R^2	0.2246		0.0790	

Note: OR = odds ratio in logistic regression. ME = marginal effects on censored expected value in Tobit regression.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

7. Political elite capture in rural dibao's targeting

(a) Effect of political elite connection on Dibao participation and transfer value

In this section, we empirically test the possible political elite capture effect in rural Dibao's targeting. We estimate the influence of political elite connection on rural Dibao participation and transfer value received using the following equation:

$$DB_{ij} = f(Elite_{ij}, X_{ij}, Z_j) \tag{5}$$

We first explore the probability of receiving rural Dibao as a function of household political elite connection, controlling for household head characteristics, household characteristics, and village characteristics. Specifically, in Eq. (5), $DB_{ij}$is a dummy variable equal to 1 if household i in village j received Dibao. $Elite_{ij}$ represents the measure of household's political elite connection, which is also a dummy variable and equal to 1 if any household member or close relative is political elite. X_{ij} is a vector of household head and household characteristics, and Z_j is a vector of community characteristics. Both vectors X_{ij} and Z_j are described in Table 2. This equation also controls for province fixed effects to capture the unobserved provincial heterogeneity. As the dependent variable is binary, we estimate a logistic regression model and report the odds ratios (OR).

Second, we investigate whether political elite connection affected the rural Dibao transfer value received by households using the same specification as in Eq. (5). Because DB_{ij} in this case is a continuous variable representing the Dibao transfer value received by household i in village j and is censored at zero, we use a tobit regression model and report the marginal effects on the censored expected value.

Table 9 presents the results on the effects of political elite connection on rural Dibao participation and transfer value received based on Eq. (5). We find that political elite connection had a significant positive influence on both Dibao participation and transfer value received. Specifically, the logistic regression results (columns 1 and 2) show that having political elite connection was associated with a 44.1% increase in the odds of rural Dibao participation, and the tobit regression results (columns 3 and 4) show that having political elite connection helped increase household's rural Dibao transfer value by 19.74 yuan per person per year. These results suggest that, similar to many CBT programs in developing countries, China's rural Dibao is subject to political elite capture in its targeting practice (Besley et al., 2012; Caeyers & Dercon, 2012; Kilic et al., 2015; Pan & Christiaensen, 2012; Panda, 2015). These findings are also consistent with qualitative studies on elite capture in rural Dibao's targeting (Geng, 2012; Kuhn et al., 2016; Li & Walker, 2016; Wei, 2014).

(b) Which kinds of political elite connection matter more?

Enabled by detailed information on political elite connection available in the CHIP 2013 data, we further investigate the heterogenous effects of different kinds of political elite connection in rural Dibao. First, we compare the political elite capture effects between household members and close relatives. We use a set of mutually exclusive dummy variables to measure household political elite connection. These dummy variables include household has no political elite connection (default), any household member is political elite but no household close relative is political elite, and any household close relative is political elite but no household member is political elite. Because our purpose is to compare the difference of political elite capture effects between household members and household close relatives, those with both any household member or any close relative to be political elite are excluded (n = 111). Controlling for the same variables as in Table 9, we examine the effects of these political elite connection variables on rural Dibao participation and transfer value received based on logistic and tobit regression models respectively.

Second, we also investigate which types of political elite in household had a greater effect on rural Dibao participation and transfer value received. The political elites in household are subdivided into three types: village leader in the village of residence, political leader outside village of residence, and political party member without leader position. In order to compare elite capture effects across the different types of political elite in household, those who had two or more types of political elite in household are excluded (n = 16). We then use a set of mutually exclusive dummy variables to estimate the effects of having different types of political elite in household. Controlling for the same variables as in Table 9 and whether any household close relative is political elite, we estimate the respective logistic and tobit regression models on Dibao participation and transfer value received to examine the elite capture effects across different types of political elite in household.

Results in Table 10 show that, compared to households with no political elite connection, those with either a household member or close relative as political elite both appeared to have greater odds in Dibao participation and higher transfer values received. Further, the political elite capture effect from close relatives was larger in magnitude than that from household members. Specifically, households with a close relative but no household member as political elite had higher odds (OR = 1.642) than those with a household member but no close relative as political elite (OR = 1.422). The tobit regression results shows similar patterns regarding the Dibao transfer value received: those with a close relative but no household member as political elite received higher amounts of Dibao transfer (marginal effects = 24.30) than those with a household member but no close relative as political elite (marginal effect = 18.94).

The results of elite capture effects across different types of political elite in household are presented in Table 11. Among three types of political elite in household, having a household member either as a political leader outside village of residence or as a political party member without leader position was associated with greater odds of Dibao participation and higher transfer value received, while having a household member as village leader in the village of residence did not seem to have a political elite capture effect. Specifically, having a household member as a political leader outside village of residence was associated with an odds ratio of 2.427 for Dibao participation as compared to those with no household member as political leader, and the associated Dibao transfer value boost was 49.80 yuan. These effects were larger in magnitude than for households with a member as a political party member without leader position (OR = 1.319 for Dibao participation and marginal effects = 13.99 for Dibao transfer value received). It is somewhat surprising that the political elite capture effect from having a household member as a village leader in the village of residence was not significant statistically, which has been considered a key factor in community-based targeting of welfare programs.

Why were village leaders unable to capture Dibao benefits for their own households, despite that they are considered to have large influence on Dibao eligibility identification? Given that our results are estimated for 2013, two important policy developments may have contributed to this result. First, to rein in the increasing number of cases of gaining Dibao access through relationships or connections, the Ministry of Civil Affairs issued two regulations that led directly to increased transparency in Dibao's CBT and diminished influence of village leaders in this process. In December 2012, the "Methods for Screening and Approving Dibao Benefits"

Table 10
Comparison of elite capture effects between household members and relatives (N = 9862).

	Logistic regression results on Dibao participation		Tobit regression results on Dibao transfer value received	
	OR	SE	ME	SE
Household has no political elite connection (Default)				
Any household member is political elite but no household close relative is political elite	1.422***	0.130	18.938***	5.290
Any household close relative is political elite but no household member is political elite	1.642***	0.312	24.296**	11.088
Log likelihood	−3149.3065		−11192.694	
Likelihood ratio test chi2	1854.98***		1942.62***	
Pseudo R^2	0.2275		0.0799	

Note: In both regression models, all control variables in Table 9 are included. The groups are mutually exclusive, and households with both any household member or any close relative to be political elite are excluded (n = 111). OR = odds ratios in logistic regressions. ME = marginal effects on censored expected value in Tobit regressions.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 11
Comparison of elite capture effects across different types of political elite in household (N = 9957).

	Logistic regression results on Dibao participation		Tobit regression results on Dibao transfer value received	
	OR	SE	ME	SE
No household member is political leader (Default)				
Any household member is village leader in village of residence only	0.992	0.176	1.397	9.726
Any household member is political leader outside village of residence only	2.427***	0.538	49.798***	12.760
Any household member is political party member without leader position only	1.319***	0.137	13.994**	6.046
Log likelihood	−3171.1276		−11253.202	
Likelihood ratio test chi2	1860.08***		1947.89***	
Pseudo R^2	0.2268		0.0797	

Note: In both regression models, all control variables in Table 9 are included. The groups are mutually exclusive, and those who had two or more types of political elite in household are excluded (n = 16). OR = odds ratios in logistic regressions. ME = marginal effects on censored expected value in Tobit regressions.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

specified a set of standardized procedures to be used in Dibao's participatory appraisal within the village committees. This regulation made the standards and procedures of Dibao's CBT widely known and closely monitored, limiting the room of direct influence from village leaders. In October 2013, the "Notification about Establishing and Strengthening the Long-term Mechanism for Social Assistance Supervision and Inspection" specified a series of monitoring methods and established of a filing system of Dibao recipients who are close relatives of Dibao administrators and/or village leaders, further removing the discretionary power bestowed to village leaders in Dibao's CBT.

Second, the Chinese government launched a nationwide, far-reaching anti-corruption campaign following the 18th National Congress of the Communist Party held in 2012. It is the ruling party's largest anti-graft effort, covering nearly all levels of officials and all localities of China. As part of this grand campaign, several rectifications on corruption in rural Dibao's targeting was carried out nationwide. One particular focus in these rectifications was favoritism and other misconducts of village leaders in carrying out rural Dibao.

Under these conditions, village leaders no longer dared to capture Dibao benefits directly for their own households. They may turn to more inconspicuous strategies to manipulate rural Dibao's targeting to serve their own interests, as revealed by recent qualitative evidence (Li & Walker, 2016). For example, they may allocate Dibao benefits to their non-poor close relatives' households as well as other non-poor political elites' households in their village. Helping their close relatives to gain access to Dibao benefits is required by the reciprocity social norms in a kindship-based society in rural China (Kuhn et al., 2016). In order to gain support and endorsement in local elections or exchange for other economic or political interests, village leaders may choose to help households with political elites outside village of residence or party members to capture Dibao benefits in order to maintain and expand their political connections (Wei, 2014).

8. Conclusion and discussion

As one of the largest unconditional cash transfer programs in the world, the rural Dibao program was designed as a key component of China's grand campaign to eliminate rural poverty in recent years. The success of rural Dibao relies on how effective it can target poor households and lift their income. Although the central government stipulates its poverty targeting to be based on means testing, a decentralized community-based targeting (CBT) approach has been used widely in rural Dibao's implementation given the challenges in measuring household income accurately in the rural setting. The popularity of CBT in rural Dibao's practice reflects the consideration of its information advantages, which is helpful to improve Dibao's targeting performance with lower administrative costs. A set of rigorous evaluations has found sizable targeting errors in rural Dibao, which prompts us to pay closer attention to its targeting performance and examine empirically the potential reasons for its targeting errors.

Using recent nationally representative rural household survey data from CHIP 2013 and decomposable targeting differential measures, this article systematically evaluates rural Dibao's targeting performance based on income and multidimensional poverty measures, and further investigates the effects of political elite capture in its CBT implementation. The results suggest that, first, when based solely on income poverty measures, rural Dibao's targeting performance was quite poor. Second, although the central government policies stipulated poverty identification to be based on income, local communities in rural China considered multidimensional poverty-related factors in their determination of Dibao eligibility. Third, when based on multidimensional poverty, Dibao's targeting performance was better than that based solely on income poverty. Forth, the decomposition results of targeting differential shows that Dibao's intra-village targeting accounted for more of its targeting performance than inter-village targeting. Fifth, political elite capture effects were evident in both Dibao participation and transfer value received. Moreover, the political elite capture effect from close relatives was larger in magnitude than that from household members. Within the latter, having a household member being a village leader in the village of residence had no significant elite capture effect, whereas having members with a political leader position outside the village of residence or being a non-leader political party member was associated with increased access to Dibao benefits.

One important finding of this study is the reductions in the estimated targeting errors in rural Dibao when we move from using only income poverty to multidimensional poverty measures. These results echo those reported in recent studies on rural Dibao's targeting performance using different large-scale data sources (Golan et al., 2017; Han & Gao, 2017; Han & Xu, 2013). In reality, both local officials and poor people in developing countries tend to delineate poverty from a multidimensional perspective (Narayan et al., 2000), so multidimensional poverty measures are more commonly used as actual eligibility criteria in CBT implementation than solely income poverty measures. This is partly why evaluation results in conventional targeting analysis based on income poverty tend to overestimate rural Dibao's targeting errors, especially its exclusion errors. This important finding can help inform and enhance the field of welfare research not only in China but also around the world by adopting appropriate poverty measures in targeting evaluation.

However, findings from this article also show that, even when multidimensional poverty measures are used, there remain gaps and challenges in rural Dibao's targeting performance. Our analysis indicates that political elite capture in CBT was another source of rural Dibao's targeting errors, a finding that is consistent with evidence from some other CBT programs in developing countries (Besley et al., 2012; Caeyers & Dercon, 2012; Kilic et al., 2015; Pan & Christiaensen, 2012; Panda, 2015). We also delve further to investigate the heterogenous effects of different kinds of political elite capture in rural Dibao's CBT. While many existing studies from both China and other countries suggest that village leaders have great influences on welfare targeting (Besley et al., 2012; Panda, 2015; Chen, 2008; Hu & Wang, 2017), our nuanced analyses reveal that rural Dibao's elite capture effects were evident from having household members with a political leader position *outside* village of residence, those being a political party member *not* in a leader position, and household close relatives with a political leader position, rather than having household members with a village leader position *within* the village of residence.

This may be a result of villagers' heightened awareness of the Dibao program and greater participation in the CBT process, which helps limit village leaders' influence in Dibao access, as revealed in qualitative research (Li & Walker, 2016). In addition, China's recent stricter regulation on Dibao's targeting standards and procedures as well as the nationwide anti-corruption campaign have increased the penalty for capturing Dibao illegitimately, so village leaders are less daring to seize Dibao benefits directly. Nevertheless, village leaders may still have covert power to influence Dibao allocation, such as granting Dibao access to their close relatives or other elites such as political party members within the village. Indeed, our results show that the political elite capture effect from close relatives was larger in magnitude than that from household members.

As a consequence of several recent initiatives launched by the Chinese government, political elite capture may further decrease in the years since 2013. First, in 2014, the State Council issued the first formal law-like regulation on social assistance in China, "Provisional Regulations on Social Assistance." This regulation clearly stated the guiding principles and procedures in Dibao's targeting, further restricting the room for personal influence by local administrators and village leaders. Second, a relatively complete information system on family economic conditions has been established and applied in rural Dibao's targeting, partly preventing village leaders from manipulating the targeting procedures and outcomes. Third, a new wave of special rectifications on corruption in rural Dibao's implementation has been carried out since April 2018, which is planned to last for the next three years, possibly leading to longer-term decreases in political elite capture. Lastly, China launched a national targeted anti-poverty initiative (*jingzhun fupin*) in 2013, aiming to eradicate absolute poverty based on the current rural official poverty line by 2020. Rural Dibao is considered part of this grand initiative to provide a last-resort safety net for the rural poor. The close top-down monitoring adopted in this initiative and designated responsibilities for specific local officials to move certain poor households out of poverty serve as an additional vehicle to curb political elite capture in rural Dibao.

Drawing from our findings and these recent policy initiatives in China, two important policy and practice implications emerge. First, given the widespread application of multidimensional poverty measures as eligibility criteria in CBT implementation, the government should guide rural communities to establish more adaptive and rigorous multidimensional poverty frameworks in the community-based targeting of welfare programs like Dibao. In addition, multidimensional poverty frameworks should also be applied to the monitoring and evaluation of these programs' targeting performance. Second, meanwhile, governments and communities should be aware of the considerable discretionary power given to local leaders, and the potential for political elite capture should be curbed, especially in rural settings where such effects tend to be more prominent. Applying information management techniques in targeting procedures, enhancing transparency and accountability of the community-based targeting processes, and strengthening the monitoring and inspection systems are all essential for reducing the political elite capture effect in rural Dibao and similar programs around the world.

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